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**What is the Carroll Round?**

The Carroll Round is an international economics conference for undergraduate students held annually at Georgetown University in Washington, D.C. It takes the format of a professional academic conference at which students present their original research in international economics (broadly defined) that are typically honors theses. The goal of the Carroll Round is to foster the exchange of ideas among the leading undergraduate economics students by encouraging and supporting the pursuit of scholarly innovation. To date, over 400 students from universities and colleges in North America, South America, Western and Eastern Europe, Asia and Australia have participated, making the Carroll Round the premier conference of its kind. The conference also provides opportunities for participants to interact with prominent academic and policy economists. Alumni have moved onto top Ph.D., J.D., M.B.A., and other graduate programs, positions at the Federal Reserve, the World Bank, and other public institutions, and major private corporations.

**Notes on Paper Submissions and Conference Participation**

The Carroll Round Proceedings is a publication of synopses and full-length papers from the Carroll Round Undergraduate International Economics Conference at Georgetown University. We do not accept paper submissions from the general public. If you are interested in presenting at the conference, please log on to our website: http://carrollround.georgetown.edu. All undergraduate students who have written or are in the process of writing original work in the field of international economics (broadly defined) are encouraged to apply.
ACKNOWLEDGEMENTS

From its inception in 2001, the Carroll Round has grown from an ambitious dream of increasing discussion of economics amongst U.S. undergraduates to the premier undergraduate research conference in international economics in the country and around the world. Because this tremendous growth and the strong continuity of the conference would not be possible without the support of our donors, faculty, speakers, session chairs, and Georgetown University, the Carroll Round Steering Committee would like to represent those who have committed so much of their time and energy to making the conference a success.

We would first like to recognize Ms. Marianne Keler for her continued generosity and for establishing an endowment account to which every Carroll Round supporter can contribute toward the long-term institutionalization of the Carroll Round. Ms. Marianne Keler and Mr. Michael Kershow have been the primary contributors to and advocates of the Carroll Round since its establishment in 2001. Without this support, the Carroll Round would never have achieved fruition or continued for the past thirteen years. We thank Mr. Yunho Song, a Georgetown graduate and long-time supporter of the conference, who established an endowment fund that will partly finance the Carroll Round for many years to come. For his support and extremely generous financial contribution, we and all future participants of the Carroll Round are truly indebted.

The Carroll Round has been gifted with many other individuals committed to its cause. Therefore, we would also like to recognize Mr. Mario Espinosa, Mr. Oleg Nodelman, Ms. Colleen Murphy, Ms. Sarah Osborn, Mr. and Mrs. Kenneth Kunkel, and former Carroll Round Steering Committee members Mr. Scott Pedowitz, Dr. Andrew Hayashi, and Mr. Stephen Brinkmann. We express our gratitude to the Kanzanjian Foundation, which provided the startup funds without which it would have been impossible to develop the Carroll Round Proceedings.

Within Georgetown, the conference is indebted to Mr. Richard Jacobs, Mr. Mohamed Abdel-Kader, and Ms. Carma Fauntleroy, whom have made tireless efforts to advocate the Carroll Round cause from our campus’s development and advancement departments. We are also deeply appreciative of the efforts of Ms. Christine Smith, Mr. Thomas Esch, Dr. Venilde Jeronimo, Ms. Katerina Kulagina, Ms. Cara Sodos, Ms. Reema Ghazi, and Ms. Elizabeth Franzino from years past.

Additionally, we would like to recognize those individuals and institutions that have historically been essential to the current status of the Carroll Round. The donations of Mr. Peter Faulkner, Mr. John Kelly, Mr. James Moore, Mr. Philip Vasta, Mr. Geoffrey Yu, and the highly significant contributions from the Sallie Mae Corporation for the first five conferences have made previous endeavors possible and paved the path for future growth.

We would also like to give special recognition to former steering committee members, beyond those already mentioned, who have contributed very generous portions of their post-collegiate income to the Carroll Round after graduation. Among them, we would like to especially thank Mr. James Arnold, Ms. Meredith Ballotta, Ms. Amanda Delp, Ms.
ACKNOWLEDGMENTS

Stacey Droms, Mr. Brandon Feldman, Ms. Yasmine Fulena, Ms. Daphney Francois, Mr. Christopher Griffin, Ms. Rebecca Heide, Mr. Dennis Huggins, Ms. Cindy Jin, Mr. Dan Leonard, and Mr. J. Brendan Mullen. Beyond the financial viability of the Carroll Round, the conference has also enjoyed the grace of many proponents on Georgetown University’s campus to ensure its continuing and vibrant existence. In particular we would like to thank Dean Carol Lancaster of the School of Foreign Service, Dean Kendra Billingslea, Mrs. Denisse Bonilla-Chaouï, Mr. Beau Boughamer, Ms. Rebecca Ernest, Dr. Dan Powers, Mr. Benjamin Zimmerman, and Mr. Franz Hartl. We would like to recognize Dean Robert Galuccì as well, who supported the development of the Carroll Round from the inception of the conference to his retirement from Georgetown in 2009.

The Carroll Round has been fortunate for the last thirteen years to enjoy the substantive quality of the brightest economics undergraduates from across the world. We are particularly grateful to those professors that steer their best students to the Carroll Round, especially Professor Nancy Marion of Dartmouth College, Professor Judith Shapiro of the London School of Economics, Professor Michael Seeborg of Illinois Wesleyan University, Dr. Gianna Boero of Warwick University, and Professor Ian Walker of Lancaster University.

We also enjoy the professional experience and wisdom of some of the most respected economists in the field. For the Twelfth Annual Carroll Round, we were particularly lucky to have presentations from Professor John Taylor from Stanford University and Professor Janet Currie from Princeton University. Also critical to the substantive development of the Carroll Round and our participants’ work are the session chairs who take the time to read participants’ papers and critique their presentations at the conference. We would like to thank the 2013 session chairs for their contributions to the conference: Professor William Jack, Professor Anna Mayda, Professor Shareen Joshi, Ms. Faina Rozenthal from the OECD, Professor Anders Olofsgard, Professor Charles Udomsaph, Professor Arik Levinson, and Professor Dan Cao.

We thank the past Carroll Round Steering Committees, which have shaped and directed the development of the conference into its current state today. We are also indebted to the contributions of the Carroll Round Advisory Panel for their assistance in developing a long-term vision for the Carroll Round and for grounding the future of this institution.

Finally, though not least importantly, we would like to express our ever-growing gratitude to Dean Mitch Kaneda, the Carroll Round Faculty Advisor. Without his support, time, and passion, this endeavor would not be possible.
Each year when April is on the horizon, I realize how the Carroll Round is at once completely recognizable as the successor to the first conference weekend and unlike anything my friends on the inaugural committee imagined. Accepted paper quality has increased exponentially, and the weekend’s highlights are the students’ masterful presentations as much as the keynote speeches. None of these advances would be possible without the extraordinary work of the Georgetown students who organize the Round and of course the global contingent that descends on the nation’s capital each year. Other alumni and I remain awestruck by the effort, dedication, and commitment of each successive participant group. Despite the need always to look ahead, reviewing one’s origins is equally important. During the first year, the ingenuity and dedication of a stellar group of Georgetown students, combined with the contributions of remarkable young scholars from around the country, showed how strong undergraduate economics—and the work of undergraduate economists—can be.

The conference’s birthplace, as many know by now, was an Oxford pub called the Radcliffe Arms. Even though that tale is completely true, the Carroll Round’s roots extend firmly and unambiguously to the Georgetown University campus. For it was there that an incredible team of friends and colleagues assembled and launched the event in 2001.

Throughout the 1999-2000 academic year, I had the great pleasure of meeting and learning alongside seven outstanding economics classmates. My first meaningful discussions about economics took place that year with fellow students Andrew Hayashi and Ryan Michaels. Andrew and I were both enrolled in Professor Mitch Kaneda’s International Trade class that semester, and Ryan suffered with me through Microeconomic Theory as well as the demanding Introduction to Political Economy. I remember feeling intimidated at first by their boundless knowledge of theory and their irrepressible enthusiasm for learning. Over time I realized the extent to which I was learning from them as much as our instructors; their insights often proved more valuable than the content of weekly lectures. I also became acquainted with a second group of classmates, including Bill Brady, Josh Harris, Kathryn Magee, Brendan Mullen, and Scott Pedowitz. By the spring, our paths all pointed to Europe: Bill, Kathryn, and Scott were on their way to the London School of Economics; Brendan had chosen the University of Bristol, and Josh was destined for Poland and Hungary. Andrew, Ryan, and I planned to spend our year abroad at the University of Oxford studying a mixture of philosophy, politics, and economics. Before departing in October 2000, I knew our shared plans were not the product of mere coincidence. Something special would emerge from the experience.

Having established initial ties at Georgetown, the three of us began meeting on a regular basis to discuss our latest tutorial sessions, grueling problem sets, the future of macroeconomics and, occasionally, the latest gossip about luminaries in the field. Whereas C.S. Lewis, J.R.R. Tolkien, and the other Inklings made The Eagle and Child pub their
intellectual home away from home, we adopted the Radcliffe Arms as our haven. Over pints and pub food, Andrew’s twin passions for game theory and philosophy emerged. The future of monetary policy and development began to vex Ryan’s thoughts, while I hoped to better understand the mechanisms of cooperation, or conflict, underlying international trade institutions.

Meanwhile at Pembroke College, I encountered a group of students from universities across the country also spending their junior years at Oxford. I naturally befriended the other economists in our contingent, but I also developed close relationships with physicists, biologists, literary scholars, and art historians. In the Junior Common Room, a student lounge of sorts for undergraduates, or over traditional English dinners in the dining hall, we shared stories about life at our respective universities and the latest research we were conducting at Oxford. As thesis and postgraduate plans matured during these conversations, I appreciated ever more my exposure to alternative experiences and approaches to scholarship. The year eventually came to an end, and I worried that these exciting connections would dissolve upon return to the United States.

One evening at the start of my final term in Oxford, I thought about the importance of this dialogue and my growing affinity for international economics. I had a distressing feeling that undergraduates, especially in economics, were not afforded adequate opportunities to present their work in a serious setting. After all, I always felt privileged when Andrew, Ryan, and my fellow Pembrokians shared their original ideas with me. I thought that undergraduate economists from around the country deserved an event in which they could interact significantly with each other and the professional academic community. In March 2001, I composed a memo that outlined my solution: the Carroll Round. The following paragraph from that proposal captures my motivating thoughts:

As they prepare for careers in academia, public service, and business, undergraduate students throughout the country also have joined a momentous dialogue in collegiate, national, and global fora. Many are involved in independent research representing the next generation of critical thought in international relations. Others have enjoyed unique experiences through jobs and internship programs that expose them to the front lines of economic policy-making and statecraft. Young women and men also have championed vociferously environmental and labor-related causes through awareness and service programs. Clearly, these timely economic issues are assuming greater importance for the future of international relations and are reflected in the abundance of attendant student research, interest, and initiative. Therefore, I propose to coordinate and host, in association with Georgetown University’s School of Foreign Service and John Carroll Scholars Program, the next ‘round’ of economic and political discussion and debate—the Carroll Round.

I invited Andrew and Ryan to join me in this endeavor over pints at the Radcliffe Arms
History

even though there was no guarantee they would think it a good idea. I was confident that if such rising stars believed in the concept, other students would join in time. Having worked out more substantive ideas over the summer, I finally was prepared to call upon the other economics celebrities in my class to collaborate on the project. Bill, Josh, Kathryn, Brendan, and Scott fortunately signed on and completed the senior circle. A few months later we welcomed four more students: Cullen Drescher, Mark Longstreth, Waheed Sheikh, and future Chair Meredith Gilbert to encourage younger students and ensure continuity for the future.

With the unflagging assistance of then-John Carroll Scholars Program Director John Glavin, the proposal was circulated among university administrators. After gaining their initial support, I asked Mitch Kaneda, my most influential undergraduate teacher and a newly appointed Associate Dean of the School of Foreign Service, to review the proposal. Without hesitation—and somewhat to my surprise—he offered his assistance, embarking on an indefinite and irreplaceable stewardship of the Carroll Round. Former Dean Robert Gallucci and his staff also extended moral and financial support, which cemented our institutional place at Georgetown.

The first Carroll Round Steering Committee struggled through many difficult decisions regarding conference content, format, and funding. Should submitted papers be limited to topics in international economics? What elements must be included in submissions and presentations? How do we ensure that financial constraints do not prevent the best students from attending? Over marathon sessions in Healy Hall and at the Tombs, we developed a model for the Carroll Round that has largely remained intact. Development Officers shared our ideas with generous alumni who responded favorably and pledged individual donations. Little by little, our initial concepts materialized into reality. When School of Foreign Service alumna Marianne Keler ‘76 convinced the Sallie Mae Fund to contribute $10,000 to the Carroll Round, we both gained a lead sponsor and secured the long-term future of the conference. Since that year, Marianne has been gracious in her support and instrumental in expanding our reach to new global partners, including the American University in Bulgaria.

After distributing colorful brochures, contacting the top departments in the country, and preparing the Hilltop for the event, applications streamed in during the spring. By late March, we had narrowed our list of invited students to thirty-two. Seniors traveled to Washington from as near as the University of Virginia and as far as Stanford University. The Committee was stunned by the participants’ and their home departments’ enthusiasm. Among the more notable responses, Illinois-Wesleyan University sent four young economists to the conference and soon after published a special Carroll Round edition of their undergraduate economics journal.

The first Carroll Round officially began on Friday April 5, 2002, and the proceedings came to a close two days later. Participants enjoyed an exclusive audience with Director of the National Economic Council Lawrence B. Lindsey in the beautiful Riggs Library
before hurrying to the Federal Reserve for another private meeting with former Vice Chairmen Roger W. Ferguson and Donald L. Kohn. The two monetary policy experts shared candid stories about the effects of September 11, 2001 on the nation’s banking system and the various roles that the Federal Reserve plays in American economic activity. Dr. John Williamson of the Institute for International Economics spoke about development issues over a splendid dinner at Caffè Milano, and Dr. Edwin M. Truman, former Assistant Secretary of the U.S. Treasury for International Affairs, closed the conference with words of wisdom to students considering careers in academia and policymaking.

A total of twenty-eight papers were presented over the weekend, showcasing the impressive work of men and women now at the forefront of academia, law, and business. Georgetown professors who served as panel discussants later remarked that the quality of some presentations met or surpassed the sophistication of recent graduate-level dissertations. Judging by their comments, the conference brought together some of the best young prospects in economics as they approached the frontiers of research.

I never imagined in March 2001 that the first Carroll Round would attain the heights realized one year later, or for that matter even exist. The event has grown since then in size and scope beyond my initial hopes. The participation of Nobel Laureates from John F. Nash, Jr., in 2004 to Peter Diamond ten years later, as well as Susan Athey, the first female recipient of the John Bates Clark Medal, in 2008 mark special peaks in the evolution of the conference. Indeed, this historical slate of speakers could not be more finely tuned to the spirit of the Carroll Round. The groundbreaking work that each has contributed to the study of international economics, including numerous articles and books designed to influence lay readers and public policy decision-makers, serve as exemplars for other scholars and practitioners.

Looking to the Carroll Round’s future, I still hope that students from the developing world eventually will be able to attend. Regardless of their home institutions, I continue to enjoy meeting participants and learning about their research interests. As they share in the excitement of presenting their work and the occasional trepidation of fielding questions, I feel humbled to be among such gifted individuals. In fact, alumni from previous years have advanced to graduate study at Berkeley, Chicago, Cornell, Duke, MIT, Michigan, Minnesota, Northwestern, Oxford, Princeton, Yale, and Wisconsin as well as top government and finance positions around the country. Past participants now are tenure-track members of economics faculties including: Santosh Anagol at the University of Pennsylvania Wharton School, Andrew Hayashi at the University of Virginia School of Law, Ryan Michaels at the University of Rochester, Raphael Schoenle at the Brandeis University International Business School, and Tom Vogl at Princeton University. The cadre of former conference participants truly has grown into a professional and academic network unlike any other for young economists.

As always, I thank the Kazanjian Foundation for their generous support, which makes annual publication of the Carroll Round Proceedings possible. I also would like to
extend my unwavering gratitude to the members of the inaugural Carroll Round Steering Committee without whom this history would have remained fiction. I have great respect and admiration for successive Chairs from Seth Kundrot in 2003 to Glen Russo in 2013. Those leaders and all in between ensure the success of the Carroll Round each year and deserve our appreciation.

The Carroll Round received a donation not long ago, much like the original Sallie Mae Fund contribution, which created an endowment for the conference thanks to the largesse of School of Foreign Service alumnus Yunho Song ‘86. I distinctly remember meeting with him and some of my closest friends at the Tombs to discuss our fledgling project, uncertain that fall semester in 2001 whether it would ever see the light of day. He was instrumental then in making the Carroll Round a reality, and he now has solidified its place within the fabric of Georgetown and the School of Foreign Service. For that, all of us who have watched the conference grow extend our heartfelt gratitude. The spirit of his gift, though, should live on through us. Support from alumni, not just of the financial variety, maintains the conference’s vibrancy long after the proceedings conclude. I encourage each of you to return to Georgetown in April and to consider making any donations to the Carroll Round fund when possible.

Finally, and as always, I must thank Mitch Kaneda who has miraculously preserved my vision for the Carroll Round over the years and watched over past Committees as they built upon its initial success and joined the ranks of distinguished alumni. With his continued collaboration and the eagerness of future Georgetown students, the Carroll Round’s future will dwarf the accomplishments of its past, creating even more exciting opportunities for undergraduate economists to learn from the best in the field and, more importantly, from each other.

Christopher L. Griffin, Jr.
Georgetown Class of 2002
Carroll Round Founder
INTRODUCTION

WHY I SUPPORT THE CARROLL ROUND

Observing our undergraduates grow and develop intellectually over four years is one of the great pleasures of academic life. And playing some small role in that growth and development is wonderfully rewarding. I look forward each year to the Carroll Round because it provides an opportunity to see the work that our students as well as their peers from other universities have done.

At the same time it provides a change to reflect on how far the Carroll Round itself has come. More than a dozen years ago, Christopher Griffin, Andrew Hayashi, and Ryan Michaels returned from Oxford, where they spent their junior year, with the idea of creating a research conference of undergraduates. Ryan was one of my advisees at the time. I recall him telling me of their idea and thinking that it would take a lot to pull it off. And when I witnessed what they and several others working on the inaugural Carroll Round had done, I was duly impressed both with how large, well thought-out, and well organized it was and with the high quality of the papers. Since then, the Carroll Round has gone from strength to strength.

I have become a strong believer in the value of independent research in the undergraduate experience. By its nature, independent research is an integrative, hands-on experience that is as difficult to achieve in other ways, as it is valuable to intellectual growth. The researcher needs to define a question, devise a path to answering that question, and then solve a series of problems along the way. In doing so she or he needs to draw upon what she or he has learned in a variety of classes, gathering tools from economic theory and econometrics as well as from various applied courses. And, perhaps even more importantly, the researcher must go on to learn new things without the benefit of textbooks and coursework.

The research process begins with what might be the most difficult step – turning thoughts about an area of interest into a well-defined, answerable question. In addition to the intellectual demands that are part of independent research, the process takes the undergraduate beyond the familiar structured environment of typical course work. The outcome of the research is uncertain: Will the idea work out? Will the data be of sufficient quality to provide clear-cut answers? The process can be frustrating as well as fraught with uncertainty. Because independent research is so new, the researcher is out of his or her comfort zone. But few things are as rewarding as a research project as it comes together with answers to one’s questions and new questions to pursue.

Participating in the Carroll Round represents the culmination of the research process
to the participants. Presenting the final product is an integral part of the process and one that is made possible by the Carroll Round. I am grateful to the students who organize the conference and to those providing the financial support that makes the Carroll Round possible each year.

Robert Cumby
Professor of Economics
School of Foreign Service, Georgetown University
CARROLL ROUND PROCEEDINGS

The Twelfth Annual Carroll Round
Undergraduate Economics Conference
ABSTRACT

Is a boom (expansion) in higher education a bane or boon to an individual’s wage? Between 1988 and 1994, there was a series of expansionary higher education policies in the United Kingdom (UK) which saw a huge increase in the number of university graduates. This paper therefore attempts to study the effect of this expansion of higher education on an individual’s wage. I present a simple conceptual framework that shows that the increase in university places (expansion of higher education) leads to both private and composition effects on wages that move in opposite directions. The empirical strategy in this paper uses the fact that the expansionary policies induced exogenous variations in the number of university places for each cohort and each region within the UK. I exploit this “natural experiment” by using a difference-in-differences regression. This enables me to analyse how the expansion of higher education affects an individual’s wage. My baseline regression results suggest that the effect of the expansion was associated with a positive and highly significant 5.57 percent increase in an individual’s wage. The positive effect on an individual’s wage means that the positive private effect dominates the negative composition effect. In this context, the expansion seems beneficial to an individual’s wage.

Acknowledgments

I would like to thank my supervisor, Dr. Camille Landais, for his generous support and feedback throughout the course of this project. I am most grateful to Dr. Henrik Kleven for his feedback during my presentation and to Kevin Low, Kenneth Lim, Yi Da Chok, Chia Hwei Chong, Wenya Cheng and Dr. Judith Shapiro for their support and advice throughout this research. I would also like to thank fellow participants at the 12th Carroll Round Conference at Georgetown University, as well as EC331 seminar participants for their helpful comments and suggestions. I acknowledge the Economic and Social Data Service (ESDS) for access to the Labour Force Survey and Quarterly Labour Force Survey data. All mistakes or inconsistencies are solely mine.

1 Introduction

Labour economists have long been concerned with the question of whether an increase in educational attainment causes an increase in wages. At an individual level the empirical relationship between an individual’s education level and wages is generally clear – education is positively correlated with wages. However, beyond the individual level, at a national level, due to composition effects, it is not so clear how more people in a country acquiring more education would affect an individual’s wage.

I therefore attempt to find out how the expansion of higher education affects an individual’s wage by exploiting the dramatic government policies to expand higher education in the United Kingdom (UK). Between 1988 and 1994, there was a series of expansionary higher education policies which saw a huge increase in the number of university graduates. The proportion of each cohort attending higher education had been stable at approximately 15 percent in the early-1970s to late-1980s. However, by 1994, this proportion had increased notably to above 30 percent of each cohort.

The empirical strategy in this paper uses the fact that the expansionary policies induced exogenous variations in the number of university places for each cohort and each region within the UK. I exploit this “natural experiment” by using a difference-in-differences regression to analyse how the expansion of higher education affects an individual’s wage. The combination of these two variations (cohort and region) is treated as exogenous. I test my identification assumption by showing that among the early cohorts who were not exposed to the expansion because they had already
graduated when the expansion took place, the effect on wages for these early cohorts is not correlated with the intensity of the expansion. My empirical strategy is analogous to the one used by Duflo (2001) in her study of how the construction of primary schools affected wages in Indonesia. I find that the expansion of higher education in the UK had a positive and significant effect on wages. In particular, I find that a 1 percentage point increase in the percentage of university graduates in a given cohort leads to a 5.57 percent increase in an individual’s wage. I interpret this finding using a proposed conceptual framework, which suggests that the increase in wage is due to the positive private effect dominating the opposing negative composition effect.

In order to test the robustness of my results, I introduce more cross-sectional variation and control for further possible confounding trends by running a triple-differences regression specification. Drawing from the work of Bertrand, Duflo and Mullainathan (2004) and Donald and Lang (2007), I also discuss the validity of the standard errors of the coefficient estimates. In addition, I will discuss if my results are affected by individuals migrating to take advantage of the different intensity of expansion across the regions. Lastly, I examine if my results are biased by sample selection.

This paper is related to the existing literature in that it considers the relationship between education and wages. The existing literature can be broadly classified into two categories – papers that examine how an individual’s education decision affects his own wages and papers that examine the change in the graduate (college) wage premium due to an increase in the overall skilled-labour supply within a country.

At an individual level, empirical evidence is generally consistent that education is correlated with higher wages. Notable studies examining this relationship include Angrist and Krueger (1991), Oreopoulos (2006) and Devereux and Hart (2010). They estimate the returns to schooling as somewhere in the region of 3-7 percent. While the empirical relationship is clear, there is much theoretical ambiguity over the interpretation of this correlation. Mincer (1958) and Becker and Chiswick (1966) argued that standard human capital models suggest that education increases the productivity of workers and should hence result in an increase in their wages. Conversely, Spence’s (1973) signalling model suggests that education does not improve productivity but serves to signal a worker’s ability to potential employers. Tyler, Murnane and Willett (2000) found evidence for the signalling theory because the use of the General Educational Development (GED) certificate as a signal increased the earnings of young white dropouts by 10 to 19 percent. However, to this day, the theoretical ambiguity over the interpretation of the positive correlation between education and wages continues.

Although education is positively associated with an increase in wages, some papers have attempted to show that too much education for an individual is no good. This is known as the overeducation phenomenon. Dolton and Vignoles (2000) and Chevalier (2003) found that there was a wage penalty associated with being overeducated. However, these studies typically suffer from measurement error and other endogeneity issues.

The second broad category is concerned with what happens to the graduate (college) wage premium when there is an increase in skilled-labour supply. Using a demand and supply framework, Angrist (1995) found that because of a large number of new graduates entering the labour market, the graduate wage premium fell from 40 to 20 percent for Palestinian students. This represents a huge general equilibrium effect. Katz and Murphy (1992) and Card and Lemieux (2001) use the canonical model assumptions1 to impose a structure on the production function and wage determination process. They found that the variations in the graduate premium can mostly be explained by variations in the supply of college graduates. Fortin (2006) also found that there is a significant negative relationship between state specific own-cohort relative supplies and state-specific college premium. Walker and Zhu (2008) found little reduction in the graduate wage premium for men but they found a rise in the graduate wage premium for women. Most of these papers are limited because they assume that the changes in supply, demand and composition are exogenous. However, this assumption is likely to be

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1The canonical model assumes a competitive labour market and two types of workers (high and low-skilled). The substitution between the two types of workers is modelled using a constant elasticity of substitution (CES) aggregate production function.
violated since the characteristics of the people in the graduate and non-graduate groups are likely to be different when we compare before and after the expansion.

Carneiro and Lee (2011) noted that although the existence of composition (quality) effects is well recognised, very few empirical studies directly searched for composition effects. Some exceptions such as Juhn, Kim and Vella (2005) and Carneiro and Lee (2011) used US data and found that without controlling for quality, conventional demand and supply models tended to overstate the effect of an increase in graduate labour supply on the graduate wage premium.

The existing literature tends to treat the individual and national level analyses as separate. Individual level studies tend to ignore the composition effects associated with more people in a country acquiring more education. Conversely, national level studies focus on the graduate wage premium and do not consider what happens to individuals’ wages. This paper therefore seeks to bridge this gap by combining both the individual and composition effects in the examination of how the expansion affected individuals’ wages. The rest of this paper will be organised as follows. In Section 2, I present a simple conceptual framework. In Section 3, I describe the background of the higher education expansion. In Section 4, I discuss the data. Section 5 provides a detailed discussion of the empirical strategy. Section 6 presents the estimated results. Section 7 provides some robustness checks and further discussions. Section 8 concludes.

2 Conceptual Framework

I present a simple framework that shows that the impact of an increase in university places (the expansion of higher education) on an individual’s wage can be decomposed into two opposite effects – a private effect and a composition effect. I will subsequently use this simple conceptual framework to interpret my regression results which seek to uncover the net magnitude of these opposing effects.

Assume that firms offer an individual \(i\) (born in region \(a\) from cohort \(c\)) wages based on the individual’s schooling level \(S_i\) and \(\bar{S}_{ac}\), which is the average schooling level of the cohort in the region the individual belongs to. Firms treat \(S_i\) and \(\bar{S}_{ac}\) as given. Further suppose that \(S_i\) and \(\bar{S}_{ac}\) are both functions of \(P_{ac}\) which is the number of university places in each region for each cohort.

In equilibrium, an individual’s wage is:

\[
w(S_i, \bar{S}_{ac}) = w(S(P_{ac}), \bar{S}(P_{ac}))
\]

\(S_i\) does not affect \(\bar{S}_{ac}\). The assumption is that there are many individuals and so a person’s individual schooling decision is too small to have an impact on the average schooling level of his cohort in the region he is from. However, if all individuals take advantage of the increase in university places by increasing their individual educational levels, this would increase \(\bar{S}_{ac}\).

The change in individual wages as a result of the change in the number of university places is given by taking the total differential of the wage equation:

\[
\frac{dw_i}{dP_{ac}} = \frac{\partial w_i}{\partial S_i} \times \frac{\partial S_i}{\partial P_{ac}} + \frac{\partial w_i}{\partial \bar{S}_{ac}} \times \frac{\partial \bar{S}_{ac}}{\partial P_{ac}}
\]

This means that the impact of an increase in the number of university places depends on the private effect \(\frac{\partial w_i}{\partial S_i} \times \frac{\partial S_i}{\partial P_{ac}}\) and the composition effect which is given by \(\frac{\partial w_i}{\partial \bar{S}_{ac}} \times \frac{\partial \bar{S}_{ac}}{\partial P_{ac}}\). I will show that the private effect is positive but the composition effect is negative.

2.1 Private Effect

The private effect is \(\frac{\partial w_i}{\partial S_i} \times \frac{\partial S_i}{\partial P_{ac}}\). In general, both the signalling and human capital theories are consistent with the empirical correlation that as an individual acquires more education, his wage increases. This suggests that \(\frac{\partial w_i}{\partial S_i} > 0\). For example, Angrist and Krueger (1991) demonstrated this
positive causal relationship for the human capital theory while Tyler, Murnane and Willett (2000) found this positive causal relationship for the signalling theory. Theory also suggests that $\frac{\partial S_i}{\partial P_{ac}} > 0$. An increase in the number of university places implies that the marginal students who were previously unable to enter university would now be able to do so post-expansion. Ceteris paribus, the probability of an individual entering university increases. This motivates a student to work harder and acquire more years of schooling since it is now easier (less costly) to enter university. This interpretation is consistent with existing works such as Carneiro and Lee (2011). Since both $\frac{\partial w_i}{\partial S_i}$ and $\frac{\partial S_i}{\partial P_{ac}}$ are positive, the private effect given by $\frac{\partial w_i}{\partial S_i} \times \frac{\partial S_i}{\partial P_{ac}}$ is positive.

2.2 Composition Effect

The composition effect is $\frac{\partial w_i}{\partial S_{ac}} \times \frac{\partial S_{ac}}{\partial P_{ac}}$. By definition, $\frac{\partial S_{ac}}{\partial P_{ac}} > 0$. This is true if we assume that all the increased university places are filled, and so the average schooling level of a cohort in a region must increase by definition. On the other hand, $\frac{\partial w_i}{\partial S_{ac}} < 0$. An increase in university places is likely to decrease the quality of $\bar{S}_{ac}$ (average cohort schooling level). This is because when there are more university places, students who previously could not qualify for university are now able to do so. The marginal university student will be of lower quality than the average. Therefore even though the average cohort schooling level is increasing, the quality actually falls. This consequently leads to a fall in wages. Given that $\frac{\partial w_i}{\partial S_{ac}}$ is negative and $\frac{\partial S_{ac}}{\partial P_{ac}}$ is positive, the overall composition effect is hence negative.

2.3. Empirical Implications

Since the private effect and the composition effect move in opposite directions, the overall sign of $\frac{dw_i}{dP_{ac}}$ is ambiguous. Therefore, there is a need for empirical analysis to test which of these two effects dominates. In this paper, I assume that the series of expansionary higher education policies (the details of each of these policies will be elaborated in the immediate section) resulted in a change in $P_{ac}$ which is the number of university places in a cohort for a given region. I can only identify the net effect of the opposing private and composition effects on an individual’s wage. I am unable to disentangle how much of the wage change is attributed to each of these two opposing effects.

3 The Expansion of Higher Education

Between 1988 and 1994, there was a series of expansionary higher education policies in the UK, which saw a huge increase in the number of university graduates. In line with the existing literature such as Walker and Zhu (2008) and Devereux and Fan (2011), I assume that individuals start university at nineteen years old. Based on official statistics, Figure 1 shows that the proportion of each cohort participating in higher education (this is inclusive of universities, polytechnics and colleges) had been stable at approximately 15 percent in the early-1970s to late-1980s. However, beginning 1989, it started to increase dramatically and by 1994, this proportion was above 30 percent of each cohort.

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2 In order for this to hold, we need to assume that there is no spill-over effect (or if there is, it does not dominate) associated with having a more highly educated workforce.
At a more disaggregated level, instead of looking at higher education as a whole, I examined only universities. Figure 2 therefore presents the proportion of each cohort with a degree or higher degree as their final qualifications. Figure 2 also shows the proportion of each cohort with A-Level (or its equivalent)\(^3\) as their final qualifications.

The reason for this drastic expansion and levelling off can be attributed mainly to three policy interventions, namely, the Education Reform Act 1988, the Further and Higher Education Act 1992 and the 1994 cap on university enrolment numbers.

### 3.1 Education Reform Act 1988

Abbott, Rathbone and Whitehead (2012) noted that the purpose of the Education Reform Act 1988 was to introduce marketization and competition to the education sector. Maclure (1989) and Williams (1990) argued that in the years preceding 1988, universities were focused on research and quality of education. This was generally at-odds with the government’s social and economic objectives such as whether there were enough graduates to engage in high-value economic activities to increase economic growth in the UK. The outcome was hence fewer graduates than what the government would ideally want.

\(^3\) Performance on the A-Level exams (or its equivalent) determines entry into university.
In order to align the government’s aspirations with the universities’ objectives, the 1988 Act changed the way universities would receive public funding. Previously, the government allocated public funds to the University Grants Committee (UGC) who then apportioned and distributed the funds to the universities based on academic considerations. The 1988 Act abolished the UGC and replaced it with the Universities Funding Council (UFC). Maclure (1989) noted that the UFC was composed largely of non-academics (in contrast to the UGC) and received instructions from the government on what terms and conditions the universities have to comply with in order to receive the funding. One of these terms was an increase in university places. Consequently, universities expanded their enrolment numbers to achieve the objectives that came with funding.

3.2 Further and Higher Education Act 1992

The 1992 Further and Higher Education Act granted university status to 35 polytechnics, resulting in a direct expansion of capacity. Bathmaker (2003) noted that the purpose of bringing an end to the binary divide of universities and polytechnics was because the government felt that this would facilitate greater competition between the universities and the now former polytechnics. This would improve the universities’ efficiency and would in theory lead to a greater expansion of student numbers at reduced cost.

3.3 The 1994 Enrolment Cap

The increase in university enrolment as a result of the two Acts was so rapid and unexpected that it caused an unanticipated strain on public funding. Mayhew, Deer and Dua (2004) noted that this prompted the Higher Education Funding Council for England (HEFCE) to cap university enrolment numbers across the UK in 1994. Shattock (1998) noted that universities would be “fined” if they overshot the target numbers adopted by the Funding Councils and they would be subjected to financial “claw back” if they undershot them.

3.4 Empirical Implications

In line with the existing literature such as Walker and Zhu (2008) and Devereux and Fan (2011), I assume that the timing of this series of expansionary higher education policies is exogenous in my empirical analysis of its effect on individual wages. This is indeed plausible given that the expansion was so rapid and unexpected that the government had to even introduce an enrolment cap in 1994. However, while Walker and Zhu (2008) and Devereux and Fan (2011) do not test this assumption, I test this assumption by running a placebo regression to show that the expansion did not affect the older cohorts who were not exposed to it. I also assume that the 1988 Act took a year to take effect, and so the expansion affected those who were 19 years old (the 1970 cohort) in 1989 and ended by 1994 (which corresponds to the 1975 cohort).

Furthermore, because the 3 policy interventions took place over 1988 to 1994, the cohorts born in 1970 to 1975 were only “partially treated” by the expansion. Since I am interested in estimating the full treatment effect of the expansion on wages, I use only the cohorts that were fully exposed to the expansion (those born in 1976 to 1979) and the cohorts that were never exposed to the expansion (those born in 1962 to 1969). I do not study the 1980 cohort onwards because these cohorts were affected by the Teaching and Higher Education Act 1998. Before this Act, tuition fees were free but the Act introduced university tuition fees that had to be paid by students.

Although the term higher education encompasses universities, polytechnics and colleges, I will only be examining the expansion in terms of the universities. Furthermore, given data limitations, I am unable to disentangle the effects of each of the 3 policy interventions. This paper hence examines the three policies collectively and estimates the joint effect of these policies. I will henceforth refer to these three policies collectively as the “expansion of higher education” which resulted in an increase in the number of university places and hence graduates.

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4 The cap was subsequently removed for the 2001–2002 academic year.
5 The data that I am using does not indicate if an individual graduated from a former polytechnic or a university.
4 Data

This study uses data from the first quarter of 2002 to the last quarter of 2010. I examine those born in 1962 to 1969 (not treated) and those born in 1976 to 1979 (fully treated). The data comes from the UK Quarterly Labour Force Survey (QLFS). The QLFS tracks particular households for five waves. Given the limitations in the design of the available data, in order to ensure sample independence for repeated cross section analysis, I appended the four quarterly datasets for a given year into one and retained only respondents who were contacted for the first time at each quarter. Keeping only respondents who were contacted for the first time at each quarter does not result in a huge loss of useable data because questions on earnings or wages are only asked when an individual first and last appears in the data. I also dropped all individuals who were not born in the UK so as to ensure that all individuals in my sample were exposed to the UK education system. In order to obtain real wages, I deflated weekly wages using the British quarterly Retail Price Index (RPI) with the base period being January of the year 2000. I also combined the QLFS data with other regional data such as unemployment rates from the Office for National Statistics' (ONS) website.

5 Empirical Strategy

5.1 Identifying a Valid Treatment & Control Group

Exploiting the differences across cohorts and treatment intensities induced by the exogenous timing of the expansion, I use a difference-in-differences approach to estimate the effect of the expansion on an individual’s wage. In applied econometrics, the archetypical difference-in-differences set-up involves two dimensions – time (before and after the policy) and groups (treatment and control). Instead of time, this paper will group the data by cohorts. The use of cohorts instead of the time dimension has been utilised in various papers such as Duflo (2001) and more recently, Bleakley (2010).

One of the empirical challenges in this paper is identifying a valid treatment and control group. I am interested in testing how the expansion of higher education affected wages. Ideally, the control group should not be affected by the treatment. The individuals in the control and treated groups should also on average have similar characteristics. Therefore, the desirable but impossible experiment would be to take a set of regions within the UK and randomly select some of these regions to be subjected to the expansionary higher education policy. Assuming that individuals attend university in the region that they are born in, then the causal effect of the expansion on wages would be given by the simple comparison of the wages of those in the treated and control regions.

However, the expansion of higher education affected the whole UK. Therefore, I define my treatment and control groups based on the different treatment intensities experienced by two regions within the UK – England and Scotland. The use of different treatment intensities to form the treated and control group is not new to the literature – Feldstein (1995) and Duflo (2001) used such an approach. Given data limitations,6 I assume that individuals attend university in the region that they are born in. The existing literature, such as Carneiro and Lee (2011), also relies on this assumption. I test this assumption later in the paper and found that across the years, less than 1 percent of 16-19 year olds migrated from England to Scotland or vice-versa. This supports my assumption.

Referring to Figure 3, it is extremely striking that before the 1988 Education Reform Act, the proportion of university graduates in each cohort in both regions not only had similar trends but also similar levels of approximately 17 percent. However, after the 1988 Act, the proportion of university graduates in the post-expansion cohorts rose rapidly until the 1994 cap on university enrolment numbers. For the 1975 cohort, which was the first cohort affected by the 1994 cap, the proportion of university graduates in the cohort was 26.2 percent for England and 22.9 percent for Scotland. After the cap, the proportion of university graduates continued to increase in Scotland but began to flatten out in England. Both England and Scotland experienced a fall in the proportion of university graduates for the 1979 cohort.

---

6 The data does not say where individuals attended university.
Since the expansionary higher education policies did not directly mandate an increase in university places, the treatment intensity used in this paper is derived from comparing the proportion of graduates for the cohort that entered university in 1988\(^7\) against the cohort that entered university in the year the enrolment capped was implemented. This method of measuring the treatment intensity has been adopted in the existing literature.\(^8\) I hence obtain a treatment intensity of around 9 percentage points for England and 6 percentage points for Scotland. A treatment intensity of 9 percentage points tells us that the expansion resulted in 9 out of 100 more individuals in a given cohort in England going to university.

As for the outcome variable, wages, Figure 4 shows that cohorts before the expansion in England and Scotland experienced roughly the same levels and trends. However, the levels and trends began to diverge during the expansion and converged back to the same levels and trends after the expansion. Figure 4 seems to suggest that nothing is happening as a result of the expansion. Nevertheless, given the presence of age effects on earnings, this graph is merely suggestive. More rigorous analysis will be taken in the regressions to control for age and other effects so as to uncover the effect of the expansion on an individual’s wage.

\(^{7}\) 1988 is the year the 1988 Act was passed but 1 year before it came into effect.

\(^{8}\) This method of deriving the treatment intensity by comparing the before and after is similar to Card’s (1990) Mariel Boatlift study. Although the Boatlift did not mandate the exact number of Cubans that could leave Cuba, Card measured the number of Cubans in Miami before and after the Boatlift and attributed this difference to the “intensity” of treatment due to the Boatlift.
5.2 The Difference-in-Differences Regression Specification

Having identified the 2 dimensions for the difference-in-differences set-up – cohort and region, I run the following regression:

$$\ln w_{iact} = \alpha + \gamma Region_a + \delta_c + \beta (Intensity_a \times YoungCohort_c) + X_{iac} \theta + \varphi_t + \rho_{at} + \tau_{ct} + \epsilon_{iact}$$

The coefficient of interest is $\beta$. $\beta$ gives us the effect of the expansion on an individual's wage. $\ln w_{iact}$ is the log of real weekly wage for individual $i$ born in region $a$ from cohort $c$ in data year $t$ (the year wages are recorded). $Region_a$ is a dummy indicating which region the individual is born in. $YoungCohort_c$ is a dummy indicating whether the individual was born in 1976 to 1979 (those fully exposed to the expansion). $Intensity_a$ denotes the intensity of the expansion in the region of birth. $\delta_c$ is the cohort fixed effects, $\varphi_t$ is the year of data fixed effects, $\rho_{at}$ is the region-year of data fixed effects and $\tau_{ct}$ is the cohort-year of data fixed effects. $X_{iac}$ is a vector consisting of other control variables such as the dummies $Gender_i$ and $Migrant_i$. An individual is considered to be a migrant if he is working in a region different from his birth region. Other control variables included in $X_{iac}$ are region specific variables that vary over cohorts which will be described in the following paragraph.

5.3. The Parallel Trend Assumption & Potential Omitted Variables

The difference-in-differences strategy depends on the parallel trend assumption. This means that the trends in the outcome variable for both treatment and control groups for the pre-treatment cohorts are similar. In the absence of the expansion, we would expect the wage trends to be the same in both the control (Scotland) and the treated (England) group. However, the pattern of change in wages could vary systematically (mean reversion) across both regions. I therefore adopt the methodology used by Duflo (2001) and run a placebo experiment. Since individuals that were born in 1962 to 1969 were completely not exposed to the expansion, the change in wages between these cohorts should not differ systematically across England and Scotland. The coefficient of interest (“effect” of the expansion) should therefore yield us a small and statistically insignificant coefficient. Although this is not definitive evidence of a parallel trend (the underlying trend of wages between England and Scotland could have started converging exactly after 1988 in the absence of the expansion), it lends support to the validity of my empirical strategy.

In order to ensure the validity of the identification assumption, it is also imperative to control for region-specific variables that change over cohorts and affect the outcome variable (omitted variables). Examples would include a confounding policy that affects both regions differently and is correlated with the expansion of higher education. There were a number of policies in the UK that
changed the syllabus and national exams for 16 year olds. In 1986, the O-Level exams in England were replaced by the General Certificates of Secondary Education (GCSEs) exams. Devereux and Fan (2011) noted that the first GCSE exams were held in 1988. This policy change hence affected all individuals born in 1972 onwards. A similar change also occurred in Scotland where the Standard Grade exams replaced the O-Grade (equivalent to the O-Level) exams. This was phased in from 1984 to 1990 and hence affected all individuals born in 1968 onwards. I hence include a dummy in my regression to indicate whether or not these policies were in place for each cohort in each region.

Another example of a region-specific variable that changes over cohorts is the region’s unemployment rate at the time where an individual decides whether or not to go to university. This takes into account the differences in the local labour market that may affect an individual’s opportunity cost and hence decision to acquire more education. These will be included as controls in the regression. The relevant unemployment rates were derived from the data available from the Office for National Statistics’ (ONS) website.

6 Results

Table 1 presents the results from the difference-in-differences regression model. In Panel A, I compare the individuals born in 1976 to 1979 with those born in 1966 to 1969. Since the variation of my data comes from the region, cohort and year levels, I cluster my standard errors using the multi-level clustering command in Stata developed by Cameron, Gelbach and Miller (2011). The standard errors are hence clustered collectively by region, cohort and year.

Based on the conceptual framework presented in Section 2, if the positive private effect dominates the negative composition effect, then the coefficient estimate of \((Intensity_y \times YoungCohort_c)\) will be positive. It will be negative if the composition effect dominates. Column (1) presents the specification which does not control for any cohort-varying region-specific variables. The coefficient estimate of \((Intensity_y \times YoungCohort_c)\) suggests that a 1% point increase in the percentage of university graduates in a cohort increased the wages of the young cohort (those born in 1976 to 1979) by 2.01 percent. This is highly significant at the 1 percent level.

The results from Column (1) depend on the identification assumption that there are no omitted cohort-varying region-specific variables that are correlated with the variable of interest. As discussed in the above section, this is unlikely to be the case. Column (2) therefore controls for potential cohort-varying omitted variables by adding in a dummy that indicates whether or not a cohort is affected by other education polices. In particular, I consider whether or not the cohort is affected by the change in the national exam and syllabus for 16 year olds. This is a potential omitted variable which is correlated with the outcome variable. The regression results suggest that a 1 percentage point increase in the percentage of graduates in a cohort going to university increased the wages of those born in 1976 to 1979 by 2.6 percent. This is highly significant at the 1 percent level.

---

9 Progression at school beyond the minimum school leaving age of 16 is based on a series of nationally assessed examinations. Students aged 16 had to take either the Certificates of Secondary Education (CSE) exams or the academically more demanding Ordinary Level (O-Level) exams. From 1988 onwards, students aged 16 take the General Certificate of Secondary Education (GCSEs). The Scottish equivalent of the O-Level was the O-Grade and this was replaced by the Standard Grade from 1984 onwards. Those staying on in school take the A-Level exams or the Advanced Highers exams (Scottish equivalent of the A-Level) when they are 18 years old. Performance on the A-Level or Advanced Highers determine university entry at 19 years old.
Column (3) further controls for potential omitted variables by including unemployment rates in each region in the year that an individual is making a decision to go to university (i.e. when the individual is aged 19). Adding this variable as a control results in a coefficient estimate of 5.57 percent. This is significant at the 1 percent level and is higher than the 2.01 percent estimated in Column (1). This coefficient estimate of $\beta$ in Column (3) strongly suggests that even after controlling for potential omitted variables, the effect of the expansion on an individual’s wage is positive. The private effect thus seems to dominate.

Panel B of Table 1 presents the results of the placebo experiment where I compare individuals born in 1966 to 1969 (old cohort) with those born between 1962 and 1965 (older cohort). If before the expansion, wage had increased faster in England (the region with higher treatment intensity) than Scotland, then I would expect the coefficients of $(Intensity_{t} \times \text{OldCohort}_{t})$ in Panel B to be spuriously positive. However, the estimate of $\beta$ (“impact” of the expansion) is always small and never significant. This lends support to the parallel trend assumption.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<tr>
<td><strong>Panel A - Experiment of Interest:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individuals born 1976-1979 vs. those born 1966-1969</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Intensity*Young Cohort</td>
<td>0.0201***</td>
<td>0.0260***</td>
<td>0.0557***</td>
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<tr>
<td></td>
<td>(0.00582)</td>
<td>(0.00641)</td>
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<tr>
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<tr>
<td></td>
<td>(0.0215)</td>
<td>(0.0188)</td>
<td></td>
</tr>
<tr>
<td>Unemployment Rate</td>
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<td></td>
</tr>
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<td></td>
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<td>(0.0104)</td>
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<td>Observations</td>
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<td>40,279</td>
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</table>

| **Panel B - Placebo Experiment:** |              |              |              |
| Individuals born 1966-1969 vs. those born 1962-1965 |              |              |              |
| Intensity*Old Cohort             | -0.00103     | -0.00623     | -0.00983     |
|                                  | (0.00459)    | (0.00535)    | (0.00620)    |
| Other Policy                     | -0.0284      | 0.0310**     |              |
|                                  | (0.0292)     | (0.0143)     |              |
| Unemployment Rate                |              | -0.0750***   |              |
|                                  |              | (0.0130)     |              |
| Observations                     | 48,778       | 48,778       | 48,778       |

**Other Control Variables for both Panels:**
- Region: Yes  Yes  Yes
- Gender: Yes  Yes  Yes
- Migrant: Yes  Yes  Yes
- Cohort Fixed Effects: Yes  Yes  Yes
- Year Fixed Effects: Yes  Yes  Yes
- Region-Year Fixed Effects: Yes  Yes  Yes
- Cohort-Year Fixed Effects: Yes  Yes  Yes

Standard errors in parentheses are clustered by Region, Cohort and Year.

* *** p<0.01, ** p<0.05, * p<0.1

7 Robustness Checks and Discussions
7.1. Introducing More Cross-sectional Variation: The Triple-Differences Specification

There may be concerns that there was little variation in the treatment intensity in my difference-in-differences model. Therefore, in order to introduce more cross-sectional variation, I adopt a triple-differences set-up. Since the expansion of higher education was more likely to affect those that are of relatively higher ability, in addition to region and cohort, ability type provides a possible third dimension in which the expansion varies. Moreover, using triple-differences will also allow me to control for further possible confounding trends.

The use of ability type as the third dimension in which the expansion varies depends on two assumptions. Firstly, an individual’s ability type is relative to the rest of his own cohort. This means that within each cohort, there will be a fixed percentage that is considered high ability and a fixed percentage that is considered low ability. Across cohorts, these percentages of high ability type should approximately be the same. However, ability cannot be observed and so I use the number of O-Level (and its equivalent) passes as a proxy for ability. Even if the number of O-Level passes is not a perfect proxy for ability, it still provides me with a lower bound for the effect of the expansion on wages.

The second assumption is that the expansion only affected the high ability. Figure 5 lends support to this second assumption. The graph for the proportion of high ability type going to university shows a sudden increase for the 1970 cohort. This corresponds exactly with the timing of the expansion of higher education. However, the low ability from that same 1970 cohort did not experience this sudden increase. Indeed, as expected, the expansion of higher education only seemed to affect the high ability type.

Figure 6 presents the average wage (from 2002 to 2010) of the high ability type across cohorts in each region.

Figure 5: Proportion of Ability Types Going to University (by region and cohort)

*Note - Number of O Level Passes used as a proxy for ability.*

*Source: Quarterly Labour Force Survey (QLFS); author's calculations*
Given the presence of age effects and other confounding variables on wages, this graph is merely suggestive. Since the assumptions seem valid, I therefore run a triple-differences model:

\[
\ln w_{iacst} = \alpha + \gamma_{\text{Region}_a} + \delta_c + \omega_{\text{HighAbility}_s} \\
+ \varphi (\text{Intensity}_t * \text{YoungCohort}_c * \text{HighAbility}_s) + \chi_{iac} \theta + \sigma_{ac} + \mu_{as} + \vartheta_{cs} + \varnothing_t \\
+ \rho_{at} + \tau_{ct} + \pi_{st} + \varepsilon_{iacst}
\]

The coefficient of interest is \( \varphi \). The expansion of higher education is more likely to affect those who are of relatively higher ability. \( \text{HighAbility}_s \) is a dummy indicating which ability group an individual belongs to. In particular it is equal to 1 if an individual has 5 or more O-Level passes and 0 if an individual has less than 5 O-Level passes. \( \sigma_{ac} \) is the region-cohort fixed effects. \( \mu_{as} \) is the region-ability fixed effects. \( \vartheta_{cs} \) is the cohort-ability fixed effects and \( \pi_{st} \) is the ability-year of data fixed effects. The rest of the notation is similar to the difference-in-differences regression in Section 5. Table 2 presents the regression results.

In Table 2, Panel A, Column (3), I include all the potential omitted variables. The coefficient estimate of interest \( \varphi \) suggests that a 1 percentage point increase in the percentage of graduates in a cohort leads to 3.11 percent increase in the wage of a high ability individual from the young cohort. This is highly significant at the 1 percent level. The coefficient estimate of the impact of the expansion(\( \varphi \)), is stable across all three columns. The interaction of \( \text{Intensity}_t * \text{YoungCohort}_c * \text{HighAbility}_s \) enables us to examine how those that are most likely to be affected (the high ability type) respond to the expansion. In addition, the triple-differences approach controls for two potential confounding trends. Firstly, it controls for changes in the wage (not attributed to the expansion) of the high ability across the two regions. Secondly, it controls for other region specific policies that affected the wage of everyone living in the higher treatment intensity region (England).
The use of the triple-differences regression model is not new in econometrics. Yelowitz (1995) and Kearney and Levine (2009) used such a model in their study of the impact of state-level Medicaid policy changes on various outcomes like labour force participation and fertility. In exploiting this added variation, it is hoped that the triple-differences model may generate more robust results than the difference-in-differences results reported in Table 1 of Section 6.

Panel B of Table 2 presents the results of the placebo experiment where I compare individuals born in 1966 to 1969 with those born in 1962 to 1965. Similar to Panel B of Table 1, the coefficient of interest (“impact” of the expansion) is always small and never significant. This lends further support to the parallel trend assumption.

7.2. Are the Standard Errors Valid?

Much debate on the validity of the difference-in-differences estimation strategy revolves around the parallel trend assumption and whether there are any time varying (in our case cohort varying) omitted variables that would bias the estimates. However, Bertrand, Duflo and Mullainathan (2004) noted that issues related to the validity of the standard errors are just as important. Most papers using the difference-in-differences estimation strategy have ignored the problem of invalid standard errors.

The standard errors become invalid when each observation is correlated with the other observations. Angrist and Pischke (2009) note that this correlation is problematic on 2 levels – the Moulton problem which occurs at the cross-sectional level and the serial correlation problem which

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### Table 2: Triple-Differences - Effect of the Expansion on Wages

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Real Weekly Wage)</td>
<td>0.0519***</td>
<td>0.0517***</td>
<td>0.0511***</td>
</tr>
<tr>
<td>Young Cohort*High Ability</td>
<td>(0.00097)</td>
<td>(0.00775)</td>
<td>(0.00855)</td>
</tr>
<tr>
<td>High Ability</td>
<td>0.354***</td>
<td>0.354***</td>
<td>0.354***</td>
</tr>
<tr>
<td>Other Policy</td>
<td>(0.0192)</td>
<td>(0.0180)</td>
<td>(0.0170)</td>
</tr>
<tr>
<td>Unemployment Rate</td>
<td>-0.008723</td>
<td>0.0303</td>
<td>(0.0226)</td>
</tr>
<tr>
<td>Observations</td>
<td>29,337</td>
<td>29,337</td>
<td>29,337</td>
</tr>
</tbody>
</table>


---

Other Control Variables for both Panels:

- Region: Yes
- Gender: Yes
- Migrant: Yes
- Cohort Fixed Effects: Yes
- Year Fixed Effects: Yes
- Region-Year Fixed Effects: Yes
- Cohort-Year Fixed Effects: Yes
- Ability Group-Year Fixed Effects: Yes
- Region-Cohort Fixed Effects: Yes
- Region-Age Group Fixed Effects: Yes
- Cohort-Age Group Fixed Effects: Yes

Standard errors in parentheses are clustered by Region, Cohort and Year.

*** p<0.01, ** p<0.05, * p<0.1
happens at the time-series level. The Moulton problem occurs in my study because individuals in the same region or cohort tend to have labour market outcomes that are correlated since they are subjected to similar economic influences. The serial correlation problem is also likely to be present in my study because wages are highly correlated over time. Therefore, the standard error for the estimate of the impact of the expansion could severely understate the true standard deviation (overstate precision).

Empirical studies usually correct both problems by using the “cluster” or multi-cluster options in Stata to cluster the standard errors. I did this for the results presented in Tables 1 and 2. However, these commands rely on asymptotic approximation which requires a large number of clusters (typically more than 42). Unfortunately, my data only has two region clusters (England and Scotland), twelve cohort clusters and time-series wage data for nine years. Therefore, I have too few clusters and I am unable to use the “cluster” or multi-cluster commands to correct for both the Moulton and the serial correlation problem. The results reported in Table 1 and 2 (where I clustered the standard errors) are hence likely to be invalid.

The Moulton problem can usually be solved easily even when the number of available clusters is small. The data that I am using varies at the region, cohort and year level. I therefore collapse the data by calculating the average cohort wage for each year starting from 2002 to 2010. This leaves me with only one wage observation for each cohort for each year. Angrist and Pischke (2009) provide the intuition behind this method. They noted that the standard errors that come from grouped estimation are more reliable than clustered standard errors in samples with few clusters because the asymptotics in the grouped regression are based on the number of groups and not the group size. Moreover, the group means are close to normally distributed even with relatively small group sizes. I therefore run the grouped version of the difference-in-differences regression (as described in Section V) excluding all individual level covariates:

\[
\ln w_{act} = \alpha + \gamma Region_a + \delta_c + \beta (Intensity_a \times YoungCohort_c) + X_{act}'\theta + \varphi_t + \rho_{act} + \tau_{ct} + \epsilon_{act}
\]

Table 3 presents the results of the grouped regression using group size as weights. In Panel A, while the coefficient estimate of the effect of the expansion on wages (\(\beta\)) is positive and quite similar in magnitude to the results reported in Table 1, the estimates are no longer significant. Bertrand, Duflo and Mullainathan (2004) note that this is to be expected because aggregation techniques have relatively low power. However, what is encouraging from this analysis are the results reported in Panel B of Table 3. In Panel B, the coefficient of interest (\(\beta\)) which is the “impact” of the expansion, is always small and never significant. This lends further support to the parallel trend assumption as it corroborates with the results from Panel B in both Tables 1 and 2. In all three Tables, the placebo experiment yields small and never significant estimates of the “impact” of the expansion.
In order to gauge the severity of serial correlation in my results, I regress the residuals from my grouped regression (using the variables in Column (3) of Table 3) on its lagged residuals. This is presented in Figure 7 and suggests the presence of serial correlation.

![Figure 7: Suggestive Evidence of Serial Correlation](image-url)
While I am able to run some analysis to attempt to correct for the Moulton problem, I am unable to do so for the problem of serial correlation. When the number of clusters is small, Bertrand, Duflo and Mullainathan (2004) proposed a solution which is to ignore the time series information and collapse the data to before and after the law. However, because I have only two regions, I am unable to calculate the standard errors. This means that I cannot adopt their solution. Donald and Lang (2007) explain that this is because the t-statistic will have zero degrees of freedom in the 2X2 difference-in-differences set-up. Future work may seek to build on this paper and attempt to further address the Moulton and serial correlation issues.

7.3. Is there Expansion-induced Migration?

A major problem arises if the structure of the treated and control groups changes as a result of the policy change that one is studying. This issue of treatment-induced migration has been extremely prevalent in the difference-in-differences literature. Card (1990) found that the Mariel boatlift had no significant effect on the wages or employment outcomes of non-Cuban workers in the Miami labour force even though it resulted in a 7 percent increase in the labour force. One reason for the insignificant results could be because the structure of his treatment and control states changed as a result of the boatlift. The same issue of policy-induced migration was faced by Card and Krueger’s (1994) study of minimum wages in New Jersey. The increase in minimum wages in New Jersey (the treated state) may have induced workers from Pennsylvania (the control state) to migrate to New Jersey.

Similar to these papers, in my study there might be an expansion-induced migration which resulted in a substantial number of Scottish students going to universities in England so as to take advantage of the more intensive expansion in England. Using the Labour Force Survey (LFS) and Quarterly Labour Force Survey (QLFS) from 1985 to 1998, which sampled all individuals (whether child or adult) in a sample of households, I identified all individuals who were aged 16-19 in each of these years. I used this age group because it is the age group just before an individual enters university. I then identified their current region of residence and their region of residence one year ago. For each year (1985 to 1998), I calculated the proportion of individuals aged 16-19 in each region that lived in a different region the year before. The intuition behind this exercise is that if there was an expansion-induced migration, we would expect to see a significant change in the number of 16-19 year olds migrating from Scotland (low treatment intensity) to England (high treatment intensity) during the years of the expansion and in the years following the expansion.

Figure 8 shows the proportion of 16-19 year olds who were in a different region of residence the year before. The graph shows that consistently less than 1 percent of 16-19 year olds that were sampled migrated from Scotland to England or vice-versa in a given year. However, it showed that in some years, there were no 16-19 year olds migrating. It is highly implausible that no 16-19 year olds migrated from Scotland to England or vice-versa in a given year. I suspect that the Labour Force Survey and Quarterly Labour Force Survey may have under-sampled those aged 16-19 years old. This means that there is no point in running a regression to test for expansion-induced migration. Nevertheless, it is encouraging that across all the years, less than 1 percent of 16-19 year olds that were sampled migrated from Scotland to England or vice-versa. This lends some support to the validity of my assumption.

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10 Before 1992, the Labour Force Survey was done on an annual basis. Post 1992, the Labour Force Survey was conducted on a quarterly basis beginning from April 1992 (second quarter of 1992) and became known as the Quarterly Labour Force Survey (QLFS).

11 From the second quarter of 1992 to the third quarter of 1993, the QLFS only collected data on a person’s region of residence 3 months ago as opposed to region of residence one year ago. Before 1992 and from the fourth quarter of 1993 onwards, the LFS and QLFS both collected data on a person’s region of residence one year ago.
Given the limitations of using the LFS and QLFS, I searched for other sources of statistics. One interesting statistic that I found was the percentage of UK students attending university in their home country. A relatively stable percentage for both England and Scotland a few years before and after the expansion in 1988 would lend further support to my assumption that there was no significant expansion-induced migration. However, the Higher Education Statistics Agency only started publishing this relevant statistic for the year 2006 onwards. The difficulty in finding other useful statistics did not come as a surprise. Most data was not collected in the 1980s. Furthermore, Raffe et al. (1999) noted that it has been widely acknowledged that most data before the year 2000 are limited because they do not disaggregate the United Kingdom into England, Scotland, Wales and Northern Ireland.

As a matter of interest, it is worth noting that anecdotal evidence provides some support that few English students attend universities in Scotland and vice versa in the period that this paper examines. Raffe et al. (1999) noted that most first-degree courses in Scotland are of four years’ duration whereas most first degree courses in England are only three years long. An expert group report commissioned by UCAS, 12 provides support that while the Scottish Advanced Highers are harder than the A-Level exams, universities in England used to treat them as of equal difficulty when giving out conditional offers.

Taken together, the description of the data and anecdotal evidence provide some evidence that my results are not driven by expansion-induced migration.

7.4 Is there Sample Selection?

This paper seeks to examine how the expansion of higher education affected wages. However, the expansion of higher education may have led to an oversupply of graduates and consequently higher unemployment if there are not enough jobs in the economy. Since the sample that I have only contains wages for individuals who are working, I will then have a sample selection problem that is akin to an omitted variable bias. This is because individuals who managed to find jobs even with the oversupply of graduates may be inherently different from those who were unable to find jobs. For example, those that are employed may be inherently more hard-working. My positive estimate of $\beta$ would hence be biased upwards as it is accounting for this unobserved characteristic of those who are employed. I will then be attributing the increase in wages to the effect of the expansion when it is actually some other unobserved variables driving the positive wage increase.

In order to test if sample selection is a big issue in my study, I run the same regression model as the difference-in-differences regression (as described in Section 5) with all individual level covariates but excluding the unemployment rate covariate. Instead of wage, the outcome variable is

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now the probability of being unemployed. My sample includes all individuals who are either employed or unemployed. If the linear probability regression results suggest that the expansion did not lead to higher unemployment, then my estimate of $\beta$ is unlikely to suffer from sample selection bias and I do not need to undertake any steps such as the Heckman procedure to correct sample selection.

Table 4 suggests that the expansion actually led to a small but significant reduction in unemployment. More importantly, the results lend support to my initial findings because it is not driven by sample selection. The expansion did not lead to greater unemployment and so it is unlikely that sample selection is driving the positive estimate of the effect of the expansion on wages.

### Table 4: Effect of the Expansion on Unemployment

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Dependent Variable: Probability of being Unemployed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Experiment of Interest:</strong></td>
<td></td>
</tr>
<tr>
<td>Individuals born 1976-1979 vs. those born 1966-1969</td>
<td></td>
</tr>
<tr>
<td>Intensity*Young Cohort</td>
<td>-0.00575***</td>
</tr>
<tr>
<td></td>
<td>(0.00171)</td>
</tr>
<tr>
<td>Other Policy</td>
<td>0.00812***</td>
</tr>
<tr>
<td></td>
<td>(0.00165)</td>
</tr>
<tr>
<td>Observations</td>
<td>60,257</td>
</tr>
<tr>
<td></td>
<td>60,257</td>
</tr>
<tr>
<td>Other Control Variables:</td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>Yes</td>
</tr>
<tr>
<td>Gender</td>
<td>Yes</td>
</tr>
<tr>
<td>Migrant</td>
<td>Yes</td>
</tr>
<tr>
<td>Cohort Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Region-Year Fixed Effects</td>
<td>Yes</td>
</tr>
<tr>
<td>Cohort-Year Fixed Effects</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Standard errors in parentheses are clustered by Region, Cohort and Year

| **p<0.01, ** p<0.05, * p<0.1   |

### 7.5. Further Work

Since the expansion affected the whole of the UK, one of the empirical challenges faced in this paper was finding a valid control group. Given that all regions within the UK were treated, I attempted to introduce some cross-sectional variation by looking at the intensity of the expansion in two regions within the UK. However, the difference in intensity between England and Scotland was relatively small and this presented very little cross-sectional variation. I attempted to introduce more cross-sectional variation by considering a triple-differences regression where I used the number of O-Level passes as a proxy for ability. One potential extension of this paper would be to use more regions within the UK so as to get more cross-sectional variation in the intensity of treatment. However, as we consider more regions within the UK, it is more likely that we will face a greater probability of expansion-induced migration. Therefore, future work exploring this will require better data which provides information on an individual’s region of birth, region of residence before going to university and where he attended university.

Another way to find more suitable control groups would be to construct synthetic control groups. The intuition behind synthetic controls is that a combination of units provides a better comparison for the treated unit than any single unit alone. Abadie and Gardeazabal (2003) pioneered this synthetic control method in their estimation of the effects of terrorist conflict in the Basque country. In the context of my study, the treated group will be the whole of the UK, and we can construct synthetic controls by using other neighbouring countries.
This paper was also unable to disentangle the effects of each of the three policy interventions that took place between 1988 and 1994. I therefore treated these three policies collectively as 1 expansionary policy. The limitation with doing this is that each individual policy may have resulted in different wage outcomes as compared to the effect that they bring about collectively. Future work may want to treat each of these policies individually. However, better data is again required to do this. In particular, the data must be able to provide information as to which individuals attended former polytechnics.

This paper was also unable to disentangle the private and composition effects associated with an expansion of higher education on wages. Future work could possibly look into disentangling both these effects so that we are able to find the magnitude attributed to each of the effects.

8 Conclusion

This paper has examined the effect of an expansion of higher education on an individual’s wage. This was done in the context of the dramatic government policies in the UK which saw the proportion of graduates in each cohort increase dramatically from 15 to almost 30 percent within just a few years. The exogenous variations induced by the expansionary higher education policies provide a “natural experiment” which I exploit by using a difference-in-differences regression.

I present a conceptual framework to interpret my estimates from the difference-in-differences regression. My findings suggest that an expansion of higher education was effective in increasing wages in the UK. In particular, a 1 percentage point increase in the percentage of university graduates in a cohort led to a three to six percent increase in an individual’s wage. While there have been concerns that the negative composition effect of a higher educated workforce may offset the positive private effect of acquiring more education, this paper provides evidence that the private effect is the dominant effect in the context of the UK and the expansion of the late-1980s to the early-1990s.

Moreover, I tested my identification assumption by running a placebo experiment which showed that the expansion did not affect the older cohorts who were not exposed to it. This lends support to the parallel trend assumption. In order to further test the robustness of the results, I extended the difference-in-differences regression into a triple-differences analysis so as to introduce more cross-sectional variation and to also control for other possible confounding trends. Following which, I recognised that because I am only comparing two regions (England and Scotland), clustering my standard errors is likely to result in invalid standard errors. I take some steps to correct for this. I also provide some justification as to why expansion-induced migration and sample selection may not be too big a problem affecting this study. Although this paper has contributed some empirical evidence on the effect of the expansion of higher education on wages, future work must still be undertaken to improve the methodology and to overcome the data limitations faced by this paper.

The findings reported in this paper relate to economic theory but are also important because they have real-world implications. Governments are always concerned about reducing inequality and it does seem that expanding higher education may be a plausible solution especially since this study finds a positive relationship between wages and the expansion of higher education. Nevertheless, this study is not saying that governments around the world should focus solely on indefinitely increasing the number of university places. Beyond a certain point, the negative composition effect may outweigh whatever positive private effect there may be from acquiring more education. This is likely to happen if the higher education expansion is so drastic that even those not adept at high-skilled jobs end up being mistaken as high-skilled workers simply because they went to university. Employers can no longer believe that a university graduate is a higher productivity worker and will hence not be willing to offer higher wages. While more education serves a role in improving human capital, it should also remain effective in sorting workers to the right jobs. An over-expansion would impede education’s ability to sort workers to the right jobs. Once this happens, the negative composition effect would dominate.

Indeed, extending the famous quote of former Harvard President Derek Bok, in which he quipped that “if you think education’s expensive, try ignorance”, this paper argues that expanding higher education involves trade-offs between composition and private effects, and it would be ignorant to simply believe that expanding higher education will always necessarily lead to higher wages.
References


ESTIMATING THE EFFECTS OF PRE-COLLEGE EDUCATION ON COLLEGE PERFORMANCE

Ensign Phoebe M. Kotlikoff
United States Naval Academy

ABSTRACT

This paper assesses the effects of post-secondary education on college success by examining a large detailed cross-sectional dataset of students from the U.S. Naval Academy. We find that students who have attended a pre-college program tend to graduate at higher rates than comparable students entering directly from high school but perform at lower levels academically overall.

Acknowledgements

This yearlong research project is the undertaking of many people and represents a combined effort. I would like to thank the Trident Committee members for the opportunity to undertake this research project. I would also like to recognize the patience, kindness, dedication, and effort put forth by my two advisers, Professor Ahmed S. Rahman and Professor Katherine A. Smith, as well as the entire Economics department for supporting me in this venture.

1 Introduction

Education policy makers have historically debated the effectiveness of preparatory school programs as a method of post-high school, pre-college education. However, the difficult nature of measuring returns to education, combined with limited access to relevant data, makes coming to quantitative conclusions about the utility of preparatory school programs challenging. This paper assesses the effects of post-secondary education on college success through propensity score matching and instrumental variable analysis by using a large detailed cross-sectional dataset of students from the United States Naval Academy (USNA).

College graduates in the United States tend to have significantly higher earnings and higher labor force participation rates than their counterparts who have only high school degrees. American workers with a bachelor’s degree or better will earn an average of $40,000 more in one year than those with a high school degree, illustrating the importance of degree attainment for future earnings (Carnevale et al. [2010]). Moreover, according to Census Bureau 2013 employment projections, the unemployment rate for college graduates aged twenty-five and over is 4.5 percent compared to 8.3 percent for high school graduates. Despite the rising importance of college education to future income, there is growing concern that many college entrants are unprepared to succeed in undergraduate studies, contributing to the 42 percent drop-out rate among students pursuing their bachelor’s degrees (Alliance for Excellent Education [2011]).

Although record numbers of U.S. high school students are entering college, four in ten are academically unprepared for college-level studies. One method of providing additional preparation to students is to enroll them in pre-college programs that act as an intermediary institution between high school and college. However, these remedial programs are expensive, costing over $3 billion in 2011 (Alliance for Excellent Education [2011]). This paper examines the impact of participation in pre-college remedial education on student preparation for undergraduate success, controlling for intrinsic ability.

This analysis is performed using data from USNA. We use a large cross-sectional dataset of students from the USNA graduating classes of 1988 – 2011, categorizing students into those who have attended the Naval Academy Preparatory School (NAPS), an independent pre-college program selected by USNA known as a Foundation school, or another college prior to USNA, and those entering directly from high school. On average, over 20 percent of each graduating class attended some type of pre-college program, and another 3 percent were admitted from colleges around the country. Using a combination of propensity score matching and instrumental variable analysis to mitigate selection bias, we determine the
empirical relationships between assignment to a post-secondary education program and future success in college. Because NAPS and Foundation school programs are comparable to other pre-college programs in terms of curriculum and environment, the results of this analysis can be extrapolated to apply to pre-college programs nationally, helping to inform U.S. education policy more broadly.

Due to non-randomness in selection of students into pre-college education programs, traditional economic evaluation techniques are ineffective in investigating educational returns. The USNA Admissions Board assesses each candidate’s background characteristics, and designates those students who will start at a pre-college program. The main characteristics, considered by the board are Math and Verbal SAT scores and high school class rank. However, there is a broad range of acceptance based on each background characteristic, and each individual is considered independently. This leads to enormous overlap in many background characteristics between the treatment and control groups.

For this reason, we turn to propensity score matching and instrumental variables to eliminate the selection bias associated with assigning students to pre-college education programs. Results are determined by comparing individuals with similar background characteristics in order to identify returns to a number of performance variable estimation including graduation rates, academic course grades, and class rank. The data is split into treatment and control groups. The control observations are individuals who matriculate into USNA directly from high school. The treatment groups include those who attended NAPS, a Foundation school, or another college before USNA.

There are a number of benefits to analyzing only students from USNA. United States college completion rates have declined nationally, due both to changes in the preparedness of entering students and in collegiate characteristics. Analyzing students from USNA allows for a focus on an institution whose characteristics have remained fairly consistent over time, in order to isolate the effects of student preparedness on college success. Moreover, USNA maintains robust and detailed records on each midshipman, including high school information, SAT/ACT scores, attendance records over all four years, and grades during each semester. This degree of detailed accounting of student characteristics and performance is not typical of standard private institutions of higher education. Therefore, this study accounts for biases inherent in other studies in order to isolate the true effects of remedial preparatory programs. Our access to more detailed midshipmen background and performance records facilitates the use of methods like propensity score matching, which mitigate potential misinterpretation caused by selection bias. Our detailed dataset allows for a comparison of treated and untreated groups. Further, midshipmen at USNA are kept in a virtual test-tube environment. The liberty policies, uniform regulations, drug-tolerance policy, and military requirements provide controls for many variables that would be otherwise uncontrollable and unknowable in alternative environments. In addition, first year classes are nearly always identical from student to student due to required coursework. This type of comparison is not an option for studies using data from other colleges. However, USNA is comparable to any top tier civilian undergraduate institution. It is a fully accredited college with a standard curriculum.

The NAPS program is a USNA-run preparatory school designed to ease students into the rigors of higher education. Students who are not admitted to USNA directly from high school may be offered an appointment to NAPS, a tuition-free preparatory school program. Students at NAPS have Navy Reserve status and attend pre-college or college level courses during the day for an entire academic year before matriculation into USNA. The Naval Academy Foundation sponsors the Foundation school program. Students not directly admitted to USNA may also be considered for a slot at a Foundation school. Foundation schools include a wide range of military and non-military preparatory schools around the country. Foundation school students are sponsored by the Naval Academy Foundation on a need-based system but are asked to pay at least 40 percent of tuition.

The results of this study will not only identify the specific returns to investment in NAPS and Foundation schools but will also assess the effectiveness of post-secondary education on a national level. The NAPS program is comparable to pre-college programs that send students to colleges and universities all over the U.S. The Foundation school program places students in independent preparatory school programs alongside students who will go on to attend a wide range of civilian undergraduate institutions. Conclusions about the returns to the NAPS and Foundation school programs can, therefore, be applied to
pre-college programs on a national level.

This paper is organized into the following sections: an overview of relevant literature, an explanation of methodology, a description of the data, and a discussion of the empirical results.

2 Background Literature

In this section we discuss the decline of college graduation rates, current evidence for returns to remediation, the evolution of remedial education programs, and finally the rise of pre-college programs to better prepare students for college.

College completion rates in the United States are declining, while the wage gap between those who earn an undergraduate degree and those who do not is widening. The higher wage premium on a college degree has led to an increase in the percentage of students entering college, but there has not been a proportional increase in graduation rates. Bound et al. (2009) hypothesize that both lack of student preparation and deteriorating college characteristics contribute to declining graduation rates. On one hand, the increasing wage premium encourages higher numbers of more weakly prepared students to begin degree programs, but many subsequently drop out. Of the bottom quartile of the student sample tested, the probability of a student attending college jumped from 21.7 to 44.0 percent over 20 years. At the same time, only 5 percent graduated with a bachelor’s degree over the same time period, indicating that more underprepared students are beginning college, but the percent actually attaining degrees remains static. Moreover, the study finds that much of the decline is a result of supply-side changes to institutional characteristics like student-teacher ratio and per-student funding. This is supported by the fact that while college graduation rates have declined, high school graduation rates have stayed fairly constant over the past several decades. Moreover, out of the bottom quartile of college attendees in the dataset, graduation rates fell from 25.8 to 11.4 percent over two decades. This suggests that of those students on the margin who do decide to attend college, factors other than preparation are also contributing to declining completion rates. The assumptions of the Bound et al. (2009) paper initiate an inquiry into the effectiveness of pre-college remedial programs.

Literature on this topic uses the term “remedial” to describe coursework that students should have mastered before entering college. Previous literature has investigated the effectiveness of remedial coursework for students already enrolled in college. According to a study by Attewell, Lavin, Domina, and Levey (2006), remediation programs for students during their first year in college decrease the likelihood of graduating on time by 6 percent. This follows from the fact that if students are enrolled in remedial programs during their first year, they are falling behind in coursework that their fellow students are taking, and falling behind the four-year schedule of required coursework necessary to graduate on time. Adleman (1999) also suggests an inverse relationship between participation in remedial coursework and subsequent graduation. However, once the data was adjusted to include a measure for high school preparation, the disparity in graduation rates disappeared. Lavin, Alba, and Silberstein (1981) attempt to control for background characteristics through a study on remedial coursework at CUNY that was assigned but not mandatory. They found positive returns from remediation in the form of a slight increase in probability of graduation. Although this study represented a step toward addressing the selection issue, it neglected to account for the fact that students who would voluntarily participate in a remediation program were likely to be more vested in their educational success.

Bettinger and Long (2005) analyze the implications of remedial coursework in mathematics on persistence in attaining a bachelor’s degree. The results controlled for background skills and came to three significant conclusions. First, the students placed in remedial courses in math and English were less likely to drop out of their four-year colleges or transfer to two-year colleges. Second, placement in remediation programs did not lower overall likelihood of attaining a bachelor’s degree. Finally, those students placed in remedial programs who completed those programs were more likely to attain a bachelor’s degree than students who did not complete remedial coursework but were otherwise similar. There was also weak evidence that suggested students in remediation would go on to achieve better grades in their first college-level math courses. The Bettinger and Long study made a complicated comparison between students taking very different classes during their first year of college. In this study, USNA students take very
similar courses during the first year of study, allowing for a more direct comparison of academic performance. The literature on this subject suggests that a preparatory year of remedial coursework might dramatically improve on-time graduation rates since it leads to the conclusion that if students are taking a year to prepare themselves for college work, they will be able to follow the expected schedule of courses and graduate from an undergraduate institution in the expected four years with a degree.

There are many options for addressing the problem of student under preparedness for undergraduate education. Many colleges assess student preparedness during the admissions process and then assign them to remedial classes during their freshman year, but this is not the only option for unprepared students. Increasing emphasis has been put on the importance of community colleges and pre-college programs rather than remedial courses in college. Yet little is known about the effectiveness of such programs. This paper contributes quantitative evidence about the returns of pre-college remedial programs, not remedial courses taken as a college freshman. Soliday (2002) suggests that remediation can help students acquire critical skills and enable them to integrate themselves into college populations. Pre-college programs offer an interim year for students who graduate from high school with college aspirations but lack the experience in high-level coursework and the self-discipline to succeed as freshmen students in an undergraduate environment. Preparatory schools like NAPS and Foundation schools give students a taste of the independence and rigor of college, while simultaneously improving their preparedness academically. However, at an annual cost of over one billion dollars for U.S. public colleges alone, critics of remediation wonder if such programs should be offered at all (Breneman and Haarlow [1997]).

Thus, this paper examines in what ways pre-college programs are helping better prepare students for the rigors of higher education at the undergraduate level. The preparatory school programs that feed into USNA are designed to prepare students not only for the academic challenges that await them, but also for the high-stress lifestyle of a busy college student. A postgraduate (PG) preparatory year has become popular for many students who are academically unprepared or not competitive for selective four-year undergraduate programs. There are currently 144 schools nationwide offering a PG year for high school graduates (Boarding School Review1). Pre-college programs are designed to better prepare students for the academic rigors of college life. Therefore, participation in a pre-college program should align with some measurable improvement in college readiness, whether in terms of academic success or graduation rates.

A particular problem with current literature on this topic is its inability to hone in on the cohort of students who fall on the margin of acceptance to high-level undergraduate programs. Literature documents a trend in which students from less affluent families tend to need remedial education at higher rates and also drop out at higher rates than more affluent students (Attewell et al. [2006]). While affluence is a proxy for many other background characteristics (education level, health, future earnings), it is important to note that while students are attending USNA, tuition costs and personal living expenses do not play a role in the probability that they will drop out. Consequently, the framework of USNA provides a unique perspective on the issue of cost. As midshipmen, students are not responsible for paying tuition and are required to graduate in four years. In this study, we are then able to eliminate much of the variance associated with examining the performance of students at the margin. At other colleges, a solid sampling of marginal students is difficult to find because many will drop out for a variety of reasons. However, at USNA family income plays a far less significant role in pushing students to drop out of school due to cost or other factors, allowing us to examine the educational returns to a cohort previously difficult to isolate.

Moreover, the literature justifies the extrapolation of conclusions drawn from service academy data to the larger population of undergraduate students. According to extensive research, particularly that

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1 http://www.boardingschoolreview.com/
of Carrell and West, the use of data specific to USNA in undertaking this analysis does not limit the scope of the results to the same population. Although the average Midshipman has many more restrictions and mandatory obligations than the average college student, the results of this study have implications that apply to all types of remedial education outside of the walls of USNA. Moreover, the environment of USNA is controlled in ways described above, which create a dataset particularly suited to this type of longitudinal policy study.

The importance of this study lies in the fact that the controversy over the effectiveness of pre-college remedial programs has been “sporadic, underfunded, and inconclusive” (Merisotis and Philips [2000]). Moreover, many of the existing studies only add to the controversy, either due to conclusions based on qualitative rather than quantitative analysis, inability to obtain a control group, or failure to address the issue of selection bias. In this paper, we take a hard quantitative look at treated and untreated groups using statistical analysis tools that control for selection bias. Moreover, rather than studying remedial coursework in the college setting, we focus on pre-college programs that serve to bring students up to a level at which they should be prepared to start college level coursework.

In summary, previous literature does not adequately investigate the role of pre-college remediation programs. This is due, in part, to the lack of a standard around which all pre-college education methods can be assessed. There is no method of quality assessment across remediation programs. Without assessment, there is no way to determine best practices or analyze programs comparatively. This, in turn, perpetuates a lack of assessment (Bettinger and Long [2004]). Moreover, many studies employ a flawed methodology in their assessment of pre-college utility, comparing treatment and control groups without controlling for selection bias (Bettinger and Long [2004]). This paper applies directly to the debate by examining the specific cohort of students for whom remediation is pertinent. The complex USNA admissions policies create an environment in which many students who are assigned to a pre-college program have very similar background characteristics to students who are admitted directly to USNA. This paper isolates that overlap in characteristics, exploiting the detailed and robust Midshipmen performance records, to analyze the utility of pre-college to the students who might actually benefit from it, rather than the entire student body. Therefore, this paper explores a new niche in assessing whether pre-college is a useful tool in preparing students to succeed in the college environment, and ultimately become degree-holding graduates.

3 Methodology

The general objective of this type of study is to compare differences in outcomes between “treated” and “non-treated” individuals. In this case outcomes are measures of educational achievement, and treatment is enrollment in a pre-college program. Specifically, the untreated group of students in the study is the direct admissions group, and the treatment group is split into three smaller cohorts: NAPS students, Foundation school students, and prior college students.

In order to ensure robust conclusions, this paper utilizes three methods to assess returns from pre-college programs: ordinary least squares (OLS) regression, propensity score matching (PSM), and instrumental variable (IV) analysis. First, we use ordinary least squares regression as a basic method by which to determine the relationship between participation in a pre-college program and certain performance metrics. Next, we generate a propensity score for each individual in our dataset. A propensity score is an individual’s probability of attending a given pre-college program based on his/her background characteristics. We can then algorithmically match treated and untreated individuals with similar propensity scores and calculate the differences in their performance at USNA in a technique called propensity score matching. The propensity score proves to be a useful tool for instrumental variable analysis as well. In the third section of this study, we use the propensity score as an instrument in a

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regression to measure the estimated differences in performance between those who participate in a pre-college program and those who do not.

Ideally, a study would compare the outcomes of those who receive treatment with the outcomes of those same individuals if they were not given the treatment. However, this is an experimental impossibility. Due to the constraints of an observational study, we must find a way to simulate experimental conditions. In this study, that means looking at individuals with similar background characteristics who either attended a pre-college program or did not attend a pre-college program. For this reason, this study uses observed data with propensity score matching and instrumental variable analysis techniques to compare the differences in outcomes between a treated group and a control group.

Propensity score matching methods of analysis are particularly useful for assessing the overlap between a treated and control group.

In this study, let $Y$ be the outcome variable – this includes a number of options: graduation rates, first year academic GPA, first year aptitude scores, choice of major, overall order of merit, and so forth (each is considered in separate specifications). Let $T$ be the treatment. Specifically, $T = 1$ indicates a member of the treated group (in this case those who attend NAPS, or in separate specifications those who attend a Foundation school or prior college), and $T = 0$ indicates a member of the control group (in this case those who enter USNA directly from high school).

The goal is to estimate the mean impact on the measured outcome variable from the treatment, obtained by averaging the impact across all the individuals in the population. $ATE$ is the average treatment effect. In general, it is modeled using this equation:

$$ATE = E[Y|T = 1] - Y|T = 0]$$

where $E(*)$ represents the average or expected value of the outcome. In this study, one specification of this model is:

$$ATE = E[G|N = 1] - G|N = 0]$$

where $G$ is the probability of an individual graduating, and $N$ is a binary variable documenting that an individual either participated in NAPS ($N = 1$) or did not participate in NAPS ($N = 0$). The average treatment effect is a measure of the returns to education between the treated and control groups without considering selection bias. If participants are randomly assigned to treatment, the average difference in outcomes between the treated and control groups is a measure of the impact of the treatment. However, in this case treatment is intentionally non-random – selection for pre-college or remedial programs is based on individual characteristics, some of which are perhaps unobservable, and these characteristics very likely also impact the outcome.

Rather than picking students at random for remediation, students who fulfill program specific criteria are offered assignment to one of the described feeder programs. The non-randomness of the process means the results suffer from a rather severe selection bias. Assuming $X$ is a matrix of co-variates capturing student characteristics that potentially affect student outcomes, consider estimating the following linear specification:

$$Y_{it} = \alpha + \beta * T_{it} + \delta * X_{it} + \epsilon_{it}$$

$\beta$ is intended to capture the average treatment effect. However, given the selection bias, the OLS estimate of $\beta$ will be inconsistent because $E[\epsilon|T] \neq 0$. For example, in this study, one estimate analyzes the effect of attending NAPS on a student’s overall academic of merit at graduation:

$$AOM_{it} = \alpha + \beta * (NAPS_{it}) + \delta_1 * MathSAT_{it} + \delta_2 * VerbalSAT_{it} + \epsilon_{it}$$
where the error term includes the fact that those students who are given the treatment of attending NAPS are selected for treatment based on their background characteristics. An OLS estimate that includes the background characteristics above will take into account the broad range of performance between treatment and control groups. However, without estimating the matched cohort only, the error term will still be significantly correlated with a given treatment. This study eliminates the demonstrated selection bias by employing propensity score matching techniques. In essence, these techniques use the information from the covariates of those from the control group to observe what would happen to treated individuals if they had in fact not participated in the treatment. By comparing how outcomes differ for treated individuals relative to observationally similar non-treated individuals, it is possible to estimate the effects of the treatment program.

As previously mentioned, many studies on this subject (NCES [1996]; Drosinos [2004]; Fitzpatrick [2001]) utilize simple ordinary least squares regression, or some similar variation, to assess returns from pre-college education programs. OLS regression does have some factors of control in terms of comparing students with similar backgrounds. However, it also includes the entire dataset in analysis, including those students who would never be assigned to pre-college and those who would rarely be accepted before assignment to some type of remedial program. Here lies the benefit of propensity score techniques: propensity score matching addresses the issue of self-selection and allows a decomposition of treatment effects on outcomes through a number of very detailed metrics: average treatment effect (ATE), effect of treatment on the treated (TT), and the potential effect of treatment on the untreated (TUT) (Heckman et al. [2010]).

Given that the selection process for treatment is not perfectly known, the first step is to estimate the likelihood of treatment based on the background characteristics of the students. This entails estimating a “propensity score” for each student.

\[
\text{Propensity Score (PS)} = E(N|X)
\]

In this case, N is a binary variable that reflects participation in the NAPS program. We also examined the propensity score for the treated group when treatment is F for the participation variable for Foundation students, and C for prior college students. The variable X refers to a matrix of background characteristics described above: Math and Verbal SAT scores, rank in high school graduating class, and measure of high school quality. The conversion of background information that affects the treatment selection process into a single scalar variable helps alleviate the “curse of dimensionality” originally described by Rosenbaum and Ruben (1983).

There are a number of ways to estimate and use the propensity score to help combat selection bias and thus capture the true effects of treatment. In this study, the primary method of analysis was propensity score matching (Heinrich et al. [2010]). Propensity score matching methods are designed to ensure that impact estimates of treatment are based on outcome differences between comparable individuals. This approach exploits the entire sample by employing matching algorithms that use the estimated propensity scores to match untreated individuals to treated ones.

There are two assumptions that must be satisfied in order to implement propensity score matching: the Conditional Independence Assumption (CIA) and the Common Support Condition (CSC). The CIA assumption states that there is a matrix of background characteristics, X, which directly impacts selection into the treatment or non-treatment group. However, once this matrix of characteristics is controlled for, the treatment assignment is, according to Heinrich, comparable to random assignment. This assumption acknowledges the presence of selection bias but also defines the ability to reduce that bias by controlling for differences between groups.

The CSC assumption states that for any value of X, the probability of being treated and being untreated is between 0 and 100 percent. In other words, there is a positive probability of being both treated and untreated. This assumption sets up the idea of overlap in background characteristics between the treated and untreated groups. In order to “match” scores, there must be observations in which the background characteristics are similar. This similarity is dependent on the existence of overlap between the background variables of both the treated and untreated groups.
The first step is to estimate the propensity score, typically using a logit or probit function:

\[ E[T_{it}|X_{it}] = S(X_{it}) \]

where \( S(X_{it}) \) describes how covariates influence the decision over whether or not to give treatment. This logit or probit function converts background information from many variables into a single measure of the expected likelihood of a person receiving treatment.

This leads into a discussion of the matrix \( X_{it} \), the background characteristics on which students are matched. A quantitative study like this relies on large amounts of descriptive data that can be manipulated to even the playing field between those who attended a pre-college program and those who did not. However, literature stresses the importance of being parsimonious in terms of variable inclusion in the first stage of analysis (Heckman et al. [2010]). When creating propensity scores in the first stage, we must only include variables that have a direct impact on both selection to treatment and the outcome variable of interest in the specification. This eliminates certain descriptive statistics from our dataset. For example, while gender and ethnicity are important background characteristics of an individual, they have no explicit impact on an outcome measure like academic performance in the first semester of undergraduate studies. Although they may indirectly affect performance due to their correlation with variables like wealth and quality of previous education, gender and ethnicity variables will increase variance. For this reason, it is essential to select first-stage matching variables that describe only information pertinent to the examined outcome variables. A more in-depth discussion of first-stage model specifications is located in the empirical results section.

After creating a propensity score for each individual, the next step is to match up individuals with “similar” propensity scores from treated and control groups. There are a number of matching algorithms we can employ, the most common of which are nearest neighbor matching, radius matching, and kernel and local-linear matching. Nearest neighbor matching is one of the most straightforward matching procedures. An individual from the control group is matched with an individual from the treatment group in terms of the closest propensity score. One can vary this approach to include matching with or without replacement where, in the former case, a member from the control group can be used more than once as a match (this is potentially important for us as far more students enter the Academy directly as opposed to going through NAPS or a Foundation school) (Caliendo and Kopeinig [2005]). In this study, we employed nearest neighbor matching on the closest nearest neighbor, five nearest neighbors, and twenty nearest neighbors, all with replacement. To avoid the potential risk of poor matching, radius matching specifies a maximum propensity score distance (sometimes called a “caliper”) by which a match can be made. This approach differs in that it uses not only the nearest neighbor, but also all of the comparison group members within the caliper. That is, it uses as many comparison cases as are available within the caliper, but not those that are poor matches based on the specified distance (Caliendo and Kopeinig, [2005]). Finally, kernel and local linear matching are non-parametric matching estimators that compare the outcome of each treated person to a weighted average of the outcomes of all those in the control group. The highest weight is placed on those with scores closest to the treated individuals (Caliendo and Kopeinig [2005]).

While there is no clear rule for determining which algorithm is most appropriate, a key consideration is that algorithm selection involves a clear bias/efficiency tradeoff. Nearest neighbor matching minimizes bias by using only the most similar observations but ignores a lot of information, while local linear matching produces more efficiency but increases the bias by potentially using poorer matches. Although there are many more matching algorithms, these are the methods that balance both sides of the bias/efficiency trade off. They are also the methods that we used to analyze the data in this study (Caliendo and Kopeinig [2005]).

Estimating the returns to pre-college education from programs like NAPS, Foundation schools, and prior college is suited to the technique of propensity score matching by virtue of the amount of data available and the end goal: measuring the effect of a treatment on outcome in an observational scenario in which there is inherent selection bias. It was essential to find a way of measuring treatment effects while
taking into account the fact that treatment selection is nonrandom and dependent on a range of variables in designing this study. Moreover, there is no value for any background characteristic for which the probability of treatment is either perfectly zero or perfectly one. This overlap between groups creates a scenario ideal for the use of propensity score matching, while also eliminating more standard methods of analysis due to selection bias.

Another method for eliminating selection bias in treatment versus control studies is to use an instrumental variable. In this study, we used the propensity score itself as an instrumental variable in a second two-stage analysis. In the first stage, we created the propensity score, \( \text{NAPS}_t \), an estimate of the likelihood of an individual attending NAPS based on a matrix of background characteristics. In the hopes of creating a useful instrumental variable, we selected a very inclusive first-stage equation to calculate the propensity score. It is critical to include variables that affect selection to NAPS but do not directly affect outcome variables like academic order of merit, graduation rates, or academic grades. Our model had to not only include the background characteristics we selected for our propensity score matching model but also information on an individual’s ethnicity, home of record, gender, and any other variables that would affect the probability of being assigned to a precollege program.\(^3\)

After calculating \( \text{NAPS}_t \), the second stage of the instrumental variable methodology is to regress performance variables on the instrumental variable and the shortened matrix of background characteristics. The coefficient on the propensity score, \( \text{NAPS}_t \), is a measure of the impact of treatment on the dependent performance variable. One note to make about using the instrumental variable method is that standard errors are biased and appear smaller than they are. This is a result of using the propensity score as a variable, when it is, in fact, an estimation itself. The propensity score has its own standard error associated with it, so using it as a variable in the second stage regression compounds the errors, but we only observed the measured error from the second stage.

4 Data

The data cover USNA students from 1985 through 2011, a total of 29,939 graduates. The full sample includes 22,743 midshipmen who entered directly from high school, 4796 who went through NAPS, 1929 who went to a Foundation school, and 1039 who attended another college before USNA.\(^4\)

Along with distinguishing between midshipmen who enter the Academy directly and those who first attend NAPS or a Foundation school, the data contain a rich assortment of student characteristics. In terms of background information, the data identify each individual’s age, race, gender, SAT scores, high school name, high school location, and high school rank. In terms of potential educational outcome measures, the data include each individual’s grades for all courses taken, name of declared major, aptitude grades, and academic, military and overall orders of merit.\(^5\) Summary statistics including a breakdown of treated and control groups by type of precollege program are displayed in Table 1a and Table 1b.

<table>
<thead>
<tr>
<th>Background Traits</th>
<th>Direct Average</th>
<th>NAPS Average</th>
<th>College Average</th>
<th>Foundation Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Verbal SAT</td>
<td>651.6</td>
<td>585.3</td>
<td>633.604</td>
<td>636.475</td>
</tr>
<tr>
<td></td>
<td>(63.5)</td>
<td>(65.9)</td>
<td>(67.178)</td>
<td>(58.846)</td>
</tr>
<tr>
<td>Math SAT</td>
<td>673.6</td>
<td>603.4</td>
<td>657.012</td>
<td>655.35</td>
</tr>
<tr>
<td></td>
<td>(57.6)</td>
<td>(58.9)</td>
<td>(59.297)</td>
<td>(52.332)</td>
</tr>
</tbody>
</table>

\(^3\) Because USNA is committed to ensuring each graduating class maintains gender, racial, and geographic diversity, these are valid instruments. In order to ensure that the graduating class, after expected attrition, is made up of a diverse group of students from all 50 states and U.S. territories, the admissions process motivates treatment.

\(^4\) For information on institutions specifics of NAPS, and Foundation schools, see Appendix 1.

\(^5\) For information on all performance and background variables, see Appendix 3.
Table 1A includes information on student background profiles. These background characteristics should be interpreted as follows: Verbal SAT is a record of the student’s highest reported verbal SAT score. Math SAT is a record of the student’s highest reported math SAT score. High School Rank (percent) is a percentile rank of each student within his or her respective high school class. A rank of 1.00 means the student was ranked top in his/her class. A rank of .50 means the student was ranked in the very middle of his/her graduating high school class: for example, 45th out of 90 students. The variable Age on IDay gives an accurate measure of a student’s age on the day he/she reported with the rest of his/her class to Induction Day at USNA. The next five variables are geographic indicator variables indicating 1 for the region in which a student’s home of record is located. The geographic regions are broken down as follows: “Central” states include Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. “Northern” states include Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. “Pacific” states include Alaska, Arizona, California, Hawaii, Nevada, Oregon, Utah, and Washington. “Southern” states include Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. Finally, “Western” states include Colorado, Idaho, Kansas, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, and Wyoming. In model specifications, Central is the excluded variable and when using all state dummies Alaska is the excluded variable. Varsity Athlete (indicator) is an indicator variable for whether an individual participated on a Varsity Sports team for any of the semesters while at USNA. Military Mother and Military Father are both indicator variables for whether the individual’s parents ever served in any of the armed forces. High School Quality Measure is a variable that analyzes the academic quality of individual high schools on the same scale as the SAT: from 200 to 800.

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6 Induction Day refers to the report day for incoming freshman about to begin their indoctrination summer at USNA.
Table 1b. Summary Statistics for Key Variables – USNA Performance

<table>
<thead>
<tr>
<th>USNA Performance</th>
<th>Direct Average</th>
<th>NAPS Average</th>
<th>College Average</th>
<th>Foundation Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graduated (indicator)</td>
<td>0.79</td>
<td>0.77</td>
<td>0.815</td>
<td>0.848</td>
</tr>
<tr>
<td></td>
<td>(0.4)</td>
<td>(0.42)</td>
<td>(0.388)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Start Group 1</td>
<td>0.355</td>
<td>0.255</td>
<td>0.357</td>
<td>0.278</td>
</tr>
<tr>
<td></td>
<td>(0.478)</td>
<td>(0.436)</td>
<td>(0.479)</td>
<td>(0.448)</td>
</tr>
<tr>
<td>Start Group 2</td>
<td>0.211</td>
<td>0.261</td>
<td>0.194</td>
<td>0.192</td>
</tr>
<tr>
<td></td>
<td>(0.408)</td>
<td>(0.439)</td>
<td>(0.396)</td>
<td>(0.394)</td>
</tr>
<tr>
<td>Start Group 3</td>
<td>0.274</td>
<td>0.359</td>
<td>0.341</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>(0.446)</td>
<td>(0.439)</td>
<td>(0.474)</td>
<td>(0.494)</td>
</tr>
<tr>
<td>End Group 1</td>
<td>0.313</td>
<td>0.189</td>
<td>0.291</td>
<td>0.235</td>
</tr>
<tr>
<td></td>
<td>(0.464)</td>
<td>(0.391)</td>
<td>(0.454)</td>
<td>(0.424)</td>
</tr>
<tr>
<td>End Group 2</td>
<td>0.2</td>
<td>0.228</td>
<td>0.186</td>
<td>0.181</td>
</tr>
<tr>
<td></td>
<td>(0.4)</td>
<td>(0.42)</td>
<td>(0.389)</td>
<td>(0.385)</td>
</tr>
<tr>
<td>End Group 3</td>
<td>0.281</td>
<td>0.36</td>
<td>0.339</td>
<td>0.431</td>
</tr>
<tr>
<td></td>
<td>(0.449)</td>
<td>(0.48)</td>
<td>(0.474)</td>
<td>(0.495)</td>
</tr>
<tr>
<td>Major Switch</td>
<td>0.898</td>
<td>0.961</td>
<td>0.909</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>(0.302)</td>
<td>(0.193)</td>
<td>(0.288)</td>
<td>(0.237)</td>
</tr>
<tr>
<td>AC grades1</td>
<td>2.703</td>
<td>2.34</td>
<td>2.847</td>
<td>2.544</td>
</tr>
<tr>
<td></td>
<td>(0.677)</td>
<td>(0.583)</td>
<td>(0.68)</td>
<td>(0.595)</td>
</tr>
<tr>
<td>AC grades1</td>
<td>2.728</td>
<td>2.28</td>
<td>2.777</td>
<td>2.491</td>
</tr>
<tr>
<td></td>
<td>(0.644)</td>
<td>(0.567)</td>
<td>(0.654)</td>
<td>(0.58)</td>
</tr>
<tr>
<td>AC grades1</td>
<td>2.87</td>
<td>2.34</td>
<td>2.916</td>
<td>2.585</td>
</tr>
<tr>
<td></td>
<td>(0.685)</td>
<td>(0.627)</td>
<td>(0.704)</td>
<td>(0.624)</td>
</tr>
<tr>
<td>Academic Average</td>
<td>2.902</td>
<td>2.39</td>
<td>2.964</td>
<td>2.651</td>
</tr>
<tr>
<td></td>
<td>(0.661)</td>
<td>(0.586)</td>
<td>(0.614)</td>
<td>(0.592)</td>
</tr>
<tr>
<td>Normalized OOM</td>
<td>0.454</td>
<td>0.696</td>
<td>0.472</td>
<td>0.568</td>
</tr>
<tr>
<td></td>
<td>(0.281)</td>
<td>(0.238)</td>
<td>(0.276)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Normalized AOM</td>
<td>0.429</td>
<td>0.68</td>
<td>0.478</td>
<td>0.563</td>
</tr>
<tr>
<td></td>
<td>(0.284)</td>
<td>(0.262)</td>
<td>(0.279)</td>
<td>(0.276)</td>
</tr>
<tr>
<td>Normalized MOM</td>
<td>0.445</td>
<td>0.628</td>
<td>0.458</td>
<td>0.492</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.277)</td>
<td>(0.281)</td>
<td>(0.287)</td>
</tr>
<tr>
<td>Academic Average</td>
<td>2.941</td>
<td>2.513</td>
<td>2.984</td>
<td>2.703</td>
</tr>
<tr>
<td></td>
<td>(0.505)</td>
<td>(0.409)</td>
<td>(0.499)</td>
<td>(0.434)</td>
</tr>
<tr>
<td>Military Average</td>
<td>3.318</td>
<td>3.19</td>
<td>3.41</td>
<td>3.314</td>
</tr>
<tr>
<td></td>
<td>(0.323)</td>
<td>(0.309)</td>
<td>(0.316)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Professional Average</td>
<td>3.322</td>
<td>2.946</td>
<td>3.271</td>
<td>3.144</td>
</tr>
<tr>
<td></td>
<td>(0.393)</td>
<td>(0.367)</td>
<td>(0.401)</td>
<td>(0.359)</td>
</tr>
<tr>
<td>Youngsterdrop</td>
<td>0.111</td>
<td>0.151</td>
<td>0.1</td>
<td>0.086</td>
</tr>
<tr>
<td></td>
<td>(0.314)</td>
<td>(0.358)</td>
<td>(0.3)</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Plebedrop</td>
<td>0.053</td>
<td>0.059</td>
<td>0.054</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.223)</td>
<td>(0.235)</td>
<td>(0.225)</td>
<td>(0.206)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>20,629</td>
<td>4,796</td>
<td>1,039</td>
<td>1,929</td>
</tr>
</tbody>
</table>

Standard deviations appear below observations in parenthesis. See Appendix 3 for variable descriptions.

Table 1B includes information on performance variables for student assessment while at USNA.
Outcome variables should be interpreted as follows: *graduation* refers to the graduation rate of each cohort. *Start Group 1* is a binary variable giving a value of one for a student who originally elects to pursue a degree as a group one major. Group 1 majors include all of USNA’s engineering majors. It follows that *Start Group 2* and *Start Group 3* are binary variables given a value of one for students who begin their studies at USNA as Group 2 or Group 3 majors. Group 2 majors are USNA’s non-engineering but math and science majors. Group 3 majors are USNA’s humanities and social science majors. For a full list of USNA’s majors by group see Appendix 2. Conversely, *End Group 1*, *End Group 2* and *End Group 3* are all binary variables which indicate the major group in which students conclude their time at USNA or from which major group they graduate. The variable *Majorswap* is a binary variable that indicates the likelihood of a member of that cohort switching majors while a student at USNA.

The next four variables are measures of academic course GPAs during the first four semesters at USNA. Academic grades include all academic coursework but exclude military and professional course grades.

*OOM* refers to the student’s normalized overall order of merit at graduation. Overall order of merit combines measures including academic and professional course grades, military performance, conduct, physical education, and athletic performance. *AOM* refers to the normalized academic order of merit at graduation. *MOM* refers to students’ normalized military order of merit at graduation. Military order of merit is a measure of military performance that includes students’ military grade, conduct grade, professional course grades, athletic performance, and physical education grade. In the interpretation of these variables, it is crucial to recognize that these are not measures of military, academic, or overall performance in a pure sense. Rather, they describe relative performance compared to the performance of all other students in a graduating class. In the results section, a higher or lower *MOM*, *AOM*, or *OOM* signifies a student performing better or worse relative to his/her classmates.

The next three variables are measures of academic, military, and professional course GPA averages over four years of study. The first, titled *Academic Average*, refers to the average course GPA in all academic courses for the first four semesters excluding professional and military coursework. The second, titled *Military Average*, refers to military performance measures including physical education grades, conduct grades, professional course grades, and military performance grades. The supervising officer assigns the military performance grade. Finally, the variable *Professional Average* is a measure of an individual’s average professional grades over four years at USNA.

The variables *Youngsterdrop* and *Plebedrop* are binary variables that indicate the likelihood of a member of that cohort leaving USNA as either a sophomore or freshman.

Consider the summary statistics above. First, note that average differences between treated and non-treated groups for variables such as SAT scores and high school rank are quite large. For example, the average math SAT scores for incoming high school students is 70 points higher than those of students who first attend NAPS. Table 1a and Table 1b display key differences in both background characteristics and performance metrics between treated and control groups before matching. Simply looking at the averages for background characteristics, we find that there appears to be a dramatic difference in the magnitude and spread of the high school percentile variable and the high school quality rank variable. We also see a significant difference in the means of performance variables like academic course grades. The difference in means but large overlap in terms of standard deviation is what motivates an examination of similar characteristics when examining only a matched cohort.

It is useful to see graphically how the overlap in data motivates the use of propensity score matching. Figure 1 illustrates the overlap in Math SAT scores among the four feeder sources: NAPS, Foundation, college, and direct entry.
Figure 1 – Math SAT Score Density by Feeder Source

Figure 2 – High School Percentile Density by Feeder Source
Figure 1 illustrates the dramatic amount of overlap in math SAT scores between the feeder program individuals and the direct entry individuals. This result is also true for verbal SAT scores and for high school percentile rank (see Figure 2). The significant overlap is perfect for matching propensity scores between groups in order to analyze unbiased treatment effect.

After individuals from the treatment and control groups are matched based on propensity scores, we estimated the treatment effect by comparing the mean outcome values of the matched cohort for the treatment group and control group.

Again, if we consider Table 1a and Table 1b, while the mean values for characteristics appear to demonstrate clear demarcation lines between treated and control groups, standard deviations among the variables are large, suggesting a great deal of overlap in student characteristics between the two groups. Consider, for example, the distributions of math SAT scores between treated (NAPS) and non-treated, displayed in Figure 3. The large section of overlapping scores between groups informs our decision about which analysis techniques to use. First, a discontinuity design based strictly on SAT scores would not work. Second, the admissions office was very likely using much more information than just SAT scores in determining selection. For our purposes, the overlap that exists between groups in many student characteristics allowed for the use of propensity score matching to properly estimate treatment effects.

Figures 1, 2, and 3 illustrate the overlap in background characteristics across the different feeder sources. As discussed earlier, one of the assumptions required for use of propensity score matching is the Common Support Condition (CSC), which states the probability of being assigned treatment falls between 0 and 100 percent for any background characteristic X. The overlap in background characteristics illustrated by Figures 1, 2 and 3 legitimizes the use of propensity score matching as a method by which to mitigate selection bias and assess the effects of treatment.
Examining scatterplots of correlations not only reinforces the hypothesis that there is no definite split between background characteristics of treated and control individuals but suggests that individual observations fall all over the map, with only cloudy correlation. For example, Figure 4 depicts the cloud of observations that represent the positive correlation between Math SATs and Verbal SATs. While there is an obvious positive trend depicting the relationship between SAT scores, there is no clear line of demarcation at which the admissions board would be able to make a cut-off value for direct admission. The data are spread out into one large cloud of observations with a large variance. This is evidence that the CIA assumption previously discussed is fulfilled by the dataset and helps inform variable selection.

Figure 4 – Correlation Between Math SAT scores and Verbal SAT scores

![Figure 4](image)

There is massive variation in the data, which both eliminates the possibility of having an unbiased comparison of two groups based on the mean, while simultaneously setting up an ideal scenario for propensity score matching. This variance is mirrored in correlation comparisons of data over time. Figure 5 illustrates a similar cloud of varied observations between overall academic order of merit and Math SAT scores. Figures 4 and 5 illustrate the heterogeneity in background characteristics. For example, Figure 5 illustrates the high density of individuals with SAT scores in the range between 500 and 800 whose overall academic orders of merit (AOM) vary from being in the top 10 percent to the bottom 10 percent by class. Heterogeneity in background characteristics emphasizes the importance of selecting a model specification that includes multiple variables and background characteristics. Even though we might assume that if an individual got a very high score on the math SATs, he/she would also get a very high score on the verbal SATs, the figures above would disprove our assumption. Therefore, it is key to include both SAT variables in our analysis. The multidimensionality of background characteristics is a
crucial aspect of the data to consider when generating propensity scores. Finally, Figures 4 and 5 demonstrate the fact that multi-collinearity should not create much of an issue when undertaking OLS, logistic, or IV regressions. While background characteristics like Math and Verbal SATs are correlated with each other as well as with USNA performance metrics, Figures 4 and 5 illustrate the accompanying heterogeneity.

Figure 5 – Correlation Between Math SAT scores and Overall Academic Order of Merit

5 Model Estimation

This paper utilizes three methods to assess returns from pre-college programs: ordinary least squares (OLS) regression, propensity score matching (PSM), and instrumental variable (IV) analysis. OLS regression is designed to assess a linear relationship between the treated and control groups. Although it is important to include in this paper, OLS gives results that are potentially biased because it relies on the average between the entire treated and control groups. By using PSM analysis, we can specify the cohort of interest to include only those individuals with similar background characteristics who either attended or did not attend a pre-college program. In this way, PSM eliminates students who, based on their background characteristics, either would never or would always have been assigned the treatment of a pre-college program. This allows for a closer examination of the direct effects of the
treatment on treated students. Finally, the propensity score generated in PSM is a useful tool for the third method of treatment analysis. The propensity score allows for regression analysis using the propensity score as an instrument. This IV analysis is a method of regression analysis that provides a more specified estimate of the impact of pre-college programs.

In deciding which variables to use as the determinants in analyzing returns to pre-college education, we considered information about the USNA admissions process to inform our analysis. The USNA admissions board relies on a measure called the “candidate multiple” (CM) to weigh a student’s background characteristics and potential for success as a Midshipman. The criteria that fall into the CM are broken down by percent. Rank in high school class is given the highest weight, at 27 percent of the CM. Because USNA is an engineering school from which all students graduate with a Bachelor of Science, admissions decisions weigh heavily in favor of an individual’s propensity to succeed in high-level math and science courses. For this reason, math SAT scores make up 24 percent of the CM, but verbal SAT scores make up only 12 percent. Technical interest, or a student’s expressed desire to study a technical subject, accounts for 14 percent of the CM. Official high school recommendations are weighted 11 percent. High school extra-curricular activities are weighted at 8 percent, and the final 4 percent of CM weight is assigned according to whether a student expresses an interest in a career in the military (Fitzpatrick [2001]). This information on the candidate multiple suggests which variables should be included in OLS, PSM, and IV analysis. In addition, the dataset used in this analysis includes the specific key characteristics that are used by the admissions board to determine the CM.

5.1 Ordinary Least Squares and Logistic Regression

Equations for the OLS and logistic regression models are based on examining the effect of the binary treatment variable (either NAPS, Foundation, or College) on a range of performance variables. For OLS and logistic regressions, equations take the following forms:

\[
Y_{it} = \alpha + \beta \times (NAPS_{it}) + \delta_1 \times \text{MathSAT}_{it} + \delta_2 \times \text{VerbalSAT}_{it} + \delta_3 \times \text{HSRank}_{it} + \delta_4 \times \text{HSQuality}_{it} + \epsilon_{it} 
\]

Where \(Y_{it}\) is \(AOM_{it}, GradStat_{it}, AcGrade1_{it}, AcGrade2_{it}, AcGrade3_{it},\) and \(AcGrade4_{it}\). The OLS equations include a binary variable that indicates participation in NAPS, controls for Math and Verbal SAT scores, high school rank, and high school quality. The coefficient \(\beta\) is the measure for the impact of NAPS on the dependent performance variable. The performance variables which we examined using OLS are academic order of merit, graduation rate, and academic grades during the student’s first four semesters as a midshipman.

5.2 Propensity Score Matching

In propensity score matching, the first stage equation is a regression similar to those above. In the second stage, we employed a matching algorithm to match individuals from the treatment and control groups based on their calculated propensity scores. Propensity score matching allows us to examine more closely the direct impact of NAPS on the cohort of students who are treated. Unlike OLS, PSM examines only those students who fall into the matched cohort of treated and untreated students. Similar to the regressions above, the USNA admissions policies suggest the use of four key background variables in calculating the propensity score. In the context of the Conditional Independence Assumption (CIA), the information on the candidate multiple determines the correct specification for background characteristics that we used in order to mitigate selection bias. Admissions puts heavy weight on high school rank and SAT scores. Therefore, these are the characteristics that most directly affect selection into the treatment group, or assignment to a pre-college program, and therefore are included in our first stage propensity score matching model.

Matching criteria for the first stage propensity score must impact both the selection for treatment and the final outcome variable (Caliendo and Kopeinig [2008]). However, variables must not be affected
by treatment and therefore must be fixed over time or measured before treatment. Over-specifying the first stage model can exacerbate what is referred to as the common support problem: where there is no overlap in background characteristics for treated individuals in the un-treated sample, those treated individuals are dropped from analysis. This is a danger of propensity score matching; there is the potential for eliminating a significant number of treated observations, leading to incomplete results. At the same time, isolation of a specific cohort of the data is part of what informs returns to treatment and eliminates selection bias (Bryson, Dorsett and Purdon [2002]). Specifically, this paper compares the academic performance of students with background characteristics that are comparable to those of students who actually attended preparatory school, rather than to all students admitted to USNA. Finally, there is danger in over-specifying the model and inflating variance (Lechner and Smith, 2002; Bryson, Dorsett, and Purdon [2002]). Others suggest that all variables related to the outcome that are proper covariates should be included in any first stage specification (Rubin and Thomas [1996]).

In this study, we chose to run a very inclusive specification and a second specification that only included a few choice-matching criteria. This provides a robustness test as well as ensuring that the first stage is an accurate model on which to predict the second stage. For the less inclusive specification, we used Math SATs, Verbal SATs, high school rank, and high school quality in the first stage equations. Equations for the propensity score matching section of this paper take the following forms:

\[
Y_{it} = \alpha + \delta_1 \cdot \text{MathSAT}_{it} + \delta_2 \cdot \text{VerbalSAT}_{it} + \delta_3 \cdot \text{HSRank}_{it} + \delta_4 \cdot \text{HSQuality}_{it} + \varepsilon_{it} \tag{8}
\]

where \(Y_{it}\) is \(\text{NAPS}_{it}\), \(\text{Foundation}_{it}\), or \(\text{College}_{it}\). In this case, the propensity score is the estimated value of \(\text{NAPS}_{it}\), \(\text{Foundation}_{it}\), or \(\text{College}_{it}\). In the second stage, we employed nearest neighbor, caliper, and kernel matching to compare the difference in means of the propensity score of the treatment and control group between matched observations.

### 5.3 Instrumental Variable Regression

In the final method of comparing treatment and control groups, we employed the propensity score as an instrumental variable. This comparison again utilizes the propensity score. In order for the propensity score to be a valid instrument, it must include information that is not directly attributable to success at USNA but directly influences admission to NAPS. This is the definition of the exclusion principle. In this case, the inclusion of the state variable makes \(\text{NAPS}_{it}\) a valid instrument. Due to the mandate that USNA graduate a diverse class of officers who reflect the makeup of the fleet and the commitment of USNA to graduating officers from every state and US territory, USNA admissions wants to ensure that students from all states and territories are successful enough at USNA to graduate. Admissions can directly influence this success by assigning individuals to pre-college programs. Therefore, a student’s home state effects his/her likelihood of assignment to pre-college but not directly his/her performance at USNA. The first stage equation for IV analysis is in the following form:

\[
\text{NAPS}_{it} = \alpha + \delta_1 \cdot \text{MathSAT}_{it} + \delta_2 \cdot \text{VerbalSAT}_{it} + \delta_3 \cdot \text{HSRank}_{it} + \delta_4 \cdot \text{HSQuality}_{it} + \delta_5 \cdot \text{Varsityathlete}_{it} + \delta_6 \cdot \text{Gender}_{it} + \delta_7 \cdot \text{(Ethnicity Dummy)}_{it} + \delta_8 \cdot \text{(State Dummy)}_{it} + \delta_9 \cdot \text{(Year Dummy)}_{it} + \varepsilon_{it} \tag{9}
\]

After calculating \(\text{NAPS}_{it}\), we insert those values into a regression formula and observe the coefficient on that variable. The second stage models are in the following forms:

\[
Y_{it} = \alpha + \psi \cdot (\text{NAPS}_{it}) + \delta_1 \cdot \text{MathSAT}_{it} + \delta_2 \cdot \text{VerbalSAT}_{it} + \delta_3 \cdot \text{HSRank}_{it} + \delta_4 \cdot \text{HSQuality}_{it} + \varepsilon_{it} \tag{10}
\]
where $Y_{it}$ is $AOM_{it}$, $GradStat_{it}$, $AcGrade1_{it}$, $AcGrade2_{it}$, $AcGrade3_{it}$, and $AcGrade4_{it}$. The variable $\psi$ is the coefficient on $NAPS_{it}$, which gives an estimate of the treatment effect on performance variables.

6 Empirical Results

Across all three methods of analysis, qualitative results remain consistent. Pre-college education programs, both NAPS and Foundation school, are associated with positive returns to college graduation rates. However, students who attend these pre-college programs will perform at a lower level academically overall than similar students who do not attend pre-college programs. Moreover, results indicate positive returns to academic grades during the first semesters at USNA, followed by insignificant results, and in PSM analysis, negative returns to academic grades in the third and fourth semesters at USNA.

6.1 Ordinary Least Squares and Logistic Regression

Before we undertake any regression methods that expressly address selection bias, it is useful to examine how ordinary least squares and logistic regression describe returns to educational outcomes based on participation in a preparatory school program. Table 2 illustrates the coefficients on the binary independent variable $NAPS$ in OLS and logistic regressions with each of the performance variables listed as dependent variables, and $NAPS$, $HighestMathSAT$, $HighestVerbalSAT$, $hspercentile$, and $HsOfficialStClassRank$ as the independent variables.

Coefficients on the $NAPS$ variable paint an interesting picture. Positive returns to NAPS participation on academic grades during the first semester (0.1475) diminish in magnitude and eventually become negative by the third semester (-0.0341). Returns on military performance are negative by the second semester. *Academic order of Merit* is negatively impacted by attendance at NAPS, causing a decrease in normalized $AOM$ of 2.76 percent. Logistic results suggest that those who attend NAPS are less likely to drop out controlling for background characteristics. In fact, individuals are 1.3 times more likely to graduate having gone to NAPS.

The OLS and logistic regression methods of analysis are important tools but may fail to explicitly account for the endogeneity associated with this type of treatment study. Since the regression coefficients are based on the entire data sample, a linear relationship between the background variables and the probability of going to NAPS is assumed. Ordinary least squares regression is a method with fundamental pitfalls for this type of analysis, which has both a treatment and control group. Results from a linear regression might be extremely sensitive to the averages of each group. If we consider individuals on the very high end of performance metrics, there will be observations in each group who would inevitably go to NAPS or not go to NAPS based on their background characteristics. For example, an individual with perfect SAT scores ranked first in his/her high school class has a very low probability of being assigned to a remediation program. Conversely, an individual with 400 SATs for math and verbal and a very low high school rank has a very low probability of being admitted directly to USNA. However, when using OLS or logistic regression and trying to create a linear relationship between treatment and control groups, the observations that are unlikely to appear in either group might skew the linearity of the regression and affect the averages. For this reason, OLS and logistic regressions could produce biased estimates of treatment effects. However, it is still useful to analyze the results of OLS and logistic regressions because they provide a baseline result from which we can turn to PSM and IV analysis.

| Table 2 - OLS and Logistic Regression - Impact of NAPS on Outcome Variables |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                                 | Grad AOM        | Graduation Rate | Ac Grade 1      | Ac Grade 2      | Ac Grade 3      | Ac Grade 4      |
| NAPS                            | 0.0276***       | 1.303***        | 0.1475***       | 0.0232**        | 0.0341***       | -0.078***       |
The coefficients on the independent variables Math SAT, Verbal SAT, High School rank, and High School quality have the expected signs and magnitudes. Higher Math and Verbal SAT scores are associated with a higher AOM, higher likelihood of graduation, and positive returns in all four semesters of academic grades. High School rank and High School quality are also associated with positive returns to AOM, Graduation Rate, and all four semesters of academic grades.

6.2 Propensity Score Matching First Stage – Creating a Matching Specification with Background Estimators

Table 3 – Coefficients for First Stage Matching Using NAPS

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>High School Quality Measure</td>
<td>-0.0036***</td>
<td>-0.004***</td>
<td>-0.0035***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>High School Rank (Percent)</td>
<td>-0.886***</td>
<td>-0.358***</td>
<td>-0.374***</td>
</tr>
<tr>
<td></td>
<td>(0.129)</td>
<td>(0.166)</td>
<td>(0.218)</td>
</tr>
<tr>
<td>Verbal SAT</td>
<td>-0.006***</td>
<td>-0.005***</td>
<td>-0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Math SAT</td>
<td>-0.0098***</td>
<td>-0.008***</td>
<td>-0.008***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0004)</td>
<td>(.0004)</td>
</tr>
<tr>
<td>Age on IDay</td>
<td>--</td>
<td>1.33***</td>
<td>1.35***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(.0274)</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>--</td>
<td>0.821***</td>
<td>0.877***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.052)</td>
<td></td>
</tr>
<tr>
<td>Asian American</td>
<td>--</td>
<td>0.699***</td>
<td>0.71***</td>
</tr>
<tr>
<td></td>
<td>(0.084)</td>
<td>(0.086)</td>
<td></td>
</tr>
<tr>
<td>African American</td>
<td>--</td>
<td>0.789***</td>
<td>0.791***</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.056)</td>
<td></td>
</tr>
</tbody>
</table>
Table 3 illustrates the first stage of the two-stage PSM analysis. In the first stage, we generated the propensity score that is then algorithmically matched in the second stage. For each specification, all coefficients are statistically significant. The first stage coefficients suggest that gender, race, and age are much more influential in determining whether an individual will attend NAPS than his/her SAT scores are. The direction of coefficients suggests that being female, a minority, or a year older increases the probability of the student being sent to NAPS. This is a scenario in which the specificity of the model is causing certain coefficients to absorb the impacts of variables not included in the model. In this case, the model is over-specified to include variables that should not have an impact on the graduation rate. Gender and ethnicity should theoretically have little impact on outcome measures like academic grades or graduation rates. However, it is still useful to analyze the effect of these variables and consider what other factors they are absorbing, particularly family income and parents’ education level. These variables will show up again as part of the instrumental variable estimation section to satisfy the exclusion restriction.

The first model is the primary model of interest for this study. The admissions board weighs SAT scores and high school class rank the heaviest when assigning a CM score to each candidate. Therefore, it follows that our specification for assessing the probability of being assigned to NAPS, offered a place at a Foundation school, or just rejected from USNA entirely should depend upon those same key metrics. The coefficient magnitudes and directions follow from using logic about the definition of pre-college education and the purpose of NAPS. SAT scores are accompanied by small negative changes in the propensity to go to NAPS. High school rank absorbs most of the model effects, suggesting that being ranked highly in one’s graduating high school class is the strongest contributing factor as to whether a student is offered an appointment to NAPS. Finally, the relative rank of the high school one attends contributes marginally to attendance at NAPS. Those who attend more highly ranked high schools will be marginally less likely to be sent to NAPS. Of note, the low coefficient of determination, R squared, suggests that 39.9 percent of the variation on the left side of the regression equation is explained by variation on the right side of the equation.

Model 2 includes the background characteristics of sex, ethnicity, age, SAT scores, high school class rank, and high school quality measure. This is a very inclusive specification and runs the risk of generating results with high variance. It also includes variables that theoretically have no impact on the outcome measures. Gender and ethnicity theoretically have little impact on outcome measures like academic grades or graduation rates. However, for robustness purposes it is crucial to include this specification as a first-stage model.
When we eliminate gender, race, and age from the model, the magnitude of coefficients is mostly absorbed by the high school rank variable. This follows the conclusion that the standard errors are serving as proxies for variables for which we have no data. In a similar way, a measure for age is a double-edged sword when included in the first stage specification. NAPS (and Foundation school) students tend to be older than the typical midshipman who enters the Academy straight from high school. There is the possibility that any positive effects in terms of academic performance are simply a result of the fact that they are one year older and are therefore more likely to succeed in college simply because they have greater maturity. However, the data includes significant overlap in age between treated and untreated populations, so a simple control should prevent any systematic error. At the same time, the Age on Induction Day variable strongly predicts whether a student attended a pre-college program, introducing bias that may skew results. Despite the inclusion of seemingly irrelevant variables, the first model has an R squared value of .6077. In other words, 60 percent of the variation in the dependent variable is explained by variation in the independent variables.

Finally, the third model includes a geographic region proxy variable based on the region in which the individual went to high school. The specification is relative to the central variable. Again, this variable should not have a direct impact on graduation rates, but education by state and by region of the United States is very different. However, even with the inclusion of these new variables, the R squared value stays relatively constant at .6152. The second-stage results for each specification are highlighted in the next section of this paper.

6.3 Propensity Score Matching Second Stage – Matched Results

The results of this study are broken down into three major sections: results for NAPS students, results for Foundation school students, and results for students who attended a four-year college before matriculating at USNA.

The following tables document the cohort differences in a number of outcome variables between NAPS students and direct entry students, Foundation students and direct entry students, and prior college students and direct entry students.

For robustness purposes, we include five matching methods for each matched outcome variable. NN(1), NN(5), and NN(20) refer to nearest neighbor matching results using the closest nearest neighbor, the five nearest neighbors, and the 20 nearest neighbors. Caliper refers to caliper matching with a radius of .001 units. Kernel refers to kernel matching using the normal Gaussian method.

6.3.1 NAPS

Table 4a illustrates second stage matched results comparing NAPS and direct entry students. If we consider the aim of the NAPS program is to prepare students for a rigorous four years of academic work at USNA, the key performance metrics by which we measure success are graduation rates and academic performance metrics. As documented in Table 4a, the cohort of NAPS students graduate at a rate nearly 10 percent higher than those who do not attend a precollege program controlling for background characteristics. Even the most modest estimate of positive returns to graduation rates, using only the single nearest neighbor method, generated an estimate that those who attend the NAPS program graduate at a rate 7.3 percent higher than those students of similar backgrounds who do not attend the NAPS program. This is a significant result as it suggests positive returns to the NAPS program for a key performance metric. Graduating as many students as possible is not only in the interest of the U.S. Navy but is an expressed goal of national education policy makers. As was discussed in the introduction to this paper, degree attainment is a determinant of future wage earnings.

Although returns to graduation rates are positive, returns to class rank are significantly negative. Matched results suggest that overall order of merit is negatively impacted by attendance at the NAPS program. Matching based on the twenty nearest neighbors suggests that overall order of merit is decreased by 4.2 percent for NAPS attendees compared with direct entrants. Academic order of merit is similarly affected by attendance at NAPS. Academic order of merit is decreased by over 6 percent based on all four matching methods. Military order of merit is even more negatively impacted, since it decreased by 6.5
percent using the most modest estimate. One conclusion from these results is that the NAPS program helps with retention rates of marginal students while failing to help them improve academically. There are a few possible explanations for these results. It is possible that pre-college programs like NAPS and Foundation schools imbue students with skills that may not help them earn higher grades but help them persevere through a difficult college experience. This could be a result of students being one year older and more mature than they were coming directly out of high school. Another explanation for graduation rates is that NAPS students feel added pressure to finish their degree program at USNA because they have already committed an extra year to the program. Meanwhile, the academic performance generalizations could be a result of NAPS students seeing similar course material repeatedly. For example, a NAPS student might take calculus during their senior year of high school, again at NAPS, and then again at USNA during their first semester as a Midshipman. Familiarity with the material could explain higher performance during the first semester. Then, once students begin taking unfamiliar courses during the second semester, their higher performance diminishes.

An unmatched academic grades comparison indicates significant negative returns to the NAPS program. However, matched results show a trend of positive returns to the NAPS program in the first semester of academic coursework followed by diminishing returns and eventually negative returns in the third and fourth semesters. The magnitude of academic grade improvement in the first semester is only about half as great as the magnitude of improvement for NAPS students in their STEM course grades in the first semester. For example, the most modest estimate of academic grade improvement in the first semester for NAPS students is .152, using only the single nearest neighbor as a match. By the second semester returns are insignificant. In the third semester returns are significantly negative, but results should be interpreted cautiously due to increased heterogeneity. The most modest estimate using the twenty nearest neighbors is still -.095. Returns are also negative in the fourth semester, with the most modest estimate still at a value of -.076. When we analyze academic grades and reasons behind the positive returns in the first semester followed by diminishing and then eventually negative returns, it is crucial to note that major selection occurs at the end of the second semester of an individual’s freshman year. This means that third semester academic course grades include noise associated with each individual picking his/her own major and beginning his/her major courses. These results may also reflect the fact that students take courses in pre-college programs that they then repeat during their first year at college. However, after repeating a course they have already taken, these students find themselves unprepared for new coursework. This could signify superficial positive returns to academic grades in the first semester of college, since students are simply repeating what they have already been exposed to, not demonstrating a higher performance level than the matched cohort of students who did not attend pre-college.

USNA has a mandate to graduate at least 70 percent of each class with a STEM degree. This puts a large amount of emphasis on academic performance in the STEM fields. Unmatched results comparing grades in STEM courses for the NAPS cohort and the direct entry cohort suggest negative returns during the first four semesters. However, the matched results tell a different story. The matched results indicate that there are positive returns to STEM course grades in the first semester at USNA. These positive returns range from .296 to .316 on a 4.0 scale. The magnitude of the matched results indicates that those who attended the NAPS program have positive returns in their first semester STEM grades on the order of 7.5 percent higher grades. During the second semester these positive returns diminish to insignificance. By the first semester of the sophomore year at USNA the returns to STEM grades are significantly negative. Between the third and fourth semester returns are between -.113 and -.06. While the magnitude of these negative returns is smaller, they are still statistically significant. These matched results suggest that the NAPS program is not helping students improve their grades in technical courses after the first semester, and due to some aspect of the NAPS cohort, the group performs significantly worse in STEM course grades than individuals with similar backgrounds who entered USNA directly from high school.

Explanations for these negative returns include the possibility of peer effects having an impact on the academic performance of NAPS students. Another explanation is that by the third semester of academic coursework, variance and noise have increased to the point that a realistic comparison of science, technology, engineering, and math GPAs is unreasonable. During the first year at USNA, the vast
majority of students are immersed in the same coursework at the same time. This allows for a fairly consistent comparison across all students for the first year. However, by the third semester, students have begun their major coursework and have more freedom in their schedules to take on other classes and participate in other activities. This adds significant noise to the comparison after year one.

Returns to military coursework mirror the same trend. Returns to the NAPS program in the first semester are significantly positive, with a minimum magnitude of .099 in the positive direction using caliper matching. Returns diminish to insignificance, but by the third semester, the beginning of an individual’s sophomore year, returns are significantly negative with a minimum magnitude of -.059. By the fourth semester returns on military performance are again insignificant.

These results are somewhat troubling considering the fact that NAPS participants have been immersed in a military style preparatory school program for a year before entering USNA. They have already undergone one military indoctrination summer and have been active duty members of the U.S. Navy for an entire year before they begin courses at USNA. The expectation is that NAPS participants are better prepared for the military aspects of USNA than the comparable cohort of direct applicants. However, results suggest that the positive returns of a year of military experience are of small magnitude and are fleeting, or that non-NAPS students catch up and pass their NAPS peers in terms of military performance.

Effects on major course grades are insignificant in a student’s sophomore year. However, during a student’s junior year there are negative returns on major’s course grades from having attended the NAPS program. Even according to the most modest estimate using the twenty nearest neighbors, major grades are decreased by -.087 in the first semester of the student’s junior year, and -.087 in the second semester, junior year.

The final significant outcome measures include that of an individual’s propensity to leave USNA before graduation. Youngsterdrop and plebedrop both indicate that the NAPS program has a positive impact on retention during sophomore year. Freshman and sophomore retention is of particular interest for USNA because those individuals who are unwilling to commit themselves to service after graduation will typically leave the Academy of their own accord during their first two years before they incur debt. According to matched results, NAPS participants are between 4.1 and 6.1 percent less likely to drop out during their youngster year and between 4.3 and 6.3 percent less likely to drop out during their freshman year.

The End Group 1 and End Group 3 variables are insignificant across the board. However, the End Group 2 variable suggests positive returns to ending in a group 2 major if a student attends NAPS. This significant result may reflect the fact that group 2 includes the general science major. NAPS students are between 5.6% and 6.8% more likely to be a group 2 major. Interestingly, of the 1049 group 2 majors who graduated from USNA after attending NAPS, 276 of them majored in General Science (26 percent). However, out of the 4389 group 2 majors who graduated from USNA without attending a pre-college program, only 363 majored in General Science (8 percent). This leads to the conclusion that while NAPS students are more likely to become group 2 majors, they are overwhelming graduating with a General Science degree.

Finally, the rate at which students swap majors is a representation of academic preparedness for a demanding level of coursework. Matched results indicate that the cohort of NAPS students switch majors between 9.8 and 11.7 percentage points more often than direct entry students.

Propensity score matching leads to the conclusion that there are significant positive returns to investment in the NAPS program. Students are better prepared for (or at least more familiar with) their first semester coursework. There are also significant positive returns to graduation rates and retention. From a macroeconomic viewpoint, this conclusion is crucial for the implications of the NAPS program. If a year of pre-college is improving graduation rates by 10 percent, many marginal students could benefit from similar treatment. As long as students graduate and receive a degree, they will be part of a different workforce with more resources and available jobs, regardless of whether their pre-college prepared them academically.
Table 4a – Second Stage Matched Results Comparing NAPS and Direct Entry Students

<table>
<thead>
<tr>
<th></th>
<th>Unmatched</th>
<th>NN(1)</th>
<th>NN(5)</th>
<th>NN(20)</th>
<th>Caliper</th>
<th>Kernel</th>
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<td>(0.017)</td>
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6.3.2 Foundation Schools

Trends in the Foundation school matched results mirror some of the results from matched results on the NAPS cohort. Table 4b illustrates the unmatched and matched comparison of effects of Foundation school treatment. The cohort of Foundation students graduate at a rate nearly 10 percent higher than those who do not attend a precollege program. The most modest estimate of positive returns to graduation rates, using the caliper method, generates an estimate that those who attend a Foundation school graduate at a rate 8.0 percent higher than students of comparable backgrounds who do not attend Foundation school. This is similar to the result gleaned from data on NAPS participants.

Unlike for the NAPS cohort, returns to class rank are positive for the Foundation cohort. Matched results suggest that overall order of merit is positively impacted by attendance at the Foundation program. However, these results are marginal and significant only for two of the five matching methods. Matching based on the caliper method suggests a 2.2 percent positive change in class rank due to attendance at a Foundation school. Kernel matching, on the other hand, suggests a 3.6 percent negative shift in class rank based on attendance at a Foundation school. Academic order of merit results are similarly confusing, and no results are statistically significant. Mirroring the positive returns to military performance grades, the military order of merit measure is positively impacted by attendance at a Foundation school in four out of the five matching methods. Military order of merit is increased by 4.5 percent using the most modest estimate, the caliper method.

In terms of academic coursework, results for the Foundation cohort mirror NAPS results. There are significant positive returns to the Foundation school program in the first semester of academic coursework. Even the most modest estimate using the twenty nearest neighbors suggests a .134 increase in academic grade improvement. However, by the second semester these positive returns are diminishing and only significant in two out of the five matching methods. By the third semester, returns have become negative although they are still only significant in two out of the five matching methods. The magnitude of the negative returns is much lower than the magnitude of positive returns in the first semester, with the most modest estimate based on twenty nearest neighbors is a difference of -.044. The fourth semester results are insignificant. The resulting magnitudes are comparable to the magnitude differences between the NAPS and direct cohort. In other words, these results are similar to NAPS results in both trend and magnitude.

Looking more specifically at positive returns to STEM grades from the Foundation school program, unmatched results suggest large magnitude negative returns in all four semesters. However, the matched results show a familiar trend. First semester positive returns to STEM grades are significant across the board except for using kernel matching. Even the most modest estimate suggests .136 positive difference in STEM grade point average using the caliper method of matching. By second semester, positive returns have diminished to insignificance, and by the third and fourth semesters there are significant negative returns to attending a Foundation school. The negative returns are significant across all methods of matching, and even the most modest for third semester is -.109 using the five nearest neighbors, and -.061 for the fourth semester using the caliper method. Comparing Foundation results to NAPS results, the magnitude of returns to STEM grades is halved in the first semester and nearly doubled in the third semester. In other words, the initial positive returns in the first semester are much smaller than returns to the NAPS program, and the negative effects in the third semester are much larger.

These matched results again suggest the troubling conclusion that Foundation schools are not
only not helping, but due to some aspect of the pre-college cohort, the group performs significantly worse in STEM course grades than individuals with similar backgrounds who entered USNA directly from high school.

Explanations for these negative returns again include the possibility of peer effects having an impact on the academic performance of Foundation students. Another explanation is that by the third semester of academic coursework, students are taking so many different courses and have different majors that variance and noise have increased to the point that a comparison is not feasible.

The returns to military performance grades are surprising based on the trends seen in academic and STEM grades. Foundation students perform better militarily than comparable direct entry students in each semester across nearly all matching methods. Moreover, the magnitude of performance stays fairly consistent. First semester, kernel matching gives the most modest estimate of positive returns to be .086. Kernel matching is again the most modest at .072 for second semester and .075 third semester. By the fourth semester, positive gains from Foundation school have diminished, with the most modest estimate suggesting positive returns of .032 based on an analysis of twenty nearest neighbors.

The variables that describe the type of major from which a student graduates are broken down by USNA designation. The *End Group 1* and *End Group 2* variables are insignificant across the board. However, the *End Group 3* variable suggests positive returns to ending in a group 3 major if a student attends a Foundation school. As described above, group 3 majors include the humanities and social sciences. Specifically, the cohort of Foundation school students is, by the most modest estimate, 6.7 percent more likely to graduate as a group three major than the matched cohort of direct entry students. Effects on major course grades are statistically insignificant during both the sophomore and junior year.

Like NAPS students, Foundation school students are less likely to leave USNA before graduation. The *Youngsterdrop* and *Plebedrop* variables both indicate that the Foundation school program has a positive impact on retention during freshman and sophomore year. According to matched results, Foundation school students are between 4.8 and 6.8 percent less likely to drop out during their younger year, and between 2.1 and 3.2 percent less likely to drop out during their freshman year. This may reflect the fact that Foundation school students feel the burden of preparatory school tuition. While NAPS is free for students, Foundation schools require families to contribute some tuition based on financial need. Those students who attended Foundation schools may feel extra pressure to graduate from USNA based on the fact that their families have contributed financial resources to their success. Also similar to the NAPS cohort results, matched results for Foundation students indicate that the treated cohort switch majors between 4.9 and 5.9 percentage points more often than direct entry students.

The conclusions about the Foundation school cohort of treated students echoes the conclusions about the returns for the NAPS program. Propensity score matching suggests positive returns to sending students to Foundation schools. Students perform better in their first semester coursework, are more likely to graduate, and less likely to drop out during their freshman and sophomore years. Foundation schools also appear to contribute to significant positive performance in the military aspect of USNA life. This makes sense based on the fact that many Foundation schools are military based preparatory school programs. As in the NAPS conclusions, positive returns to academic performance appear to dwindle into insignificance and eventually turn negative by the third and fourth semester. This suggests the disturbing possibility that negative returns to investment in preparatory school programs are not isolated to the USNA specific NAPS program, but that this result may be a symptom of programs nationwide.

Table 4b – Second Stage Matched Results Comparing Foundation and Direct Entry Students

<table>
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<tr>
<th></th>
<th>Unmatched</th>
<th>NN(1)</th>
<th>NN(5)</th>
<th>NN(20)</th>
<th>Caliper</th>
<th>Kernel</th>
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</thead>
<tbody>
<tr>
<td><strong>Graduation</strong></td>
<td>0.058***</td>
<td>0.095***</td>
<td>0.096***</td>
<td>0.09***7</td>
<td>0.095***</td>
<td>0.08***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.016)</td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.016)</td>
<td>(0.01)</td>
</tr>
<tr>
<td><strong>OOM</strong></td>
<td>0.109***</td>
<td>-0.022*</td>
<td>-0.015</td>
<td>-0.014</td>
<td>-0.022*</td>
<td>0.036***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.011)</td>
<td>(0.008)</td>
</tr>
<tr>
<td><strong>AOM</strong></td>
<td>0.123***</td>
<td>-0.008</td>
<td>-0.003</td>
<td>0.0004</td>
<td>-0.009</td>
<td>0.048***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.012)</td>
<td>(0.008)</td>
</tr>
<tr>
<td></td>
<td>MOM</td>
<td>AC grades1</td>
<td>AC grades2</td>
<td>AC grades3</td>
<td>AC grades4</td>
<td>MIL grades1</td>
</tr>
<tr>
<td>----------------</td>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
<td>--------------</td>
</tr>
<tr>
<td></td>
<td>0.045***</td>
<td>-0.155***</td>
<td>-0.232***</td>
<td>-0.283***</td>
<td>-0.256***</td>
<td>0.045***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.013)</td>
</tr>
<tr>
<td></td>
<td>-0.046***</td>
<td>0.148***</td>
<td>0.042*</td>
<td>-0.045</td>
<td>-0.035</td>
<td>0.103***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.02)</td>
<td>(0.019)</td>
<td>(0.015)</td>
</tr>
<tr>
<td></td>
<td>-0.047***</td>
<td>0.143***</td>
<td>0.044**</td>
<td>-0.054**</td>
<td>-0.028**</td>
<td>0.113***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.02)</td>
<td>(0.019)</td>
<td>(0.015)</td>
</tr>
<tr>
<td></td>
<td>-0.047***</td>
<td>0.134***</td>
<td>0.035*</td>
<td>-0.044*</td>
<td>-0.037*</td>
<td>0.115***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.018)</td>
<td>(0.017)</td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.015)</td>
</tr>
<tr>
<td></td>
<td>-0.045***</td>
<td>0.148***</td>
<td>0.046</td>
<td>-0.045</td>
<td>-0.034</td>
<td>0.101***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.02)</td>
<td>(0.025)</td>
<td>(0.018)</td>
</tr>
<tr>
<td></td>
<td>-0.011</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Standard errors in parentheses. See Appendix 3 for variable descriptions. *** .01, **.05, *.1 significance.
6.3.3 Prior College

An analysis of educational returns for students who attended a prior year of college bear almost no comparison to the matched NAPS and Foundation school results. Students who attended college prior to USNA see positive returns to nearly all performance variables across nearly all methods of matching. Table 4c illustrates the unmatched and matched comparison of effects of college on performance at USNA. It is important to note that propensity score matching is used to compare students of similar backgrounds who are either assigned treatment or not assigned treatment. In this case, by virtue of rejection from the Academy, this cohort of students had the means and desire to enroll in another college and re-apply to USNA for the following year. Therefore, it is unrealistic to make an apples to apples comparison of this type of treatment with other “pre-college” treatments like NAPS and Foundation schools. However, it is informative to examine returns of a year of college in order to draw conclusions about the effectiveness of pre-college preparatory programs versus other education systems on a broader national scale.

Prior college students graduate at a higher rate than the similar cohort of direct entry students; however, the magnitude of the difference in graduation rates is not as dramatic as the comparison between Foundation and direct entry, or NAPS and direct entry groups. The kernel method is the most modest in estimating that prior college students graduate at a rate 3.7 percent higher than matched direct entry students. Matching based on the five nearest neighbors estimates a graduation rate for prior college students that is 6.8 percent higher than direct entry students.

Returns to class rank are also positive. Matched results suggest that overall order of merit is positively affected between 6.1 and 8.4 percent by a year of outside college. Academic order of merit results are significant on three out of the five matching methods and suggest higher rank by between 3.0 and 5.6 percent. The military order of merit measure is also significant on three out of the five matching methods and is positive between 3.6 and 6.0 percent.

In terms of academic coursework, results for the college cohort are large in magnitude and positive across all four semesters. First semester positive returns on academic grades range between .21 using the kernel method and .373 using 20 nearest neighbors. Second semester the most modest estimate using kernel matching is .132 and the highest magnitude match is .282 using 20 nearest neighbors. Third semester results range between .15 and .291, and fourth semester results range between .152 and .28. All four semesters have large magnitude positive returns to academic grades from a prior year of college.

Returns to STEM grades mirror the returns to academic grades, but with even more dramatic magnitudes. First semester positive returns are between .274 on the low end kernel estimate, and .526 matching on the nearest neighbor. This suggests that those students who attend a year of college are outperforming students of similar backgrounds who were admitted directly to USNA by over .5 on a 4.0 scale. In other words, their STEM grades are 12.5 percent higher than the comparable direct cohort. Second semester returns are between .155 and .347. Third semester returns are between .17 and .409, and fourth semester returns are between .144 and .295. Not only are returns to STEM grades significantly positive, but also the positive returns persist far past the first semester into the fourth semester, unlike the positive returns seen from the NAPS and Foundation programs.

These matched results suggest that having a year of college before attending USNA can provide students not only with the course familiarity to succeed in their freshmen courses, but it also equips them with other skills that cause them to outperform direct entry students of similar backgrounds in later semesters when coursework is less standard and is more unfamiliar. These results beg the question of why we do not simply send unprepared students to a year of community college or other college and do away with the NAPS and Foundation school programs.

The returns to military performance grades are again positive and significant across all four semesters and in all five methods of matching. First semester returns range from positive .185 to .213. By second semester the magnitude has decreased to a range between .052 and .101. However, by the third semester, the range has increased again to between .102 and .138. By the fourth semester, returns to military performance have increased again to between .138 and .213. These results are not only positive, but the magnitude is higher than the consistent positive returns to Foundation school programs.
There are marginally significant returns to graduating as a group 1 major or a group 3 major. Results on the *End Group 2* variable are insignificant across the board. The *End Group 1* variable suggests positive returns to ending in a group 1 major if a student attends a year of college before matriculating at USNA. As described above, group 1 majors include only the engineering majors at USNA. Specifically, the cohort of college students is, by the most modest estimate, 4.4 percent more likely to graduate as a group one major than the matched cohort of direct entry students. However, results are only significant for three of the five matching methods. Similarly, although results are only significant for two of the five matching methods, college students are, on the low end, 4.5 percent more likely to graduate as humanities or social science majors than their direct entry counterparts.

Interestingly, retention rates for freshman and sophomore year are less significant and of lower magnitude than retention rates for the NAPS and Foundation cohorts. The *Younsterdrop* variable is only significant on two out of the five matching methods, and the college cohort is only between 3.5 and 4.0 percent less likely to attrite during sophomore year. Attrition rates for freshmen year are insignificant for all matching methods. Finally, unlike the NAPS and Foundation cohort, college students are significantly more likely to tutor their peers, according to the *Tutor* variable. Returns suggest that the cohort is between 2.3 and 3.1 percent more likely to be a student tutor than the comparable cohort of direct entry students.

Propensity score matching suggests quantitative positive returns to having a year of college experience before attending USNA. In some ways, this conclusion seems obvious: after a year of college, a student will be more successful at managing the college lifestyle. However, these results also seem to condemn the practice of sending students to a year of preparatory school. If the cohort of students who attend a year of college before USNA perform significantly better than their comparable counterparts in all aspects of academy life, should the Academy just send all unprepared students to a year of college or community college before coming to USNA, and do away with preparatory school programs? Boiled down, these results suggest that a year at college does significantly more for a student’s long-term performance in college than preparatory schools do. However, it is important to consider the particular cohort of students who make up the college treatment group because of the selectivity issue inherent to interpreting these results. These are students who had the resources and ability to get into and attend another college instead of USNA for one year. They are also a group of people with the drive and motivation to go through a second freshman year at USNA after first attending another school. This separates them from the cohort of students who are sent to NAPS and Foundation schools.

| Table 4c – Second Stage Matched Results Comparing College and Direct Entry Students |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                                 | Unmatched       | NN(1)           | NN(5)           | NN(20)          | Caliper         | Kernel          |
| Graduation                      | 0.036*          | 0.061**         | 0.068***        | 0.06***         | 0.061**         | 0.037*          |
|                                 | (0.018)         | (0.025)         | (0.018)         | (0.017)         | (0.025)         | (0.016)         |
| OOM                             | -0.019          | -0.061***       | -0.084***       | -0.087***       | -0.062***       | -0.022          |
|                                 | (0.013)         | (0.018)         | (0.015)         | (0.014)         | (0.018)         | (0.013)         |
| AOM                             | 0.012           | -0.03           | -0.05***        | -0.056***       | -0.03           | 0.009           |
|                                 | (0.013)         | (0.019)         | (0.015)         | (0.014)         | (0.019)         | (0.013)         |
| MOM                             | -0.014          | -0.036          | -0.057***       | -0.06***        | -0.036          | -0.016          |
|                                 | (0.014)         | (0.019)         | (0.015)         | (0.014)         | (0.019)         | (0.013)         |
| AC grades1                      | 0.205***        | 0.332***        | 0.363***        | 0.373***        | 0.33***         | 0.21***         |
|                                 | (0.031)         | (0.044)         | (0.034)         | (0.032)         | (0.044)         | (0.031)         |
| AC grades2                      | 0.128***        | 0.257***        | 0.277***        | 0.282***        | 0.258***        | 0.132***        |
|                                 | (0.029)         | (0.042)         | (0.033)         | (0.031)         | (0.042)         | (0.03)          |
| AC grades3                      | 0.144***        | 0.288***        | 0.278***        | 0.291***        | 0.29***         | 0.15***         |
|                                 | (0.031)         | (0.045)         | (0.035)         | (0.033)         | (0.046)         | (0.032)         |
| AC grades4                      | 0.147***        | 0.272***        | 0.278***        | 0.28***         | 0.273***        | 0.152***        |
|                                 | (0.03)          | (0.042)         | (0.031)         | (0.029)         | (0.042)         | (0.028)         |
| MIL grades1                     | 0.184***        | 0.207***        | 0.21***         | 0.213***        | 0.208***        | 0.185***        |
6.3.4 Instrumental Variable Regression

The first specification utilizing the IV includes the same first stage background characteristics used in the propensity score matching specification: Math SATs, Verbal SATs, high school rank, and high school quality. In addition, the first specification includes gender, ethnicity dummy variables, and state dummy variables. The second stage specification includes only the four main variables: Math SATs, Verbal SATs, high school rank, and high school quality.

We regressed six performance variables as dependent variables in order to analyze the effect of NAPS on USNA performance. We examined the first two semesters of academic grades, the binary variable indicating graduation, and the normalized academic order of merit. These performance variables provide a snapshot with which to compare propensity score matching and OLS.

The IV regression on AcGrade1 and AcGrade2 indicates positive returns to the first semester at
USNA, with NAPS participation adding .604 in academic grade point average. However, by the second semester, returns have diminished to insignificance. The graduation logistic results indicate a similar result as the propensity score matching: NAPS participants graduate 1.43 more than non participants with comparably the same background characteristics. Finally, similar to the PSM results, academic order of merit is negatively impacted by 3.6 percentage points. Table 5a indicates coefficients on the IV and the contribution of the four main variables to the model.

Table 5a – IV Regression Using Propensity Score As Instrumental Variable – Specification 1

<table>
<thead>
<tr>
<th></th>
<th>Ac Grade 1</th>
<th>Ac Grade 2</th>
<th>Graduation Rate</th>
<th>Grad AOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>IV - Pscore</td>
<td>0.604***</td>
<td>-0.0001</td>
<td>1.434**</td>
<td>0.036**</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.001)</td>
<td>(0.201)</td>
<td>(0.0157)</td>
</tr>
<tr>
<td>Highest Math SAT</td>
<td>0.0038***</td>
<td>-0.0000011</td>
<td>1.004***</td>
<td>-0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.000003)</td>
<td>(0.0004)</td>
<td>(0.00004)</td>
</tr>
<tr>
<td>Highest Verbal SAT</td>
<td>0.002***</td>
<td>0.000001</td>
<td>0.9998</td>
<td>-0.0008**</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.000003)</td>
<td>(0.0003)</td>
<td>(0.00004)</td>
</tr>
<tr>
<td>High School Rank (Percentile)</td>
<td>0.119</td>
<td>-0.0007</td>
<td>1.57*</td>
<td>-0.033</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.002)</td>
<td>(0.329)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>High School Quality Measure</td>
<td>0.002***</td>
<td>0.000002</td>
<td>1</td>
<td>-0.0008***</td>
</tr>
<tr>
<td></td>
<td>(0.00009)</td>
<td>(0.000002)</td>
<td>(0.0002)</td>
<td>(0.00003)</td>
</tr>
</tbody>
</table>

<table>
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<th>Number of Observations</th>
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<th>21117</th>
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<th>16533</th>
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</thead>
<tbody>
<tr>
<td>R-squared</td>
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<td>0.0001</td>
<td>0.119</td>
<td>0.3219</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.1188</td>
<td>-0.0002</td>
<td>--</td>
<td>0.3217</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. See Appendix 3 for variable descriptions. *** .01, ** .05, * .1 significance.

The second specification includes dummy variables by year as well as by state. This more inclusive model has similar results as the one above, but with nearly doubly the magnitudes on the coefficient of the IV. Academic grade impact diminishes from .9906 in the first semester to insignificance by the second semester. Graduation rates are improved by 3.44 times for NAPS participants versus non-participants. Finally, academic order of merit decreases by 6.9 percentage points. Table 5b indicates the coefficients on the second stage, second specification IV model.

Table 5b – IV Regression Using Propensity Score As Instrumental Variable – Specification 2

<table>
<thead>
<tr>
<th></th>
<th>Ac Grade 1</th>
<th>Ac Grade 2</th>
<th>Graduation Rate</th>
<th>Grad AOM</th>
</tr>
</thead>
<tbody>
<tr>
<td>IV - Pscore</td>
<td>0.9906***</td>
<td>-0.0001</td>
<td>3.442***</td>
<td>0.069***</td>
</tr>
<tr>
<td></td>
<td>(0.0513)</td>
<td>(0.0013)</td>
<td>(0.48)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Highest Math SAT</td>
<td>0.0043***</td>
<td>-0.0000011</td>
<td>1.005***</td>
<td>-0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.000003)</td>
<td>(0.0004)</td>
<td>(0.00004)</td>
</tr>
<tr>
<td>Highest Verbal SAT</td>
<td>0.0022***</td>
<td>0.0000005</td>
<td>1.001***</td>
<td>-0.0007***</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.000003)</td>
<td>(0.0003)</td>
<td>(0.00004)</td>
</tr>
<tr>
<td>High School Rank (Percentile)</td>
<td>0.3269***</td>
<td>-0.001</td>
<td>2.457***</td>
<td>-0.016</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. See Appendix 3 for variable descriptions. *** .01, ** .05, * .1 significance.
7 Conclusions

The current literature in this field suggests several implications of pre-college education on college performance. First, college graduation rates are declining as a result of lack of student preparation. In contrast to the findings of Adleman (1999) and Attewell, Lavin, Domina, and Levey (2006), results from this study suggest that pre-college education can significantly improve college retention rates and increase graduation rates. Specifically, graduation rates for NAPS and Foundation students were between 7 and 10 percent higher than for comparable direct admissions students. In terms of degree attainment, pre-college education improves a student’s likelihood of making it through a four-year selective institution with a degree. As discussed in the body of this paper, there are several possible reasons for this result. Echoing the hypothesis of the Soliday (2002) paper, it is possible that the impact of pre-college programs like NAPS and Foundation schools is not quantified in the form of higher grades but does contribute to the development of skills which help students persevere where similar students without pre-college experience drop out before attaining a degree. Another explanation for generalizations about graduation rates is the idea that pre-college students feel added pressure to attain a degree due to their investment in the form of time have and, in the case of Foundation students, financial resources to their education.

This study makes a unique contribution to current literature through analysis of performance semester by semester over four years. However, results suggest troubling conclusions about how preparatory school influences a student’s academic performance in the classroom. Although returns from preparatory school programs are highly positive in the first semester, the trend is that these positive returns diminish rather than persist through a student’s four years at college. In fact, propensity score matching techniques suggest that the significance of the positive returns stops after the first semester, and diminishes to the point that returns from pre-college are negative. This generalization has several implications. First, preparatory school programs are preparing students for specific introductory level courses rather than giving them study skills and familiarity with college level work. Second, there is too much noise after the first semester to assess the impact of remedial education in a meaningful way. The third potential conclusion is that remedial education participants respond to peer effects that create a cohort in which educational persistence is lauded, while academic performance is undervalued. This would explain how the cohort of pre-college participants actually drag each other down academically, leading to negative returns to academic grades in the third and fourth semesters. This would also help explain the negative returns to academic order of merit that span all forms of pre-college education other than participation in prior college.

As discussed in the body of this work, the NAPS program is similar to many national preparatory programs. Moreover, the inclusion of data on Foundation school students allows us to extrapolate conclusions to a national scale. Unfortunately, this suggests the disturbing conclusion that investing in pre-college programs is not a viable method for improving human capital attainment for the U.S. workforce.

Pre-college education plays an important role in student development and particularly in student persistence toward earning a degree. However, the following question can be raised: is the cost of these remedial type programs worth the increase in graduation rates at the expense of academic performance? Is
the goal of selective institutions to push students toward a degree at all costs or to actually improve educational achievement through pre-college programs? These are questions that must be considered to accurately assess the cost versus benefit of pre-college education.

8 Appendix 1 – Institutional Specifics

This paper takes into account the inherent selection bias that accompanies assignment to a remedial program. However, in this paper we examine pre-college remediation as a method for better preparing high school graduates for their college courses. Although USNA does have a few remedial courses for students who are unable to keep up in freshman level courses, as well as some students who validate freshman requirements, the vast majority of students take the same array of courses during their freshman year. Rather than examining remedial coursework undertaken when students are already enrolled at USNA, this study views each feeder program as a type of remediation, to which students are assigned based on background characteristics. Remediation is assigned as a condition of future appointment to USNA, eliminating the bias associated with optional remediation.

8.1 Background on the Naval Academy Preparatory School (NAPS)

The primary pre-college program of interest in this study, NAPS, was founded in 1915 to assist enlisted sailors in making the transition from military to academic life. Today, NAPS candidates receive standard benefits as active duty service members, including healthcare, standard pay, room, and board. Tuition for NAPS candidates is fully paid by the Department of the Navy. Finally, NAPS candidates are ensured matriculation into USNA barring any criminal or other serious offences. The average class at USNA is made up of over 15 percent NAPS graduates, with the 2011 class being comprised of over 17 percent NAPS graduates. Over the years, the mission of NAPS and the program’s selection criteria has gradually evolved. Today the institution’s mission is to “prepare selected candidates morally, mentally, and physically, with emphasis on strengthening the academic foundation of individual candidates for officer accession through the U.S. Naval Academy” (www.USNA.edu). That is, the goal of NAPS is to provide potential USNA candidates (from either high school or the fleet) with the necessary academic skills to succeed in future college endeavors, thus providing positive returns to their human capital.

The NAPS program itself is run just like many of the top preparatory schools around the United States. NAPS students must take courses in English, Math, Chemistry, and Physics. Students are given an assessment at the beginning of the academic year and placed in courses according to their current level in each subject. An Academic Dean oversees the academic curriculum. A commanding officer, an executive officer, three company officers and two senior enlisted leaders run the school. Similar to preparatory schools around the country, NAPS students are housed in a dorm-like barracks building in Newport, Rhode Island. This environment away from home gives students a taste of the independence they will feel again as college freshmen. This aspect of preparatory school life is uniquely important to the development of self-motivated and driven students with the capacity to succeed as independent people away from home.

8.2 Background on the Naval Academy Preparatory School (NAPS)

Students who do not attend NAPS and are not admitted directly to USNA may be offered appointment to a different type of feeder program known as a Foundation school. USNA provides selected students the opportunity to enroll in other pre-college programs known as
“Foundation” schools. Foundation students have up to 60 percent of their tuition covered by the Foundation Program and have a 95 percent guarantee of transfer to the Academy. Families are expected to contribute resources to pay for at least 40 percent of tuition based on their income level. Students offered the opportunity to go to Foundation school have the option to apply to fifteen civilian and four military preparatory schools including Hargrave Military Academy, the Kent School, Peddie, and various other civilian and military preparatory schools (www.USNA.edu). A full list of current Foundation preparatory schools is included at the end of this section.

This program differs significantly from the NAPS program. Rather than being offered a place at a specific institution like NAPS, Foundation school students may choose their desired preparatory school, introducing variation in location, cost, and quality of education. Foundation school students make up a smaller cohort of precollege entrants at 6 percent of each entering USNA class. The Foundation program provides a different perspective on returns to investment in pre-college education program.

Similar to the NAPS program, the Foundation school program is designed as a preparatory year for students who are academically unprepared for USNA. Foundation students participate in what is known as a post-graduate or “PG” year. At preparatory school, they enroll in courses that include at minimum English, science, and math. Foundation schools fall into one of three categories: military preparatory schools, preparatory schools affiliated with a college or university, or independent preparatory schools.

Military preparatory schools, like the New Mexico Military Institute, are the most similar to the NAPS environment due to their militaristic nature. At military preparatory schools, students wear uniforms, participate in JROTC, and are organized in a hierarchical structure led by the most senior cadets.

Preparatory schools affiliated with a college or university, like Greystone Preparatory, boast access to the academic resources of a degree-granting institution. At Greystone, students are able to enroll in “advanced placement” or college level courses during their PG year in order to better prepare for college.

Finally, independent preparatory schools like the Salisbury School, boast a history and tradition of accepting students for a PG year in order to improve their academic preparedness and allow them an extra year as high school athletes to improve the likelihood of being recruited to a college for athletics.

The range of schools that participate in the Naval Academy Foundation program includes schools across all of the US. They are a cross-section of typical preparatory school programs. Like other preparatory schools, Foundation schools place high emphasis on academic performance, athletic performance, and college matriculation. Taken together, conclusions from the treatment groups described above can be extrapolated to broader national education strategy due to the unique characteristics of the USNA dataset.

Naval Academy Foundation Schools
1. Avon Old Farms School, Avon, Connecticut
2. Blair Academy, Blairstown, New Jersey
3. Greystone Preparatory School at Schreiner University, Kerrville, Texas
4. Hargrave Military Academy, Chatham, Virginia
5. The Hill School, Pottstown, Pennsylvania
6. The Hun School of Princeton, Princeton, New Jersey
7. Kent School, Kent, Connecticut
8. The Kiski School, Saltsburg, Pennsylvania
9. The Marion Military Institute, Marion, Alabama
10. The Mercersburg Academy, Mercersburg, Pennsylvania
11. New Mexico Military Institute, Roswell, New Mexico
12. Northfield Mount Hermon School, Northfield, Massachusetts
13. Northwestern Preparatory School, Crestline, California
14. The Peddie School, Hightstown, New Jersey
15. Portsmouth Abbey School, Portsmouth, Rhode Island
16. Salisbury School, Salisbury, Connecticut
17. Valley Forge Military Junior College, Wayne, Pennsylvania
18. Western Reserve Academy, Hudson, Ohio
19. Wyoming Seminary, Kingston, Pennsylvania
Appendix 2 – United States Naval Academy Majors by Group

Group 1 – Engineering and Weapons:
Aerospace Engineering
Computer Engineering
Electrical Engineering
General Engineering
Mechanical Engineering
Naval Architecture
Ocean Engineering
Systems Engineering

Group 2 – Mathematics and Science:
Chemistry
Computer Science
Cyber Operations
General Science
Information Technology
Mathematics
Oceanography
Operations Research
Physics
Quantitative Economics

Group 3 – Humanities and Social Sciences:
Arabic
Chinese
Economics
English
History
Political Science
## 10 Appendix 3 – Variable Descriptions

### Background Characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>African American</strong></td>
<td>Binary variable indicating whether a student classifies themselves as African American</td>
</tr>
<tr>
<td><strong>Asian American</strong></td>
<td>Binary variable indicating whether a student classifies themselves as Asian American</td>
</tr>
<tr>
<td><strong>Caucasian</strong></td>
<td>Binary variable indication whether a student classifies themselves as Caucasian</td>
</tr>
<tr>
<td><strong>Hispanic</strong></td>
<td>Binary variable indication whether a student classifies themselves as Hispanic</td>
</tr>
<tr>
<td><strong>Age on IDay</strong></td>
<td>A student's age on their first day at the Naval Academy, Induction Day</td>
</tr>
<tr>
<td><strong>Central</strong></td>
<td>A binary variable indicating whether a student is from Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, Ohio, or Wisconsin</td>
</tr>
<tr>
<td><strong>Northern</strong></td>
<td>A binary variable indicating whether a student is from Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, or Vermont</td>
</tr>
<tr>
<td><strong>Pacific</strong></td>
<td>A binary variable indicating whether a student is from Alaska, Arizona, California, Hawaii, Nevada, Oregon, Utah, or Washington</td>
</tr>
<tr>
<td><strong>Southern</strong></td>
<td>A binary variable indicating whether a student is from Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, or West Virginia</td>
</tr>
<tr>
<td><strong>Western</strong></td>
<td>A binary variable indicating whether a student is from Colorado, Idaho, Kansas, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, or Wyoming</td>
</tr>
<tr>
<td><strong>Verbal SAT</strong></td>
<td>A student's highest reported SAT score for the verbal section</td>
</tr>
<tr>
<td><strong>Math SAT</strong></td>
<td>A student's highest reported SAT score for the math section</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td>A binary variable indicating gender where 1=female</td>
</tr>
<tr>
<td><strong>High School Quality Measure</strong></td>
<td>A measure of the academic quality of individual high schools on the same scale as the SAT: from 200 to 800</td>
</tr>
<tr>
<td><strong>High School Rank (Percent)</strong></td>
<td>A student's percent rank in their high school class where .99 signifies being in the top 1% of high school graduating class</td>
</tr>
<tr>
<td><strong>Military Father</strong></td>
<td>Binary variable indicating whether the student's father was in the military</td>
</tr>
<tr>
<td><strong>Military Mother</strong></td>
<td>Binary variable indicating whether the student's mother was in the military</td>
</tr>
<tr>
<td>Performance Variables</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>AC grades1</td>
<td>First semester academic grade point average</td>
</tr>
<tr>
<td>AC grades2</td>
<td>Second semester academic grade point average</td>
</tr>
<tr>
<td>AC grades3</td>
<td>Third semester academic grade point average</td>
</tr>
<tr>
<td>AC grades4</td>
<td>Fourth semester academic grade point average</td>
</tr>
<tr>
<td>Academic Average</td>
<td>Average course GPA in all academic courses for the first four semesters excluding professional and military coursework</td>
</tr>
<tr>
<td>AOM</td>
<td>Normalized class rank based on eight semesters of academic grades</td>
</tr>
<tr>
<td>Graduated (indicator)</td>
<td>A binary variable indicating whether a student graduated</td>
</tr>
<tr>
<td>Major Switch</td>
<td>A binary variable indicating whether a student changed their major while at USNA</td>
</tr>
<tr>
<td>MajorGrade3</td>
<td>Third semester majors courses grade point average</td>
</tr>
<tr>
<td>MajorGrade4</td>
<td>Fourth semester majors courses grade point average</td>
</tr>
<tr>
<td>Majorgrade5</td>
<td>Fifth semester majors courses grade point average</td>
</tr>
<tr>
<td>MajorGrade6</td>
<td>Sixth semester majors courses grade point average</td>
</tr>
<tr>
<td>MIL grades1</td>
<td>First semester military grade point average</td>
</tr>
<tr>
<td>MIL grades2</td>
<td>Second semester military grade point average</td>
</tr>
<tr>
<td>MIL grades3</td>
<td>Third semester military grade point average</td>
</tr>
<tr>
<td>MIL grades4</td>
<td>Fourth semester military grade point average</td>
</tr>
<tr>
<td>Military Average</td>
<td>Average course GPA in all military performance grades for the first four semesters excluding professional and military coursework</td>
</tr>
<tr>
<td>MOM</td>
<td>Normalized class rank based on eight semesters of military performance grades</td>
</tr>
<tr>
<td>OOM</td>
<td>Normalized class rank based on combined AOM and MOM, eight semesters of academic grades and military performance grades</td>
</tr>
<tr>
<td>Plebedrop</td>
<td>A binary variable indicating whether a student left USNA during their freshman year</td>
</tr>
<tr>
<td>Professional Average</td>
<td>Average course GPA in all professional course grades for the first four semesters excluding professional and military coursework</td>
</tr>
<tr>
<td>Start Group 1</td>
<td>A binary variable indicating whether a student elected a major in group 1 during their freshman year</td>
</tr>
<tr>
<td>Start Group 2</td>
<td>A binary variable indicating whether a student elected a major in group 2 during their freshman year</td>
</tr>
<tr>
<td>Start Group 3</td>
<td>A binary variable indicating whether a student elected a major in group 3 during their freshman year</td>
</tr>
<tr>
<td>STEM grades1</td>
<td>First semester STEM grade point average</td>
</tr>
<tr>
<td>STEM grades2</td>
<td>Second semester STEM grade point average</td>
</tr>
<tr>
<td>STEM grades3</td>
<td>Third semester STEM grade point average</td>
</tr>
<tr>
<td>STEM grades4</td>
<td>Fourth semester STEM grade point average</td>
</tr>
<tr>
<td>Tutor</td>
<td>A binary variable indicating whether a student was involved in the student-tutor program while at USNA</td>
</tr>
<tr>
<td>Varsity Athlete (indicator)</td>
<td>A binary variable indicating whether a student was a varsity athlete while at USNA</td>
</tr>
<tr>
<td>Youngsterdrop</td>
<td>A binary variable indicating whether a student left USNA during their sophomore year</td>
</tr>
</tbody>
</table>
MEMORANDUM

From: Ms. Erin Johnson, Academy’s HRPP Office

To: MIDN 2/C Phoebe Kotlikoff, Economics Department

Subject: APPROVAL OF HUMAN SUBJECT RESEARCH

Ref: (a) SECNAVINST 3900.39D  
(b) 32 CFR 219  
(c) USNA HRPP Policy Manual

USNA Assurance # DoD N-40052  
HRPP Approval # USNA.2012.0006-1R-EM4-A

1. The Superintendent, as the Institutional Official (IO), reviewed and approved your research protocol “The Effects of Post-Secondary Education on Midshipman Success at the United States Naval Academy” involving human subjects. The co-investigators are Assoc Prof Katherine A. Smith, Asst Prof Ahmed S. Rahman and MIDN 2/C Edward Butler from the Economics Department. It was determined to be exempt under 32 CFR 219.101(b)(4).

2. Research which is determined to be exempt under 32 CFR 219.101 is exempt from all regulatory requirements, unless there is a substantive change that could potentially alter the assessment of the exempt status. If there is a substantive change you must submit an amendment to your protocol in sufficient time to process the revisions and secure approval from the Superintendent. On an annual basis, a status update of all exempt studies will be conducted.

3. We would appreciate a notification of closure when the research has concluded according to Section XIII of the USNA HRPP Policy and Procedures manual and to provide this office with copies of any articles or presentations resulting from this research. Additionally, any presentations or publications must include acknowledgement of IRB approval using the HRPP approval number.

4. If you have any questions, please contact this office at 410-293-2533 or HRPPoffice@usna.edu.

ERIN JOHNSON  
Academy’s HRPP Office
MEMORANDUM

From: Chair, Institutional Review Board (Code 28)
To: Superintendent, United States Naval Academy

Subj: HUMAN SUBJECT RESEARCH BY MIDN 2/C PHOEBE KOTLIKOFF (ECONOMICS DEPARTMENT)

Ref: (a) SECNAVINST 3900.39D
     (b) 32 CFR 219
     (c) USNA HRPP Policy Manual

Encl: (1) Protocol Package for MIDN 2/C Phoebe Kotlikoff (Form 2, 3, 4, 5, CITI and Supplemental Information)

1. I have reviewed the research protocol submitted by MIDN 2/C Phoebe Kotlikoff from the Economics Department on “The Effects of Post-Secondary Education on Midshipman Success at the United States Naval Academy.” Co-investigators are Asst Prof Ahmed S. Rahman, Assoc Prof Katherine A. Smith, and MIDN 2/C Edward Butler from the Economics Department.

2. This project evaluates the effects of attending a post-secondary education program on student performance at undergraduate institutions by using data from the USNA. Through regression analysis, the project will empirically demonstrate potential relationships between the level of participation in pre-college programs and success in undergraduate studies. De-identified data will be obtained from Institutional Research.

3. This research is determined to be exempt under 32 CFR 219.101(b)(4). Research which is determined to be exempt under 32 CFR 219.101 is exempt from all regulatory requirements, that includes continuing review, unless there is a substantive change that could potentially alter the assessment of the exempt status.

JUDITHANN HARTMAN

Date: 12-11-11

☑ Approved as recommended  ☐ Conditionally Approved  ☐ Disapproved

Comments:

M. H. MILLER
Vice Admiral, U.S. Navy
Superintendent
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FINANCIAL AND SOVEREIGN DEBT CRISSES IN SPAIN: FISCAL LIMITS AND SPILLOVERS

Sasha Scarlett Indarte
Adviser: Mario Solis-Garcia
Macalester College

ABSTRACT

Sovereign debt crises have four consistent features: 1) financial crises tend to coincide with them; 2) they are followed by credit crunches; 3) the domestic costs of default are higher where financial institutions hold large portions of their sovereign’s debt; and 4) sovereign risk premiums are countercyclical and exhibit nonlinear dynamics with respect to debt levels. These facts indicate that spillover between financial and debt crises are important means of amplifying economic downturns. Current models cannot replicate all four of these facts because they either lack investment, and endogenous fiscal limit on the accumulation of sovereign debt, or a nonlinear solution. I create a dynamic stochastic general equilibrium (DSGE) model with collateralized sovereign bonds used by entrepreneurs to obtain investment funds and an endogenous fiscal limit that instigates default. These two components are essential in explaining facts one through three. I solve my model globally through the monotone map method so that it accurately matches the nonlinear behavior of sovereign risk premiums and accounts for fact four. I calibrate my model to Spanish data from 1999-2012 to test if it captures these four facts as well as the cyclical behavior of macroeconomic aggregates.
I construct a search and matching model in the Diamond-Mortenson-Pissarides framework with two sectors, public and private. I argue that individual Nash bargaining between public workers and the government does not appropriately model the US economy. Instead, I add a public sector union that bargains with the government over wages. The addition of a public sector union reduces the cyclicality of public wages, bringing the cyclical business cycle facts of the public sector roughly in line with empirical observations. I will end by suggesting policy options that could reduce employment volatility in light of this bargaining structure.

1 Introduction

Observations of US data suggest that public wages and employment do not vary as much as their private sector counterparts over the business cycle. There is empirical evidence that some unemployed workers shift their job search to the public sector during cyclical downturns due to the relatively high public wage that occurs because of its acyclical nature relative to its private counterpart. Past theoretical work has suggested that a policy of countercyclical public vacancy creation and procyclical public wages would lower employment volatility. However, as public wages are not as procyclical as public wages in the data, this suggests that there is an additional constraint on the public sector’s wage setting and vacancy creation mechanism. I model this constraint as a public sector union that the government must bargain with when setting wages in the public sector. I show that this union has countercyclical effective bargaining power. When the model is simulated with shocks to private sector productivity, it generates a public wage premium that is countercyclical, as is observed empirically.

2 Literature Review (Abridged)

The cyclical characteristics of employment and wages implied by the DMP model have been an active area of research since Shimer (2005) showed that simulations of the model with standard parameter estimates are unable to generate the large volatility in employment relative to productivity that is observed empirically. Quadrini and Trigari (2007) add a public sector to the DMP model and analyze the impact of exogenously set public wages and vacancies. Their paper concludes that a public sector with the small public wage premium and relatively acyclical public wages observed empirically create greater employment volatility. Gomes (2012) adds to this research by modeling a public sector version DMP model and determining that the optimal government policy consists of counter-cyclical vacancy postings and procyclical wages, as well as a small private wage premium in the steady-state.

These optimal policies are not observed empirically. Studies by Lane (2003) and Lamo, Perez, and Schuknecht (2008) find less cyclical public wages relative to private wages. The overall ratio of public to private sector wages is less conclusive, with estimates of a public wage premium that vary significantly based on controls used and the period under study. I will explore the implications of various

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1 This abridged version of the full paper leaves out an appendix with the intermediate steps of some derivations.
steady-state wage premiums on cyclical unemployment characteristics in light of this inconclusive literature.

My model follows in the tradition of Quadrini and Trigari (2007) and Gomes (2012) by adding a public sector to the standard DMP model. However, I will endogenize public sector wage setting and vacancy creation in order to explain the deviations from the optimal policy outlined by Gomes. I will demonstrate that if public sector wage setting is modeled as Nash Bargaining between individual workers and the government, then the outcome is the optimal policy of Gomes. This will motivate the addition of a public sector union which bargains with the government over wages. This model will produce some of the characteristics of cyclical employment noted in empirical studies.

3 Model (abridged)

3.1 Basic Aspects

The size of the labor force is normalized to 1. Individuals can be employed in the private sector, employed in the public sector, or unemployed. Unemployed workers follow directed search, thus they must search in either the public or the private sector but cannot simultaneously search in both. Gomes (2012) provides empirical evidence of directed search in the United States. The labor force equation is:

\[ 1 = l_t^g + l_t^p + u_t^g + u_t^p \]

Where \( l_t^g \) and \( l_t^p \) are the fraction of the labor force employed in the public sector and private sectors at time \( t \), respectively and \( u_t^g \) and \( u_t^p \) are the fraction of the labor force who are unemployed and searching in the public and private sectors respectively.

In sector \( i \), for \( i = p, g \), searching workers and firms with vacancies find each other according to the matching function \( m(u, v)_i \) which is assumed to be increasing and concave in both \( u_i \) and \( v_i \), which represents the number of vacancies in that sector. \( m_t^i \) represents the number of new matches in sector \( i \) at time \( t \). The matching function is also assumed to have constant returns to scale. For the purposes of the later calibration I will assume the standard Cobb-Douglas matching function below.

\[ m_t^i = \mu_i (u_t^i)^{\eta_i} (v_t^i)^{1-\eta_i}, i = p, g \]

Note that this implies that the technology of the matching function, \( \mu_i \), and the elasticity of the matching function with respect to unemployment, \( \eta_i \), can be different between the public and private sector. This reflects the possibility that the search frictions are different between the two sectors.

In each sector, a fraction \( \lambda_i \) jobs are destroyed each period. When a job is destroyed, the worker formerly occupying that job becomes unemployed. This separation rate may be different between two sectors.

\[ l_{t+1}^i = m_t^i + (1 - \lambda_i)l_t^i, i = p, g. \]

Thus, the labor force consists of the workers who retain their jobs from the previous period, plus the new matches of formally unemployed workers with vacancies. In the steady state, the fraction of the labor force in each sector will be constant, as new matches will be exactly offset by separations in each period.

The rate at which vacancies are filled is the ratio of new matches each period to the number of vacancies and is represented by \( q_t^i \). The job-finding rate for workers in each sector is the ratio of new matches to the number of unemployed searching in that sector and is represented by \( p_t^i \).
\( q_t^i = m_t^i v_t^i, p_t^i = m_t^i u_t^i, i = p, g \)

The average duration of a vacancy and the average duration of unemployment in a sector are the inverses of the vacancy-filling rate and the job-finding rates: \( 1/q_t^i \) and \( 1/p_t^i \), respectively.

3.2 Households

The labor force, normalized to 1, is viewed as a representative household. Members of this household pool their income and split it equally across all members. This enables the household to perfectly self-insure against idiosyncratic variation in income, in the tradition of Merz (1995). The household derives utility from \( c_t \), the good produced by the private firms, and \( g_t \), the public sector good produced by the government and distributed free to households. The value of unemployment to the household is \( v(u_t) \) and the discount factor is \( \beta \). The household maximizes:

\[
E_t \sum_{t=0}^{\infty} \beta^t [u(c_t, g_t) + v(u_t)]
\]

Subject to the budget constraint: \( c_t + B_t = (1 + r_t - 1)B_{t-1} + w_t^p l_t^p + w_t^g l_t^g + T_t. B_t \) is the amount of one period bonds, \( r \) is the real interest rate, and \( T_t \) are lump sum taxes paid to the government.

3.3 Workers

The value function of an employed worker in sector \( i \) and period \( t \), \( W_t^i \), is his wage in the current period plus the expected value of the job in the next period, taking into consideration the possibility that the job ends. If the job ends, the worker receives the value of unemployment in the next period, while if the job does not end, the worker receives the value of a job again in the next period.

\[
W_t^i = w_t^i + E_t \beta [(1 - \lambda^i)W_{t+1}^i + \lambda^i U_{t+1}^i], i = p, g.
\]

The value function of unemployment in period \( t \) searching in sector \( i \) is dependent on the value of being unemployed that is forgone when employed, \( v \) and the expected value of the next period, taking into consideration the possibility that the worker obtains a job next period. The flow value received when unemployed, \( v \), can be viewed as the value of leisure, household production, or unemployment compensation. My model will not explicitly consider unemployment compensation. If the worker obtains a job in the next period, he receives \( W_{t+1}^i \), while if he does not obtain employment he receives the value of unemployment again in the next period.

\[
U_t^i = v + E_t \beta [p_t^i W_{t+1}^i + (1 - p_t^i)U_{t+1}^i], i = p, g.
\]

Due to the assumption of directed search, the unemployed will adjust which sector they search in so that the value of unemployment is equal in each sector.

\[
W_t^p = U_t^p = W_t^g = U_t^g
\]

Due to the assumption of directed search, the unemployed will adjust which sector they search in so that the value of unemployment is equal in each sector.

\[
W_t^p = W_t^g = U_t
\]

Substituting equation 8 into equation 7 and simplifying defines the share of unemployed searching in the public sector: \( s(t) = u_t^p u_t^g \), where \( u_t \) is the overall unemployment rate: \( u_t = u_t^p + u_t^g \).

\[
m_t^p E_t \beta [W_{t+1}^p - U_{t+1}^p](1-s_t) = m_t^g E_t \beta [W_{t+1}^g - U_{t+1}^g]s_t
\]

The intermediate steps can be found in the appendix (only included in full paper). As \( m_t^p (1-s_t) \) and \( m_t^g s_t \) are the job-finding rates in their respective sectors (\( p_t^p \) and \( p_t^g \)), this equation states that the unemployed will adjust which sector they search in such that an unemployed worker is indifferent regarding the sector.
in which he searches. This occurs when the net gain of finding employment in each sector multiplied by
the probability of finding employment in that sector are the same for both sectors.

3.4 Private Firms

Workers produce a private good with productivity $y_t^p$, which is the same for all private sector
workers. The cost of posting a vacancy is the constant $k^p$. Thus the value function for a vacancy is:

(10) $V_t = E_t[q_t^p J_{t+1}^p + (1 - q_t^p)V_{t+1}^p] - k^p$

The value of a vacancy is the expected gain from filling the vacancy in the next period and receiving the
value of filled job, or not filling the vacancy and receiving the value of a vacancy next period. The cost of
posting the vacancy is incurred this period, and must therefore be subtracted from the value of a vacancy
as well.

When a vacancy and a worker meet, a match is formed. For each filled job, the firm receives the
value of production, and pays the worker his wage each period. Thus, the value function for a filled job
is:

(11) $J_t = y_t^p - w_t^p + E_t[(1 - \lambda_p) J_{t+1}^p]

A filled job provides the firm with the worker’s output, $y_t$, minus the worker’s wage, plus the expected
value of the job next period. If the job continues, the firm receives the value of a job again next period. If
the job ends, the firm receives nothing next period.

As is standard, I assume free entry for firms, which ensures that firms post vacancies until there is
no gain from posting a vacancy, i.e. $V=0$. Using this and combining equations10 and 11 gives the job
creation condition:

(12) $k^p q_t^p = E_t[(1 - \lambda_p) J_{t+1}^p]

The intermediate steps are provided in the appendix. This equation states that firms produce vacancies
until the expected cost of the vacancy, which is the cost per period times the expected duration of the
vacancy, $1/q_t^p$, must be equal to the expected value of a job, which is the output of the job, minus the
wage paid, plus the savings in expected vacancy posting costs if the job is retained.

3.5 Private Sector Wage Determination

I assume that private sector firms and workers split the surplus from their match according to
Nash bargaining. Wages are negotiated each period. The surplus of a match for the worker is the
difference between the value of being employed if the match forms and the value of unemployment if it
does not. The surplus of a match for the firm is the difference between the value of the filled job if the
match forms and the value of a vacancy if it does not. The wage is the value that maximizes the total
surplus of the match, where workers receive a fraction $b^p$ of the match and firms receive $1 - b^p$:

(13) $\max_{w_t}^p (W_t^p - U_t)^{bp} (J_t^p - V_t^p)^{1-bp}

According to the free entry condition, $V_t^p = 0$. Thus, the first order condition for the bargaining solution
can be written as:

(14) $(W_t^p - U_t) = b^p(W_t^p - U_t + J_t^p)$
This is the standard FOC of DMP models. By substituting in the values of employment, unemployment, and a filled job, and imposing the free-entry condition, we can derive a wage equation:

\[ w_t^p = b^p y_t^p + (1 - b^p) v + b^p \theta_t^p k_t^p \]

The intermediate steps are in the appendix. This is similar to the standard wage equation of DMP models. The private wage is a weighted average of the productivity of the job and the value of outside options. These options are represented by the value of household production, and the tightness of the labor market, \( \theta_t^p = v_t^p u_t^p \) which reflects the ease with which the worker would be able to gain employment if he lost his job.

### 3.6 Government

The government hires workers that produce the public good \( g_t \) and pays costs \( k^s \) to post vacancies which are subtracted from production. Thus total production of the public good is:

\[ g_t = y_t^g l_t^g - k^s v_t^g \]

Public sector wages are financed through lump sum taxes:

\[ T_t = w_t^g l_t^g \]

In Gomes (2012), the government was able to set both wages and vacancies to achieve the optimal outcome. The optimal outcome was defined as the set of wage and vacancy policies that would maximize the representative household’s utility. Thus, Gomes was solving a social planner’s problem, where the social planner had unilateral control over public wages and vacancies, but did have to take the search frictions (i.e., the form of the matching function) as given. Since the policies outlined by Gomes are not observed empirically, I assume there must be an additional constraint on the public sector that prevents the government from setting wages unilaterally. First, I will consider the case where the government must bargain with individual public sector workers when setting the wage. However, I will show that this implies the same result as the optimal model of Gomes, instead making the constraint that government must bargain with a public sector union. As I model the government as participating in a bargaining game with workers, I need to define the value of the surplus of a match for the government. The value of a vacancy for the government is the weighted probability that the vacancy is filled next period, minus the cost of posting the vacancy, where the cost of the vacancy is weighted by the relative preference for the public good, given by \( \gamma = u(c_t, g_t) / u(c_t, g_t) \). As the public good is provided for free, it has no observable price. However, given the household’s utility function for public and private goods, \( \gamma \) represents the marginal utility of a public good given the current levels of public and private goods. Thus, higher \( \gamma \) represents a higher potential utility gain for households from the production of an additional public good. During these periods, the government places a higher value on the vacancy posting cost associated with a public sector vacancy. As will be shown below, this weighting enables the government to achieve Gomes’s optimal policies when wages are bargained with individual workers.

\[ V_t^g = E_t \beta [q_{i+1}^g J_{i+1}] - \gamma k_t^g \]

The government receives the value of a filled job if a match is made, and pays the cost of the vacancy, weighted by the household preference for public goods given the current ratio of public and private goods consumed.

The value of a filled job for the government will be similar to the private sector, as the government accounts of the productivity of the job, the wage paid to the worker, and the probability that
the job ends. However, the value of the output \( y^g_t \) will be weighted by the relative preference for the public good, \( \gamma \).

\[
J^g_t = \gamma y^g_t - w^g_t + E_d \beta [ (1 - \lambda^g) J^g_{t+1} ]
\]

As in the private sector, the government receives nothing if the job ends, while it receives the value of a job in the next period if the job is retained. In equilibrium, the government will post vacancies until the value of the job is equal to the cost, where the government weighs the cost by the preferences for the public good. This gives the job creation condition for the public sector:

\[
k^g q^g t = E_d \beta [ \gamma y^g_{t+1} - w^g_{t+1} + (1 - \lambda^g) k^g q^g_{t+1} ]
\]

This is the public sector analog to the free-entry condition. The expected cost of a vacancy is the period cost of a vacancy, weighted by preferences for the public good, multiplied by the expected duration of the vacancy. The government will create vacancies until the expected cost of a vacancy equals the value of a filled job. As the government accounts for public preferences for its good when determining the costs and benefits of vacancies and filled jobs, it is able to achieve the optimal steady-state policy outlined by Gomes (2012) when public wage determination occurs at the individual level, provided certain conditions are met. This is shown below.

### 3.7 Public Sector Wage Determination: Individual Bargaining

In the case where public employees are nonunionized and bargain with the public sector individually, the following equations determine the split of the surplus:

\[
w^g_t = \max(W^g_t - U^g_t)^b g (J^g_t - V^g_t)^{1-b g}
\]

This is exactly the same as in the private sector where \( b^g \) is the share of the surplus received by the workers. Thus, the sharing rule is:

\[
(W^g_t - U^g_t) = b^g (W^g_t - U_t + J^g_t)
\]

Once again, this is the same as in the private sector. By utilizing the public and private sector job creation conditions, we are able to obtain the share of workers searching in each sector. This is given below:

\[
k^g b^g v^g_t (1 - b^g) (1 - s_i) = \gamma k^g b^g v^g_t (1 - b^g) s_i
\]

The intermediate steps can be found in the appendix. This equation defines the fraction of unemployed workers searching in the public sector under individual Nash Bargaining. It shows that the share of the surplus obtained by workers in each sector, multiplied by the willingness of firms and the government to open vacancies as measured by the number of vacancies in each sector multiplied by the cost of posting vacancies, must be equal across both sectors. As the government weights the cost of posting vacancies by preferences for each good, the share of unemployed searching in each sector takes preferences into account. This equation is Gomes’s FOC for the optimal split of search between sectors provided the Hosios condition is satisfied in both sectors. The Hosios condition states that the share of the surplus that goes to the workers in each sector is equal to the elasticity of the matching function with respect to unemployment in that sector. This implies that or \( b^f = \eta^f \), for \( i=p,g \). Intuitively, this means that in order for firms to post an efficient level of vacancies, the added likelihood that a match in formed due to the creation of a vacancy must equal share of the surplus from a match that firms can expect to receive.
It can also be shown that the individual bargaining case results in the optimal level of public vacancy creation. By taking the sharing rule and utilizing the equations for $W^g - U$, and $J^g$, we can show that:

$$
(24) \ k^g q_i^g = \beta[(1 - b^g)(y_i^g) - v\gamma + (1 - \lambda^g)k^g q_i^g - b^g k^g v^g s, u_i]
$$

This is Gomes’s first order condition for public vacancies, provided the Hosios condition is met. The level of vacancy creation will be such that the expected social cost of a vacancy, which is the product of the per period cost of a vacancy and the expected duration of a vacancy $1/q_i^g$ is equal to the social value of a vacancy. The social value of a vacancy is the value of production, minus the value of home production forfeited when a worker becomes employed, plus the savings in vacancy costs when the vacancy is filled, plus a term that accounts for the fact that when the public sector creates a vacancy it accounts for the congestion externality associated with vacancy creation. This congestion externality is the shift in worker search toward the public sector when an additional public sector vacancy is created. This shift in worker search makes it more difficult for private sector vacancies to find workers, as there will be fewer workers searching in the private sector. The above condition states that under individual Nash Bargaining with the Hosios condition satisfied, this externality will be internalized by the public sector, resulting in an optimal level of public sector vacancy creation.

The remaining first order condition of Gomes (2012) is the level of private sector vacancy creation. However, Gomes demonstrates that if the first order conditions for $s$ and $v_i^p$ are met, the first order condition for $v_i^p$ is satisfied as well. Thus, the optimal steady-state public sector policy outlined by Gomes is met with individual Nash Bargaining between public sector workers and the government, provided the Hosios condition is met. Gomes determines that optimal public sector wages and vacancies are such that there should be a private wage premium in the steady-state, and public wages should be as cyclical as private wages. As these details of public sector employment are not observed empirically, the individual Nash Bargaining model derived above is not an appropriate way to endogenize public sector wage setting and vacancy creation.

### 3.8 Public Sector Wage Bargaining with Unionized Labor Force

Now I consider the case where public sector wages are bargained by a standard right-to-manage union and the government. The motivation for this stems from the general result of search and matching models which include trade unions, which suggests that unions are able to obtain higher wages for their members by increasing workers’ bargaining power. It also stems from the basic fact that the public sector is much more unionized than the private sector in the United States. In addition, (Morin, 2010) demonstrated that in a two sector economy with segmented labor markets, a unionized sector will have less cyclical wages due to the ability of the union to insulate itself partially from a drop in productivity. As the empirical characteristics of public employment are similar to these theoretical results, I will consider a similar model to Morin. However, my model will include directed search, not segmentation.

The public sector includes all public sector workers, both employed and those searching for employment in the public sector. The public sector union’s objective function is characterized by maximizing the welfare of its membership, both employed and searching in the public sector, in each period.

$$
(25) \ Max I_i^g W_i^g + u_i^g U_i
$$

The wage rate will be set such that it maximizes the total surplus of the public sector matches. As in the private sector, each employed worker has fallback value of $U_i$, while the government receives nothing in the event wage negotiations fail. The Nash Bargaining problem is therefore written as:

$$
(26) \ Max[I_i^g (W^g - U)]^{bg}[I_i^g J_i^g]^{1-bg}
$$
Where $b^g$ is the fraction of the surplus received by the union. I assume the fraction of those currently searching in the public sector is fixed at the time of wage negotiation. The size of public sector employment can be manipulated indirectly by the union, as the government posts vacancies such that the job creation condition holds given the wage determined by negotiations with the public sector union. Thus, the first order condition for the Nash Bargaining problem is:

$$ (27) \quad t J_t^1 b^g W - U^b + t (1 - b^p) J^1 b^g W - U^b J_w + t b^g J^1 b^g (W - U)^b g - 1 W_w = 0 $$

Note that all variables are in terms of the public sector. Essentially, the total number of workers searching and employed in the public sector is fixed at the time of wage negotiation; however, the union affects the ratio of employed/unemployed workers because the government will determine the number of vacancies to post given the wage negotiated. The number of vacancies posted given the number of unemployed workers searching will determine the number of new matches formed through the matching function.

The FOC can be rewritten as:

$$ (28) \quad W - U = \tilde{b}(W - U + J) $$

As in Morin (2010), this equation can be interpreted as stating that the union gives workers an effective bargaining power of $\tilde{b}$, where $\tilde{b} = b\mu g l^g / [\mu g l^g + (1 - \mu g) m^g]$. The derivation is in the appendix. Effectively, the union’s bargaining power is adjusted by the size of employment in the public sector relative to the ease at which new matches can be formed. This equation can be rearranged to provide a wage equation for the public sector:

$$ (29) \quad w_t^g = \tilde{b} y_t^g + (1 - \tilde{b}) w + \tilde{b} \theta_k k^g $$

The worker’s wage in the public sector is a weighted average of the productivity of the job, adjusted by the preferences for the public good, and the value of the worker’s outside option. Workers outside options include the value of household production, and the likelihood of obtaining a new job if they become unemployed, as measured by the labor market tightness, $\theta^g$.

### 4 Calibration (abridged)

The parameters will be set such that the steady-state value for public sector employment and total unemployment are, $l^g = .15$ respectively. These correspond to the US post-WWII average according to Gomes (2012). The separation rates for the public and private sectors, $\lambda^g, \lambda^p$ will be set at .03 and .06 respectively, to match US data also according to Gomes. Vacancy costs, $k^g, k^p$, will be set at 1.1 and 1.5, which correspond roughly to the research of Boca and Rota (1998). The discount rate, $\beta$, will be set at .99. Estimates of the elasticity of matches with respect to unemployment vary, so I will assume the standard $\eta^p = .5$ and $\eta^g = .2$ as estimated by Gomes. I assume the Hosios condition holds in the private sector, so $b^p = 5$. There are few estimates of $b^g$, so I will follow the method of Morin (2010) and assume a value of .7. The value of household production, $\nu$ and the technology of the matching function for each sector, $\mu^i$ will be set in order to replicate the target steady-states values of unemployment and the share of employment in the public and private sectors.

Private productivity will follow an AR(1) process with an autoregressive parameter of .95.

$$ (30) \quad \ln(y^g_t) = (.05) \ln(y^p_t) + .95 \ln(y^g_{t-1}) + \epsilon_t $$
$y_r^p$ is the steady-state value of private productivity, normalized to one. The steady-state value of public sector productivity will also be normalized to one. $\epsilon$ will be normally distributed with mean zero and standard deviation $.008$, as in (Morin, 2010).

Partial Table of Parameters and Steady-State Values:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda^p$</td>
<td>.06</td>
</tr>
<tr>
<td>$\lambda^g$</td>
<td>.03</td>
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<tr>
<td>$\theta^p$</td>
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<tr>
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</tr>
<tr>
<td>$w^g/w^p$</td>
<td>1.015</td>
</tr>
</tbody>
</table>

Note that in the steady-state there is a public wage premium of approximately 1.5%. This is slightly less than the 2 percent Gomes applied exogenously in his baseline calibrated model, but is still significantly higher than the 3 percent private wage premium implied by his optimal model. It is the change in this wage ratio that I am particularly interested in for the simulations.

5 Simulation

Next, I simulated the model’s response to private sector productivity shocks which follow the AR(1) process described above. I am primarily concerned with the overall variability of public and private employment and wages, as well as the correlation between the public and private sectors. Trigari (2007) provides estimates for those factors of U.S. data. His estimates for the period from 1979-2003 are provided in the table below.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Trigari Empirical Findings</th>
<th>Baseline Case</th>
<th>Public Sector Union</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corr($l^p$, $l^g$)</td>
<td>.38</td>
<td>.49</td>
<td>.47</td>
</tr>
<tr>
<td>Std($l^p$)/Std($l^g$)</td>
<td>.54</td>
<td>.66</td>
<td>.72</td>
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<tr>
<td>Corr($l^p$, GDP)</td>
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<td>.71</td>
<td>.74</td>
</tr>
<tr>
<td>Corr($l^g$, GDP)</td>
<td>.21</td>
<td>.17</td>
<td>.15</td>
</tr>
<tr>
<td>Std($l^p$)/Std(GDP(c))</td>
<td>.95</td>
<td>.54</td>
<td>.61</td>
</tr>
<tr>
<td>Std($l^g$)/Std(GDP(c))</td>
<td>.51</td>
<td>.24</td>
<td>.32</td>
</tr>
<tr>
<td>Corr($l^p/l^p$, GDP(c))</td>
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<td>-.30</td>
<td>-.35</td>
</tr>
<tr>
<td>Corr($w^g$, $w^p$)</td>
<td>.63</td>
<td>.91</td>
<td>.58</td>
</tr>
<tr>
<td>Std($w^g$)/Std($w^p$)</td>
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<td>.83</td>
<td>.79</td>
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<tr>
<td>Corr($w^g$, GDP(c))</td>
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<td></td>
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<td>Std($wp$)/Std(GDP(c))</td>
</tr>
<tr>
<td>------------------</td>
<td>---------------------</td>
<td>-------------------------</td>
<td>------------------------</td>
</tr>
<tr>
<td></td>
<td>.26</td>
<td>.85</td>
<td>.75</td>
</tr>
<tr>
<td></td>
<td>.78</td>
<td>1.05</td>
<td>1.10</td>
</tr>
<tr>
<td></td>
<td>.52</td>
<td>1.13</td>
<td>.94</td>
</tr>
</tbody>
</table>

This table shows that public employment and wages do not follow private employment and wages over the cycle. The main reason for this is that public employment, and public wages to a lesser extent, do not vary as much as their private sector counterparts. To the extent that they do vary, they do not vary in sync with GDP movements as much as private sector employment and vacancies do. Note that according to both Gomes (2012) and Trigari (2007), it is optimal to have public wages track private wages over the cycle (with an adjustment for friction parameters). However, these papers differ over whether public vacancy creation (and consequently public employment) should track private vacancy creation. However, as shown by Trigari (2007), empirically public employment does not track private employment.

To facilitate comparisons to Trigari’s data, I simulated both the unionized model and the benchmark case for 100 periods, corresponding to his 25 year data. Output is recorded in the table above for comparison to Trigari’s data. My model was able to capture the broad facts that neither public wages nor employment tracks their private counterparts over the cycle. In addition, public wages and employment were both less variable than their private counterparts, as in the data. The biggest deviation in my simulations from the data was that employment was not nearly as variable as in the data and wages were still too correlated with production. I suspect that the lack of variability in employment is due to the Shimer puzzle. Wages are so flexible that they adjust quickly enough to prevent swings in employment similar to empirical observations. Thus, neither public nor private sector employment varied as greatly as it should. Relatedly, the model had wages that were in fact more variable than implied by the data, although the unionized case performed better than the baseline version of the model. Overall, it appears the addition of the union led to less cyclical public wages as intended, beyond that the results are mixed, with the model only roughly matching the data and not necessarily performing substantially better than the baseline case.

6 Discussion of Model and Results (abridged)

An issue to consider when evaluating this model is that the public sector DMP literature thus far assumes that the government is interested in maximizing the welfare of the representative household. It is likely, that the government uses public employment to attain other objectives beyond of cyclical unemployment targets. For example, many estimates of the public wage premium conclude that it is much higher for certain groups, such as those with less education or minorities. It is possible that the government uses public employment as a form of redistribution to these groups. If this is the case, it may not be optimal for the government to follow the policy recommendations of Gomes, nor would the addition of unionized bargaining be necessary, as it is the objective function that is improperly stated.

7 Conclusion (abridged)

In this paper, I endogenized public sector wage setting and creation by modeling the public sector wage setting mechanism as Nash Bargaining between the government and a public sector union. I then subjected the calibrated model to private sector productivity shocks, and demonstrated that the model is capable of reproducing the stylized facts of public employment and wages that don’t strongly follow their private counterparts, as well as public employment and wages that exhibit less variability overall than
their private counterparts. This occurs because the public sector union is able to partially insulate its workers from changes in business cycle conditions.

As demonstrated by previous literature, the countercyclical nature of the public wage premium implies increased employment volatility than would occur if public wages followed private wages more closely over the cycle. I did not explicitly demonstrate a mechanism by which the government could achieve this outcome in light of public sector unionization. However, Pissarides (1986) showed that a tax on employed workers, which is used to finance job creation, could achieve efficient levels of unemployment. This is because the structure of the union is such that it overvalues employed workers at the expense of unemployed workers, leading to greater unemployment. Although my model is structured with two sectors and directed search, I suspect that the effect would be similar in my model. However, I leave that to further research.

References
Labor search models have mostly examined labor search dynamics from an individual agent’s point of view. Recently researchers have begun to examine labor search from a household perspective. However, no models have incorporated both household search and non-participation. I extend a model of household search from Guler, Guvenen, and Violante (2012) to include labor force non-participation as an option for members of a two-person, joint-utility maximizing and income pooling couple. I explain how couples in the model react to new wage offers and which wage offers to one individual trigger job quits or labor force exits from the other. The behavior of the couples is highly sensitive to the value of household production, and the individual decision to participate in the labor force is highly dependent on the labor force status of the individual’s spouse.

Acknowledgements
I would like to thank Arik Levinson and James Albrecht for their extensive mentoring and advice. I would also like to thank Yi Jie Gwee, Billy Jack, Gianluca Violante, Glenn Russo, Stephen McDonald, and commenters at the Carroll Round for their comments and suggestions. All mistakes, of course, are my sole responsibility.

1 Introduction and Literature Review
For decades, economists have recognized the importance of modeling search frictions in labor markets. Because unemployed workers must wait for job offers or seek out job offers, the basic supply-and-demand model is an insufficient tool for understanding the labor market. Models incorporating search frictions have become widespread and influential as a integral part of micro-founded macroeconomics. The 2010 Nobel Prize in Economics was awarded to Diamond, Mortensen, and Pissarides for work in this field.

The vast majority of labor search theory has focused on modeling an individual worker as the agent in question. However, in reality, individuals within households pool resources and may take into account the labor force status of their household members while searching for jobs. Flabbi and Mabli (2012) find that recent surveys of labor search and matching mention no works that acknowledge the potential importance of modeling household rather than individual search.

Burdett and Mortensen (1977) briefly sketch a model of household search where unemployed individuals split their time between search and leisure. Aside from Burdett and Mortensen (1977), however, search theory has largely ignored the problem of household search until recently. The few papers that deal with household search are mostly a recent phenomenon.

Guler, Guvenen, and Violante (2012) are the first after Burdett and Mortensen (1977) to provide a theoretical framework specifically aimed at characterizing the problem of household search. Guler, et. al (2012) construct a model of household search in which two homogeneous individuals engage in simple sequential search, pool income and maximize a joint utility function. In the model in Guler, et. al (2012), the optimal choice of the couple is to engage in a “breadwinner cycle”, where a worker-searcher couple switches the roles between the spouses when the unemployed spouse draws a wage higher than the employed spouse until both spouses face wage draws that are sufficiently high that both workers stay employed. Guler, et. al (2012) is the model I will extend and build on in this paper.

Regarding labor force non-participation, Frijters and van der Klaauw (2006) estimate a non-stationary job search model where unemployed workers have the option of permanently exiting the labor force and provide evidence that workers leave the labor force after long periods of unemployment because their wage offers fall as unemployment duration increases. Pries and Rogerson
(2009) extend the labor market search problem to include the non-participation state and assume stochastic labor force participation costs that cause flows into and out of non-participation. Examining the role of labor force nonparticipation in labor markets is of particular importance because of the role of nonparticipation in the Great Recession; as Elsby, et. al (2010) show, flows from unemployment to nonparticipation have increased greatly during the Great Recession and are particularly important in understanding unemployment duration during the recovery.

However, to my knowledge, no theoretical works incorporate both household labor search and labor force non-participation, and outlining a model that achieves that is the goal of this paper. If resource sharing within households can bias the empirical results in the papers aforementioned, it stands to reason that household income pooling may impact the decision to participate in the labor force.

The rest of the paper is organized as follows. Section 2 introduces the household search model with labor force non-participation and the properties of the model. Section 3 discusses how the model changes as one parameter, the value of household production, changes. Section 4 concludes.

2 Model

I modify the model outlined by Guler, et. al (2012) to include the option of staying out of the labor force. As in Guler (2012), a "couple" is an infinitely-lived economic unit comprised of two individual workers that are ex-ante identical; that is, they face the same wage distribution, rate of wage offers, and home production capabilities.

Couples pool income and maximize a joint utility function that is concave over income. The flow utility function of couples is quasi-linear with respect to the value of home production; that is, \( u(w, m) = v(w) + m \) where \( w \) is the total income of the couple and \( m \) is the level of home production. The couples are risk averse with respect to income, so the function \( v \) is weakly concave. In addition, \( v \) satisfies the Inada condition that the marginal utility of income approaches infinity as income approaches zero. The couple has a discount rate of \( r < 1 \).

Individuals can be in any one of three states: working (W), searching and unemployed (S), or engaging in home production (H). Throughout the paper I will refer to the states of couples by combinations of these letters; e.g., a couple where one individual is working and one is engaging in home production is in the state WH.

Working individuals earn a wage but are offered no jobs (there is no on-the-job search) and have no home production. An unemployed individual flow income and has no home production, but is also receiving job offers. An individual that is out of the labor force receives no wage and generates flow home production of value \( h \) and receives no job offers.

Unemployed workers engage in simple sequential search from an exogenous wage offer distribution. The wage offer distribution is given by the cumulative distribution function \( F(w) \). The wage distribution is bounded by \( [w, \bar{w}] \). The flow payment for an unemployed worker \( b \) is such that \( b < w \). Wage offers are received at an exogenous poisson rate of \( \alpha \) and offers are independent and identically distributed. Upon receiving a wage offer, a worker can either take the job and become a worker at the received wage, or reject the wage offer and continue searching. There is no recall of rejected wage offers; a worker must either accept or reject the offer before continuing to search.

Finally, workers may at any time instantly switch between the states of unemployment and household production at zero cost, and employed workers can at any time quit to unemployment or leave the labor force at zero cost.

A couple can therefore be in nine (2-permutations of 3) states, but since individuals within the couple are ex ante identical in their wage offers and home production capabilities, the problem is

---

1 I have included in the appendix and exposition of the risk-neutral case, in which \( v(w) \) is linear and \( v(0) = 0 \). If the value of household production is sensible, the risk-neutral case is exactly the same as the model without household production.

2 One real-life interpretation of this condition is that there exist goods that the couple must purchase on the market that cannot be produced at home.
symmetric and only six (2-combinations of 3) states need be considered: HH, SH, SS, WS, WW, and WH.

Finally, a note on the functional form of utility. I choose quasi-linear as the functional form for the following reason: Because of the Inada condition on \( v(w) \), we can guarantee that at least one individual will be in the labor force. Therefore, there can either be no home producers or one home producer. Since I only allow for individuals to be discretely in or out of the labor force, there are effectively only two possible levels of household production available to the couple. The return to home production could very well be non-linear, but since couples can only have two levels of household production, I can simply normalize the household production term such that the value of no home producers is 0, and the value of one home producer is \( h \).

**Value Functions**

The value functions are as follows, where the subscript of \( V \) denotes the state of the couple; \( V_{WS}(w) \), for example, is the value function for a couple with one worker and one searcher where the worker’s wage is \( w \). Although workers can theoretically be in six states, note that the value function for an HH couple is undefined because of the Inada condition assumption. A couple will always prefer the state SH or SS to HH, since in the states SH and SS, the couple receives a strictly positive level of flow income. Since individuals and freely switch between unemployment and household production, a couple can freely switch between states SH, SS, and HH, so a couple will therefore never be in state HH. The Inada condition does not rule out any other states because in all other states there is at least one searcher or worker, which receive unemployment flow payment \( b \) or flow wages \( w \) respectively.

\[
V_{SH} = v(b) + h + \alpha \int \max \{V_{WH}(w) - V_{SH}, V_{WS}(w) - V_{SH}, 0\} dF(w) \tag{1}
\]

\[
V_{SS} = v(2b) + 2\alpha \int \max \{V_{WH}(w) - V_{SS}, V_{WS}(w) - V_{SS}, 0\} dF(w) \tag{2}
\]

\[
rV_{WS}(w_1) = \begin{cases} 
 v(w_1 + b) + \alpha \int \max \{V_{WH}(w_2) - V_{WS}(w_1), V_{WW}(w_1, w_2) - V_{WS}(w_1), V_{WS}(w_2) - V_{WS}(w_1), 0\} dF(w_2) & \text{if } w_1 < w_2 \\
 0 & \text{if } w_1 \geq w_2 
\end{cases} \tag{3}
\]

\[
rV_{WH}(w_1, w_2) = v(w_1 + w_2) \tag{4}
\]

\[
rV_{WH}(w) = v(w) + h \tag{5}
\]

The value functions will not be dependent on the amount of time the couple has spent in the state, since the value functions are determined by the discounted flow utilities, wage draws are i.i.d., and there is no saving or borrowing component to the problem. Couples will therefore only consider changing their labor force status when a searching individual encounters a job offer, because absent a wage offer a couple’s decision making problem remains the same over time. If couples are at all times choosing their utility maximizing state, there is never any reason for the couple to be in two different states at two different times unless the couple encountered an accepted a wage offer.

One implication of this is that if a couple ever rationally chooses either states WW or WH as the result of a wage offer, they stay in that state forever. If that state was optimal at the time of the wage offer, then the state must also be optimal at all times after the moment the couple accepted the wage offer because the decision to change states is time invariant. The couple’s constraints do not change over time because neither individual is in the searching state and therefore not receiving job offers. We therefore only need to consider decision-making for states SH, SS, and WS and how couples in those states react to different wage offers.

This property is clearly unrealistic and a mathematical simplification. However, in reality, couples accumulate assets and borrow money, exogenous separations occur, and the parameters of the problem change over time (for example, if a couple has a baby, suddenly household production may become valuable and trigger a change of state even in the absence of a job offer). Although it would be
useful to examine models that have exogenous job separations or asset accumulation, that is outside the scope of this paper.

The equations for value functions (4) and (5) are straightforward expressions of the discounted present value of the flow values of the states. Their flow values are equal to the utility of consumption plus the household production term in the case of the WH state.

The value functions for the states in which one or more individuals are searching are more complicated. For a SH couple, a couple has three options upon receiving a wage offer:

1. Accept the wage offer and become a WH couple, in which case the couple gains $V_{WH} - V_{SH}$.
2. Accept the wage offer and become a WS couple, in which case the couple gains $V_{WS} - V_{SH}$.
3. Reject the wage offer and stay a SH couple, in which case the couple gains 0.

For a SS couple, since in continuous time the probability that the couple encounters two wage offers simultaneously is infinitesimally small, I only consider the couple’s choices when they receive one wage offer. The rate of encountering job offers is $2\alpha$ because the couple has two searchers, each with search rate $\alpha$. Since individuals can seamlessly move between the search and home states, the choices are similar to those of the SH couple that draws a wage offer: accept the offer and become either a WH or a WS couple, or reject the offer and remain a SS couple.

For a WS couple, upon receiving a wage offer, there is an additional option. If the searching spouse accepts the job offer, the WH and WS states at the new wage offer are still available since the employed spouse has the option to quit to either search or home production. In addition, if the employed spouse can continue working and the couple can become a WW couple.

Finally, the values of $V_{SH}$ and $V_{SS}$ are constant and not contingent on a particular wage draw. Therefore, if the value of one of either states SH or SS is larger than the other, then there is never any need to consider the other state because couples can freely and immediately switch between the two states. I first consider the case where $V_{SH} > V_{SS}$, and the consider the case where $V_{SH} < V_{SS}$.

2.1 The Permanent Home Worker

Suppose that the value of household production is such that $V_{SH} > V_{SS}$. Then, the following proposition characterizes the labor force dynamics of the couple (the proofs for this and other propositions are given in the Appendix [full paper only]):

**Proposition 1.** If $V_{SH} > V_{SS}$, then there exists a unique reservation wage $w^* \in [w, \bar{w}]$ such that SH couple will accept a job offer if and only if the wage is above $w^*$. Furthermore, for all wages $w \in [w, \bar{w}]$, the WS option is dominated by either the SH or the WH option, and a SH couple will never accept a wage offer and become a WS couple.

In other words, a SH couple will remain in the SH state until they draw a wage above the reservation wage $w^*$. Upon drawing that wage, the searching individual will accept the wage offer and the at-home individual will stay at home (so the couple will become a WH couple) rather than enter the labor force as a searcher (in which case the couple would be a WS couple). Note that since the couple never becomes a WS couple, they also never become a WW couple, since the only way to become a WW couple is for a WS couple to encounter and accept a wage offer. The couple is therefore only ever in one of two states, SH and, after receiving a sufficiently high wage offer, WH.

In this case, the "H" member of the couple will always remain out of the labor force. Since the contribution of the household member is the linear portion of the couple’s quasi-linear utility function and the same between states SH and WH, the couple’s utility maximization problem amounts to
maximizing the utility contribution from the wages of the labor force participant. This is exactly the same problem as maximizing utility of a simple individual sequential search problem.

Figure 1: The flow dynamics for a permanent home worker couple.

\[
\begin{align*}
\text{SH} &\xrightarrow{\text{Accept if } w > w^*} \text{WH}
\end{align*}
\]

2.2 The Double Participation Problem

I now turn to the case where \( V_{SS} > V_{SH} \). In other words, when neither individual has a job offer, the couple's optimal state is for both individuals to search for jobs. Since the couple can freely switch between the SS and SH states, we do not need to consider the possibility of the couple choosing state SH. The only states the couple chooses between are SS, WS, WH, and WW.

Recall that if a couple rationally chooses states WH or WW, the couple will stay in that state forever, since the parameters of their decision never change if no members of the couple are receiving job offers. Thus, while the values of the WH and WW states are important, there is no decision-making involved in those states. There is, however, a decision-making problem in the SS and WS states. I will first examine the problem of the SS couple, and then that of the WS couple.

2.2.1 The Dual-Searcher Problem (SS couples)

For a SS couple, upon receiving a single wage offer there are three options: become a WH couple at the wage offer, become a WS couple at the wage offer, or remain a SS couple. Referring to the value functions, when an SS couple draws a wage \( w \), the couple examines the set \( \{V_{SS}, V_{WS}(w), V_{WH}(w)\} \) and chooses the state associated with the maximal of that set.

Say spouse 1 in an SS couple draws the wage offer \( w \). The couple will accept a wage offer whenever \( V_{SS} < \max\{V_{WS}(w), V_{WH}(w)\} \). Otherwise, the couple will reject the offer. If the offer is accepted, the wage offer will trigger spouse 2 to exit the labor force (the couple becomes a WH couple) if \( V_{WH}(w) > V_{WS}(w) \); otherwise, the couple accepts the job offer and spouse 2 continues to search (the couple becomes a WS couple).

The goal is to determine what ranges of wage offers will result in which choices. In other words, what wages do couples accept, and of those wages, which ones trigger labor force exits? First note the following two propositions:

Proposition 2. \( V_{WS}(w) \) is increasing in \( w \)

Proposition 3. \( V_{WH}'(w) > V_{WS}'(w) \) for all wages \( w \in [\hat{w}, \bar{w}] \)

Finally, note that \( V_{WH}(w) \) is increasing in \( w \), which is obvious from observing (5), and that \( V_{SS} \) is a constant with respect to \( w \). These properties of the value functions show that the intersections of \( V_{WH}(w) \), \( V_{WS}(w) \), and \( V_{SS} \) are unique.

I denote the wage that makes the couple indifferent between states SS and WS as \( w^{**} \); that is, \( V_{SS} = V_{WS}(w^{**}) \). I denote the wage that makes the couple indifferent between states SS and WH as \( w_{SS=WH} \); that is, \( V_{SS} = V_{WH}(w^{**}) \). Finally, I denote the wage that makes the couple indifferent between states WS and WH as \( w^{h} \); that is, \( V_{WS}(w^{h}) = V_{WH}(w^{h}) \).

Case 1: \( w^{**} < w_{SS=WH} \)
The couple’s reservation wage will be $w^*$. For wages between $w^*$ and $w^h$, the couple accepts the wage offer and becomes a WS couple. For all wages above $w^h$, the couple accepts the wage offer and becomes a WH couple.

It may be the case that if $h$ is very small, it may be the case that $w^h > \bar{w}$; that is, there is no wage in the wage distribution that makes the couple prefer state WH to state WS. If the couple never chooses state WH, then the couple effectively only needs to consider the states SS, WS, and WW; in which case the problem is exactly the same as in Guler, et. al (2012). I explore this case later in Section 3.

Case 2: $w^* > w_{SS=WH}$

The couple’s reservation wage will be $w_{SS=WH}$. For wage offers above $w_{SS=WH}$, the couple will accept the wage offer and take the WH state at the wage offer. Because

$$\frac{d}{dw} V_{WS}(w) < \frac{d}{dw} V_{WH}(w),$$

the WS option will always be dominated by the WH option for all wage offers $w > w_{SS=WH}$. In other words, the SS couple will never accept a wage offer and become a WS couple.

Note that in the second case, there is no need to examine the problem for a WS couple. In the second case, the WS option is always either dominated by the SS or the WH option, so any WS couple will immediately switch to the SS or WH option. Thus, in the following section where I examine the problem for a WS couple, I assume that $w^* > w_{SS=WH}$.

### 2.2.2 The Single Searcher Problem (WS couples)

Throughout this section, I will assume (without loss of generality) that in a WS couple, spouse 1 is the employed spouse with wage $w_1$ and spouse 2 is the searching spouse. Upon spouse 2 receiving a wage offer $w_2$, the couple has four options: become a WW couple with wages $w_1$ and $w_2$, become a WS couple with wage $w_2$, become a WH couple with wage $w_2$, or stay a WS couple with wage $w_1$. Upon receiving a wage offer, a couple finds the maximum of the set $\{V_{WW}(w_1, w_2), V_{WH}(w_2), V_{WS}(w_2), V_{WS}(w_1)\}$ and chooses the state associated with that value function.

**The Accept-Reject Decision**

The couple will accept the wage offer if and only if at least one of the following conditions hold:

1. $V_{WW}(w_1, w_2) > V_{WS}(w_1)$
2. $V_{WS}(w_2) > V_{WS}(w_1)$
3. $V_{WH}(w_2) > V_{WS}(w_1)$

Define $\varphi^+(w_1)$ as the lowest wage such that the WW state is weakly preferred to the WS state. That is, $V_{WW}(w_1, \varphi^+(w_1)) = V_{WS}(w_1)$.

Figure 2: The flow dynamics for SS and WS couples.
Similarly, define \( \phi^- (w_1) \) as the lowest wage such that the WS state with the new wage offer is preferred to the old WS state. That is, \( V_{WS}(\phi^- (w_1)) = V_{WS}(w_1) \). Recall from Property 1 that \( V_{WS} \) is strictly increasing in the wage; this equation therefore implies that \( \phi^- (w_1) = w_1 \). In other words, when the couple draws a higher wage offer than the wage currently earned from spouse 1, the couple prefers the WS state with spouse 2’s new wage offer over the old WS state.

Finally, define \( \phi^o(w_1) \) as the lowest wage such that the WH state with the new wage offer is preferred to the old WS state. That is, \( V_{WH}(\phi^o(w_1)) = V_{WS}(w_1) \).

A wage offer \( w_2 \) that exceeds any of \( \phi^+, \phi^-, \phi^o \) will be accepted. In other words, the reservation wage for the accept-reject decision of the couple, \( \phi(w_1) \), is given by

\[
\phi(w_1) = \min\{\phi^+(w_1), \phi^-(w_1), \phi^o(w_1)\}
\]

This expression can be simplified further. Note that the decision-making of a WS couple need only be considered for WS couples with wage \( w_1 < w_h \), where \( w_h \) is the threshold wage such that \( V_{WS}(w_h) = V_{WH}(w_h) \). This is because if a WS couple has wage \( w_1 > w_h \), there is no reason for the couple to be in the WS state, since the value of the WH state with wage \( w_1 \) is higher.

Now, assume for the sake of contradiction (FSOC) that \( \phi^o(w_1) < w_1 \); that is, the wage that makes the couple indifferent between the WH state and the old WS state is lower than the wage in the old WS state. Then, it must be the case that \( V_{WH}(w_1) > V_{WH}(\phi^o(w_1)) = V_{WS}(w_1) \), which implies that \( w_1 > w_h \).

The implication of this is that if the analysis of the WS couple is limited to relevant WS couples; that is, WS couples with wages low enough that it makes sense for them to be WS couples, then \( \phi^o(w_1) > w_1 = \phi^- (w_1) \). The reservation wage for the accept-reject decision of the couple can therefore be simplified to

\[
\phi(w_1) = \min\{\phi^+(w_1), \phi^-(w_1)\}
\]

and we do not need to consider \( \phi^o \).

**Choosing States if the Wage Offer is Accepted**

The next question, naturally, is: if a WS couple accepts a wage offer (that is, \( w_2 > \phi(w_1) \)), what state does the couple choose? Recall that if the couple accepts the wage offer, the couple evaluates the maximum of \( \{V_{WW}(w_1, w_2), V_{WS}(w_2), V_{WH}(w_2)\} \) and chooses the associated state.
Recall that upon receiving a wage offer \(w_2\), \(\varphi^+\) compares states WW and WS, \(\varphi^-\) compares the two available WS states (with \(w_1\) and \(w_2\), and \(w^h\) is the threshold wage for which WH is preferred to WS. The final comparison that needs to be made is the comparison between the WW and WH state, so I define a new threshold wage function, \(\psi(w_1)\), as the threshold wage such that \(V_{WH}(\psi(w_1)) = V_{WW}(w_1, \psi(w_1))\) and \(V_{WH}(w_2) > (\leq) V_{WW}(w_1, w_2)\) \(\forall \) \(w_2 > (\leq) \psi(w_1)\). In other words, \(\psi(w_1)\) is the lowest wage offer such that the WH state is preferable to the WW state. The following proposition provides some characterization of the shape of \(\psi\):

**Proposition 4.** Given a \(w_1\), \(\psi(w_1)\) is a singleton and increasing in \(w_1\). In addition, \(\forall w > w^h\), \(\psi(w) > \varphi^+(w)\), and \(\psi\) intersects \(\varphi^+\) at \(w^h\).

Before examining the WS couple’s state decision conditional on acceptance, it will be useful to examine Figure 3, which is a generic visualization of \(\varphi^+, \varphi^-, w^h\), and \(\psi\) in the two-dimensional wage space.

In Figure 3, the wage of the worker in the WS couple is denoted along the horizontal axis as \(w_1\), and the wage offer to the searcher is denoted along the vertical axis as \(w_2\).

In addition to plotting \(w_2 = \varphi^+(w_1)\) and \(w_2 = \psi(w_1)\), I also plot their inverses, \(w_1 = \varphi^+(w_2)\) and \(w_1 = \psi(w_2)\). The reasoning is as follows: If the wage offer \(w_2\) is accepted, the couple needs to reevaluate the role of worker 1; that is, the value of the WW state with wages \(w_1\) and \(w_2\) needs to be compared to the WS and WH states with the new wage \(w_2\) (in which case the first worker quits to search and home, respectively). In terms of the value functions, the couple compares \(V_{WW}(w_1, w_2)\) to \(V_{WS}(w_2)\) and \(V_{WH}(w_2)\).

Because individuals in the couple are ex-ante identical, the threshold wages for comparing these states are also given by \(\varphi^+\) and \(\psi\). That is, \(V_{WW} (\varphi^+(w_2) + w_2) = V_{WS}(w_2)\) and \(V_{WH}(\varphi^+(w_2) + w_2) = V_{WH}(w_1)\). These threshold wages are traced by \(w_1 = \varphi^+(w_2)\) and \(w_1 = \psi(w_2)\), respectively, which are the mirror images of \(w_2 = \varphi^+(w_1)\) and \(w_2 = \psi(w_1)\) across the 45\(^\circ\) line.

Conditional on acceptance, the couple chooses state WH if and only if \(V_{WH}(w_2) > V_{WS}(w_2)\) and \(V_{WH}(w_2) > V_{WW}(w_1, w_2)\). The first condition holds if and only if \(w_2 > w^h\), and the second holds if and only if \(w_1 > \psi(w_2)\). This region is denoted by the dotted in Figure 3 bound below by \(w^h\) and to the right by \(\psi(w_2)\).

The couple chooses state WS at the new wage offer if and only if \(V_{WS}(w_2) > V_{WH}(w_2)\) and \(V_{WS}(w_2) > V_{WW}(w_1, w_2)\). The first condition holds if and only if \(w_2 < w^h\) and the second holds if and only if \(w_1 < \varphi^+(w_2)\). This region is denoted by the white spaces bounded by \(w^*\) and \(w^h\), and above by \(\varphi^-(w_1)\) and \(\varphi^+(w_1)\) in Figure 3.

Finally, the couple chooses state WW with the old and new wage offers if and only if \(V_{WW}(w_1, w_2) > V_{WH}(w_2)\) and \(V_{WW}(w_1, w_2) > V_{WS}(w_2)\). The first condition holds if and only if \(w_1 > \psi(w_2)\), and the second holds if and only if \(w_1 > \varphi^+(w_2)\). This region is denoted by the lightly shaded region in Figure 3.

Finally, there is a dark shaded region in the upper right-hand corner of Figure 3, bounded on the left and below by \(w^h\). In this example, couples with wage offers in that corner would prefer to

---

3 Since the individuals in the couple are ex-ante identical, the threshold functions are symmetrical. It is also possible to read the diagram with the roles switched; that is, the worker is denoted along the \(w_2\) axis and the searcher is denoted along the \(w_1\) axis.
be WW couples at the two high wages, but according to the model we should never observe couples in that region, because in order to reach that region, a couple needs to first become a WS couple at a wage above $w^h$, and then receive and accept a wage offer above $w^h$. However, a couple

Figure 3: The Worker-Searcher Problem in the 2-Wage Space: $w_1$ denotes the worker’s wage, and $w_2$ denotes the searcher’s wage

with a single wage offer above $w^h$ would never choose to be a WS couple, since the WH option dominates. Thus, one implication of the model is that we should not observe WW couples where both workers have very high wages.

In the next section I will discuss properties of the above diagram in terms of intersections of the threshold functions as the value of household production $h$ is varied.

3 Comparative Statics: The Value of Household Production

This section has been omitted for length.

4 Conclusion

To date, search theory has yet to combine the concept household income pooling with the phenomenon of labor force non-participation. In this paper, I have laid out a simple model of the labor force participation problem from a household perspective. In this model, an individual’s decision to participate in the labor force is highly dependent on the labor force status of the spouse. While the breadwinner cycle aspect of the baseline case remained unchanged by adding a non-trivial level of household production, the region of no quits was no longer relevant for sufficiently high levels of household production. If households pool income, then understanding labor force non-participation should be thought of as a household decision rather than an individual decision.

In Section 3, I demonstrated how the search problem is characterized differently as the value of household production varies. Since an examination of the data is beyond the scope of this paper, I cannot conclude with which range of $h$ best characterizes real-life household search. A natural empirical extension to this paper would be to examine the Survey of Income and Program
Participation (SIPP) data to determine what behavior best characterizes joint search with non-participation.

This is clearly a simple model of household search and there are many theoretical extensions that are beyond the scope of this paper. Some potential extensions include ex ante differences between the spouses in either wage distribution or household production values, the possibility of household savings or borrowing, and non-discrete labor force participation decisions.

Finally, given the importance of labor force participation to the recovery from the Great Recession, it would be interesting to examine changes in labor force participation since the Great Recession from the viewpoint of households, rather than individuals, as economic units. It will be interesting to incorporate the household determination of labor force participation decisions in relation to business cycles and labor force dynamics in recessions and recoveries.

References
DISCRIMINATORY EUROPEAN UNION MEMBERSHIP: ENLARGEMENT PROCESS AND DISTRIBUTIONAL CONFLICTS

Nikola Andreev
Adviser: Jeffrey Nilsen
American University in Bulgaria

ABSTRACT

This paper checks the validity of the hypotheses of Schneider (2005) that discriminatory European Union membership enables the enlargement process and is the main tool used by the incumbent countries to re-distribute the gains from a new member. The so-called discriminatory EU membership stands for a phase-in membership with temporary limited access to some of the Agricultural and Structural funds or to a certain labor market. Also, the discriminatory membership offers EU members the opportunity to settle the distributional conflicts that emerge in the negotiation process. The paper gives an up to date look at the issue by introducing more than 20 percent (200/872) observations after the final enlargement round and thus gives a finer distribution of the conditions that lead to the restricted membership. The results can also serve as an indicator by future applicants for possible implications.

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1 Introduction: Enlargement Process and Distributional Conflicts.

As the EU has grown in size substantially from its Inner Six members so have the members’ points of view and claims. In 2012 there were twenty-seven countries in the European Union, five in a process of accession negotiations and three potential candidates, one an acceding country. But the future of the EU enlargement seems more and more uncertain - the pie gets bigger and bigger but so does the pieces that it has to split among the beneficiaries of the gains of EU enlargement. The grand idea standing behind the European Union is the common free market and single rules to be followed in the European community. The only way this can be achieved is by gradually expanding the club. Of course, the issues that are arising are much more complicated than just adding the name of a particular country to the list of members. The European Union is appealing to a big number of countries because of the benevolent economic environment and free trade area but also from the financial benefits that an applicant country would enjoy from full-right membership. On the other hand, it is clear that the benefits that a country will enjoy once accepted in the EU will not come from a thin air. Of course, when a country joins the EU it makes contributions to the budget and so the amount of money that can be distributed for each of the EU policies grows but the distributional conflicts emerge when deciding who is taking and how much.

Schneider (2005) illustrates this point by talking about Turkey’s application for EU membership. While the application was submitted almost twenty-five years ago, it is still in the process of negotiation. When in 2004 the EU started the accession negotiation many incumbent countries were surprised and reluctant to let Turkey in. The reason for the conflicts comes from the cross-section of an applicant’s economy structure and relative structure of the incumbent countries. Germany, for example, insisted on closing its borders to a free labor movement, and France similarly declared a position against Turkey’s access to agricultural subsidies. Germany has a substantial part of its population made of immigrants from Turkey, and that is why it is afraid that an opportunity of free labor mobility is likely to cause a flood of cheap labor, thus, shaking the labor structure in Germany. On the other hand, France is the biggest
beneficiary of agricultural subsidies in EU and possible access of Turkish farmers to those funds might cause a relative leakage of funds (that otherwise France would enjoy) to Turkey.

The enlargement can only happen by following the unanimity rule–every single state can decide to either approve or refuse to admit an applicant to the Union if it is not satisfied in any way with it membership. Also, it is easy to make the assumption that governments are rational players whose main aim is to increase the national welfare and thus get reelected again (Persson, Tabellini 2002). Based on those principles, a state firstly decides whether to accept an EU membership if this will make it better off afterwards and, secondly, approve a further enlargement of the Union again if this will make it better off. So, if France experiences relative loss because of Turkey’s relatively big and less efficient agricultural sector (compared to other incumbents) this will make France brakemen of the enlargement process. So far every enlargement round would have failed due to those conflicts unless there is some form of a transitional allocation of membership rights. This is the so-called Discriminatory European membership. So far all European Union enlargements have triggered such distributive conflicts and have never taken place without some form of a transitional period. A study with a main focus on the reasons of such distributional conflicts is vital for predicting the success of further enlargements as well as the demand of discriminatory memberships. Moreover, studying the magnitudes of those issues can be the key to successful solutions, which aid the process of EU enlargement.

2 The Theoretical Model – Derivation

This paper distinguishes four possible outcomes of the enlargement round when a state applies for membership. The first one is full-right membership–that is, the state and its citizens have all the rights guaranteed by the EU law and are eligible for all the subsidies. The second option is the discriminatory membership when the ascending state faces some restrictions in its participation in some labor markets or its eligibility for EU subsidies. After that comes the inner-union distribution, when countries with a conflict with the applicant are compensated by the other incumbent countries so that the enlargement takes place. Finally, there is non-membership, which is just a failure of the enlargement round for a particular applicant.

The theoretical model should take into consideration the process of negotiation that leads to those outcomes and elaborate on them. The incumbent members are divided into two subgroups – the relative winners of enlargement and those, which may face an overall loss after the accession. The proponents of the enlargement win from the new markets: from the unification of policies and the stability that comes with the size of the union. On the other hand, a relative loser is the one that would be competing with the applicant for the funds in its favorite policy area. For example, Greece would be reserved to let Bulgaria in because of its relatively poor regions and thus we would be eligible for funds that otherwise Greece would be granted. Thus, a member against would base its support of the enlargement on the redistribution of the enlargement gains in such a way as to ensure outcome that will not make it worse off. Here, an introduction of the incumbents in the two groups on an individual level would not make the results finer because they act in similar fashion.

The bargaining process takes the form of a game that involves three players: members-pro, members-against enlargement, and the applicant country. The accession negotiations between the payers give the necessary variation of the variables that produce a differentiated membership result. Also, each state is aware of the others position and current utility level. So, the cards are on the table and we have an ultimatum game with perfect information.

The paper also distinguishes between rival and non-rival policies. An example of a non-rival policy would be the Common Environment Policy. The number of countries that have to comply does not affect negatively the countries themselves. So the conflicts must result from the rival policies. Let us take a look at the Common Agriculture Policy (CAP). The countries competing for financing from this policy field are basically paying a zero sum game. If Bulgaria receives a particular Euro, Greece would not get it. Throughout the paper I would use France as the main recipient of agricultural subsidies and state that can face financial outflow from this policy. Greece, on the other hand, would be an example of
the group of states that would protect the European Reconstruction and Development Funds (ERDF), as it has a number of relatively poorly developed regions.

The most important part of the model is to acknowledge that there is heterogeneity of preferences of the incumbents toward the policy fields. Member states receive more funds from one policy area and less from another. The tendency is that the more funds a state receives from a particular policy field the more likely is to experience distributional conflicts. The paper distinguishes between two rival and two non-rival policies. I do that without loss of generality because an incumbent associates itself with one of the two groups—one that favors more agricultural subsidies and another for structural help. This strategy can be extrapolated to every rival strategy. This is the very reason why the member states are divided in two groups. On one side there are the proponents of enlargement that are the relative winners of enlargement and on the other there are relative losers that will compete with the applicant for the same policy field funds.

I follow Schneider (2005) to study four policy fields: Free Movement of Labor (FML), Common Fisheries Policies (CFP), Common Agricultural Policy (CAP) and Common Structural Policies (CSP). Those are a good sample because in all enlargement rounds restricted rights were granted that allows for a sufficient variation of the dependent variable (the probability that a discriminatory membership is granted).

The two non-rival strategies are the Common Fisheries and Free movement of Labor Policies. The CFP mainly concerns the fishing areas and the quotas that can be harvested. This policy has not been a hot topic of discussion since both Bulgaria and Romania do not share a sea with any other incumbent members and the issues in the Black sea have long been settled in between. The FML is, on the contrary, a topic of huge debate. It mainly concerns the right of citizens to sell their labor on foreign labor markets in the EU. Bulgaria and Romania are countries with much lower income compared to the EU and it is logical to expect a mass migration of labor from the Balkans to the Western countries. The incumbents, on the other hand, are afraid that this would ruin their whole labor structure.

The rival policies are the Common Agricultural Policy and the Common Structural Policy. The CAP and the CSP are the biggest redistribution schemes in the EU and thus are prominent for the community. Also sufficient data information is available.

2.1 The Theoretical Model – Assumptions.

The model rests on a standard political model that says that governments choose a strategy that will increase the net utility of the country and thus ensure their re-election. In the case of EU membership this net utility (denoted by \( u_{ij} \)) each member \( M_i \) will be composed by several elements, or the gains that states will get from harmonization of different policies, \( p_j \). Those policies are the ones that are voted in the Parliament and are subject to the common decision making process. This paper follows (Schneider 2005) in that I recognize two policies that are denoted by \( p_1 \) and \( p_2 \). The reader should think about those as policies such as the CAP and CSP. Of course, non-rival policies would work just as fine. For example, Germany might associate itself with the group of states that would be against the FML against one that is affected more than CFP. As the goal of this paper is to show the heterogeneity of preferences and that each member benefits more from one and less from the other policy area, introducing a finer look at the policy areas would not give a better result. The only difference on an empirical level is that those differ in their consumption rivalry, \( \lambda \), with a decreasing number of new member states increasing the benefits for each member previously eligible for those funds. \( p_1 \) and \( p_2 \) are constants – in the accession negotiations the incumbents and members change the distribution of benefits by either a phase-in membership or inter-member distribution. Furthermore, political costs are denoted by \( \mu \), and will come from the heterogeneity of the preferences. Cooperation benefits are denoted by \( b_n \), and will increase with the size of the Union, \( M \). Finally, budgetary costs are denoted by \( R \).

The model continues with introducing the players in the theoretical game. There are the two groups of members—\( M_1 \) and \( M_2 \), so that each incumbent has to define itself with one of them. For example France will be in the subgroup that will differentiate the CAP and Greece on the other hand will advocate the protection of the CSP funds. It is important to make the following note here. If France
benefits mostly from the CAP funds compared to CSP funds this does not make it completely indifferent to those regional development funds. So if new comers are eligible for reconstruction funds this will also hurt France. The parameter $a_{ij}$, for $0 \leq a_{ij} \leq 1$, shows that the larger the coefficient the larger Greece gains from CAP compared to the CSP.

2.2 The Theoretical Model – Membership Benefits.

The incumbent states identify themselves as a members of the one of the two groups–members-pro and members against. This happens on the characteristics of their economy. So the net utility of the incumbents will be mirror like for each of the two subgroups depending on which group they have associated with.

$$U_1= [b_i + p_1 M_1 - \lambda_2 + a_{i1} p_2 M_2 - \lambda_1] - [R M^{-1} M^\mu]$$

$$U_2= [b_i + p_2 M_2 - \lambda_2 + a_{i2} p_1 M_1 - \lambda_1] - [R M^{-1} M^\mu]$$

*The equations state that the net utility comes from the cooperation benefits ($b_i$) that come with the size of the Union ($M$) plus the portion the member gets from its preferred policy plus the funds that the members of the other subgroup will take from their major policy. The equation continues with subtraction of the budget contribution ($R$) divided by the number of states ($M$) plus correction for the heterogeneity of policy ($M^\mu$) and adding the funds that the other will get from our main policy.

In the long run, each new member starts to make contributions to the budget. But historically, those have not been enough to compensate the relative losers from the enlargement and settle the distributional conflicts. Also, the bigger the number of major beneficiaries within a certain policy field, the higher the probability that the incumbents will experience a net utility loss after the enlargement. On the other hand, no matter which subgroup the incumbents belong to, they experience a net utility gain from the cooperation and a decrease of governance costs.

When a candidate country applies for a membership it will either align with subgroup $M_1$ or $M_2$. The members of the same group favor a common policy area as their main subsidy source. So the incumbents will experience a distributional conflict with the applicant and thus be reluctant to grant a full-right membership status. This happens whenever enlargement gain from the applicant does not make up for the loss of the funds from their favorite policy area, let say $p_1$. In this case the second group can make sure that the enlargement will take place only if there is a redistribution of gains within the EU or the applicant is granted a discriminatory membership. The inner-union distribution can be increased budget for the $p_1$ policy area. Schneider (2005) mentions Spain and Portugal as an example of inner-union distribution of gains. Germany had agreed to increase its budget contributions ($R$) to satisfy Greece that wanted to impose veto on the enlargement because of the new member states’ eligibility for the CSP funds.

The model needs to replicate the bargaining process in order to have a claim to be predictive. It is based on the possible outcomes that result from the negotiations. Members of group one who have their main policy area threatened will prefer phased-in membership to inner-union redistribution. $M_2$ will be in favor of full membership or conditional membership to non-membership or inner-union distribution at their expense (like Germany increased contribution to the budget ($R$)). The applicant will prefer the unconditional membership or an inner-union distribution to discriminatory membership or non-membership.

2.3 The Theoretical Model – Bargaining Process.

The paper will take the same approach as Schneider (2005) and will examine the negotiation process dividing it in three stages. :

1. Let say that there is an applicant $A_i$ that want to join the EU. Let say it will associate itself with the $M_2$, based on the characteristics of its economy, and thus its main benefits will come from
structural aid $p_2$. Thus during this stage the members of $M_1$ will be the proponent of the expansion and will make an offer to $M_2$ concerning the allocation of net utility gains. The offer might be either to impose restrictions on the new applicant eligibility for $M_2$’s preferred policy or inner union redistribution at the relative winners’ cost–$d_{M1}$. $M_1$ will always offer discriminatory membership whenever possible in order to minimize $d_{M1}$ that is their loss. The expectation is that this strategy highly increases the probability of imposing a differentiated membership rights to the new comers.

2. During the second stage concerns $M_2$ either refuse or accepts $M_1$’s proposal. The reservation point is the utility level that the $M_2$ members have before the expansion. If the $M_2$ accept the offer this would become the common position during the accession negotiations and if not the enlargement round fails for this particular candidate.

3. The third level describes the decision of the third player $A$. There are two possible outcomes – either accepts the offer for membership or does not.

Using $d_{M1}$, $d_{M2}$ or $d_A$ (the reservation point of the different players that result from the accession) as variables of governments’ concern can make the estimation of the bargain process relatively easier and correct. The discriminatory membership is an option that $M_1$ offers in stage one. This option is then considered in stage two by the members against only to be rejected or accepted in stage three. So the model looks at the already fulfilled rounds. In the study there are no observations that are non-membership outcome and thus cannot give a prediction for the conditions that are premises for a non-membership outcome. On the other hand, every enlargement round so far has triggered some form of distributional conflict and the main focus of the paper is studying the factors that predict the discriminatory membership. Since the restricted EU membership is accepted in stage three the model starts from there. Then it goes back to through stage two and one so that the connection between the cause-effect of the discriminatory EU membership is studied.

During the **third stage** the applicant makes the decision to either accept the offer or join the EU based on the gains that it will enjoy after the accession less the restrictions imposed by the incumbents and other alternatives like integration in other free markets. The accession will take place only if the aggregate welfare of the state will increase. The component of interest here is the restrictions that are imposed by the incumbents ($d_A$). We need to calculate the maximum restrictions that the applicant is ready to accept just before being indifferent to a membership status.

The equation describing the aggregate utility gain has the following components and is the similar components as (1) but there are the specifications like $(M+A)$ and $(M_1+A)$ which represent the fact that the applicant has already associated itself with the group of incumbents that favor the same policy $(M_1)$. The benefit that will come of the cooperation benefits and are proportional with the size of the EU : $b_i(M+A)$; the amount of gains the entrant will enjoy from its favorite policy area :$p_1(M_1+A)\lambda$. the exponent (–$\lambda$) means that the amount of the policy field will be divided by the size and corrected for the rivalry of the policy $\lambda$, also, $p_1$ is a coefficient telling how much the particular members associate themselves with one policy area compared to another; the equation continues with the amount it will get from its favorite policy $M_1$: $a_{i2}p_1(M_1)\lambda + a_{i1}p_2(M_1)\lambda$, where $a_{i2}$ corrects the state’s appraisement of the other available policy field; then the budgetary cost is subtracted: $R(M+A)^{-1}$; subtract the opportunity cost of other options: $\delta_i$; also the cost that comes as a result from the heterogeneity of policy preferences : $-(M+A)^\mu$ and $d_A$ – which is the restriction within the favorite policy filed. The whole equation is:

$$b_i(M+A)+ p_1(M_1+A)\lambda+ a_{i2}p_1(M_1)\lambda + a_{i1}p_2(M_1)\lambda- R(M+A)^{-1} \delta_i-(M+A)^\mu - d_A \leq 0 \quad (1)$$

So the maximum restriction within the policy field that the applicant would be willing to accept is:

$$\text{max}[d_A]= b_i(M+A)+ p_1(M_1+A)\lambda+ a_{i2}p_1(M_1)\lambda + a_{i1}p_2(M_1)\lambda- R(M+A)^{-1} \delta_i-(M+A)^\mu. \quad (2)$$
In the second stage, the members from M₁ decide whether to accept or decline M₂’s proposal for settling the distributinal conflicts or to refuse it and thus fail the enlargement around for the particular member.

The second equation represents M₂’s recalculation of its utility counting the new applicant in its favorite policy area. Again the agents are the same but mirrored from M₂’s point of view.

\[ b_i(M+A) + \alpha_{i2}p_1(M_1) - \lambda_{i2} - R(M+A)^{1-}(M+A)^{\mu} + d_{M2} - \alpha_{i1}p_2(M_2) - \lambda_{i1} - p_2(M_2) - \lambda_{i2} + R^M - b_iM \leq 0 \]

Here the \( d_{M2} \) stands for the re-distributed gains that it needs to add to its utility to make up for the loss of the funds it was previously eligible in the favorite policy area that now shares with the applicant. The more re-distributed gains the incumbent member gets, the better so we need to seek for the minimum number that it will be ready to accept to let the enlargement take place.

\[ \min[d_{M2}] = \lambda_{i2} - (M_2 + A)^{-\lambda_{i2}} - R[M^{-1} - (M+A)^{-1}] + (M+A)^{\mu} - b_iA. \] (3)

At the end of the model, I take a look at the first stage of the negotiations when the members form M₁ make the offer to M₂. Of all the available options they cannot offer full-right membership because it will be turned down by the M₂s. They can offer an inner-union re-distribution that would be on their cost. The third equation (3) represents the utility of the M₁s taking into account the new applicant. Here they do not compete for the same favorite policy area and thus the gains are more than the costs. On the other hand, it needs to deduct a cost agent \( (d_{M1}) \) that represents the amount of re-distributed gains it will offer to the M₂s.

\[ b_i(M+A) + p_1(M_1) - \lambda_{i1} + \alpha_{i2}p_2(M_2 + A) - \lambda_{i2} - R(M+A)^{1-}(M+A)^{\mu} - d_{M1} - \alpha_{i1}p_1(M_2 + A) - \lambda_{i1} - p_2(M_2) - \lambda_{i2} + R^M + b_iM + \alpha_{i2}p_1(M_2 + A)^{-\lambda_{i1}} \leq 0 \]

Thus the maximum amount of re-distribution costs that the members of M₁ are ready to offer is:

\[ \max[d_{M1}] = b_iA + a_{i2}p_2(M_2 + A)^{-\lambda_{i2}} + M^{\mu} + R(M^{-1} - (M+A)^{-1}) - (M+A)^{\mu}. \] (4)

The solution would offer an alternative to the enlargement fail (that is, the outcome would be a discriminatory membership). In other words, M₁’s second best choice (superior to non-membership) is to offer the applicant a limited access to the p₁ policy. The graph (from Schneider [2005]) shows the results on the theoretical model. The functions and their graphs exhibit the conditions under which the enlargement outcome is differentiated membership. They are graphed according to the variable ‘size of the union’ as to assess the impact on the size of the EU on the probability that a differentiated membership is granted. If \( F(\min[d_{M2}]) \) is >0 this means that a discriminatory membership is more probable than not. It is estimated that above size of twenty-three members in the EU, the subgroup M₂ (the group of members that the applicant have associated itself with) is going to demand the discriminatory membership. For \( F(\max[d_{A}] - \min[d_{M2}]) \) <0 we have that for number of members less than thirty-five, the candidate will be willing to accept a discrimination membership. The function \( F(\max[d_{M1}] - \min[d_{M2}]) \) shows the possibility for an inner-union distribution. Here, for values less than zero (at size of EU 6) the estimation shows that neither an inner-union re-distribution can compensate the negatively affected members nor the applicant can accept so much restriction.

\[ 0 \leq \min[d_{M2}] \text{ and } 0 \leq \max[d_{A}] - \min[d_{M2}]; \]
What those two conditions tell us is that the maximum amount of restrictions that an applicant would still accept has to be enough to satisfy the loss of incumbent members that would seek re-distribution. This is the first hypothesis that Schneider (2005) proposes:

4. The bigger the likelihood that there are distributional conflicts the higher the chance that redistribution will happen on the cost of the applicant – differentiated membership.

Additionally, the fact that a discriminatory membership has been offered to the applicant does not mean that the enlargement will take place. The ascending country should also comply with the side payments that are due to the membership status. So EU enlargement can also take place if the members-pro settle on an inner union redistribution at their expense. Therefore, the second hypothesis is that

5. The greater the outer opportunities the state may have the less chance of discriminatory membership to be requested.

6. The higher the chance the incumbents settle on an inner union distribution the smaller the chance for discriminatory union membership.

3 Empirical Tests and Results

This part of the paper tests these hypotheses and shows how the distributional conflicts and influence the outcome of imposing differentiated membership. The test is based on the research done by Schneider (2005) but builds by including the Balkan enlargement round of Bulgaria and Romania. The data is a cross-sectional analysis of the all six enlargements and thus increases the observations with 200 observations as the data captures the couple relationship between an incumbent and an applicant for each of the four policies. The model gives a prediction about the probability that a discriminated membership is granted.

The variable is coded 1 if the applicant accepts the differentiated membership. In other words, the Free Movement of Labor variable is 1 if the ascending state accepts the limitation of its workers to be able to sell their products on a particular foreign market. The Common Structural Policy and the Common Agricultural Policy take the value one if a country has to agree on limited access to the funds to be redistributed under those funds.

3.1 Empirical Tests and Results: Variables

Demand for Differentiation is a variable that tries to capture the conflicts that emerge from the size of the union. It is coded as 1 if there is discrimination in a certain policy field. Share of GDP per capita as EU average is a continuous variable and takes the value of the GDP per Capita of the applicant as EU average. The tendency is that poor counties would be more eager to join the EU than rich ones but the incumbent will be less likely to let them in. Budgetary Ceiling is a variable that takes values as the ceiling of its own resources as a portion of EU’s. It is logical to assume that the more important a candidate is for the EU the less the probability that a discriminatory membership is requested. This
variable is useful in to determine the trade-off between an inner union redistribution and discriminatory membership.

The following list of variables controls for the robustness of the coefficients. *Regime type* takes a value between 0 and 10 that stands for the democracy level in the country. The information is taken from the Polity IV data set. Marshall (2007). In sum, this variable shows how democratic are the governments of the ascending countries. *Change to Majority Vote* is a dummy that takes the value of 1 if the decision-making rules have been changed from unanimity to majority voting. *Change of Voting Power* takes the value of the change in voting presence of each member based on the number of representatives in the parliament as a part of the total representatives.

*Budgetary Contribution* follows the budget contribution that each new member would make. The idea is that the bigger the contribution it makes the more ready the incumbents will be ready to accept the applicant unconditionally. *Rivalry* is the dummy that discounts by the rival and non-rival policies. It takes value of 1 if the policy area is a zero-sum in its consumption. *Dependency of Preferences* takes the value of 1 if the particular member did not requested differentiated membership right is a certain policy area but other incumbent did.

### 3.2 Empirical Tests and Results: Model Estimations

In general, the results are consistent with the theoretical hypothesis and support the findings of Schneider (2005). Also the Wald test is highly significant so it is easy to reject the null that the variables are jointly equal to zero.

**Table 1: Results**

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of Expected EU Members</strong></td>
<td>0.084* (0.028)</td>
<td>0.122 (0.033)</td>
<td>0.089 (0.028)</td>
</tr>
<tr>
<td><strong>GPD per Capita as EU average</strong></td>
<td>-0.021* (0.002)</td>
<td>-0.021* (0.001)</td>
<td>-0.023* (0.001)</td>
</tr>
<tr>
<td><strong>Amount of Exports/ GDP applicant</strong></td>
<td>0.005 (0.002)</td>
<td>0.008* (0.001)</td>
<td>0.005 (0.001)</td>
</tr>
<tr>
<td><strong>Trade Union</strong></td>
<td>-9.036* (1.929)</td>
<td>-11.89* (1.469)</td>
<td>-9.71 (1.926)</td>
</tr>
<tr>
<td><strong>Demand for Differentiation</strong></td>
<td>1.146 (0.143)</td>
<td>1.929* (0.262)</td>
<td>1.029* (0.159)</td>
</tr>
<tr>
<td><strong>Ceiling on EU Budget</strong></td>
<td>-1.79 (0.603)</td>
<td>-2.07 (0.505)</td>
<td>-1.917 (0.624)</td>
</tr>
<tr>
<td><strong>Change to Majority Voting</strong></td>
<td>0.376/ (0.303)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Rivalry</strong></td>
<td>0.282/ (0.171)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Dependency of Preferences</strong></td>
<td>1.323/ (0.189)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>EU Budget Contributions</strong></td>
<td>-0.042/ (0.011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Regime Type (Democracy level)</strong></td>
<td>-1.82/ (0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Change of Voting Power in EU council</strong></td>
<td>-1.015/ (0.173)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Agriculture</strong></td>
<td>0.661 (0.133)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Free Movement of workers</strong></td>
<td>0.658 (0.068)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Structural Funds</strong></td>
<td>0.189 (0.146)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>-0.595 (0.218)</td>
<td>2.791 (0.702)</td>
<td>3.063 (0.836)</td>
</tr>
<tr>
<td><strong>Number of Observations</strong></td>
<td>1072</td>
<td>1072</td>
<td>1072</td>
</tr>
<tr>
<td><strong>Wald χ²</strong></td>
<td>287.90</td>
<td>862.85</td>
<td>582.54</td>
</tr>
<tr>
<td><strong>Pseudo R²</strong></td>
<td>0.2919</td>
<td>0.516</td>
<td>0.3192</td>
</tr>
</tbody>
</table>

*significant at *P*>0.001
A larger number of members increases the likelihood that discriminatory EU membership will take place. This means that with the growing number of members the tendency is to settle the distributional gains on behalf of the new applicants and less on inner-union distribution. This supports the first hypothesis that indeed the discriminatory EU membership is a powerful tool in the hands of the incumbent to solve the conflicts between the incumbents and the applicants and thus ensure the future growth of the Union.

The variable *Regime Type* (Democracy level) is highly significant and shows that the bigger the democracy level the bigger the probability for phase-in membership. This is contra intuitive. While the sign is negative and one would expect that the bigger the democracy level the smaller the chance for a discriminatory membership. This is probably due to the fact that no matter how the government looks the EU demands results in the pre-membership period.

The Amount of Exports/GDP variable shows what portion of the applicant product is formed by trading volume with the Union. Like Trade Union variable, it tries to show in which direction it is going to be more profitable for the applicant to form a free market union. The bigger the trade between the Union and the applicant, the more willing it will be to accept a discriminatory membership and enjoy the free market environment. On the other hand, if the state is relatively rich and less dependent on trade with the EU than the probability that this state accepts a discriminatory membership decreases. The same reasoning is valid for the Trade Union--the bigger the volume of trade between the applicants, the bigger their bargain power and likelihood of forming a free market area in-between.

The variable *Rivalry* shows that there is much more tension going on when we talk about the rival CAP and CSP, instead of the non-rival policies. This is not surprising as there is the biggest share of funds. However, those coefficients are marginally significant.

### 4 Empirical Tests and Results: Probability Distribution of the Discriminatory Membership Outcome

The aim of this paper is to give a distribution, or probability, that a country is discriminated against in its membership status based on some main variables that trigger distributional conflicts. Those independent variables are the size of the EU, the applicant’s GDP per capita as EU average and the Demand for discrimination ceteris paribus. Table 2 gives the results. On the vertical axis there are the variables of interest at their most important values. A single value of this variable is then tested with all the other variables at their different rates.

For example, let me illustrate the information that the first line gives. The Expected number of EU member is nine. The whole line shows what the probability is that a discriminatory EU membership is granted if there were nine members in the union. This is estimated at different rates of the other variables ranging from minimum to maximum. Thus the probability of the discriminatory membership can be measured for the extreme cases of min and max and the some of the values between them. In the Min column, all other variables are at their lowest values. Like the *GDP per Capita* as in this part where *Expected number of EU members* is at focus the *GDP per Capita* is put with all the other variables. So the Min column says what the probability is that an applicant receives a discriminatory EU membership if the incumbents are nine and the applicant is with the lowest GDP per Capita compared to the incumbents.

What is particularly interesting in the results is that the values tend to be higher in the Worst Sample values (min) than in the Median, which is contra-intuitive. This means that if a variable is either too high or too low relatively it will trigger a discriminatory membership. I attribute that to the great distance between the GDP per Capita of the Bulgaria and Romania and the average of the EU. The significance of the GDP per capita EU average has increased compared to the contribution to the budget for example with would decrease the percentage probability in the 75th percentile of the all other variables. Moreover, the Regime Type has also lost its significance as to moderate the max values. Ideally, if the regime type were at its max values this would mean that the governments are reliable partners for the EU and would not face restrictions. However, both Bulgaria and Romania have relatively
high scores of nine out of ten and received the restrictions. This is one of the reasons why we see certain discrimination when all the variables are at their max values.

Table 2: Probability Distribution of a Discriminatory EU Membership.

<table>
<thead>
<tr>
<th>Variable of Interest</th>
<th>All other Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected Number of EU members</td>
<td>Min</td>
</tr>
<tr>
<td>9</td>
<td>4.55</td>
</tr>
<tr>
<td>10</td>
<td>5.85</td>
</tr>
<tr>
<td>12</td>
<td>9.29</td>
</tr>
<tr>
<td>15</td>
<td>16.96</td>
</tr>
<tr>
<td>25</td>
<td>60.6</td>
</tr>
<tr>
<td>27</td>
<td>69.63</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Share of GDP per capital to EU average</th>
<th>All other Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max</td>
<td>4.55</td>
</tr>
<tr>
<td>25th Percentile -72.8%</td>
<td>31.19</td>
</tr>
<tr>
<td>Mean</td>
<td>49.59</td>
</tr>
<tr>
<td>75th Percentile -35.6 %</td>
<td>61.56</td>
</tr>
<tr>
<td>Min</td>
<td>65.13</td>
</tr>
</tbody>
</table>

An entirely new piece of information that this paper gives is the line that gives an Expected Number of EU members 27. It supports the tendency that the bigger the union the more likely it is that an applicant will join it by accepting a discriminatory membership. It also supports the newly established tendency that if a variable is in its extreme the chance that the state will not be accepted without some restrictions.

One of the main differences of the results of this paper and the results of Schneider (2005) is that the accession negotiations become more and more rational. Before the Balkan Enlargement round there has been a significant mismatch between the discriminatory membership and its ability to fully explain the settlement of the distributional conflicts. At that time even at the worst sample values are at their minimum the discrimination was unlikely to occur. After the Balkan enlargement the case is more rational: the chance for discrimination is significantly higher in their minimum values.

5 Conclusion

This paper showed the discriminatory membership as a tool to redistribute the distributional conflicts that emerge as a consequence of the European Union enlargement rounds. Thus, this phased-in membership can be seen as an opportunity of failure for the enlargement. The conclusion was drawn from the analysis of the main costs and benefit of an enlargement round. Among all the possibilities as full membership, inner union redistribution, discriminatory membership and non-membership the discriminatory EU membership has always been the most likely strategy. Only if the applicant refuses the discriminated membership than there might be some inner union redistribution of gains but not always the case. This strategy needs to be seen as a main mean to ensure the future growth of the EU.

6 References


WHAT MAKES A NOBEL PRIZE? THE DETERMINANTS OF OUTSTANDING SCIENTIFIC RESEARCH

Leung Weiwen
Singapore Management University

ABSTRACT

This paper examines cross-country differences in outstanding research output, measured in terms of Nobel Prize winning research and number of Highly Cited Researchers. There is considerable evidence that both corruption and democracy have an impact on outstanding research output; the regression results are robust to the addition of many variables and removal of outliers, among others. However, the evidence that openness to ideas (as measured by Inglehart and Welzel (2010)) matters for outstanding research output is weak. In particular, the correlation between openness to ideas and outstanding research output disappears after controlling for corruption and democracy.

For the whole paper, please see the link below:

HOT AND COLD FLUSHES IN BUSINESS CYCLES—WHAT DO NETWORKS HAVE TO DO WITH IT?∗

Fabian Trottner

London School of Economics

Abstract

This paper investigates the hypothesis that microeconomic shocks and their amplification through the intersectoral trade network are the main driver of macroeconomic fluctuations. Intersectoral supply linkages may induce productivity spillovers that cause microeconomic shocks to amplify and survive at the aggregate level. A model is proposed to formalize this notion and to motivate the empirical application to the data. Network volatility is derived as the volatility that would arise in an economy where aggregate fluctuations are solely due to network transmitted, microeconomic productivity shocks. The empirical implementation of the model suggests that network volatility accounts for patterns in macroeconomic volatility across major world economies. Finally, I exploit the mechanical workings of network volatility to conclude that decreases of output volatility are often driven by falling levels of network centrality in Manufacturing and Agriculture, whilst high levels of volatility can be linked to the increased network importance of Financial Intermediation and Business Services.

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1 Introduction

Sectors use other sectors’ output as intermediate inputs of production. The resulting connections may facilitate productivity spillovers, causing the propagation of microeconomic, sector-specific shocks to the aggregate level. It is proposed that the aggregate phenomenon output volatility can be understood as a

∗Please note that the present paper is a shortened version of the original work. For the full length paper, please contact fabian.trottner@gmail.com.
synchronized response to microeconomic shocks, where the intersectoral trade network facilitates the amplification of microeconomic shocks, allowing for their survival in the aggregate.

When attempting to explain the origins of aggregate output volatility, the debate in macroeconomics has for a long time been centered around aggregate shocks that change the framework conditions under which agents operate in the economy. However, this paper aims to investigate the role of idiosyncratic sector-level shocks in explaining output volatility. Conceptually, it is assumed that intersectoral supply and use linkages between sectors allow

A growing literature has therefore asked, whether microeconomic shocks can be the main driver of macroeconomic fluctuations. Microeconomic shocks are to be understood as sector or even firm specific productivity shocks that are idiosyncratic in nature. Examples may include the impact of the introduction of online commercial platforms such as Amazon or eBay on retail trade or the invention of the MRI on the health sector. In principle, productivity shocks can originate from many sources, for example from advances in R&D, innovative management decisions or changes in capacity utilization and particularly strikes on the firm (e.g. UPS in 1997) or sector (e.g. the Textile Workers Strike of 1934) level. This paper assumes these shocks to be exogenous in nature and does not require them to arise from any particular source.

The impact of microeconomic shocks on aggregate variables is subject to debate and faces the challenge of the standard diversification argument. As the economy gets more disaggregated into a larger number of sectors, idiosyncratic shocks should tend to average out in the aggregate, since, by the law of large numbers, negative shocks in some sector offset positive shocks in other sectors. The theorems in Dupor (1999) are manifests of this critique.

In order to provide conditions under which such arguments fail, I find it useful to interpret the economy as a complex system. Complex systems possess the property of emergence, that is the arising of aggregate structures, properties and patterns out of the micro-level, simple interaction of a multiplicity of agents Goldstein (1999). The emergent structures are generally not stable and governed by waves of positive and negative feedback.

Seeing that the economy can be modeled as a complex system (see for example Arthur et al. (1997)), I propose that the aggregate phenomenon output (growth) volatility can be understood as a synchronized response to microeconomic shocks, where the intersectoral trade network facilitates the amplification of microeconomic shocks, allowing for their survival in the aggregate.

To further conceptualize this, this paper proposes the distinction between a sector’s idiosyncratic productivity on the one hand and its network productivity on the other hand. The former corresponds to the productivity that we observe in the data and is related to the idiosyncratic, isolated production technology of an individual sector. The latter is to be interpreted as an emergent phenomenon of the interaction of many sectors in a network, where supply linkages facilitate spillovers between sectors. Importantly, when modeling a sector’s optimization problem in a competitive equilibrium set-up, we argue that a sector’s productivity corresponds to its network productivity.

Building on this idea, this paper proposes a model that isolates the impact of network induced productivity spillovers on aggregate volatility. The main result is given by the following expression for aggregate volatility in the model economy, which I will refer to as network volatility. It is the volatility that would be
derived only from network transmitted, microeconomic shocks.

\[ \sigma_{\text{network}} = \sqrt{\sum_{i=1}^{n} \zeta_i^2 \sigma_i^2} \]  

(1)

Here \( \zeta_i \) denotes sector \( i \)'s centrality in the network, which is shown to be equal to the average degree to which sector \( i \)'s idiosyncratic productivity affects other sectors' network productivity. \( \sigma_i \) denotes a sector's idiosyncratic productivity volatility. By imposing network induced productivity spillovers between sectors, the model hence allows for a decomposition of aggregate volatility into its microeconomic network origins.

Using data from the EU-Klems database and World Input Output Database, network volatility is computed for a total of eleven countries from the 1970s until 2007. Examining countries individually and using panel data methods, it is concluded that network volatility possesses statistical relevance, confirming its economic relevance. We therefore find that changes in the network structure of an economy may provide a good explanation for the evolution of aggregate output volatility.

This paper thereby adds value to the literature by providing a straightforward theoretical framework that links idiosyncratic productivity shocks, network structures and output volatility in a manner that allows for the empirical implementation of the results. It thereby bridges a gap between two parallel lines of research.

The vast majority of advances in this field is of a theoretical nature. Long and Plosser (1987) provide a framework for the study of general equilibrium properties in a multi-sector economy where sectors are interlinked through intermediate input demand structures. Their insights suggest that those supply linkages affect the ease by which sectors can compensate a given local productivity shock. Horvath (1998) challenges the Dupor (1999) diversification argument by arguing that as sectors increasingly differ in their importance as suppliers of intermediate inputs, the effects of a microeconomic shock are less likely to average out in the aggregate.

Carvalho (2010) uses as similar argument to show that the presence of hub-like sectors can counter the law-of-large-numbers argument and therefore enables microeconomic shocks to have an aggregate effect. Acemoglu et al. (2012) and Acemoglu et al. (2010) further develop this view, demonstrating how such asymmetries can cause cascade effects. Other important contributions are Jones (2011), Durlauf (1993) and Jovanovic (1987), who impose strong intersectoral complementarities to study the effects of microeconomic structures on economic growth and output volatility respectively. Their theoretical findings provide conditions under which aggregate phenomena can be driven by changes in the microeconomic composition of the economy. Building on Jovanovic (1987), Burlon (2012) and Ballester et al. (2006) relate aggregate volatility to the connectedness of an economy, showing that increased levels of output volatility can mathematically be linked to increased connectivity of the economy.

Yet, most of these contributions, do not attempt to empirically test their theoretical results. However, recent work by Gabaix (2011) and Carvalho and Gabaix (2013) empirically links output volatility to microeconomic structures, yet does ot conceptualize the role of networks in their approach.

This paper aims to bridge this prevalent gap between theoretical insights and empirical applications. I present a theoretical framework that conceptually incorporates networks and their effect on aggregate volatility, yet the approach maintains a simplicity that allows for direct empirical implementation of the
results. The scope of the empirical study thereby represents the most comprehensive use of the available data in the literature so far.

The structure of this shortened paper is as follows. Section 2 presents the theoretical framework, section 3 presents the baseline empirical results and section 4 concludes.

2 A Model Linking Idiosyncratic Shocks, Network Structures and Output Volatility

2.1 The model

Network productivity

I present an alternated version of a standard multi-sector general equilibrium model in Acemoglu et al. (2012). An economy is defined as a triple \((N, w, \Phi)\), where \(N\) is a set containing a total of \(n\) sectors in the economy, \(w\) is a \(n \times n\) dimensional matrix \((w_{ij})_{i,j \in N}\), capturing the intersectoral input-output relationships and \(\Phi\) is a distributional vector.

Following the key argument outlined earlier, intersectoral supply and use linkages may allow for the formation of linkages between closely connected sectors, imposing complementarities in the form of spillovers between sectors. The key innovation of the model is hence the introduction of network productivity \(TFP_i\) to conceptualize the idea of network induced productivity spillovers. Network productivity for a given sector \(i\) is modeled as a function of both the network and other sectors’ idiosyncratic productivity levels. That is for all sectors \(i\) in \(N\), we impose network productivity \(TFP_i\) takes the following structural form:

\[
TFP_i = f_i(z, w) = \prod_{j \in N} z_{ij}^{\beta_{ij}}
\]  

(2)

, where \(z = (z_i)_{i \in N}\) is the \(n\)-dimensional vector of idiosyncratic sectoral productivity levels, where we assume that for all sectors \(i\), \(z_i > 0\). The parameters \(\beta_{ij}\) capture the potential complementarity between sectors \(j\) and \(i\). That is, \(\beta_{ij}\) measures to which degree sector \(i\)’s network productivity depends on idiosyncratic shocks to sector \(j\). In particular, we will think of these coefficients to be determined by a function \(w\) of the intersectoral trade network, \(w : N \times N \times w \rightarrow \mathbb{R}_0^{+1}\).

The environment

Each sector competitively supplies a unique good to the market in a closed economy. In their production, the sectors use both labour and other sectors’ final goods as intermediate inputs. It is assumed that for all \(i\) in \(N\), sectoral output \(x_i\) is given by a standard Cobb-Douglas function. Following the previous discussion, each sector’s productivity corresponds to its network productivity, given that we are examining each sector

\[\text{Note that this preserves the standard case in the literature as a special case, namely } \beta_{ij} = 0 \text{ for } i \neq j.\]
as part of the larger network. That is:
\[ x_i = l_i^{\alpha} T P_i^\alpha \prod_{j \in N} x_{ji}^{\gamma_{ji}(1-\alpha)} \]

, where \( l_i \) denotes the amount of labour and \( x_{ji} \) denotes the amount of sector \( j \)'s output that is used as a factor of production. An underlying assumption of the model is that the input output network allows us to identify the parameters of the production function. We further assume CRTS by imposing that \( \gamma_{ji} = w_{ji} \), that is for all \( i \) in \( N \), \( \sum_{j \in N} \gamma_{ji} = 1 \).

We can substitute (2) into the production function to obtain the following structural form for sector \( i \)'s output.
\[ x_i = l_i^{\alpha} \prod_{j \in N} x_{ji}^{\gamma_{ji}(1-\alpha)} \]

(3)

Let it further be assumed that for all \( i \) in \( N \), \( \varepsilon_i := \log(z_i) \sim \mathcal{F}_i \). That is \( \mathcal{F}_i \) denotes the sector-specific cumulative distribution of idiosyncratic productivity shocks to sector \( i \). capturing the stochastic component of the model.

Given a set of prices \( p = (p_i)_{i \in N} \) and the unit wage \( h \) of the economy, sectors maximize profits \( \pi_i = p_i x_i - h l_i - \sum_{j \in N} p_j x_{ji} \).

For the demand side of the economy, assume that the economy is populated by a unit mass of identical consumers with Cobb-Douglas preferences over the \( n \) goods:
\[ u(c_1, c_2, \ldots, c_n) = \prod_{i=1}^{n} c_i^{1/n} \]

(4)

, where \( c_i \) denotes the consumption of the representative good provided by sector \( i \). Labour is not included as an optimization parameter for the consumer, implying a wage-inelastic labour supply. This allows for the normalization of \( l_i \), that is \( \sum_{i \in N} l_i = l = 1 \). The household consequently supplies a unit of labour, inelastically following the demand in the different sectors of the economy. Furthermore, it is assumed that there is no initial endowments of goods and that the consumer’s only source of income is labour. The budget constraint is hence given by \( \sum_{i \in N} p_i c_i \leq h l \).

**Competitive Equilibrium**

Under the assumption of perfect competition, \( h \) is equal to the aggregate nominal value added, that is nominal GDP in the economy. The following proposition decomposes the equilibrium output in the model economy into a function of intersectoral complementarities as well as the sectors’ idiosyncratic productivity shocks.

**Proposition 1.** The logarithm real value added in the economy is equal to
\[ y \equiv \log(h_{\text{real}}) = \log(Y) = v' \varepsilon + \Omega \]

(5)

, where \( \Omega \) is a constant independent of the random vector of shocks, \( \varepsilon \) is a \( n \times 1 \)-dimensional vector with
entries \((\varepsilon_i)_{i \in N}\) and \(v\) is a \(n \times 1\)-dimensional vector of the form \(v = \left(\frac{\sum_{i \in N} \beta_{ij}}{n}\right)_{i \in N}\).

\(\sum_{i} \beta_{ij} / n\) captures the average impact of shocks to sector \(i\)'s idiosyncratic productivity on other sectors’ network productivity, that is the average size of the spillover effects originating from sector \(i\). It is intuitive to define a sector’s centrality in the network according to that measure.

**Definition 1.** Given an economy \((N, w, \mathcal{F})\) and the matrix of parameters of potential complementarity \((\beta_{ij})_{i,j \in N}\), sector \(i\)'s centrality \(\zeta_i\) is equal to

\[
\zeta_i = \frac{\sum_{j \in N} \beta_{ij}}{n}.
\]

We can consequently rewrite (5) as

\[
y = \sum_{i \in N} \zeta_i \varepsilon_i + \Omega \tag{6}
\]

The model allows us to introduce a measure of centrality in input-output networks that is motivated by the notion of network induced productivity spillovers and their causal connection to the intersectoral trade network of the economy. The next part will show, how we can use (5) to obtain an intuitive expression for aggregate volatility.

### 2.2 Aggregate volatility and the network structure

With regards to the distributional properties of the vector of idiosyncratic shocks I assume that \(\mathbb{E}[\varepsilon] = 0\), \(\forall (\varepsilon_i) = \sigma_i^2, \forall i \in N\) and \(\text{Cov}[\varepsilon_i \varepsilon_j] = 0, \forall i \neq j\). The first assumption is a normalization, the second assumption allows for differing levels of productivity volatility across sectors and the third assumption reflects the desires property that shocks should be idiosyncratic in nature.

Given these assumptions and (5), it is easy to derive output volatility in our model economy, which we will refer to as the standard deviation of logged real value added. We call this network volatility, as it is volatility that arises solely out of the network induced amplification of microeconomic shocks.

**Proposition 2.** The standard deviation of logged real value added, referred to as output volatility, is given by:

\[
\sigma_{\text{network}} = \sqrt{\text{Var}(y)} = \sqrt{\sum_{i} \zeta_i^2 \sigma_i^2} \tag{7}
\]

The theoretical framework hence allows for the decomposition of aggregate volatility into a weighted average of sectoral idiosyncratic volatility levels, where the weights are given by a sector’s centrality in the network. Volatile sectors that have strong links to the rest of the economy should consequently matter most when looking at aggregate volatility.

### 2.3 Quantifying potential complementarity

In order to be able to test the model empirically, we propose a tentative structural form for the coefficients of potential complementarity \(\beta_{ij}\).

Accounting for all possible higher order levels of connection, this paper makes use of the concept of Strongest Intersectoral Connection (SSC), as introduced by Xu et al. (2011), as a measure of connectivity in
input-output tables. We hence define for all \( i, j \) in \( N \) the strongest intersectoral connection \( SSC_{ij} \) to take the following form:

\[
SSC_{ij} = \begin{cases} 
\max_{p_{ij} \in P_{ij}} a_{ik}a_{k,k_1}\ldots a_{k_{k-1}j} & i \neq j \\
 a_{ij} & i = j 
\end{cases}
\]  

(8)

where \( a_{ij} \) is defined as outlined above as \( a_{ij} := \frac{w_{ij}}{V_j} \). That is we iterate over all possible simple paths \( p_{ij} \) of all lengths from sector \( i \) to \( j \), in order to find the strongest connection between the two sectors, which in turn is defined as the maximum amount of output of good \( i \) that sector \( j \) needs, indirectly or directly, in order to produce one unit of output. We view this measure as a lower bound for the strength of the connection between two sectors\(^2\).

As the concept of strongest intersectoral connection neglects the heterogeneity of links in the network, it is proposed to use Domar weights to account for the differing values of a connection between two sectors. We hence propose the following definition.

**Definition 2.** Given an input-output matrix for an economy \((N, w, F)\) the coefficients of network induced intersectoral interdependence are defined for all \( i, j \in N \) as \( \beta_{ij} = SSC_{ij} \ast V_j Y \), where \( Y \) denotes nominal value added.

We decompose potential complementarity into the network induced productivity interdependence between two sectors and the relative size of a sector in the whole network. The first component allows the ranking of other sectors by their network importance as input suppliers to a given sector \( j \). Crucially, the introduction of the Domar weights doesn’t change that weighting for any given sector \( j \) and is in that sense neutral. But looking at a sector’s centrality \( \zeta_i \) and ultimately at aggregate volatility, the weights allow us to evaluate whether a sector is important as an input supplier to the relevant sectors in the economy.

### 3 An Empirical Implementation of the Model

#### 3.1 Constructing the empirical measures

In order to assess the empirical validity of the theoretical model, we construct network volatility and observed output volatility empirically and test for equality between the two measures.

To estimate observed output volatility for a given country \( c \) at time \( t \), we follow common best practice in the literature and obtain a rolling-window measure\(^3\). We obtain quarterly real GDP data from the OECD for the period Q4:1960 to Q3:2012. The Hodrick-Prescott filter is applied to the logged time-series of quarterly real GDP, using \( \lambda = 1600 \) as a smoothing parameter, and the residuals are collected. Aggregate output

\(^2\) Alternatively, using the matrix \( A = (a_{ij})_{i,j \in N} \) and realizing that the \( ij \)-th entry \((a_{ij})^k\) of \( A^k \) sums all indirect contributions of sector \( i \) to sector \( j \)'s production via walks of length \( k \), we can define the strength of the network connection \( S_{ij} \) between sectors \( i \) and \( j \) as \( S_{ij} = \sum_{k=1}^{n} (a_{ij})^k \). Whilst \( SSC_{ij} \) only picks out the strongest out of all simple paths between \( i \) and \( j \), this measure will account for all walks that exist between two sectors of maximum length \( n \) and will therefore provide an upper bound for the connectivity of sectors. Importantly, \( S_{ij} \) allows for loops and repeated nodes within a walk and thereby implies dynamic structures of the amplification mechanism that our simple framework cannot account for. We therefore consider \( S_{ij} \) as a robustness check in the full version of this paper.

\(^3\) An alternative measure will be included as a robustness check.
volatility for a given quarter is then defined as the nearly-centered 10-year rolling window of the standard deviation of the residuals (that is we consider the standard deviation of the residuals of the 21 quarters to the left and 19 quarters to the right of a given quarter\(^4\)). Observed aggregate volatility in a given year \(t\) is then computed as the mean over the quarterly volatility levels in that year.

For the baseline analysis, network volatility, as defined in (7) is computed by holding sectoral idiosyncratic productivity volatility levels invariant, whilst varying the centrality of each sector in each year. Sectoral productivity volatility is computed by considering sectoral productivity growth rates from the gross output perspective\(^5\) and obtaining the standard deviation of the entire time series for each sector \(i\) in each country \(c\), denoted \(\bar{\sigma}_{ci}\). This seems appropriate for two reasons. Firstly, holding sectoral volatility constant allows to isolate the effect of the changes in the network structure on the evolution of network volatility and avoids possibly circular arguments. Secondly, as we fit ARCH(1) models to estimate sectoral volatilities as part of the robustness checks, these do in fact not seem to vary significantly over time for most sectors.

To overcome the limitations in the data, it is further assumed that the matrix of strongest intersectoral connections \((SSC_{ij})_{i,j \in N}\) is a technological characteristic of a country that does not vary over time. We compute \((SSC_{ij})_{i,j \in N}\) for all countries using the 1995 input-output table and varying the Domar weights over time.

We hence compute, for each country \(c\) at time \(t\), network volatility by considering the expression

\[
\sigma_{\text{network},ct} = \sqrt{\sum_{i=1}^{n} \left( \frac{\sum_{j \in N} SSC_{ij,1995} \cdot v_{jt}}{\pi_{it}} \right)^2} \cdot \bar{\sigma}_{ci}^2.
\]

Following this approach, we compute observed and network volatility for the following countries: Austria, Canada, Denmark, Finland, France, Germany, Japan, Netherlands, Spain, the UK and the US. We proceed by firstly establishing the statistical relevance of network volatility in the determination of output volatility. Building on that, we develop narratives as to how changes in the underlying network structure of the economy can explain some of these patterns in output volatility.

### 3.2 Network volatility and output volatility

Before proceeding to regression analysis, Figure 1 presents plots of network volatility, \(\sigma_{\text{network}}\), and observed output volatility, \(\sigma_{\text{observed}}\), for all countries considered in the empirical study. Eyeballing the graphs, we find that that network volatility seems to track major patterns in observed output volatility very closely in many countries. Pictorial analysis suggests that within most countries, higher levels of output volatility seem to coincide with higher levels of network volatility.

To test this, we impose equality between both measures, arguing that higher levels of network volatility should correspond to higher levels of output volatility. We test the hypothesis by following an approach similar to the one considered in Carvalho and Gabaix (2013) by running cross-country panel regressions, aiming to minimize possible spurious-regression-type problems may occur in country-specific least squares regressions.

\(^4\) This allows us to continuously compute quarterly output volatility for each quarter until Q4:2007, despite the missing Q4:2012 observation in the time-series of logged output.

\(^5\) Following the discussion in Basu and Fernald (1997), we use sectoral productivity growth data that is computed from the gross output rather than the value added perspective.
We hence consider a specification of the following form:

\[ \sigma_{\text{observed},t} = \alpha_c + \alpha_t + \beta \sigma_{\text{network},t} + \epsilon_{ct} \]  

(9)

where \( \alpha_c \) denotes a country fixed effect, \( \alpha_t \) denotes a time fixed effect and \( \epsilon_{ct} \) is an idiosyncratic error term. We run the regression both with and without time fixed effects. The specification without year fixed effects can be interpreted as the cross-sectional analog to single country regressions and should confirm the pictorial analysis. The specification with time fixed effects allows us to control for factors affecting output volatility equally in all countries at a given point in time. Crucially this implies that this specification identifies \( \beta \) through differences in timing of changes in network volatility and therefore through changes in network volatility that are not common across countries over time. It therefore allows us to minimize misguided inference from spurious-regression-type problems in regressions on a country-specific level\(^6\).

We construct heteroskedasticity and autocorrelation-robust standard errors using the Newey-West estimator with 2 lags.

The results are reported in Table 1.

<table>
<thead>
<tr>
<th>Year Fixed Effects</th>
<th>NO</th>
<th>YES</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>413</td>
<td>413</td>
</tr>
</tbody>
</table>

Table 1: Output Volatility and Network Volatility: Cross-country evidence

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{\beta} )</td>
<td>179.502***</td>
<td>98.768**</td>
</tr>
<tr>
<td>(6.17;29.08)</td>
<td>(2.29;43.16)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: We run the regression \( \sigma_{\text{observed},t} = \alpha_c + \alpha_t + \beta \sigma_{\text{network},t} + \epsilon_{ct} \), where \( \sigma_{\text{observed},t} \) is our baseline measure of rolling-window measure of output volatility, \( \sigma_{\text{network},t} \) is our baseline empirical implementation of network volatility, \( \alpha_c \) is a country fixed effect, \( \alpha_t \) is a time fixed effect. t-statistics and Newey-West Standard Errors (2 lags) in parentheses. *** \( p < 0.01 \), ** \( p < 0.05 \), * \( p < 0.1 \)

Whilst the seemingly good fit between network volatility and output volatility that we observed for many of our individual countries could potentially be spurious due to common time trends, our cross-country analysis provides evidence to the contrary. The regression confirms the link between observed output volatility and our theoretical notion of aggregate volatility. The estimator is positive and significant at the 1% level of significance and its significance survives at the 2.5% level if year fixed effects are included in the regression.

Arguably, the specifications for both individual countries as well as for the panel regression should not suffer from identification problems originating from reversed causality, as the model proposes an equal rather than a causal relationship between the dependent and the independent variable.

I also experimented with including a common linear time trend rather than time fixed effects. For this specification \( \hat{\beta} \) was equal to 136.197 and highly significant with an associated t-statistic of 3.38\(^7\).

---

\(^6\) For similar specifications, see for example Carvalho and Gabaix (forthcoming), Jaimovich and Siu (2009) (studying the relation between output volatility and changing demographic structures) and Blanchard and Simon (2001) (studying the relation between output volatility and inflation volatility).

\(^7\) Additional robustness checks, including alternative measures of both output and network volatility, as well as panel regressions controlling for additional factors and testing for the role of network cohesion were undertaken, but are not included in this excerpt. Narratives with regards to the underlying network drivers of changes in output volatility are also available in the full length paper.
Figure 1: The co-evolution of observed volatility (solid, red line) and network volatility (dotted, blue line) plotted for a sub-sample of countries.
4 Conclusion

The discussion in this paper provides a contribution to the existing research on the microeconomic origins of output growth volatility. The proposed theoretical framework is simple and based on an intuitive understanding of the economy as a complex system, where network linkages are interpreted as a propagation mechanism for the survival of local microeconomic shocks in the aggregate.

This result is meaningful in that it is not straightforward that microeconomic structures should have remarkable explanatory power, given the large set of potential other factors that might affect the macro economy (such as monetary and fiscal policy, globalization, political institutions, wars). Here it is important to note that the purpose of this research is not to argue that these rather aggregate shocks are irrelevant, but to help reduce the prevalent conceptual dependence on them.

With regards to the link between output volatility and welfare, our findings provide interesting insights into the consequences that industrial organization and structures can potentially have. Our insights confirm that policy-makers should prefer diversified structures, where no sector is of disproportional importance as a supplier of intermediate inputs. Also, our narratives regarding the structural drivers provide scope for direct policy-intervention through for example taxes and subsidies, accounting for the disproportional externality that sectors with high network centrality pose on other sectors.

Despite the limitations of this approach, it is found that network structures provide a useful and stimulating framework to think about the origins of macroeconomic fluctuations and are capable of providing interesting empirical narratives with regards to the structural drivers of the observed patterns in output volatility.

References


THE EFFECT OF EU ENLARGEMENT ON INTERNATIONAL STUDENT MOBILITY

Ilyas Zhuknov
The University of Warwick

ABSTRACT

This research project is the first empirical evidence of the importance of the removal of national border and associated mobility barriers in promoting international student mobility (ISM) using European Union (EU) enlargement of 2004 and 2007. A panel data set of bilateral internationally mobile student flows for twenty-six EU member states (except Luxembourg) from 1999 to 2009 is used to test this hypothesis on the basis of gravity model framework. The effect is positive and significant. Symmetry of the effect might indicate that this research has managed to discover genuine effect of opening the border, thus feasibly making it applicable to migration literature in general. Among the main determinants are destination’s international exposure and freedom; origin’s student population, income per person, financial support and control of corruption. Based on these findings, some general recommendations are put forward to enhance these flows.

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Last but not least, I am thankful to the Carroll Round organizing committee for the opportunity to present this research project at the 12th Carroll Round Conference in Georgetown University, Washington, DC.

1 Introduction

The European Union (EU) experienced the largest single enlargement in terms of population and number of countries in 2004, followed by further accession of Romania and Bulgaria in 2007. Undoubtedly, such enlargement had huge implications on every aspect of the EU. Despite the important role of higher education in such integrated governance system (de Prado Yepes, 2007), the enlargement effect on European higher education, particularly on international student mobility (ISM), is barely discussed and not empirically studied. Therefore, this research project aims to examine how EU enlargement has affected the size of ISM. Effectively, as generalization, it implies how removal of national border and associated barriers to study abroad affects ISM.

1.1. Relevance

There has always been a heightened political importance attached to ISM, which plays an important socioeconomic role. Therefore, higher education modernization with special emphasis on ISM has become one of the main priorities of EU policy over the last decades as a contributing factor on growth, employment, innovation and welfare through development of highly skilled labor force in European single market, according to human capital theory (ENEE [2007]). For instance, a number of papers (Bracht et al. [2006]; Teicher [2007]; Parey & Waldinger [2007]) show that ISM increases employability in today’s increasingly international labor market. Additionally, ISM stimulates deeper cultural integration and contributes to build a sense of European identity.

The EU has supported ISM in tertiary education since 1976, through Joint Studies Programmes. (Rodrigues [2012]). After a pilot program of student exchange (1981-1986), ERASMUS (European Region Action Scheme for the Mobility of University Students) Program was launched in 1987. As an illustration of its success, nearly 3 million EU students have taken part since it started (European Commission). It has become a part of the Socrates programme since 1995 and the EU’s Lifelong Learning Programme more recently.

Likewise, the Sorbonne Declaration of 1998, the Bologna Declaration of 1999, and subsequent milestones, designed to bring standardization, single quality assurance, and mutual recognition of
academic qualifications, were initiated to reduce divergence in higher education systems in Europe and increase their international competitiveness and attractiveness primarily through promotion of ISM, which eventually led to formation of European Higher Education Area (EHEA) in 2010 (Papatsiba [2006]).

Recently, the European Council set a minimum 20 percent target rate for higher education in the EU to have on average a ‘period of higher education-related study abroad’ by 2020 (Myklebust, [2011]). This signifies that political and socioeconomic importance of ISM in the EU is not only valid, but also ascending, especially when higher education is becoming more as a tradable service in a highly globalized world, where the size of global ISM has quadrupled since 1975, reaching 3.7 million students in 2009 (OECD [2011]).

1.2. Motivation

There is no empirical evidence showing how EU enlargement has affected ISM. Even migration literature, the second best approximation, gives contrasting and inconclusive results. Therefore, the present study offers an advantage of sharing clear empirical evidence on the significance of removal of national border and associated barriers to study abroad in determining ISM by analyzing EU enlargement of 2004 and 2007. To test the hypothesis of its significant effect, gravity model is applied in its log-linearized and multiplicative forms using panel data of bilateral student flows between twenty-six EU member states over the period 1999-2009. The hypothesis is confirmed, implying at least 40%-45% increase in ISM, symmetric in both directions, as a result of enlargement. Among important pull factors are the degree of freedom and international exposure of a host country, whereas among significant push factors are the size of student population, average income level, financial support and control of corruption in a sending country.

1.3 Outline

The paper is organized as follows: Section 2 reviews the relevant literature and presents the paper’s main contributions and the hypothesis. In section 3, one outlines theoretical framework and methodologies employed. Section 4 presents the data and preliminary statistical analysis. Section 5 includes interpretation of the econometric analysis and verifies the hypothesis of the project. Finally, Section 6 states the conclusion, evaluation and possible policy implications, and then it highlights project’s limitations and proposes further improvements.

2 Literature review

ISM has been extensively studied from theory building to regression analysis. The present research project is related to literature on determinants of ISM. Particularly, more attention is given to studies using the gravity model due its empirical strength in analysis of flows (Deardorff, 1984:503), though an overview of other studies in determinants of ISM is provided in Table A1 in the appendix.

2.1 Gravity model

Starting from the first application of Newton’s law about universal gravitation (1687) in the social sciences by H. Carey in the 1860s, gravity-type model was introduced in the realm of economics by Tinbergen (1962), in migration economics by Lowry (1966) and Lee (1966) and more recently in literature of ISM determinants. To the author’s knowledge, there are only three papers: Bessey (2012), Rodriguez Gonzalez et al. (2010) and Van Bouwel & Veugelers (2009).

These papers concur that there are increasing student outflows from Eastern Europe. For instance, Van Bouwel and Veugelers (2009), by adding regional dummy for EU new member states (NMS), find its significance in determining ISM. Others find increasing outflows from NMS in their descriptive statistics analysis. However, they refer nothing about EU enlargement effect on ISM.

2.2 EU enlargement as a determinant

The present study focuses on EU enlargement effect. Despite a wide range of literature on various implications of EU enlargement, its effect on ISM is barely discussed and studied.

2.2.1 Academic mobility

There is only one paper, which has very soft evidence about EU enlargement effect on academic mobility. Guth (2008) investigates the impact of Eastern enlargement in 2004 on the mobility
of scientists from NMS to older member states (OMS). The analysis is based on extensive empirical study of the MOBEX2 Project (Mobility and Excellence in the European Research Area) that has some focus on prospective doctoral students. Against its initial expectations, the paper finds no significant effect of opening of the borders and following free movement rights on the mobility of early researchers. This effect is modest even in movements to the UK, where access to its labor market has not been restricted for NMS from the beginning.

However, it does not necessarily imply the similar pattern for ISM on the whole since doctoral students only constitute part of these flows, whereas students at bachelor and master levels tend to be much more mobile. Moreover, these results might be biased as the primary analysis of the MOBEX2 Project has predominantly focused on the flows between Poland and Bulgaria (sending) and the UK and Germany (receiving), so that the results has been broadly generalized to the rest of the EU.

Additionally, Rodriguez Gonzales et al. (2010) observe that ERASMUS Program enlargement in 1998/99 by inclusion of NMS and Turkey increased the flows of ERASMUS students, whose positive effect lasted up to 2003 and dissipated after that. The significance of this enlargement has not been tested empirically as it is out of their main focus of analysis, but the change in numbers of exchange students is sizeable as shown in their descriptive statistics. Although such positive effect is observed for enlargement of ERASMUS Program, it could be the case for the EU enlargement as well.

2.2.2. Migration in general

Since the study of ISM is particular element of the migration phenomenon, literature on EU enlargement effect on migration could contribute some relevant insights, as Bessey (2012) finds that they have fairly similar determinants. Majority of papers uses descriptive statistics for the empirical analysis and indicates that there has been increase in the number of migrants from NMS to OMS after EU enlargement but overall at a modest level.

Nevertheless, Kahanec et al. (2009) point out to the uneven distribution of flows across countries, showing that immigration from NMS is the largest to Ireland and the UK. These two countries have opened access to their labor markets after the enlargement, whereas most of OMS have been reluctant to remove their restrictive ‘transitional measures’ in migration policy up to 2009. Thus, it is argued that the actual effect of enlargement on migration flows would be sizeable in the absence of such restrictions.

In respect that Barrell et al. (2010) emphasize temporary nature of the flows and Zaiceva & Zimmermann (2008) point out migration of predominantly younger population, significant positive effect from EU enlargement on ISM could be assumed since migration includes student flows, for whom free movement rights are applicable. (European Union, 2004)

However, Kans (2011) disproves such a proposition on the basis of his empirical simulations using structural NEG approach, showing that liberalization of migration policy does not lead to substantial increase in migration flows.

2.4. Contribution

To sum up, there is no empirical evidence showing how EU enlargement has affected ISM. Even migration literature, the second best approximation, gives contrasting and inconclusive results. Therefore, this research project is the first to offer an advantage of sharing clear empirical evidence on the significance of “removal of national border and associated barriers to study abroad” in determining ISM by analyzing EU enlargement of 2004 and 2007.

Moreover, the second major contribution of this study is that it supplements gravity literature on ISM determinants by providing robust and comprehensive results. Effectively, it extends current analysis on the topic by considering larger sample, more determinants and extensive sensitivity check of results via application of consistent econometric techniques that some previous studies have been ignorant about. Besides, using panel data allows estimating more sophisticated models and avoiding biases common to cross-section or time-series analysis.

2.5. Hypothesis

The research hypothesis states that the size of ISM increases noticeably as a result of EU enlargement. It is expected due to the predictions of neoclassical theory of migration, based on the rational choice approach of the cost-benefit models. (Borjas, 2008:321-364)
It stresses that a potential student is likely to go abroad to study if the present value of expected benefits exceeds costs of moving (monetary and non-monetary). It includes transportation costs, foregone gains during moving, physical costs of leaving family\(^1\) and friends, accommodation costs, tuition fees and mobility barriers such as passport/visa control. For instance, Choudaha and Chang (2012) emphasize the role of student visa regulations in determining ISM: tightening visa requirements in 2010 resulted in sizeable drop of student inflows in Australia, whereas Canadian increasingly friendly student visa policy contributed to 30 percent increase of student inflows in 2011.

While under European Community Law students have the right to easily study in another member state as long as they are not a financial burden on the host state. (European Union, 2004) Therefore, opening of national border and following free movements of students between member states, as a result of EU enlargement, reduce costs of moving given certain level of expected gains ceteris paribus, thus increasing ISM to a certain extent.

3 Methodology

3.1 Theoretical framework

ISM is not a random process, but rational choice that implies two independent and sequential decisions: to migrate and where to migrate. While the first represent microeconomic approach, the second refers to the macroeconomic approach (Bunea, 2012). The gravity model, supported by neoclassical migration theory, successfully incorporates both approaches, but focuses more on macro dimension. Therefore, this research project predicts gravity relationship for ISM analogous to Newton’s law of universal gravitation:

\[
IS_{ij} = \alpha_0 \frac{H_i^{a_1} S_j^{a_2}}{D_{ij}^{a_3}}
\]

\(IS_{ij}\) is international student flow from country “\(i\)” to country “\(j\)”. \(H_i\) includes pull factors, operating within host country to make that country relatively more attractive than others, whereas \(S_j\) consists of push factors that operates within sending country, initiating student’s decision to study abroad. Mainly, they include country’s population, income levels etc. Distance between “\(i\)” and “\(j\)” is denoted as \(D_{ij}\), representing not only physical distance, but also cultural and linguistic distances that alter costs of moving. \(a_1, a_2, a_3\) are elasticities and \(\alpha_0\) is a constant common to all country-pairs (all years). According to Buch et al. (2004), it captures additional distance costs.

Bigger effect from push/pull factors or both increases IS flows between countries. However, such effect diminishes the farther apart the two countries are. This phenomenon is known as distance decay or Tobler’s first law of geography (Tobler, 1970). Greenwood (1997:648-720) considers that distance elasticity declines over time due to globalization and modern information, communication and transport technologies, thus decreasing costs of going abroad.

3.2. Empirical model

In order to apply this model empirically, three transformations are used: log-linearization for convenient elasticity interpretation of the coefficients; augmentation to increase explanatory power of the model; and inclusion of stochastic term to account for deviations from theory since analogy between Newtonian gravity and ISM is not precise. Additionally, time dimension is included because of panel data analysis.

\[
\ln(IS_{ijt}) = \ln(\alpha_0) + \alpha_1 \ln(H_{it}) + \alpha_2 \ln(S_{jt}) + \alpha_3 \ln(D_{ij}) + \phi E_{ijt} + u_{ijt}
\]

Without loss of generality, two-error component model is considered:

\[
u_{ijt} = \mu_{ijt} + \lambda_i + \nu_{ijt}, \nu_{ijt} \sim iid N(0,\sigma_v^2)
\]

for: \(i, j = 1,2...26, i \neq j\) and \(t = 1,2...11\)

In order to test the hypothesis, enlargement dummy variable, \(E_{ijt}\), is included:

\[
E_{ijt} = \begin{cases} 
1, & i \text{ and } j \in NMS \text{ after their accession} \\
0, & \text{otherwise}
\end{cases}
\]

Essentially, it captures overall effect of EU enlargement (both 2004, 2007) and implies impact of opening national border and removing associated mobility barriers. As discussed in section 2.5, significant positive sign of its coefficient “\(\phi\)” is expected.

\(^1\) Accounting for socio-cultural dimension implicates the new economy of migration, so-called “social choice approach” (Wolf et al. 1997)
Additionally, separate dummies for host ($E_{it}$) and sending ($E_{jt}$) NMS are considered, in order to account for direction of IS flows, as many studies mention increasing outflows from NMS:

$$E_{ij} = \begin{cases} 1, & i \in \text{NMS after their accession} \\ 0, & \text{otherwise} \end{cases}$$

$$E_{jt} = \begin{cases} 1, & j \in \text{NMS after their accession} \\ 0, & \text{otherwise} \end{cases}$$

Asymmetric flows, particularly, major movements from NMS to OMS are expected: $\phi_H < \phi_S$ 

"$\mu_j$" and "$\mu_i$" are unobserved time invariant factors specific to individual pair of countries, one for each direction of flows. "$\lambda_t$" represents the effect common to all pairs of countries for given year $t$. "$\nu_{ijt}$" is independent identically distributed (iid) disturbance term with zero mean and constant variance for all observations, assumed to be pairwise uncorrelated.

Alternatively, one estimates a multiplicative version of the gravity equation using Poisson pseudo-maximum likelihood (PPML) estimation following approach of Santos Silva and Tenreyro (2006):

$$IS_{ijt} = \exp(x'\beta) + \mu_{ij} + \mu_{ji} + \lambda_t + \nu_{ijt}$$

for $IS_{ijt} \geq 0$ and $E[\nu_{ijt}|x'] = 0$; where $x'$ is vector of all explanatory variables; $\nu_{ijt} = \ln \varepsilon_{ijt}$.

3.3. Econometric issues

First of all, omitting at least one of the terms ($\mu_{ij}, \mu_{ji}, \lambda_t$) of error component model, when they are present, results in endogeneity bias, arisen from non-stochastic disturbance. Therefore, if applicable, one adds year and country-pair dummy variables (LSDV) or use either fixed-effects or random-effects estimations, based on the results of Hausman specification test (Hausman [1978]).

Secondly, log-transformation of the dependent variable leaves out all zero-valued observations. As 12 percent (856 out of 7150) of observations have no IS flows, unbalanced truncation of the sample may delude results. Therefore, transformed dependent variable, $\ln (IS_{ijt} + 1)$, is applied as a standard way of dealing with prevalence of zeros.

Thirdly, one uses robust clustered standard errors for two reasons. Firstly, they consistently estimates true standard errors even under heteroskedasticity, which is largely expected because dissimilar country-pairs exhibit different variation, and whose presence is confirmed. Also, they are robust to misspecification and serial correlation within panel, which is also highly expected due to presence of the same country-pairs over time.

As a robustness check, one applies PPML estimation that account for last two issues simultaneously. It avoids selection bias from the unbalanced truncation, as its multiplicative form naturally allows estimating the dependent variable in level, $IS_{ijt}$, which includes zero-valued observations and better copes with heteroskedasticity issue. Additionally, PPML is much more superior estimation technique, just because only sufficient condition for estimators’ consistency is that conditional expectation of the mean be correctly specified: $E[IS_{ijt}|x'] = \exp(x'\beta)$.

4 Data

The analysis covers cross-section of twenty-six EU countries over period of 1999-2009. Hence, multidimensional balanced panel dataset consists of 7150 observations of 650 bilateral IS flows (26x25 pair of countries).

4.1. Dependent variable

As the dependent variable, this paper employs ‘bilateral internationally mobile student flows’ from UNESCO Institute for Statistics (UIS) to proxy for ISM. It includes ‘degree mobility’, which covers students who pursue a tertiary education degree outside their country of residence, but excludes ‘credit mobility’, which covers students under short-term, for credit-study and exchange programs that last less than a full academic year. On the one hand, such measure underestimates total number of students who have at least some experience of being internationally mobile. On the other hand, it helps to capture genuine effect of EU enlargement on ISM, because ‘credit mobility’ programs such as ERASMUS has been available to NMS a long before their accession since 1998. Although it does not allow for a distinction between temporary and permanent nature of flows and does not contain any information on the former educational attainment of students, the numbers are still valid as a measure of
overall ISM.

Figure 1. Total IS flows of period 1999-2009 by countries

Figure 2. IS inflows and outflows

Figure 3. Percentage growth of IS flows

Figure 1 reveals that the UK, Germany and France are the most popular destinations for students from the rest of the EU. Figure 2 illustrates continuously increasing outflows from NMS, whereas increasing inflows to NMS only after the enlargement. However, Figure 3 demonstrates fall in growth rates both for NMS and OMS in 2004, possibly because of general uncertainty and adjustment period arisen out of enlargement process. Nevertheless, hereinafter IS flows mostly start increasing at a faster rate, though still being subject to fluctuations, possibly due to economic cycles such as the financial crisis of 2007/08. These figures imply stimulating effect of the border removal on ISM, predominantly to NMS. However, inference cannot be made simply based on the descriptive analysis since IS flows might be subject to other unobserved factors.
4.2. Control variables

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>unit of measure</th>
<th>source</th>
<th>obs</th>
<th>mean</th>
<th>overall between</th>
<th>within</th>
<th>min</th>
<th>max</th>
<th>skew</th>
<th>kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>IS flows</td>
<td>tertiary level students</td>
<td>UIS</td>
<td>7150</td>
<td>548.4</td>
<td>1897.7 1802.9</td>
<td>595.9</td>
<td>0.0</td>
<td>30186.0</td>
<td>0.6</td>
<td>61.3</td>
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<tr>
<td>Gravity var.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student population</td>
<td>tertiary aged people (000)</td>
<td>UIS</td>
<td>7150</td>
<td>1195.8 1409.9 1407.5</td>
<td>97.7</td>
<td>30.3</td>
<td>5046.6</td>
<td>1.3</td>
<td>3.2</td>
<td></td>
</tr>
<tr>
<td>Weighted distance</td>
<td>kilometers</td>
<td>CEPH</td>
<td>7150</td>
<td>1467.0 737.5 738.0</td>
<td>0.0</td>
<td>160.9</td>
<td>3779.7</td>
<td>0.7</td>
<td>2.9</td>
<td></td>
</tr>
<tr>
<td>Economic var.</td>
<td>real GDP/capita</td>
<td>WDI</td>
<td>7150</td>
<td>23.6 8.6 8.4 2.0</td>
<td>6.7</td>
<td>41.1</td>
<td>0.2</td>
<td>1.9</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labour market var.</td>
<td>% of labour force</td>
<td>WDI</td>
<td>7150</td>
<td>8.2</td>
<td>3.8 3.1</td>
<td>2.2</td>
<td>2.1</td>
<td>19.9</td>
<td>1.2</td>
<td>4.2</td>
</tr>
<tr>
<td>Educational var.</td>
<td>HE quality</td>
<td>ARWU</td>
<td>7150</td>
<td>1.1 2.3 2.3</td>
<td>0.3</td>
<td>0.0</td>
<td>11.0</td>
<td>2.7</td>
<td>10.3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>HE financial support</td>
<td>% of total educ. expend.</td>
<td>Eurostat</td>
<td>7150</td>
<td>16.0 11.6 10.7</td>
<td>4.6</td>
<td>0.1</td>
<td>59.0</td>
<td>1.4</td>
<td>5.7</td>
</tr>
<tr>
<td></td>
<td>int. exposure</td>
<td>foreign/tertiary</td>
<td>Eurostat</td>
<td>7150</td>
<td>0.1 0.1 0.1</td>
<td>0.0</td>
<td>0.0</td>
<td>0.3</td>
<td>1.7</td>
<td>5.8</td>
</tr>
<tr>
<td></td>
<td>Educ. opportunities</td>
<td>tertiary/upper secondary</td>
<td>Eurostat</td>
<td>7150</td>
<td>1.0 0.3 0.3</td>
<td>0.2</td>
<td>0.3</td>
<td>2.0</td>
<td>0.9</td>
<td>3.6</td>
</tr>
<tr>
<td>Political var.</td>
<td>Voice and account.</td>
<td>percentile rank (0;100)</td>
<td>WGI</td>
<td>7150</td>
<td>84.6 10.8 10.5</td>
<td>2.5</td>
<td>55.8</td>
<td>100.0</td>
<td>0.5</td>
<td>2.5</td>
</tr>
<tr>
<td></td>
<td>Rule of law</td>
<td>percentile rank (0;100)</td>
<td>WGI</td>
<td>7150</td>
<td>80.7 15.2 14.8</td>
<td>3.2</td>
<td>37.3</td>
<td>100.0</td>
<td>0.7</td>
<td>2.6</td>
</tr>
<tr>
<td></td>
<td>Corruption control</td>
<td>percentile rank (0;100)</td>
<td>WGI</td>
<td>7150</td>
<td>79.6 15.4 15.0</td>
<td>3.5</td>
<td>47.3</td>
<td>100.0</td>
<td>0.4</td>
<td>2.1</td>
</tr>
</tbody>
</table>

Table 1. Summary statistics

Selection of ISM determinants follows integrative approach of Van der Gaag et al. (2003) and is supported by consumer behavior, human capital, migration and demand theories. Table 1 supports an appropriateness of controls in explaining bilateral IS flows by demonstrating their large variation between countries and small variation within each country.

Tertiary aged student population is included to control for tendency that larger countries send more students abroad and have more capacity to absorb additional incoming students (Fig.1). Positively correlated with the dependent variable, correlation coefficients vary between 0.17 and 0.36, providing descriptive evidence for the importance of ‘mass’ in the gravity equation.

Another important variable is average income level, measured as real GDP per capita adjusted to differences in PPP. It captures the fact that wealthier countries have better options to send students abroad and their higher standard of living makes an appeal to majority of students. In addition, unemployment rate, measured as percentage of total labor force, captures country’s labor market condition. Countries with lower rates are attractive as prospective place of work after graduation.

Moreover, financial support for tertiary students decreases expected costs of higher education ceteris paribus, thus allowing more prospective students to enter universities. International grants and scholarship facilitate IS flows, whereas support given domestically tends to retain students.

Additionally, there are two important pull factors. First of all, it is international exposure of country’s higher education institutions, measured as proportion of foreigners out of total tertiary level students. For instance, survey by Opper et al. (1990) emphasizes that students are highly motivated to experience international setting, even more than quality considerations. Nevertheless, country’s quality of higher education institutions is another significant driver, according to human capital theory of education. As proxy to teaching and research quality, this paper counts the number of institutions in the top 100 of Academic Ranking of World Universities (ARWU).

Among push factors, many papers refer to educational opportunities that capture the possibility that students have to seek higher education abroad because of under-supply of university places in their home country. It is measured as proportion of students in tertiary level relative to those in upper secondary education. Data on all above variables are constructed from Eurostat, complemented with data from UIS and World Bank’s World Development Indicators (WDI).

Also, the CEPII database provides geographic information about weighted distance, contiguity, linguistic similarity and colonial link. These various distance measures, as discussed in Section 3.1, alter moving costs. Hence, larger IS flows are expected for close, contiguous countries that share common language and history.

Additionally, Karemera et al. (2000) emphasize political impact, as better-governed countries tend to attract and retain migration. Therefore, measures of freedom (VA), stability (RL) and corruption control (CC) are taken from World Bank’s World Governance Indicators (WGI). Since sources from which this data is extracted are internationally recognized, values reported are accurate and of high quality.

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<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>POLS (one-way)</th>
<th>FE (two-way)</th>
<th>RE (two-way)</th>
<th>PPML FE</th>
<th>PPML FE (two-way)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected sign</td>
<td>ln(5 flows)</td>
<td>ln(5 flows+1)</td>
<td>ln(5 flows+1)</td>
<td>ln(5 flows+1)</td>
<td>ln(5 flows+1)</td>
</tr>
<tr>
<td>Total enlargement</td>
<td>-0.102</td>
<td>-0.0404</td>
<td>0.343***</td>
<td>0.591***</td>
<td>0.538***</td>
</tr>
<tr>
<td>(H) enlargement</td>
<td>(0.0823)</td>
<td>(0.0782)</td>
<td>(0.0490)</td>
<td>(0.0696)</td>
<td>(0.0697)</td>
</tr>
<tr>
<td>(S) enlargement</td>
<td>0.386***</td>
<td>0.163**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(H) ln(stud. pop.)</td>
<td>0.864***</td>
<td>0.847***</td>
<td>-0.653***</td>
<td>0.706***</td>
<td>0.657***</td>
</tr>
<tr>
<td>(H) ln(income)</td>
<td>0.382</td>
<td>0.424</td>
<td>1.460***</td>
<td>1.910***</td>
<td>1.857***</td>
</tr>
<tr>
<td>(H) ln(unempl)</td>
<td>0.242*</td>
<td>0.185</td>
<td>0.0164</td>
<td>0.0415</td>
<td>0.0208</td>
</tr>
<tr>
<td>(H) ln(infin. support)</td>
<td>0.0212</td>
<td>-0.0207</td>
<td>-0.0140</td>
<td>-0.0158</td>
<td>-0.0314*</td>
</tr>
<tr>
<td>(H) ln(VA)</td>
<td>1.870**</td>
<td>1.749**</td>
<td>0.586</td>
<td>1.864***</td>
<td>1.997***</td>
</tr>
<tr>
<td>(H) ln(RL)</td>
<td>0.782</td>
<td>0.727</td>
<td>0.358</td>
<td>0.427</td>
<td>0.385</td>
</tr>
<tr>
<td>(H) ln(CC)</td>
<td>1.953**</td>
<td>2.135***</td>
<td>0.240</td>
<td>-0.700**</td>
<td>-0.836**</td>
</tr>
<tr>
<td>(H) ln(int. exposure)</td>
<td>-0.854</td>
<td>-0.812*</td>
<td>-0.976***</td>
<td>-1.040***</td>
<td>-0.763***</td>
</tr>
<tr>
<td>(H) HE quality</td>
<td>0.528***</td>
<td>0.503***</td>
<td>0.273***</td>
<td>0.261***</td>
<td>0.261***</td>
</tr>
<tr>
<td>(H) ln(finance)</td>
<td>0.0957**</td>
<td>0.0583</td>
<td>0.0991***</td>
<td>0.0977***</td>
<td>0.0866***</td>
</tr>
<tr>
<td>(S) ln(stud. pop.)</td>
<td>0.526***</td>
<td>0.510***</td>
<td>0.0906</td>
<td>0.0771</td>
<td>0.540***</td>
</tr>
<tr>
<td>(S) ln(income)</td>
<td>0.417</td>
<td>0.402</td>
<td>-0.315</td>
<td>0.164</td>
<td>0.0312</td>
</tr>
<tr>
<td>(S) ln(unempl)</td>
<td>0.267</td>
<td>0.250</td>
<td>0.279</td>
<td>0.294</td>
<td>0.179</td>
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<tr>
<td>(S) ln(finance)</td>
<td>0.0214</td>
<td>0.0508</td>
<td>-0.0118</td>
<td>0.0197</td>
<td>-0.00549</td>
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<tr>
<td>(S) ln(VA)</td>
<td>0.119</td>
<td>0.109</td>
<td>0.0684</td>
<td>0.0740</td>
<td>0.0683</td>
</tr>
<tr>
<td>(S) ln(RL)</td>
<td>0.0957**</td>
<td>0.0583</td>
<td>0.0991***</td>
<td>0.0977***</td>
<td>0.0866***</td>
</tr>
<tr>
<td>(S) ln(CC)</td>
<td>0.526***</td>
<td>0.510***</td>
<td>0.0906</td>
<td>0.0771</td>
<td>0.540***</td>
</tr>
<tr>
<td>(S) ln(int. exposure)</td>
<td>-0.177**</td>
<td>-1.461*</td>
<td>-0.849**</td>
<td>0.417</td>
<td>0.309</td>
</tr>
<tr>
<td>(S) ln(finance)</td>
<td>-1.742***</td>
<td>-1.795***</td>
<td>0.121</td>
<td>-0.816**</td>
<td>-0.942***</td>
</tr>
<tr>
<td>Constant</td>
<td>-20.65**</td>
<td>-21.90***</td>
<td>0.875</td>
<td>-10.31</td>
<td>-27.34***</td>
</tr>
<tr>
<td>2001 year</td>
<td>-0.0234</td>
<td>-0.0255</td>
<td>-0.0565</td>
<td>-0.0234</td>
<td>-0.0255</td>
</tr>
<tr>
<td>2002 year</td>
<td>0.0466</td>
<td>0.0454</td>
<td>-0.0525</td>
<td>0.0466</td>
<td>0.0454</td>
</tr>
<tr>
<td>2003 year</td>
<td>0.000694</td>
<td>0.0175</td>
<td>-0.108</td>
<td>0.000694</td>
<td>0.0175</td>
</tr>
<tr>
<td>2004 year</td>
<td>0.0889</td>
<td>0.0970**</td>
<td>-0.190**</td>
<td>0.0889</td>
<td>0.0970**</td>
</tr>
<tr>
<td>2005 year</td>
<td>-0.565***</td>
<td>-0.524**</td>
<td>-0.622***</td>
<td>-0.565***</td>
<td>-0.524**</td>
</tr>
<tr>
<td>2006 year</td>
<td>-0.395***</td>
<td>-0.352***</td>
<td>-0.597***</td>
<td>-0.526***</td>
<td>-0.395***</td>
</tr>
<tr>
<td>2007 year</td>
<td>-0.395***</td>
<td>-0.352***</td>
<td>-0.597***</td>
<td>-0.526***</td>
<td>-0.395***</td>
</tr>
<tr>
<td>2008 year</td>
<td>-0.487***</td>
<td>-0.451***</td>
<td>-0.853***</td>
<td>-0.757***</td>
<td>-0.487***</td>
</tr>
<tr>
<td>2009 year</td>
<td>-0.107</td>
<td>-0.0715</td>
<td>-0.718***</td>
<td>-0.637***</td>
<td>-0.107</td>
</tr>
</tbody>
</table>

Robust standard errors corrected for clustering by country-pair in parentheses. *** = p<0.01, ** = p<0.05, * = p<0.1

Hausman test between (4) and (5) suggests (4), since country-pair effects and regressors are correlated: chi2(28)=164.16; p > chi2 = 0.000

Table 2. Key results
5 Results

Table 2 includes eight different specifications. Columns 1-6 analyze total effect of enlargement, whereas last two columns separate its effect to account for relative strength of directions of IS flows. All variables except dummy variables, HE quality and IS flows under PPML estimation are expressed in natural logarithms. The year dummies are measured relative to that of 1999, to prevent collinearity; and their standard errors are omitted for space consideration. Different criteria such as goodness of fit ($R^2$), Akaike Information Criteria (AIC) and heteroskedasticity-robust RESET test (Ramsey [1969]) are used to check adequacy of these models (where applicable).

5.1. Main results

Inferences of this study are primarily based on the results of columns 7 and 8 that apply multiplicative gravity model using PPML FE estimation due to being the best-fitted\(^5\) and correctly specified model, thus satisfying the sufficient condition for consistency. RESET test shows no evidence of $[E[IS_{ij}|x'] = \exp(x'\beta)]$ misspecification and possibility of omitted variable bias. While column 8 reveals symmetric increase in IS flows, specification 7 estimates strongly significant and positive coefficient on enlargement dummy variable, thus confirming the hypothesis that removal of national border and associated mobility barriers increases IS flows approximately by at least 40-45 percent after controlling for various factors, discussed below:

For instance, pooled ordinary least squares (POLS), standard estimation method in gravity analysis, has restrictive assumption of a single intercept, same parameters over time and across pair of countries ($\alpha_{ij} = 0, \alpha_{ji} = 0, \lambda = 0$), whereas country-pairs are fundamentally different. Therefore, contradicting effects (-10 percent, -4 percent) of enlargement in columns 1 and 2 suffer from unobserved heterogeneity bias, because of not controlling for fixed pair-specific factors that are correlated with IS flows and with explanatory variables. Although it tries to capture some heterogeneity by considering common language, colonial link, contiguity and distance differences, most of cultural, historical, geographical and political factors (specific to country-pairs) are difficult to observe, let alone quantify.

Therefore, column 3 applies fixed-effects (FE) estimation, which effectively accounts for unobserved heterogeneity by allowing intercept to vary over country-pairs for each direction of IS flows. As a result, it gives significant positive coefficient on enlargement dummy and considerably alters estimates of other regressors. Hence, removal of national border and associated barriers to study abroad increases IS flows by 40 percent. Since within transformation (Wallace and Hussain, 1969) of FE leaves out all time invariant variables, it effectively eliminates the need to include them. On the one hand, it enhances accuracy of analysis, as there is a long-standing difficulty with measuring these factors. On the other hand, they are out of primary focus of the current analysis.

However, assuming one-way error component model ($\lambda = 0$) in the presence of time effects gives inconsistent estimates, especially for large sample of country-pairs over fixed period. Thus, by adding (jointly significant) year-dummies, specifications 4 and 8 controls for effects of any omitted variables affecting IS flows that vary over time, but constant across country-pairs. For instance, as discussed in Section 4.1, IS flows are subject to economic cycles such as the financial crisis of 2007-2008, and possibly to general uncertainty or adjustment period arisen out of enlargement process. Furthermore, highly significant coefficients on last six year-dummies might indicate integration of EU member states in the space of single economic market. As a result, the coefficient substantially rises, implying enlargement effect of the order of approximately 60 percent.

Alternatively, specification 5 applies random-effects (RE) estimation that usually gives more efficient estimates than FE under assumption\(^8\) of exogeneity of all explanatory variables and country-pair effects, treated as part of random disturbances. However, this assumption is rejected, based on Hausman test. Since violation of the assumption infers biased estimates under RE, the analysis of the current paper is based on FE approach, consistent in both cases. Appropriateness of FE has been expected, as data consist of ex ante predetermined selection of country-pairs for finite period of 11 years. (Egger, 2000, Baltagi, 2005:12)

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\(^5\) Model performs strongly, accounting for 95% of the variation in IS flows ($R^2 = 0.948$)

\(^6\) Coefficients are highly sensitive because of conditioning on large set of control variables

\(^7\) Head and Mayer (2001) discuss problems of measuring economic distance

\(^8\) Wooldridge (2008:493) emphasizes practical unlikeliness of such assumption
The significance of enlargement effect is robust, though slightly lower, under multiplicative form of gravity using PPML FE in columns 6 and 7. As discussed in Section 3.3, these results are much more prepotent. First, using IS flows in levels naturally accounts for zero-valued observations, thus avoiding bias from transformation. Nevertheless, robustness of results for subset of only positive values of IS flows implies that $\ln \left( IS_{ijt} + 1 \right)$ transformation is valid. Also, PPML is consistent in the presence of heteroskedasticity, whereas transformed error term ($\ln e_{ijt}$) in log specifications is likely to be correlated with covariates, simply because of Jensen’s inequality $E(\ln y) \neq \ln E(y)$, thus violating assumptions of classical disturbance-term (Santos Silva & Tenreyro [2006]). This explains lower coefficient on enlargement dummy variables in columns 6 and 7.

5.2. Auxiliary results

Additionally, columns 6 and 7 predict other significant determinants of IS flows. The level of freedom (3 percent) and international exposure (0.8 percent) are important pull factors, which, as expected, considerably attract students. Apparently, it characterizes the most developed member states with long-standing, internationally recognized reputation of their higher education system such as the UK, Germany and France (Fig.1), which are a mainstay of international students and foreigners.

Among critical push factors are tertiary-aged population (0.9 percent), average income per person (1.2 percent) and (international) financial support (0.15 percent), which, as expected, extensively facilitate outflows of students. Contrary to initial expectation, lower level of corruption encourages IS outflows at surprisingly large rate (1.1 percent). Possibly, less corrupted countries tend to have more evenly distributed income among population, so that foreign education is affordable not only to the high class, but also to lower and middle-income groups. Based on these findings, one can assure that majority of push factors are common in one: financial considerations play an increasingly crucial role.

Finally, although specifications 1, 2 and 5 are biased, they could suggest that students tend to choose less distant options to study, where the official language is more or less familiar.

5.3. Overview

The hypothesis of this paper is proved by strongly significant and positive coefficients on the enlargement dummy variable, implying that ISM increases at least by 40 percent as a result of opening the national border. Contrary initial expectations, this effect on ISM is symmetric in both directions of flows, implying that enlargement has facilitated outflows from NMS relatively at the same rate as inflows to NMS, though their absolute numbers differ a lot.

Additionally, some of ISM determinants, that previous studies find influential, turn out to be insignificant, possibly due to analyzing countries that are highly integrated and similar in nature. However, Rodriguez Gonzalez et al. (2010) and Van Bouwel & Veugelers (2009) also analyze EU member countries, but reveal significantly positive coefficient on quality. Similarly, the latter finds significance of educational opportunities. Possibly, such controversial results partially come from their restrictive models. For instance, despite fixed-effects application to their panel data of thirty European countries over 1996-2006, Rodriguez Gonzalez et al. (2010) consider only unilateral IS flows in one direction, whereas Van Bouwel & Veugelers (2009) use cross-country analysis between nineteen European countries in 2005. However, since the results, under columns 1-5 and 8, largely overlap with previous studies, major issue is that their (standard) application of log-linearized gravity model is subject to (overestimation) bias arisen from transformed error term ($\ln e_{ijt}$), which is no longer random in the presence of heteroskedasticity (Santos Silva & Tenreyro [2006, 2011]). Finally, overall results are not driven by outliers, since being robust to excluding the UK, Germany and/or France.

6 Conclusions

This research project is the first empirical evidence that revealed importance of removal of national border and associated mobility barriers in promoting ISM using EU enlargement of 2004 and 2007. Symmetry of the effect might indicate that this research has managed to discover genuine effect of opening the border, thus feasibly making it applicable to migration literature in general. Moreover, it suggests that conclusions based solely on descriptive statistics analysis are inadequate and subject to biases arisen out of ignoring various factors that are unobserved, but important. Therefore, one should not over-rely on descriptive analysis especially when considering similar countries as highly integrated EU member states.
Additionally, this paper finds other important determinants of ISM by dint of application of sophisticated panel models and consistent econometric techniques that some previous empirical studies have failed to do. The findings are also superior over surveys, which are based on small sample of respondents, whose actual actions might largely differ from desired or supposed ones.

6.1 Limitations

However, the present analysis is also subject to some limitations. First of all, it is a time-in-sample bias. Although the coefficient on enlargement variable is sensitive to a sample period, its alteration is not so large. Therefore, this paper refers to the lowest approximation of enlargement effect since the main focus of the analysis is to determine its significance, but not the exact value. Secondly, some factors are measured by proxy variables that might not effectively capture their true impact. Finally, it assumes a static relationship; whereas there might be presence of hysteresis of IS flows, though considering dynamic panel data drastically changes the focus of this analysis.

6.2 Implications

The most affected groups by ISM are higher education institutions, societies and nations. Thus, the findings of this paper are of particular interest to policymakers. For instance, a positive enlargement effect could encourage Croatia (acceding country that will become 28th member of the EU on 01.07.13) and candidate countries including Macedonia, Iceland, Montenegro, Serbia and Turkey to join the EU for more expected benefits from their accession. Similarly, these results might be practical to other blocs of countries that are interested in higher education integration through ISM. An increase in mobility capital through the removal of educational barriers could be a decisive incentive in fostering further mobility exponentially.

Additionally, information about drivers of ISM is valuable source for higher education institutions in their strategic actions in response to internal and external factors in increasingly competitive environment where higher education is becoming more as a tradable service in highly globalized world. Similarly, on the country level, governments could manipulate student flows by effectively altering relevant determinants of ISM, which might be feasible on general migrants as well.

6.3 Future improvements

This paper is subject to further extensions and modifications. One could re-estimate the model conditioning on other/larger set of controls, better proxy variables, alternative econometric techniques (Tobit) and more sophisticated (dynamic) models. Alternatively, one could re-estimate the results for a subset of bachelor, master or doctoral level students, if such separate data exist. Due to typical age differences between these groups, different factors play role in the determination of their mobility. Also, one could consider possible third-party effect by extending analysis to other countries. Finally, one could undertake an in-depth analysis using interaction terms with enlargement dummy variable, thus allowing for possibility of structural change and estimating determinants’ relative effects on NMS and OMS flows.

Appendix

### Survey analysis

<table>
<thead>
<tr>
<th>Authors</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oppen et al. (1990)</td>
<td>International experience (+), learn foreign language (+), academic motives (+)</td>
</tr>
<tr>
<td>Orr et al. (2011)</td>
<td>Educational background (+), foreign language abilities (+)</td>
</tr>
<tr>
<td>Wiers-Jenssen (2011)</td>
<td>Educational background (+), international exposure (+)</td>
</tr>
<tr>
<td>Gonzalez et al. (2011)</td>
<td>Price level (-), geographic distance (-), quality of HE (+), warm climate (+)</td>
</tr>
</tbody>
</table>

### Regression analysis

<table>
<thead>
<tr>
<th>Authors</th>
<th>Countries</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lee &amp; Tan (1984)</td>
<td>From 103 countries to the USA, France and the UK</td>
<td>Distance (-), per capita income (+), cost of living (+), GNP growth rate (+), excess demand (+), share of science (-), staff-student ratio (-), real cost per student (+), colonial links (+)</td>
</tr>
<tr>
<td>Cummings (1984)</td>
<td>From 34 countries to the USA</td>
<td>Population (-), financial capacity (+), HR capacity (+), domestic opportunities (-), interdependence (+), previous overseas students (+)</td>
</tr>
<tr>
<td>Agarwal &amp; Winkler (1985)</td>
<td>From 15 developing countries to the USA</td>
<td>Income (+), educational opportunity (-), English speaking (+), French speaking (+/-), probability of migration (+/-)</td>
</tr>
<tr>
<td>McMahon (1992)</td>
<td>From 18 developing countries to the USA</td>
<td>Economic strength (-), global trade (+), state priority on education</td>
</tr>
</tbody>
</table>
### Table A1. Overview of empirical studies on the determinants of international student mobility

<table>
<thead>
<tr>
<th>Sign</th>
<th>Variable</th>
<th>Definition</th>
<th>Unit</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>n/a</td>
<td>IS flows</td>
<td>Internationally mobile students enrolled at tertiary level education (ISCED5,6), includes degree mobility, but excludes credit mobility</td>
<td></td>
<td>UIS</td>
</tr>
<tr>
<td>H: +</td>
<td>Student population</td>
<td>Tertiary age population</td>
<td>thousands people</td>
<td>UIS</td>
</tr>
<tr>
<td>H: +</td>
<td>Average income per person</td>
<td>Real GDP per capita adjusted to differences in purchasing power parity (PPP), constant 2005 international US dollars. Measure of wealth of country’s population; country’s standard of living and quality of life, since PPP adjusts to differences in cost of living and inflation rates</td>
<td>thousands $</td>
<td>WDI</td>
</tr>
<tr>
<td>-</td>
<td>Weighted distance</td>
<td>Weighted distance between two countries based on bilateral distances between the biggest cities of those countries</td>
<td>kilometers</td>
<td>CEPII</td>
</tr>
<tr>
<td>+</td>
<td>Contiguity</td>
<td>Dummy variable set equal to 1 for contiguous countries</td>
<td>1; 0</td>
<td>CEPII</td>
</tr>
<tr>
<td>+</td>
<td>Colonial link</td>
<td>Dummy variable set equal to 1 for having a colonial link</td>
<td>1; 0</td>
<td>CEPII</td>
</tr>
<tr>
<td>+</td>
<td>Common language</td>
<td>Dummy variable set equal to 1 for language spoken by at least 9% of the population in both countries</td>
<td>1; 0</td>
<td>CEPII</td>
</tr>
<tr>
<td>H: +</td>
<td>HE quality</td>
<td>Number of higher education institutions included in top 100 of Academic Ranking of World Universities (ARWU)</td>
<td>universities</td>
<td>ARWU</td>
</tr>
<tr>
<td>H: -</td>
<td>Unemployment rate</td>
<td>Unemployment rate as % of total labor force</td>
<td>percentage point</td>
<td>WDI</td>
</tr>
<tr>
<td>H: +</td>
<td>Financial support</td>
<td>Financial aid to students as % of total public expenditure on education, at tertiary level of education (ISCED 5,6)</td>
<td>percentage point</td>
<td>Eurostat</td>
</tr>
<tr>
<td>S: -</td>
<td>Educational opportunity</td>
<td>The proportion of students in tertiary education (ISCED5,6) relative to the number of students in upper secondary education (ISCED 3)</td>
<td>proportion</td>
<td>UIS</td>
</tr>
<tr>
<td></td>
<td>Tertiary level students</td>
<td>Enrolment in total tertiary education (ISCED 5,6)</td>
<td>students</td>
<td>UIS</td>
</tr>
<tr>
<td></td>
<td>Upper secondary</td>
<td>Enrolment in upper secondary education (ISCED 3)</td>
<td>students</td>
<td>UIS</td>
</tr>
<tr>
<td>H: +</td>
<td>International exposure</td>
<td>The proportion of foreign students relative to the number of students in tertiary education (ISCED5,6)</td>
<td>proportion</td>
<td>Eurostat</td>
</tr>
<tr>
<td></td>
<td>Foreign students</td>
<td>Students whose nationality differs from that of the country in which they enroll</td>
<td>students</td>
<td>Eurostat</td>
</tr>
<tr>
<td>H: +</td>
<td>Voice and accountability (VA)</td>
<td>Reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.</td>
<td>percentile rank (ranges from 0 (lowest) to 100 (highest) rank)</td>
<td>WGI</td>
</tr>
<tr>
<td>H: +</td>
<td>Rule of law (RL)</td>
<td>Reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract</td>
<td>percentile rank (ranges from 0 (lowest) to 100 (highest) rank)</td>
<td>WGI</td>
</tr>
</tbody>
</table>
enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. (highest) rank

| H: + | Control of corruption (CC) | Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. percentile rank (ranges from 0 (lowest) to 100 (highest) rank) | WGI |
| S: - |

Table A6. Description of variables

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Data sources:


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World Bank’s World Development Indicators (WDI). Available at: http://esds80.mcc.ac.uk/wds_wb/TableViewer/dimView.aspx?ReportId=24


Academic Ranking of World Universities (ARWU). Available at: http://www.arwu.org/
ANALYSIS OF AN EAST AFRICAN FARMER FIELD SCHOOL INITIATIVE: WHICH FACTORS HELP FARMERS THE MOST?

Hannah Hill

Georgetown University

Professor Robert Cumby, Advisor

ABSTRACT

This paper is a program evaluation of a Farmer Field School (FFS) in Kenya, Tanzania, and Uganda. This paper questions the extent to which individual characteristics enable an individual to maximize his or her benefit from the FFS. Building off previous literature on FFS initiatives and a program analysis on this FFS initiative undertaken by Davis et al. in 2010, this paper confirms the results of the previous partial equilibrium analysis and adds a full equilibrium analysis. Using a nearest neighbor propensity score matching approach, the average treatment effect on the treated (ATT) was calculated for each FFS member. This dependent ATT variable, defined as agricultural crop productivity change, was then expressed as a function of three static characteristics – gender, age, and education level – and three active characteristics – group membership, leadership position, and government participation. This report found that female household heads, the less educated, the more land rich, those participating in government, and those who were not members of groups or did not hold leadership positions benefited most. Only the coefficients on education were consistently significant across all of the country and regional models. This paper concludes that education level is the most significant factor in determining the extent to which a participant benefited from the FFS. It underscores that future iterations of the FFS should target individuals based on their education level and should work to improve the FFS model to be more beneficial to individuals with higher levels of education.

Acknowledgments

I would like to thank Professor Robert Cumby, without whose continued guidance, advice, and support, this paper would not be possible. I would also like to thank Professor Charles Udomsaph without whom my understanding of Stata would be a fraction of what it is.

1 Introduction

This research project is a full equilibrium program evaluation of a Farmer Field School (FFS) in Kenya, Tanzania, and Uganda. It asks the following question: what is the extent to which individual characteristics enable an individual to maximize his or her benefit from the FFS? This analysis will look at the impact of six characteristics on the level of agricultural productivity change from before to after the FFS implementation: three static characteristics – gender, education level, and land poverty tertile; and three active characteristics – involvement in other farmer community groups, possession of a leadership role, and participation in local government.

FFS implementation began in the 1990s in East Asia for integrated pest management projects. They now exist in more than 87 countries, including 27 African countries. What has made Farmer Field Schools so successful and why they have continued to expand is their framework as a series of demand driven development projects. The FFS focuses, first and foremost, on human capital development.1 With such a successful model, the Farmer Field Schools demand constant evaluation. It is important to evaluate

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the effectiveness of the programs to better understand the strengths and weaknesses of the model and to efficiently target places for expansion. Most of the previous literature of FFS initiatives has focused on East Asia. Studies have found the in-person interactions of the model beneficial to the vulnerable women and poor. Others have found that strong culture leads to greater cohesion and collaboration, and that analytical thinking is integral to the process.

My data source is the 2006 random-household survey of FFS and non-FFS participants in Kenya, Tanzania and Uganda that was collected by the International Food Policy Research Institute (IFPRI). The International Fund for Agricultural Development (IFAD) and Food and Agricultural Organization (FAO) launched the second phase of an FFS in those three countries in October 2005. In June 2010, Davis et al. published a report through IFPRI on this East African FFS. They asked, first, who participates and, second, what effect does "household-capital-endowment-level social characteristics" have on maximization? They found that women benefited more than men, the land-medium more significantly than the land poor or land rich, and that the less educated benefited more. However, all of these analyses are incomplete and leave many questions unanswered. The Davis et al. paper is an example of a partial equilibrium analysis. They calculated the treatment effect for participants and analyzed it along each socio-economic breakdown in isolation. This leaves one glaring question unanswered: For a land-medium, uneducated women to what extent is she able to benefit most because she is a women and to what extent because she is land-medium or uneducated? This demands a full equilibrium analysis; I will undertake such a full equilibrium analysis in this report. In my research, I will look to see first, do the patterns of the partial equilibrium analyses hold, second, what is the magnitude of the coefficients, and third, which coefficients are significant.

Depending on the size, sign, and significance of the coefficients, program implementers can decide where to up-scale FFS initiatives and who to target for funding. The decision could go in either direction. Future programs may want to target those who are able to maximize their benefit most or they may want to focus on giving additional access to people who have previously benefited less. Beyond the FFS project itself, the results of this study will provide insight onto where to focus foundational development projects. If women benefit most, non-agricultural development programs should focus on women’s empowerment; if community group membership proves effective in helping an individual to maximize benefit, development aid should focus on more collaborative efforts.

The analysis in this research will use a difference-in-difference propensity score matching (PSM) approach. Such a methodology corrects for the inherent missing counterfactual in all program evaluations and for the administration and selection bias that occurs in programs that are not random control trials (RCT). The ideal for program evaluation is to compare how a participant did after participating with where that participant would have been if they had not participated. However, there is the obvious and inherent missing counterfactual: you can’t see someone doing two things at the same time. So, one must develop a functional Average Treatment effect on the Treated (ATT) to isolate the effect of the treatment for each participant. Doing so requires a difference-in-differences approach where one first calculates the change in productivity from before to after the program for the participants and for the non-participants and then takes the difference of the two. The ideal program evaluation builds off a RCT where two similar populations were found and then the program was randomly implemented in some areas and not in

others. This lends itself to easy participant to non-participant comparisons because the participant and non-participant groups are inherently similar along all observable characteristics. However, given that the East Africa FFS analyzed in this report was not randomly but strategically implemented in certain areas, there are inherent differences between the treatment and control populations, and one cannot undertake a simple participant vs. non-participant comparison. Instead, I must match participants with similar non-participants. Those “similar” non-participants are identified using a propensity score matching procedure. The PSM procedure has three steps: 1) estimate the propensity score for each individual using factor controls essential to the outcome; 2) use an algorithm (e.g., Nearest neighbor, Kernel) to match treated and untreated; 3) assess the impact of the project using the matched sample.7 Using the difference-in-difference approach with the matched sample, one then estimates the effect of the program by subtracting the difference in the before and after implementation for the control sample from the before and after of implementation for the treatment sample for those with similar propensity scores (likelihood of participating in the program).

The dependent variable of this study is the ATT for FFS benefit, defined as the difference in agricultural crop productivity between a participant and his or her matched non-participant. Looking at the impact of the six independent variables on my dependent variable of interest, I hypothesize that even in the full equilibrium analysis, the patterns previously found for the static characteristics will hold: women will benefit more, the land-medium poverty tertile will benefit most, and the uneducated will benefit most. In addition, for the three active characteristics, I hypothesize that those who actively participate in any of these activities will be more likely to have the critical-thinking and collaborative skills needed to maximize benefit from the FFS. In undertaking my full equilibrium analysis, I will ultimately be able to determine not just that female-headed households benefited more than male-headed households, as the IFPRI report showed, but also that, for example, being in a female-headed household did more to increase your opportunity to maximize benefit from the FFS than being uneducated, or the inverse.

The paper will be structured in the following way. First, I will outline the previous literature on Farmer Field Schools in general and IFAD-FAO East Africa project more specifically. This review will also examine the literature on the PSM procedure. Second, I will evaluate the data using descriptive statistics, first outlining the characteristics of households in this dataset, and then highlighting pertinent means differences between the FFS and non-FFS participant samples. I will also explain the details of my PSM model and approach in more detail. Third, I will present the results of this analysis. Finally, I will draw conclusions and policy recommendations for future investment in this East African FFS and in development projects more broadly.

2 Literature Review: History of Farmer Field Schools and PSM Model

The first Farmer Field School (FFS) was implemented in Indonesia in 1989 as part of an integrated pest management project to educate on the use and over-use of pesticides in the region.8 Now, FFS projects exist more than 87 countries, including 27 African countries.9 They are seen as part of the framework to build demand-driven development projects: they focus on human capital development. In their seminal paper on FFS initiatives, Braun et al. attribute the comparative advantage of FFS projects in development work to their ability a) to deliver field-based learning; b) to understand the dynamics of agro-socio-ecological relationships through continual assessment; c) to have a peer-review collaborative aspect; and d) to foster individual and group capacity building.10 The methodological approach to FFS projects is to help farmers succeed by using critical decision-making skills to “study the ‘how and why’ of

9 Braun and Duveskog 20
10 Braun et al. vii
a particular topic.”11 The fast expansion of FFS programs around the globe and more specifically in Africa since the mid-1990s can be attributed to the multi-dimensional aspect of FFS. The FFS model has become increasingly attractive in the African context because it includes “special topics,” like health and nutrition programs on HIV/AIDS, malaria, and water hygiene.12 While this highlights the theory behind FFS initiatives, Figure 1 is an example of a sample daily schedule in order to better understand what an FFS looks in practice.13 As seen from the sample schedule, the FFS is a holistic learning model that helps to build a managerial skill-set for effecting farming.

Given the success of previous FFS projects, the International Fund for Agricultural Development (IFAD) Rural Poverty Report 2011 notes, “a critical role of FFSs is the ability to up-scale by spreading out.”14 To effectively and efficiently achieve this goal, there must be sufficient program evaluation; with evaluation, implementers can understand both where there is room for up-scale and to whom they should target the extension programs. It is to this need for program evaluation that this paper hopes to contribute.

Thus far, there has been little consensus on how to measure the impacts of FFS. To do this, one must decide what are the valid indicators of “success”: is it technology change, human capacity development, empowerment outcomes or something else?15 This project will focus on the changes in agricultural crop production value as a measure of “success.” This indicator is both concrete and connected to many of the other proposed indicators: technology change increases revenues by augmenting the speed of production, and high levels of production leads to empowerment as individuals have larger financial incomes to support themselves. Thus, productivity change simultaneously affects and is affected by many of the previously proposed indicators. Specifically, the dependent variable for “success” in this study will be the ATT calculated using the propensity score matching procedure: it is the difference in revenue change between a participant and his or her matched non-participant.

This project is integral to the growing literature and analysis of FFS programs. Most of the previous literature of FFS initiatives has focused on East Asia. There is a large silence in research evaluating FFS projects in the African context and this paper should help to open a discussion on FFS initiatives there. Nonetheless, the East Asian papers provide integral insight into the types of people who have previously benefited from the FFS structure. A report on a FFS in Vietnam noted that the in-person interaction of FFS projects helps to disseminate knowledge and that the “target farmers are poor smallholders that do not have high education levels.”16 Drawing from this, one can expect that it is the poorer and less educated families who will gain most from the FFS. In addition, Palis underscored the importance of culture in farmer extension schools in the Philippines. Since culture is integral to success in the collaborative process of the FFS,17 one would expect that individuals who are connected to other community groups or who actively participate in the local government to benefit more from the FFS. Lastly, a World Development report looked at the same dataset and FFS East Africa initiative to determine how the FFS initiative empowered individuals and affected well-being. In all three countries they found the effect on decision-making capacity, gender and trust, and critical thinking had significant effects at the 1% level.18 Their analysis motivates the inclusion of these types of active and involvement characteristics in my FFS analysis.

This project will focus on an FFS that was first implemented in East Africa starting in 1995. Then, in October 2005, the Food and Agriculture Organization (FAO) expanded its program for a second three-year-long phase. In coordination with the International Food and Agriculture Development (IFAD) organization, they implemented the IFAD-FAO FFS project in 8 districts of Kenya, Tanzania, and

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11 Braun and Duveskog 4
12 Ibid. 10
14 Braun and Duveskog 12
15 Ibid. 3
16 Rejesus et al. 410
17 Palis 492
18 Friis-Hansen and Duveskog 423
Uganda: Busia, Bungoma, and Kakamega; Bukoba and Muleba; Busia, Kabermaido, and Soroti. In 2006, the IFPRI collected ex-post data on the characteristics of participant and non-participant farmers and the production levels from pre- and post-FFS implementation. IFPRI selected 20 FFS programs in each country and identified non-participant villages that were similar to FFS participant villages along a series of observable characteristics to create a dataset with more than 1,000 household level observations.19

However, the placement of the FFS by the FAO within these eight districts was not random. The areas were chosen based on a) the applicability of the crops grown in that region to the FAO school model; b) the need to further integrate smallholders and extension programs; c) the need to test the new decentralized government structure; and d) the need to test links to other IFAD programs.20 The strategic implementation of this FFS creates an administration or program placement bias. The targeting of specific areas based on outlined criteria means that there are fundamental differences between the treatment and control groups that were actively identified and exploited. In addition, there is a self-selection bias.21 While the FAO chose to implement in certain areas, the decision to join a FFS was voluntary. Those who chose to participate may be different from non-participants in both observable (ex. education) and non-observable (ex. motivation) factors. The combination of the administration and selection biases means that any straight comparison between the treatment and non-treatment group will have a significant error and will overstate the effect of the FFS on the treated because the treated will be inherently more likely to succeed.

In 2010, Davis et al. undertook the first economic analysis and program evaluation of this East African FFS and published their report through the IFPRI. They asked, first, who participates in FFS and, second, what effect does “household-capital-endowment-level social characteristics” have on maximization. They broke down their analysis across gender, education, and poverty levels and found that women benefited more, the most uneducated benefited more and the land-medium (poverty tertile) benefited most, while there was little benefit to the poor and insignificant benefits to the rich.22 However, this analysis is incomplete and leaves many questions unanswered. The Davis et al. paper is an example of a partial equilibrium analysis: they looked at the change in one factor holding all other factors constant. They calculated the treatment effect and analyzed in along each socio-economic breakdown in isolation. This leaves one glaring question unanswered: For a poor, uneducated woman to what extent is she able to benefit most because she is a women and to what extent because she is poor or uneducated? This demands a full equilibrium analysis. A full equilibrium analysis quantifies the effect of several factor changes simultaneously. This full equilibrium analysis is necessary because the partial equilibrium analysis may suffer from omitted variable bias. Suppose, for example, that income did not matter, but that gender did and that female household heads were poorer. If there was a high correlation between income and gender, one may find that changes in income was significant in a partial equilibrium analysis, even though it was just picking up the effect of gender. As Dr. Micahela Saisana notes in her study, when evaluating in aggregation, the effects “may compensate the degradation of one variable by the improvement of an other variable. This stresses the necessity to always look not only at the aggregated values but also at the underlying figures.”23 Looking at the underlying figures requires a full equilibrium analysis of all characteristics simultaneously.

I will use a propensity score matching (PSM) difference-in-differences approach to undertake the program evaluation for this project. This type of evaluation addresses the two major issues with project data: first, the missing counterfactual inherent in all project data, and, second, the administration and self-selection bias that exists when the project is not a randomized control trial (RCT). The ideal for program

20 Davis et al. 2
21 Heinrich et al. 12
22 Davis et al. 31-32
evaluation is to compare how a participant did after participating with where that participant would have been if they had not participated. If one could collect this data, then one could calculate the average treatment effect on the treated (ATT) as follows:

$$\text{ATT} = (y_{i|p = 1}) - (y_{i|p = 0})$$

In words, the ATT is the output given that the farmer participated less the output had he not participated. However, there is the obvious and inherent missing counterfactual: you can’t see someone doing two things at the same time.

One can never know what would have happened to a participant if they have not participated, so the next best indicator is to establish an ATT that compares what happened to a participant with what happened to similar non-participants. The missing counterfactual demands a difference-in-difference approach. Employing this model, the ATT is calculated as:

$$\text{ATT} = [(y_{t+1|p = 1}) - (y_{t|p = 1})] - [(y_{t+1|p = 0}) - (y_{t|p = 0})]$$

The ATT is the difference between the change in yield for the participant and the change in yield for the non-participant.

The ideal for program evaluation is a randomized control trial. In such an experiment, the treatment has been randomly assigned so that “individuals assigned to the treatment and control groups differ in expectation only through their exposure to the treatment…This result tells us that when a randomized evaluation is correctly designed and implemented, it provides an unbiased estimate of the impact of the program in the sample under study – this estimate is internally valid.” An RCT lends itself to easy participant to non-participant comparisons. However, given that the East African FFS analyzed in this report was strategically implemented in certain areas, it fails the RCT assumption: there are inherent differences between the treatment and control populations and you can’t just perform a simple participant vs. non-participant comparison.

Propensity score matching helps to correct the non-randomized implementation bias. It “uses information from a pool of units that do not participate in the intervention to identify what would have happened to participating units in the absence of the intervention. By comparing how outcomes differ for participants relative to observationally similar nonparticipants, it is possible to estimate the effects of the intervention.” The idea is that after controlling for X, a vector of variables along which the treatment and control groups differ, the two subsets should be “as good as random” because the matching controls for observable heterogeneity in the two groups of data. It is essential to choose the correct variables to match individuals: including irrelevant variables increases the variance of the estimates and not including essential variables means that the dataset retains some of the original bias. Inevitably, the sample will maintain some error and bias from differences between the groups along unobservable factors (ex. motivation levels, innate intellectual ability, etc.).

The two major PSM matching procedures are nearest neighbor and kernel matching. This research paper uses the nearest neighbor procedure, but given that the kernel matching is a good future research extension, I will describe both. Nearest neighbor, one of the most straightforward methods, matches participants to non-participants with the closest propensity score, either with replacement (non-participants can be matched to multiple participants) or without replacement. The associated neighbor is defined, with j being the closest non-participant, as:

$$c(p_i) = \{j | \min \| p_i - p_j \| \}$$

Kernel matching is an expansion of nearest neighbor procedure in which participants are not just matched

\[24\] Heinrich et al. 10
\[25\] Ibid. 9
\[26\] Davis et al. 6
\[27\] Duflo et al. 3902
\[28\] Ibid. 3
\[29\] Ibid. 16
to the single non-participant with the closest propensity score, but to a set of non-participants who have close propensity scores up to a threshold and non-participants are weighted less the further they are from the participant’s propensity score. The neighborhood is defined by the following expression in which close propensities up to the threshold \( h \) are weighted \( j \):

\[
e(p) = \{ j \mid h > \| p_i - p_j \| \}^{31}
\]

Kernel matching allows the analysis to draw from a larger subset of data, creates more robust results, and decreases the bias.

3 Dataset Description and Empirical Strategy

The cleaned dataset used in this analysis contains 1,107 unique households from districts in Kenya, Tanzania, and Uganda. The breakdown of membership across the districts (including the two districts that were established by the IFPRI, the survey implementer, as offshoots of two of the original eight implementation districts) is summarized in Table 1. \(^{32}\) Kenya has the largest number of households and Uganda the smallest; Tanzania has the highest percentage of FFS members and Uganda the smallest. While the households for the survey were randomly selected, membership percentages and numbers are representative of the percentages and size of FFS reach in each of the three countries. Table 2 summarizes the breakdown of gender and education of the household head across the three samples. This research project focuses on the characteristics of the household head rather than the FFS member because this was method used by the IFPRI. In addition, the dataset contains more information on the characteristics and actions of the household head rather than the FFS member. However, it should be noted that when the household head is male, nearly 60% of the time the FFS member is female (the spouse); and when the household head is female, more than 85% of the time the FFS participant is female (the household head).

For majority of the interview sample, the household head is male (nearly 85% of the time). In addition, almost 9 out of every 10 household heads had a primary school level of education. Very few individuals surveyed had a tertiary level education; while the number of tertiary educated individuals is greatest in Kenya, it is important to note that in all three countries the majority of these highly educated individuals were FFS members. This is an example of the administration (placement) bias described above. Lastly, one of the independent variables of interest in this evaluation is poverty terciles. While there were no income variables in the dataset, land acreage ownership can be used as a proxy for poverty, as done in the Davis et al. paper: an individual is land-poor at one end of the spectrum, or land-rich at the other. The breakdown of terciles was defined for each country and the terciles are presented in Table 3. The poorest 33% of individuals surveyed in Tanzania owned less land than in the other two countries; the middle 33% of individuals in Uganda owned the greatest amount of land, although richest in Uganda individuals owned less land than in the other two countries.

This research project looks at the effect of six independent variables on productivity change. It includes three statistic variables: gender, education, and land-poverty tertile of the household head and, following previous literature, I hypothesize that female household heads would benefit more, the less educated would benefit more, and the land-medium would benefit more. In addition, it includes three active characteristics: group membership, leadership position, and government participation. Given the importance of cohesion and critical-thinking in the FFS process, I hypothesize that with any of these characteristics, an individual would benefit more. The dependent variable of interest was agricultural crop productivity change calculated as a matched ATT.

The full model will express the ATT for a given FFS participants as a function of the six identified independent variables.

\[
ATT = \beta_1(Sex) + \sum \alpha_i(Educ_i) + \sum \theta_j(Poverty_j) + \beta_2(CommPartic) + \beta_3(Leader) + \beta_4(Govt) + \varepsilon
\]

For a participant, the magnitude of his or her ATT is dependent on six observable characteristics. The size of the coefficient \( \beta \) (or \( \alpha \) or \( \theta \)) for each factor will be an indicator of the extent to which each

\(^{31}\) Essama-Nssah 23

\(^{32}\) Davis et al. 19
factor impacts an individual’s ability to maximize benefit from the FFS. Since one cannot assume a linear change in ATT with each improvement in education level or land-poverty tertile, each of those variables must be sub-divided and have their own coefficients. For example, if the hypothesis that the least educated benefit most holds, the benefit lost from getting a primary school vs. no education may be different than the education lost from getting a secondary vs. a primary school education. As a result, education can not just be included in the equation as β(Educ), but must be broken down into multiple bivariate dummies: $\alpha_1$(None) + $\alpha_2$(Primary) + $\alpha_3$(Secondary). For education, those with tertiary level education were omitted and used as the baseline comparison to avoid co-linearity among the bivariate dummies. For land poverty, it was the land-rich. The same holds for the country dummy variables when the regional dataset is used, and the Kenya FFS project serves as the baseline for the analysis.

Community participation is defined as participation in another farmer related group: a Community based organization, an NGO, a donor project, or a self-help group. The variable for government participation is an indicator of high levels of participation. The individual is considered an active participant if they participate in at least three of the following: 1) holding a religious or government leadership role; 2) having made a complaint about public service delivery in the past two years; 3) having petitioned political leaders for legal entitlements in the past two years; 4) participating in community meetings; and 5) voting in the last community wide election.

Before establishing the matched dataset and undertaking a rigorous analysis and evaluation of the East African FFS, it is important to establish the economic significance of the underlying assumptions. The first assumption is that there is a significant difference in benefits between the FFS and non-FFS participants. This ensures that there is a significant and sizable ATT. The second assumption is that there is a significant variation of benefit across each of the independent variables of interest. This implies that the independent variables will have a significant impact on the extent to which an individual maximizes benefit from the FFS. A series of means difference tests were done to test these assumptions and the results are presented in Table 4. For these means difference tests, a rough variable for the change in production revenue was constructed for each individual. The dependent variable is equal to the revenue (price*quantity) of agricultural production after the project was implemented less the revenue of production before as a percentage of the initial revenue. Outliers, identified as revenues changes more than three standard deviations from the mean, were excluded.

To test the first assumption, I looked at the difference in revenues changes between FFS non-participants and FFS participants. The difference is significant at the 1% level, suggesting that this assumption holds. Thus, there is a change in revenue from the before the project implementation to afterward that can be attributed to participation in the FFS and this change is significant. However, it must be noted that the rough means test establishes the significance of revenue change between the participant and non-participant groups on average, but gives no indication of whether the difference in revenue change between a participant household and that of its matched non-participant household will be significant.

Next, the second assumption was tested for each of the six identified independent variables. The dependent variable in each test was the percentage change in revenue using a sample of only FFS participants. Without a matched dataset I cannot identify or calculate an unbiased ATT for each FFS participant, so participant change in revenue was used in these means difference tests. However, it should be noted that this dependent variable includes both the change in revenue due to FFS participation and change in revenue due to exogenous changes over the time period (changes that would be picked up in non-participant revenue changes). Since the means difference tests require bivariate independent variables, education was defined as low – no education or primary education – and high – secondary or tertiary education, and land acreage as a proxy for poverty levels was defined as low – less than the median – or high – above the median. From the results it is clear that all differences are significant at the 1% level except group membership, which had no significance. Thus, for five of the six independent variables the second assumption holds: the independent variable has a significant impact on the extent to which an individual benefits. In addition, the results indicate that changes were significantly greater than 100% for all groups. However, since the change is greater than 100% for the control group as well (as
seen during the test for the first assumption) it is clear that there was a general trend for growth agricultural production over the period. This fact, combined with the fact that the dataset excluded outliers, decreases the fear that these results are unreasonable.

Before undertaking the full equilibrium analysis, I must establish my balanced dataset. In the evaluation paper by Davis et al., they identified the following factors as determinants of FFS participation: sex and education level of the household head, education level of the spouse, member of a savings or credit group, member of a farmer group other than FFS, earns off-farm income, the log of the age of the household head and household size, the child-adult dependency ratio, and the log of the distance to a tarmac road and to a market, both in kilometers.33 Those determinants, both those that were significant and those that were not, represent the set of factors X that will be used in the PSM for this paper. This is a comprehensive set of variables because it accounts for the four types of capital along which the samples could vary: human, physical, financial, and social.34 The variables for gender, age, and education are examples of human capital; land and distance to roads and markets are examples of physical capital, earning off-farm income and having a credit group are examples of financial capital; and membership in a saving group or in another group, as well as the household size and dependency ratio are examples of social capital. The four types of capital are the endowments that allow a person to succeed and accurately capturing these variables in the set of matching factors is essential for compiling a balanced dataset. While only some of these variables were significant in the Davis et al. matching regression, it is necessary to include all of the variables to mitigate endogeneity bias. Endogeneity bias is when selection in the treatment group is non-random and this results in correlations between the independent variable and other variables that are correlated with the outcome. 35 For example, if there is a correlation between gender and education level and the gender of the household head was not include in the X factor vector because it was not originally significant in the Davis et al. model, there would be an endogeneity bias and a miscalculation of the propensity score.

After calculating the propensity score for each household, participants and non-participants with be matched using a matching algorithm. This paper will employ the nearest neighbor-matching algorithm with replacement to create the largest possible dataset. Since the full equilibrium analysis breaks down the dataset into its smallest factor components, one might find a lack of significance due to the small data size. Thus, creating an unbiased dataset that is as large as possible is integral so that the economic regression analysis can be undertaken successfully afterwards.

3 Empirical Results: Bivariate and Regression Analysis

The empirical results of this research project can be divided into two sections: first, a bivariate analysis of a sample population average ATT, divided along the three factors that the 2010 IFPRI paper used in their analysis (gender, education and poverty), and second, a partial and full equilibrium analysis of the six factors identified as characteristics which could influence a person’s ability to benefit from the Farmer Field School. The full equilibrium analysis reveals the factors driving an individual’s ability to maximize benefit from the FFS are much more targeted than the bivariate and IFPRI analyses initially propose.

The dependent variable for this study was the ATT for agricultural crop productivity change. Crop productivity is defined as the value of crop production (quantity, * prices,) for each crop, totaled for each household, and divided by the total number of acres that the family harvested. The productivity change was then calculated as the change in agricultural production from before to after the implementation as a fraction of the production value before the FFS. The matching procedure was done by estimating a probit regression for each country using the set of factors identified by Davis et al. The

33 Davis et al. 11
35 Victor Menaldo, “What is Endogeneity Bias and How Can We Address It?” University of Washington, Political Science, January (2011): 3
results of this probit can be seen in Table 5. Propensity scores were then manually calculated for each individual using the probit regression; propensity scores range from 0, no likelihood of participation, to 1, complete certainty of participation. Next, treatment individuals were then matched to the non-treatment individual from the same country that had the closest propensity score. To better understand the accuracy of the nearest neighbor matching, histograms of the p-scores were created for the treatment and non-treatment group at the regional level. The histograms in Charts 1 and 2 show the distribution of p-scores for the treatment and control groups. For those who participated in the FFS, the distribution is not normal but skewed heavily to the right. This is consistent with the fact that the implementation was not part of a randomized control trial, but strategically placed by the FAO and program implementers. On the other hand, the histogram of those who did not participate shows a more normal distribution of p-scores, although it maybe slightly skewed to the left. Finally, the agricultural productivity change ATT was calculated as the difference in productivity change between the treatment and its matched non-treatment observation. Outliers more than three standard deviations from the mean were excluded. Given the difference in p-score distributions between the participant and non-participant, there may be a concern that the nearest neighbor matching procedure will not produce an adequately close non-participant match to all of the treatment observations. However, there was a large enough area of common support and matches were sufficiently precise given that for 95% of the matches the difference between the propensity score of the treatment and non-treatment was less than 0.01.

The bivariate ATT analysis was done for the three variables that the IFPRI study identified in their paper: gender of household head, education level, and land poverty level. The results confirmed the findings of the IRPRI analysis. The fact that the bivariate analysis matches the Davis et al. results adds confidence to the results of this research evaluation by ensuring that the full equilibrium analysis is building off the same partial equilibrium analysis as the previous study. Thus, I can be assured that any differences in results at the full equilibrium level are due to omitted variable bias, the high levels of correlation between the variables, and endogeneity bias at the partial equilibrium level rather than because the dataset and/or variable definitions are different between the Davis et al. report and this report.

The bivariate analysis was done by calculating one average ATT measure for an entire subset of the population (for example, for all of the female-headed households) using the nearest neighbor propensity score matching procedure and then comparing this subgroup ATT to the alternative subgroup with a simple test of means difference. Education level was taken as low if an individual had no or a primary level of education and high if he or she had a secondary or tertiary education. Land poverty poor was defined as individuals with less than the median acreage size for each region. For Kenya this was 2.25 acres, for Tanzania 1.5, and for Uganda 4.

Taking the region of East Africa as a whole, one can see that, on average, everyone benefited from the FFS but to varying extents. Women benefited significantly more than men and the less educated benefited significantly more than the more educated. Both gender differences and education level differences were significant at 1% level. There was no significant difference in benefit between the land-poor and the land-poverty rich, which is expected since it was the land-poverty medium who benefited most and these individuals (the middle 33%) would be divided half into the land-poverty poor and half into the land-poverty rich. These results are presented in Table 6 and Chart 3. It is important to note the breakdown of the gender of household heads: while 524 of the households in the survey had a male household headed, only 84 households had a female household head. This skewed breakdown of the household head could bias the results because there is insufficient variation and representation of female household heads.

However, the picture of benefit looks different at the country level. Not all of the findings that hold in aggregate hold at the individual country level. In Kenya, like in the aggregate, female household heads benefit more and the less educated benefit more and both of these are significant at the 1% level. In addition, in the Kenya dataset, it is the land-poor individuals who benefit more (by more than 40%) and this, too, is significant at the 5% level. The Kenyan dataset has the largest number of treatment individuals – 268 unique households – and accounts for almost half of the total sample. These results are presented in Table 7 and Chart 4. By contrast, the results in Uganda are drastically different from the
general results. For all groups except the female-headed households, individuals seem to be worse off after their participation in the FFS. The IFPRI report also found that the majority individuals in Uganda did not benefit from FFS participation. Only the differences in gender were significant (although these were significant at the 1% level) and female household heads saw a positive productivity change while agricultural productivity actually declined for male-headed households. These results are presented in Table 8 and Chart 5. Again, there is a data issue. While the observations are unbalanced for both gender and education level, the issue is most pronounced for the household head variable: just 20 households have female household heads. The small sample size raises concern that the results are not representative of the general population. Lastly, the Tanzania subset had slightly different trends than the other two countries or the regional data. Unlike the others, the richer did better and this is significant at the 1% level, and the more educated did better and this was significant at the 10% level. Male-headed households also did better, but this is not significant. These results are presented in Table 9 and Chart 6.

The bivariate factor analysis is a good starting point for the program evaluation of the East African FFS in this study. Like the original IFPRI report, the bivariate analysis is a type of partial equilibrium analysis. It shows a one-dimensional impact on the ATT, holding all else constant. It answers the questions of how does the ATT vary if you change one factor and is this variation significant. It appears from the bivariate analysis that the gender of the household head and the education level are the most important factors in determining the extent to which an individual benefits from the FFS because they are significant in three of the four models, although land-poverty tertile had some significance, as well. Due to the fact that multiple factors are significantly influencing an individual’s ATT and ability to benefit from the FFS, a program analysis of the FFS cannot end here. It is insufficient to stop here because of the high correlation between many of the factors. For example, in a regression of other factors of interest in this study on those with a primary level of education level of the household head, one finds that the gender of the household head, the other levels of education, group participation, and the possession of a leadership position are all significant at the 1% level – the majority of variables are significantly correlated with the education level of the household. These results are presented in Table 10. All else equal, a person is significantly more likely to have a primary level of education if he/she is female, if he/she is land rich, if he/she is not member of other farmer groups, if he/she does not hold leadership positions, and if he/she does not participate in the government. The high correlation between the individual factors means that saying that a person benefits more from the FFS when they are less educated is not entirely indicative of the effect of education on crop productivity change: the differences in ATT broken down solely along education level may be attributed to one or many of the correlated factors. To better parse out which factors are affecting the ATT and how, one must use a full equilibrium analysis.

The full equilibrium analysis was run for each country and then for the regional dataset. The results are shown in Tables 11, 12, 13, and 14. Columns 1, 2 and 3 are complements to the bivariate analysis. Column 4 displays the ATT as a function of the three variables of interest as identified by IFPRI and Column 5 displays the ATT as a function of the three new variables of interest. Columns 6 and 7 combine the two to show the ATT as a function of the six variables of interest, first without village fixed effects and then with them. In the pooled dataset model, there is a Column 8, which runs the full regression, including village fixed effects, but excluding the country dummies. All functions were run with robust standard errors to account for heteroskedasticity in the error term.

The results from the regional dataset include observations from Kenya, Tanzania, and Uganda. These results can be seen in Table 11. There are several things to take away from these results. First, the results confirmed the results of the partial equilibrium analysis. The coefficient on gender is positive, as is the coefficient on land-medium poverty individuals and the coefficients on education are all positive, with the coefficient increasing in magnitude for the less educated individuals. Second, the variables that are consistently significant are those related to education. The coefficient on both no and primary level education is significant across the models – in most regressions at the 5% level, both when it is taken on
its own and as one of many factors in the full equilibrium analysis. Thus, it is the education level of the participant that is most significantly impacting the extent to which he or she benefits from the FFS. In addition, the decrease in significance and value of the coefficient on education in the full model does confirm that the bivariate analysis picks up on much of the variable correlation. Third, while they are not significant, it is important to note that the coefficients on leadership and group membership do not follow my hypothesis: they are both negative. Thus, it is people who are not in other community groups and not taking leadership positions who do better. An explanation for this may be that those who are in leadership positions or who are members of other farming related groups may already have the analytical and critical skills needed to maximize productivity and thus had little to gain from participation in the FFS. This will be explored more in the conclusions. Lastly, it is important to note that the coefficients for both Tanzania and Uganda are significant, mostly at the 1% level, indicating that the level of benefit highly depends on the country of the FFS participant. However, when the country dummies were not included, the results and significance of the other variables remained similar to the previous regressions, indicating that the country is more important in determining the level of benefit rather than which factors are most influential in determining the level of benefit. The only coefficient that changes sign is that for group membership.

The results become more nuanced at the country level. The only trend that is consistent through all three is that at least one of the education variables is significant in each country. In Kenya (Table 12), the same patterns hold as the full equilibrium pooled dataset model and the Kenya bivariate analysis. While neither the gender nor land-poverty coefficients are significant, female-headed households benefit more, as do the land-medium household (followed closely by the land poor). Education is significant and it is those with a primary education who benefit most (followed closely by those with no education). Those with a primary level of education benefit significantly more at the 5% level. What is interesting is that the coefficient on gender of the household head drops from 1.09 in Column 1 to 0.74 in Column 7. This indicates that the high levels of correlation with low education and land-poverty upward bias the effect of gender on ATT when taken on its own (in the partial equilibrium analysis). Again, for the three active factors, only high government participation is positive, although none of the three are significant. In Tanzania, (Table 14) the results are slightly different. Like in Kenya, female-headed households benefit most and those with less education – in this case no education – who benefit most. It is interesting that the sign on gender of the household head is positive while it had been negative in the bivariate analysis. However, gender is not significant in either case and the difference in sign can be attributed to the inclusion of village fixed effects. In addition, it is interesting that the uneducated benefit most when it was those with a high level of education that benefited most in the bivariate analysis. While the tertiary did the worst, it was those with the primary level of education who did second worst. Thus, with a large number of individuals with a primary level of education and very few with a tertiary level of education, it may look like it is those with a high level of education did better than those with a low level of education (as seen in the bivariate analysis), even though this pattern does not hold in disaggregation. This finding only further underscores why it is inadequate to stop at the partial equilibrium or bivariate analysis. Even more, it is not the land-medium, but the land-rich who benefit most. The land-poor do the worst, and this is significant throughout the entire set of regressions. While the effect of being entirely uneducated is significant when taken on its own, it looses significance in the full factor model. Simultaneously, the land-poor gains significance at the 5% level. This, again, indicates the high level of correlation in variables. Looking at individuals in Tanzania who are land-poor, one can note that 83% have a primary level education and 93% have a primary education or less. This confirms that the variables are highly correlated. Finally, in Uganda (Table 13) one again finds that the female-headed households do best, the land-rich do best, and the less educated do best. However, it is not the lowest level of education but the secondary school educated individuals who benefit most and this is significant at the 5%. After that, those with no education benefit most. Like in Tanzania, it is the land-rich who benefit most, followed closely by the land-medium. Similar to the full dataset analysis, the coefficient on group membership and leadership position are negative and that on government participation positive. For the first time, however, the coefficient on leadership is significant. Given the little fluctuation in coefficients across the models, it is clear that there is less correlation in variables in Uganda. Still one can note from the places where there
are changes that no education is correlated with being land-medium and the three static characteristics are correlated with group membership and leadership positions.

In summary, the full equilibrium analysis reveals several points about who benefits most from participation in the FFS. First, although several factors may look significant in the bivariate analysis, this is due to the high correlation between many of the individual characteristics and the lack of controlling for village fixed effects. Ultimately, only one or two variables are significant in each model and this consistently includes at least one education variable. Second, when looking at the gender of the household head, it is unanimous that female-headed households benefit more. In addition, it is clear that the less educated benefit more and the richer benefit more, although the exact subgroup of who benefits most is country specific. Third, when looking at the active variables, while not significant (except in one instance), all models consistently demonstrate that taking leadership positions or being a group member is not beneficial while participating in government is.

4 Conclusions

The program evaluation undertaken in this research project has implications for both the future of the East African FFS and for related socio-economic development projects. The results of the analysis confirmed the Davis et al. results, but nuanced them so that development projects can be more targeted and effective in the future.

First, it should be noted that education is the most important factor in determining who benefits from the FFS. The importance of education in the FFS model fits within the larger development debate. Amartya Sen, an important individual in the field of economic development, highlights, “what people can positively achieve is influenced by economic opportunities, political liberties, social powers and the enabling conditions of good health, basic education and the encouragement and cultivation of initiatives.” The FFS is a good model in the short run to improve the livelihood of uneducated individuals. In the long run, however, the FFS needs to improve and expand its model to be more compatible with higher levels of education, perhaps segmenting its methodology for different education levels. Those with higher levels of education already possess many of the critical thinking skills that the FFS seeks to teach, so the programs should instead focus on education surrounding production and market efficiencies or managerial skills so that the more educated individuals can oversee larger plots of land and larger groups of farmers. For an example of how to target the more educated, one can also look to the model of Uganda where it is individuals with secondary education who benefited most.

Second, it is important to note that in no country did the land-poor benefit most and in Tanzania the land-poor did the worst significantly at the 5% level. Perhaps the lack of benefit has to do with the fact that the small size of the land plots inhibits economies of scale. Thus, the small-land holding farmers cannot implement the techniques they learned in an efficient way. A possible solution for this problem would be to implement future FFS initiatives in coordination with a cooperative farming project. The University of Wisconsin Center for Cooperatives defines cooperatives as development models that “combine people, resources, and capital into larger, more viable and economically competitive units.” As economically competitive units they are more likely to reap the benefits of an FFS. In addition, this fits into a broader scholarly discussion on Africa’s “missing middle.” The picture in Africa has typically been one of a myriad of microfinance enterprises along with a handful of major corporations. However, according to the African Business Magazine, “Africa’s small and medium enterprises (SMEs) offer huge scope” even though they are currently underfinanced because they are too big to receive microfinance

37 Amartya Sen, Development as freedom, Oxford Paperbacks (2001): 5
grants and too small to be effectively served by corporations. Their typical lack of support explains why the land-medium individuals stood so much to gain from the East African FFS.

Third, there is the question of why Uganda overall did not benefit as much as the other two countries. The Davis et al. provides some insight into why the FFS was less successful in Uganda:

“The FFSs’ nonsignificant impact in Uganda may be due to the presence of the National Agricultural Advisory Services (NAADS) program, which was running concurrently in the districts where FFSs were operating. For example, Soroti and Kabermaido districts were among the NAADS trailblazing districts, and NAADS started operating in Busia in 2003. The presence of a well-advanced demand-driven program in Uganda could have contributed to the weak impact of FFSs.”

Individuals are less likely to benefit from the FFS when they already have the resources and tools to learn and implement critical thinking skills in a market driven way. This same line of logic may explain why the results for two of the active characteristics, namely group participation and leadership position, had the opposite sign as what was originally hypothesized. Those who were in other farmer related groups, especially those who were taking leadership roles, would have already developed the critical thinking, analytical and collaborative skills needed to succeed in farming and crop production, and they had little to gain from the East Africa FFS. In expanding the FFS, the FAO may want to focus on areas where there are no other FFS programs and no other farmer or non-farmer related groups.

In addition, this project has many options for further research. First, this paper assumed that each independent variable has the same effect on the ATT, regardless of other variables. This is probably not entirely accurate. One can correct for this endogeneity bias by establishing a model that includes significant interaction terms. Given the high correlation of the variables it may be important to identify not just what is the effect of variable X on ATT but what is the effect of variable X given the precondition of variable Y. Interaction terms can answer this question. Second, this model could be replicated with a different dependent variable. The IPFRI report also used livestock productivity change and agricultural productivity change and including these could nuance the development of FFS projects in the future. Third, it would help to replicate the matching using the kernel matching procedure. This would make the results more robust, but would require a mechanism to feasibly identify the set of non-participant matches and their associated weights for each participant. Finally, an additional comment must be made with respect to the sample size. The sample size overall, especially at the country level, is relatively small. When one undertakes the full equilibrium analysis, one must break the dataset into its smallest factor components. This is a partial explanation for the low levels of significance in the full equilibrium model. In order to better undertake the full regression analysis and to capture the highest level of significance, a larger dataset must be used. Perhaps redoing the analysis after further expansion of the FFS would provide more significant results.

Ultimately, this research project leaves an optimistic message for the future of the East African FFS and broader development programs in the area. The results of this project confirmed and nuanced the Davis et al. report. Certain factors help an individual to benefit – and significantly benefit – from the East African FFS. By focusing on the education level of FFS members, FFS implementers can both target the extent of individual benefit and improve the FFS model to better coordinate with other development goals. The FFS is a model for growth – for agricultural crops, for the individual, and for the community. Harnessing and maximizing this growth is a feasible and worthwhile goal.

40 Davis et al. 13
Table 5: Probit for Determinants of Participation in FFS

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Kenya</th>
<th>(2) Tanzania</th>
<th>(3) Uganda</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender HHD</td>
<td>-0.08</td>
<td>-0.01</td>
<td>-0.25</td>
</tr>
<tr>
<td></td>
<td>(0.218)</td>
<td>(0.195)</td>
<td>(0.266)</td>
</tr>
<tr>
<td><em>HHD (c.f. none)</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary</td>
<td>0.08</td>
<td>-0.18</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td>(0.306)</td>
<td>(0.248)</td>
<td>(0.311)</td>
</tr>
<tr>
<td>Secondary</td>
<td>0.15</td>
<td>-0.08</td>
<td>-0.43</td>
</tr>
<tr>
<td></td>
<td>(0.340)</td>
<td>(0.263)</td>
<td>(0.359)</td>
</tr>
<tr>
<td>Tertiary</td>
<td>0.19</td>
<td>-0.80</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(0.524)</td>
<td>(0.540)</td>
<td>(0.470)</td>
</tr>
<tr>
<td><em>Spouse (c.f. none)</em></td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>-0.20</td>
<td>-0.44</td>
<td>-0.48**</td>
</tr>
<tr>
<td></td>
<td>(0.219)</td>
<td>(0.324)</td>
<td>(0.219)</td>
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<td>-0.80*</td>
<td>-0.13</td>
</tr>
<tr>
<td></td>
<td>(0.297)</td>
<td>(0.474)</td>
<td>(0.322)</td>
</tr>
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<td>Tertiary</td>
<td>-0.76</td>
<td>-0.84</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.616)</td>
<td>(0.833)</td>
<td></td>
</tr>
<tr>
<td><em>Mem. Credit or Saving</em></td>
<td>-0.66***</td>
<td>-0.68***</td>
<td>-0.86***</td>
</tr>
<tr>
<td></td>
<td>(0.193)</td>
<td>(0.214)</td>
<td>(0.246)</td>
</tr>
<tr>
<td>Group Member</td>
<td>0.60***</td>
<td>0.70***</td>
<td>-0.26</td>
</tr>
<tr>
<td></td>
<td>(0.168)</td>
<td>(0.189)</td>
<td>(0.273)</td>
</tr>
<tr>
<td>Earn off-farm Inc.</td>
<td>-0.10</td>
<td>0.26</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>(0.196)</td>
<td>(0.182)</td>
<td>(0.207)</td>
</tr>
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<td>Log (Age HHD)</td>
<td>-0.58</td>
<td>-0.50**</td>
<td>0.25</td>
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<tr>
<td></td>
<td>(0.380)</td>
<td>(0.250)</td>
<td>(0.286)</td>
</tr>
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<td>Log (HH size)</td>
<td>0.24</td>
<td>0.16</td>
<td>0.04</td>
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<tr>
<td></td>
<td>(0.210)</td>
<td>(0.224)</td>
<td>(0.146)</td>
</tr>
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<td>Dependency Ratio</td>
<td>0.00</td>
<td>-0.01</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.107)</td>
<td>(0.062)</td>
</tr>
<tr>
<td>Log (dist to road, km)</td>
<td>-0.12</td>
<td>0.05</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td>(0.141)</td>
<td>(0.083)</td>
<td>(0.110)</td>
</tr>
<tr>
<td>Log (dist to mrkt, km)</td>
<td>0.17</td>
<td>0.01</td>
<td>0.29**</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.089)</td>
<td>(0.148)</td>
</tr>
<tr>
<td>log (acerage)</td>
<td>-0.02</td>
<td>-0.05</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td>(0.122)</td>
<td>(0.138)</td>
<td>(0.155)</td>
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<td>Constant</td>
<td>2.34</td>
<td>2.81**</td>
<td>0.32</td>
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<tr>
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<td>(1.630)</td>
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<td>(1.254)</td>
</tr>
<tr>
<td>Observations</td>
<td>392</td>
<td>378</td>
<td>327</td>
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</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 6: Bivariate Means Difference Analysis, Regional Dataset

<table>
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<tr>
<th>Gender</th>
<th>Male</th>
<th>Female</th>
<th>Difference</th>
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<tbody>
<tr>
<td>Observations</td>
<td>524</td>
<td>84</td>
<td>608</td>
</tr>
<tr>
<td>Mean</td>
<td>1.57</td>
<td>2.63</td>
<td>-1.06</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>3.54</td>
<td>3.99</td>
<td>0.42</td>
</tr>
<tr>
<td>P-score</td>
<td>0.01</td>
<td></td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Educ. Level</th>
<th>Low</th>
<th>High</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>418</td>
<td>190</td>
<td>608</td>
</tr>
<tr>
<td>Mean</td>
<td>2.14</td>
<td>0.80</td>
<td>1.34</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>3.88</td>
<td>2.90</td>
<td>0.32</td>
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<td>0.00</td>
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<table>
<thead>
<tr>
<th>Povt. Level</th>
<th>Low</th>
<th>High</th>
<th>Difference</th>
</tr>
</thead>
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<td>Observations</td>
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<td>309</td>
<td>608</td>
</tr>
<tr>
<td>Mean</td>
<td>1.91</td>
<td>1.58</td>
<td>0.33</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>3.90</td>
<td>3.31</td>
<td>0.29</td>
</tr>
<tr>
<td>P-score</td>
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</table>

Table 11: Full Equilibrium Regression, Regional Dataset

<table>
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<th>ATT</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
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</thead>
<tbody>
<tr>
<td>Country (c.f. Kenya)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tanzania</td>
<td>-0.77</td>
<td>(0.509)</td>
<td>0.05</td>
<td>-0.84*</td>
<td>-0.92*</td>
<td>-1.07***</td>
<td>-1.07***</td>
<td></td>
</tr>
<tr>
<td>Uganda</td>
<td>-1.59***</td>
<td>(0.502)</td>
<td>0.05</td>
<td>-1.60***</td>
<td>-1.80***</td>
<td>-1.96***</td>
<td>-1.94***</td>
<td>-1.94***</td>
</tr>
<tr>
<td>Gender HHD</td>
<td>0.67</td>
<td>(0.580)</td>
<td>0.05</td>
<td>0.54</td>
<td>0.54</td>
<td>0.54</td>
<td>0.61</td>
<td>0.576</td>
</tr>
<tr>
<td>Education (c.f. Tertiary)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>1.16**</td>
<td>(0.523)</td>
<td>0.05</td>
<td>0.99*</td>
<td>0.99*</td>
<td>1.10**</td>
<td>0.502</td>
<td>0.576</td>
</tr>
<tr>
<td>Primary</td>
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<td>(0.376)</td>
<td>0.05</td>
<td>0.85***</td>
<td>0.85***</td>
<td>0.911**</td>
<td>0.576</td>
<td>0.576</td>
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<tr>
<td>Seconary</td>
<td>0.41</td>
<td>(0.321)</td>
<td>0.05</td>
<td>0.41</td>
<td>0.41</td>
<td>0.67*</td>
<td>0.347</td>
<td>0.347</td>
</tr>
<tr>
<td>Land Poverty (c.f. land rich)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land Poor</td>
<td>-0.06</td>
<td>(0.279)</td>
<td>0.05</td>
<td>-0.10</td>
<td>-0.14</td>
<td>-0.14</td>
<td>-0.03</td>
<td>0.283</td>
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<tr>
<td>Land Medium</td>
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<td>(0.482)</td>
<td>0.05</td>
<td>0.17</td>
<td>0.12</td>
<td>0.12</td>
<td>0.32</td>
<td>0.32</td>
</tr>
<tr>
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<td>(0.320)</td>
<td>0.05</td>
<td>-0.46</td>
<td>-0.46</td>
<td>-0.46</td>
<td>0.42</td>
<td>0.42</td>
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<tr>
<td>Leader Pos.</td>
<td>-0.27</td>
<td>(0.227)</td>
<td>0.05</td>
<td>-0.20</td>
<td>-0.20</td>
<td>-0.20</td>
<td>-0.13</td>
<td>0.219</td>
</tr>
<tr>
<td>High Govt. Partic.</td>
<td>0.12</td>
<td>(0.227)</td>
<td>0.05</td>
<td>0.17</td>
<td>0.17</td>
<td>0.17</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Constant</td>
<td>1.67***</td>
<td>(0.424)</td>
<td>0.05</td>
<td>1.76***</td>
<td>1.07***</td>
<td>1.04***</td>
<td>1.84***</td>
<td>1.84***</td>
</tr>
<tr>
<td>Village Fixed</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
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<td>591</td>
<td>591</td>
<td>591</td>
<td>591</td>
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<td>591</td>
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<tr>
<td>R-squared</td>
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<td>0.054</td>
<td>0.064</td>
<td>0.068</td>
<td>0.058</td>
<td>0.074</td>
<td>0.074</td>
<td>0.022</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
References
THE IMPACT OF EDUCATION ON WAGES: ANALYSIS OF AN EDUCATION REFORM IN TURKEY

Leyla Mocan
Wharton School of Business
University of Pennsylvania

ABSTRACT

In 1997 Turkey passed a law making middle school completion compulsory, increasing the mandatory education from 5 to 8 years. Using exposure to this law as an instrument for middle school completion, this paper estimates the causal impact of additional educational attainment on wages of Turkish workers based on data from the 2011 and 2012 Turkish Household Labor Force Survey. The reform had a significant impact on the propensity to obtain middle school diploma and the impact was greater for female students. Furthermore, the reform increased students’ propensity to complete high school and college, but decreased their propensity to obtain a vocational high school diploma. The middle school diploma, which is associated with three extra years of schooling, created 8-11 percent increase in male wages. For females, the return to the middle school diploma is two-to-three times larger than the impact on males. Increased education had no impact on labor force participation, full-time work, or the propensity to work in a small firm.

Acknowledgements

I thank Mark Duggan for his guidance and helpful comments and Alptekin Avcioğlu, Berk Avcioğlu, Ekrem Cunedioğlu and Bahadır Dursun for their help in obtaining the data. Nate Barrett, Colin Cannonier and seminar participants at the 38th Annual Conference of the Association for Education Finance and Policy in New Orleans on March 15, 2013 as well as participants of the Carroll Round Conference at Georgetown University provided valuable comments. I thank Martin Asher and Bethany Schell for their support. Summer funding for this research was provided by Wharton SPUR Program. I thank the Trustees’ Council of Penn Women and the Wharton Public Policy Initiative for providing travel funding for the AEFP Meeting and the Carroll Round. Finally, I thank Naci Mocan for his support and encouragement.
ABSTRACT

This paper describes a preliminary version of the estimation model of the quantity theory of money in the case of Mongolia. This model is made up with theoretical and empirical concepts so that we can forecast inflation using empirical suitability and consistency. This paper consists of three main parts – a description of money growth and monetary policy during and prior to the transition period, stability of the long-run relationship among price level and money growth (including velocity explanation on collected time series data). In the final part, I examine the effect of the financial market on the inflation process.

The intended primary purpose of the model is to analyze the monetary transmission mechanism and the inflation process in Mongolia including investigation and forecasting of macroeconomic variables (e.g. exchange rate, inflation, price level, interest rate) and consistence with the lags in the monetary transmission mechanism.

Acknowledgements

I would like to thank my Adviser, Prof. Jeffrey Nilsen, for his continuous support, help, and advice throughout my work, as well as my father, mother, professors and friends, who were involved in this research project. Without their help and support, the following work would not be possible. You made my dream came true.

I am thankful to my university, American University in Bulgaria for supporting me to participate in the Carroll Round Conference.

1 Introduction

Until 1990, Mongolia had a centrally planned economy for sixty years. All production and distribution activities were reserved for the state and concentrated in large monopolistic enterprises. Moreover, monetary policy was conducted by the single state bank and mainly focused on public sector credit. The central credit plan operated like a global directed scheme; moreover, interest rates were not a factor in the mobilization and allocation of resources or in managing aggregate demand.

This picture changed when Mongolia started its transition from a centrally planned to a market economy, and monetary policy has become more important since 1991. During the transition period, monetary authorities have adopted a realistic approach and stabilized inflation through a stable growth in the money supply and very high real interest rates.

Central banks use many sources of information to predict future inflation rate based on money growth (Pagan, 2002). In this paper, I also show the relationship between the measures of money growth and inflation.

The inflation and money growth model that I am evaluating has the following characteristics:

- Analyzing statistical properties of model equations and their economic consistency
- Deriving responses of selected variables and describing their suitability in the case of the Mongolian economy
- Performing additional checking of forecasting properties and endogenous part of the model

1 http://www.mongolbank.mn/eng/listmonetarypolicy.aspx?id=
The purpose of this research is to analyze the quantity theory of money to reveal whether the theory can be applicable for the economic situation of Mongolia, and the empirical section investigates the interaction between inflation and money growth in the period 1991-2012. This research is based on theoretical regression models from previous research (Friedman 1956, 1968; Klein 1956; Friedman and Schwartz 1982; Harberger 1963; McCandless and Weber 1995; Rolnick and Weber 1997). The variables included in this study have also been suggested by this previous research.

2 Literature and Methodology Review
2.1 Background

The empirical evidence in favor of and against the quantity theory has been checked around the world over the last half century. It has been tested for Taiwan (Chen, 1979), France (Riley, 1983), India (Moosa 1997), the People’s Republic of China (Chow, 1987), Greece (Karfakis 2002, Ozmen 2003) and the United States (Lucas 1980), as well as several cross-country studies (Cagan 1956, Karras 1992, Lothian 1988, and Gupta 1995). Cagan (1956) analyzed seven countries’ (Germany, Greece, Hungary, Poland, Russia and Austria) hyperinflations and found the parameters of money growth, which estimated during hyperinflation, generally satisfy the condition of dynamic stability that prevents inflation from being “self-increasing.” It also shows a high correlation between monthly inflation and money growth. Therefore, their research follows Fisher’s argument about the velocity dependence on the institutions and the technology features of the economy, and assumes velocity is constant (i.e. equal to one).

Several authors have rejected the velocity stability from quantity theory of money (QTM) as an explanation of inflation. Their research (Baba, Hendry, and Starr (1992), Estrella and Mishkin (1997), and Cochrane (1998)) claims that the income velocity (V) of monetary aggregates (M1 and M2) is not stable and not fairly close to one in majority country cases.

Arnold Harberger (1963) used Chilean data and a monetarist framework to examine inflationary dynamics. Harberger transformed the quantity theory of money (QTM) to apply a linear regression model using percentage changes. He included a General Consumer Price Index (GCPI) and current and lagged values of the money supply. Vogel confirmed the compatibility of this regression model (1974) with individual time-series regressions on 16 developing countries’ cases. He also discovered that there was a great contrast of diversity between money growth and inflation.

The numerous and remarkable economic literature generally ignores the case of Mongolia, and this is the gap that I am filling. Mongolia is one of the largest territories in Asia and is represented as a trade bridge between Russia and China. I examine how well this theory explains the relationship path of inflation and monetary variables for a 20-year period (1991-2011)

2.2 Mongolian Monetary Policy in Transition

As economists of the monetary policy division of the Central Bank of Mongolia say, “a market-based monetary policy depends on the existence of a market for money and foreign exchange. Specifically, reserve requirements, refinance windows, government and central bank bills and bonds, and credit allocation through banks or credit auctions are needed.” If the institutional framework for monetary policy and these specific monetary instruments are lacking or malfunctioning, the conduct and effectiveness of monetary policy will be impeded. Most transition economies have gradually established an institutional framework and introduced instruments and financial markets that function like those in developed countries, although they are smaller and less liquid.

The key differences between monetary policy in a transition economy and monetary policy in a developed market economy are the effectiveness of financial markets and the inflation process. Before market based monetary policy can work, there must be a market for money and foreign exchange. In other words, it is important to have reserve requirements to support government bonds (for soaking up liquidity), credit allocation through banks or credit auctions, and a removal of credit ceilings and interest rate controls on commercial banks’ rates.

2 http://www.mongolbank.mn/documents/tovhimol/
Mongolia developed the role of monetary policy in the beginning of the transition. In May 1991, a two-tier banking system was developed to replace the previous central bank system. In August 1991, the central bank introduced reserve requirements at 20 percent on business deposits and 15 percent on household demand deposits, and these have later been adjusted several times. The Banking Law of Mongolia adopted in 1996 states two primary objectives of the Mongol Bank (the Bank of Mongolia): to ensure price stability of the Mongolian Tugrug (domestic currency) and to act as a supervisor of the financial system. In terms of policy, the two-tier system has functioned as one of the highest interest rate regimes in the world. The average monthly interest rates on loans from the Mongol Bank (the Bank of Mongolia) to commercial banks charged economic entities and individuals monthly interest rates that ran as high as 17 percent in 1993. With a relatively high exchange rate and a low money multiplier, the policy of keeping a high real interest rate has been maintained throughout the transition period in order to maintain and restore confidence in the banking system.

Starting from the first half of 1998, inflation fell below 10 percent over twenty months and has stayed low (Figure 1).

Still, the Mongolian economy suffered significantly from the Asian crisis in 1997 and the Russian crisis in 1998. During this period, authorities have focused on the USD/MNT rate and, as a consequence, the effective exchange rate (both nominal and real in terms of dollar appreciation) appreciated significantly in 1997 and 1998. This appreciation has to some extent been instrumental in lowering inflation from the moderate range to the single-digits. (Figure 2)

The Central Bank of Mongolia is committed to achieving low and stable inflation and calibrates monetary policy accordingly (IMF, 2012). To do so successfully, it requires a good understanding of the factors driving inflation, and, in particular, the ability to distinguish price pressures due to exchange rate, interest rate and imported goods.

Many developing economies are highly dependent on foreign inputs. This has certainly been true for the Mongolian economy since 1991. Mongolian imports were worth 585 Million USD (62% of GDP) in June 2012. From 1997 until 2012, Mongolia imported an average of 278.7 Million USD reaching an all time peak of 663.3 Million USD in August of 2011 and a record low of 77.8 Million USD in March of 1997. Mongolia imports mainly mineral products, machinery, equipment, electric appliances, vehicles, food products, and base metals. Mongolia’s main import partners are Russia (22% of total) and China (26%). Others include Japan, USA and Germany. Therefore, an increase in the price of these inputs would necessarily affect the price level.

2.3 Can Monetary Policy be effective during Transition?

Over the transition period, Mongolia’s banking sector has faced major challenges, including a high volume of nonperforming loans. To strengthen the banking system, measures have been taken under IMF-supported programs to reduce operating costs, resolve the financial situations of insolvent banks, and increase loan recoveries. The ratio of foreign exchange deposits to broad money has, for most years, been less than 20 percent, the average for all transition countries since 1991. But the interest spread, defined as the difference at the end of the year between the rates on short-term bank loans in domestic currency and rates on deposits was, over the same period, one of the highest in the transition countries. Throughout the transition period, high interest rates have been maintained to preserve and restore confidence in the banking system. To analyze the role of policies-and, in particular, monetary policy-during the transition one must examine the relationship between monetary variables, inflation, and real economic activity. During the 1990s, Mongolia managed to diversify its markets, and China became one of its fastest growing trade partners. In 1998, exports to China reached to 30.1 percent of total Mongolian exports, followed by Russia (12.1 percent) and South Korea.

Trade (expressed in billions of US$):

<table>
<thead>
<tr>
<th></th>
<th>Exports</th>
<th>Imports</th>
</tr>
</thead>
<tbody>
<tr>
<td>1980</td>
<td>0.403</td>
<td>0.548</td>
</tr>
<tr>
<td>1985</td>
<td>0.689</td>
<td>1.096</td>
</tr>
<tr>
<td>1990</td>
<td>0.661</td>
<td>0.924</td>
</tr>
<tr>
<td>1995</td>
<td>0.473</td>
<td>0.415</td>
</tr>
</tbody>
</table>

An important relationship exists between net exports and the real exchange rate within a country. When the real exchange rate appreciates, the relative price of home country goods is higher than the relative price of goods abroad. In this case, import is likely because foreign goods are cheaper, in real terms, than domestic goods. Thus, when the real exchange rate is high, net exports decrease as imports rise. Alternatively, when the real exchange rate is low, net exports increase as exports rise. This relationship helps to show the effects of changes in the real exchange rate.

2.4 What did Mongolia learn from its transition period?

Between 1996 and 2000, practically all limitations on foreign trade disappeared and taxes were lowered, but this couldn’t bring the desired economic situation. Mongolia has long been dependent on

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5 International Monetary Fund. *International Financial Statistics Yearbook 1999*.

foreign powers. After 1990, dependence on the Soviet Union and the Comecon countries\(^7\) was transferred to Western nations and Japan.\(^8\) So far, however, this has neither slowed down social differentiation nor has it established lasting economic growth. Instead, national debt has steadily increased during the last decade, reaching 90% of GDP in 2001. Although the debt is mostly from international financial institutions and bilateral donors, servicing it still creates problems in current inflation. Inflation still remains as an unknown variable to predict. The only way to control and keep the inflation in targeted level is to have successful monetary policy and high control over money aggregates and interest rate.

3 Model Specification
3.1 Model

The QTM relationship requires two conditions. First, there be a proportional relationship between the growth rates of money supply and price level. Second, money must be neutral which results from stationary velocity of money and an unaffected real output level in the long run following the permanent changes in the growth rate of money supply. The QTM provides the independent assumption about the behavior of income velocity. In paragraphs below, there will be sufficient modifications and explanations whether velocity should be explicitly or implicitly included in the regression.

Basically, the velocity of money is the number of times a unit of currency changes hands within a given period of time (Mankiw 2000). Most theories in economics assume that the velocity of money is constant in the long run. There is disagreement about whether a constant velocity is achieved by monetary policy or velocity is already constant by its nature (De Long 2000). Conversely, most economists agree that if velocity were constant, and a nation’s central bank could implement monetary policy (increasing or reducing the amount of money in circulation), the banking system would never face with any troubles (Rousseas 2009).

3.2 Harberger – Hanson model and Quantity theory of Money

The theory is justified only to the extent that when some exogenous event disturbs the relationship between money aggregates and the price level, the price level rises sufficiently to catch up to the change in money aggregates. To show it in practice, I use Equation (3) below, which represents a “differenced in natural logarithm” form of the QTM in order to take advantage of elasticity. The econometric model based on the quantity theory of money, the Harberger-Hanson model, outlines developing countries’ macroeconomic characteristics including important missing components. They assume when the underlying production function is homogenous of degree one, inflation becomes the weighted sum of changes in money supply and import prices. Moreover, Hanson implies that the elasticity of inflation with respect to money supply growth is less than one. Empirical results strongly support the inclusion of imported prices in the quantity theory of money (Hanson 1985).

Harberger used Equation (3) to apply a linear regression model using percentage change. In Harberger equation, I, represents the interest rate. Harberger substitutes the interest rate for velocity, using the lagged change in the interest rate to proxy for the implicit cost of holding money. By using percentage changes, he avoided the spurious correlation likely to result when a country experiences high inflation. Also, the Harberger equation adds the concept of time, and the equation is rearranged in the following form:

\[
D(\log(P_t)) = D(\log(M_t)) - D(\log(Y_t)) + (\log(I_{t-1}))
\]

\[3\]

\(^7\) The Council for Mutual Economic Assistance (English abbreviation COMECON), 1949-1991, was an economic organization under the leadership of the Soviet Union that comprised the countries of European Bloc along with a number of socialist states elsewhere in the world. The Comecon was the Eastern Bloc’s reply to the formation of the Organization for European Economic Co-operation in non-communist Europe. Mongolia joined this network in 1962.

\(^8\) http://bti2003.bertelsmann-transformation-index.de/160.0.html?&L=1
where \( D(*) \) presents the difference, specifying that the variable has been transformed via natural logarithm. The variable \((I_{r,t})\) characterizes the central bank interest rates estimate lagged one period.

### 3.3 Interest rates influence on economy

Central banks regularly state monetary policies in terms of interest rates. Central banks do not control interest rates directly (including the Central Bank of Mongolia). They can target interest rates, but they only can succeed in this target by adjusting other instruments they control, such as bank reserves. If the action of the banking system, either in a change in the level of activity or after any other disturbance, is such that the interest rate fluctuates, the banking situation can conveniently be described as one of the “importance of economy”. It is a situation of “importance” because interest rates are influencing the economic situation. In simple cases, when interest rates are higher, money might feel “expensive” and “valuable”, but it could also slow the growth of the economy. Therefore, the central bank has a very powerful influence on interest rates. By pushing interest rates higher, governments can often slow the amount of money being lent, thereby reducing the amount of money in consumer’s hands, and in turn slowing the growth of the economy. Therefore, including the “interest rate” variable in equation (3) supports QTM and represents velocity as function of interest rate.

**Describing the meaning of Equation (3):**

Equation (3) has theoretical and econometric features. Price growth is the dependent variable because prices adjust due to increases in money growth (Harberger 1963, Hanson 1985). The difference operator is used in equation (3) in order to reduce the problem of false correlation (Hanson 1985). Equation (3) implies that inflation will be positively related to money growth but negatively related to real output. The parameters of \( LOG(M) \) and \( LOG(Y) \) are hypothesized to be positive if and only if simultaneous lags of the variables enter the equation (Fullerton 2000). It can be empirically tested by the following equation:

\[
D(LOG(P_t)) = a_0 + a_1D(LOG(M_t)) + a_2D(LOG(Y_t)) + a_3(LOG(I_{r,t}))+ u_t \quad (4)
\]

where \( a_1, a_2, \) and \( a_3 \) are hypothesized to be positive coefficients. The constant \( a_0 \) would reflect any trend in any average inflation unexplained by the independent variables. The last variable, \( u_t \), represents the disturbance term including its traditional properties.

\[
D(LOG(Y_t)) = b_0 + b_1D(LOG(P_t)) - b_2D(LOG(Ex_t)) + u_4 \quad (5)
\]

I include the exchange rate (USD/MNT) because of the negative relationship between imported outputs and imported input prices. Total output is assumed to decline when imported input prices increase in equation (5). We recall the theory of Purchasing Power Parity (PPP), which states that the exchange rate between one currency and another is in equilibrium when their domestic purchasing powers at that rate of exchange are equivalent.\(^9\) According to Rogoff’s (1996) explanation, “purchasing power parity is as an anchor for long-run real exchange rates”, and the implication or assumption in macroeconomics is that “PPP holds at least as a long-run relationship” (Ostfeld and Rogoff, 1995, 1996; Lane, 2001; Sarno, 2001). Consequently, long-run exchange-rate variations may bear a clear-cut relationship to those required for insulating the domestic economy from foreign price-level changes or from exogenous shocks. Variations in exchange rates due to actual adjustments in foreign price changes, therefore, cause changes in national price levels in the short and long run which may continue indefinitely. The resulting difference of exchange rates from corresponding purchasing power parities may mean a transmission of inflation across country. Therefore, exogenous forces that cause the exchange rate to depreciate will then generate domestic inflationary pressures. Alternatively, if changes in relative price levels are not compensated for by a corresponding change in exchange rates, the domestic price will change proportionally to the foreign

\(^9\) [http://economics.about.com/od/purchasingpowerparity/a/PPP.htm](http://economics.about.com/od/purchasingpowerparity/a/PPP.htm)
price level. Ordinarily, an exchange-rate depreciation/appreciation or rise in prices in one country should have a high effect on another country, since price rises in one country are measured by the exchange rates.

### 3.4 Effect of Exchange Rate on Prices

Exchange rates may change, so that the prices of imports vary even when the prices of those goods in the countries where they are produced are unchanged; or the internal prices of either country’s goods may change. Except where two changes happen to cancel one another out, either of these changes means that the relationship between prices of home goods and prices of imported goods in each country vary. The exchange rate variable in equation (5) show that the exchange rate changes, while prices within each county of all goods produced domestically remain unchanged. Two consequences may be noted here. First, an exchange rate change does lead to attributions and adjustments, even if the total level of activity is unaltered. Even if the total level of activity is unchanged, some industries may still be expanding and others contracting. Secondly, the income from export may affect savings and investments, and so in turn may induce changes in the general level of activity. In detail, therefore, exchange rate has important role to adjust Quantity Theory of Money.

Substituting equation (5) into equation (4) eliminates the quantity term from the equation to be estimated. (Equation 6)

\[(1+a_2b_2)D(\text{LOG}(P_t)) = a_0 - a_2b_0 + a_1D(\text{LOG}(M_t)) + a_2b_2D(\text{LOG}(E_{x,t})) + a_3(\text{LOG}(I_{t-1})) + u_5 \quad (6)\]

Rearranging the terms such that inflation remains as the dependent variable generates the following equation:

\[D(\text{LOG}(P_t)) = c_0 + c_1D(\text{LOG}(M_t)) + c_2D(\text{LOG}(E_{x,t})) + c_3(\text{LOG}(I_{t-1})) + u_6 \quad (7)\]

Several hypotheses can be tested from equation (7). This framework treats inflation as the weighted average of money growth and changes in the price of imported inputs. According to the literature, these explanatory variables have a direct relationship with inflation (Harberger 1963, Vogel 1974). Therefore, all the regression parameters (except the intercept) should be positive.

The quantity theory of money can be examined by testing for cointegration of the true values of \(M_t, Y_t\) and \(P_t\). If the natural logarithms of the series of these variables are I(0) or I(1) we can use Johansen’s procedure in order to test whether there is a cointegrating relationship. 10

The test of cointegration consists of two steps:

- The first step is to test whether each variable in equation (7) has a stochastic trend. To investigate it, I am going to use the unit root tests on each variable.
- The second step tests whether stochastic trends in these variables are related to each other. In another word, to check whether the stochastic component in the price level is related to stochastic component of money and real output. This can be examined by estimating the cointegrating regression of the model (7) by testing if the residual \(u_t\) has unit root. If I don’t find existence of unit root from error term, \(u_t\), while other variables have each unit root, then the variables are said to be cointegrated. In this case, the OLS estimates of the parameters of (7) are consistent. If the levels of the nonstationary variables included in equation (7) are not cointegrated, then OLS estimators of this equation would not possess any desirable asymptotic properties. Alternative test procedures for cointegration among multiple time series look for the number of common stochastic trends and are based on transformations of the original variables (Stock and Watson (1988), Johansen (1988) and Bossaerts (1988)).
4 Data Set and Methodology

4.1 Data

The main type of data that will be used for the study is time series data, which is limited to the period (1991 to 2012). The main source of data is the Central Bank of Mongolia (BOM) monthly bulletins and annual reports. The macroeconomic data, under examination consists of money supply, price level, exchange rate and real interest rate as well. Lucas (1980) argues the importance of choosing the appropriate monetary aggregate which corresponds to the variable theoretically termed “money”. The measure of money supply is the broad one (M2), which consists of currency held by non-bank public and demand deposit held at the monetary sector (M1). Economists use M2 when looking to quantify the amount of money in circulation and trying to explain different economic monetary conditions, so that, it can be considered as the economic indicator to forecast inflation. As far as prices are concerned, Consumer Price Index (CPI) is used to represent the movements in prices. The reason why I have decided to include the exchange rate (USDMNT) is simple. According to Calvo & Reinhart (2002), exchange rates are one of the key variables used in modeling open-developing economies and it has strong influence on monetary policy and price stability. In our paper, we look for a stationary long-run relation between these variables.

(Table 1 shows descriptive statistics for some of the variables used in the regression Equation 7)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Label/Description</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCPI</td>
<td>Gross Consumer price index</td>
<td>59.11</td>
<td>19.025</td>
<td>121.149</td>
</tr>
<tr>
<td>USDMNT</td>
<td>Exchange rate of USD/MNT (Mongolian Tugrig)</td>
<td>1107.92</td>
<td>473.62</td>
<td>1524.07</td>
</tr>
<tr>
<td>M1</td>
<td>Monetary aggregate M1</td>
<td>392203</td>
<td>42636.5</td>
<td>1797175</td>
</tr>
<tr>
<td>M2</td>
<td>Monetary aggregate M2</td>
<td>1494644</td>
<td>102022.6</td>
<td>7051198</td>
</tr>
</tbody>
</table>

4.2 Methodology

I now examine the time series properties of the variables from Table 1. Granger and Newbold (1974) show how spurious regression problems mean that using non-stationary time series produce biased standard errors and it causes to wrong correlations in the regression result.

First of all, the variable must be differenced (n*=n times) to get a covariance-stationary process. After that, I check properties of the variables. In my paper, the Augmented Dickey-Fuller test (Dickey Fuller, 1979) is applied to the Mongolian Data for testing the existence of a unit root, which checks the non-stationary characteristics of the variables (Table 2). The test found that some of the variables are non-stationary and thus cannot be regressed without making them stationary.

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF Statistics</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>6.356</td>
<td>-7.67</td>
</tr>
<tr>
<td>Interest Rate</td>
<td>0.658</td>
<td>N/A</td>
</tr>
<tr>
<td>M1</td>
<td>4.718</td>
<td>-12.872</td>
</tr>
<tr>
<td>M2</td>
<td>9.381</td>
<td>-9.778</td>
</tr>
<tr>
<td>Exchange Rate</td>
<td>1.858</td>
<td>-11.058</td>
</tr>
</tbody>
</table>
4.3 Results Obtained
Results of a Johansen test for cointegration is given in table 3a, 3b and 4a, 3b.

<p>| Table 3a : Johansen Test for Cointegration (Maximum Eigen Value Test) (No intercepts or trends in the VAR) |</p>
<table>
<thead>
<tr>
<th>List of the variables included in the cointegrating vector : GCPI M1 EX INT</th>
<th>Null</th>
<th>Alternative</th>
<th>Statistics</th>
<th>95% Critical value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>r=0</td>
<td>r=1</td>
<td>40.412</td>
<td>47.21</td>
<td>At least three cointegrating relationship</td>
<td></td>
</tr>
<tr>
<td>r&lt;=1</td>
<td>r=2</td>
<td>25.269</td>
<td>29.68</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=2</td>
<td>r=3</td>
<td>18.875</td>
<td>15.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=3</td>
<td>r=4</td>
<td>0.25595</td>
<td>3.76</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<p>| Table 3b : Johansen Test for Cointegration (Maximum Eigen Value Test) (No intercepts or trends in the VAR) |</p>
<table>
<thead>
<tr>
<th>List of the variables included in the cointegrating vector : GCPI M2 EX INT</th>
<th>Null</th>
<th>Alternative</th>
<th>Statistics</th>
<th>95% Critical value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>r=0</td>
<td>r=1</td>
<td>41.822</td>
<td>47.21</td>
<td>At least three cointegrating relationship</td>
<td></td>
</tr>
<tr>
<td>r&lt;=1</td>
<td>r=2</td>
<td>24.156</td>
<td>29.68</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=2</td>
<td>r=3</td>
<td>16.028</td>
<td>15.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=3</td>
<td>r=4</td>
<td>0.20255</td>
<td>3.76</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<p>| Table 4a : Johansen Test for Cointegration (Trace test) (No intercepts or trends in the VAR) |</p>
<table>
<thead>
<tr>
<th>List of the variables included in the cointegrating vector : GCPI M1 EX INT</th>
<th>Null</th>
<th>Alternative</th>
<th>Statistics</th>
<th>95% Critical value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>r=0</td>
<td>r=1</td>
<td>20.83</td>
<td>30.98</td>
<td>At least three cointegrating relationship</td>
<td></td>
</tr>
<tr>
<td>r&lt;=1</td>
<td>r=2</td>
<td>15.7</td>
<td>22.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=2</td>
<td>r=3</td>
<td>13.5</td>
<td>12.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=3</td>
<td>r=4</td>
<td>0.726</td>
<td>5.76</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<p>| Table 4b : Johansen Test for Cointegration (Trace test) (No intercepts or trends in the VAR) |</p>
<table>
<thead>
<tr>
<th>List of the variables included in the cointegrating vector : GCPI M2 EX INT</th>
<th>Null</th>
<th>Alternative</th>
<th>Statistics</th>
<th>95% Critical value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>r=0</td>
<td>r=1</td>
<td>75.017</td>
<td>30.98</td>
<td>At least three cointegrating relationship</td>
<td></td>
</tr>
<tr>
<td>r&lt;=1</td>
<td>r=2</td>
<td>22.202</td>
<td>22.89</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=2</td>
<td>r=3</td>
<td>8.537</td>
<td>12.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>r&lt;=3</td>
<td>r=4</td>
<td>0.726</td>
<td>5.76</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The Granger causality test has been done with specific lag length chosen by the Stata command `varsoc` and results are reported in table 5.
Table 5: Granger Causality Tests

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>F-statistics</th>
<th>P-value</th>
<th>Granger Causality</th>
</tr>
</thead>
<tbody>
<tr>
<td>GCPI does not Granger cause M1</td>
<td>8.9891</td>
<td>0.11</td>
<td>Unidirectional causality</td>
</tr>
<tr>
<td>M1 does not Granger cause GCPI</td>
<td>4.6551</td>
<td>0.098</td>
<td>M1-&gt;GCPI</td>
</tr>
<tr>
<td>GCPI does not Granger cause M2</td>
<td>11.305</td>
<td>0.004</td>
<td>Unidirectional causality</td>
</tr>
<tr>
<td>M2 does not Granger cause GCPI</td>
<td>1.8955</td>
<td>0.388</td>
<td>GCPI -&gt; M2</td>
</tr>
<tr>
<td>GCPI does not Granger cause Ex</td>
<td>1.0163</td>
<td>0.602</td>
<td>No causality</td>
</tr>
<tr>
<td>Ex does not Granger cause GCPI</td>
<td>3.504</td>
<td>0.173</td>
<td></td>
</tr>
<tr>
<td>GCPI does not Granger cause INT</td>
<td>0.73783</td>
<td>0.691</td>
<td>No causality</td>
</tr>
<tr>
<td>INT does not Granger cause GCPI</td>
<td>3.1492</td>
<td>0.207</td>
<td></td>
</tr>
<tr>
<td>M1 does not Granger cause INT</td>
<td>0.1787</td>
<td>0.915</td>
<td>No causality</td>
</tr>
<tr>
<td>INT does not Granger cause M1</td>
<td>2.6507</td>
<td>0.266</td>
<td></td>
</tr>
<tr>
<td>M2 does not Granger cause INT</td>
<td>0.03439</td>
<td>0.983</td>
<td>No causality</td>
</tr>
<tr>
<td>INT does not Granger cause M2</td>
<td>3.3117</td>
<td>0.191</td>
<td></td>
</tr>
<tr>
<td>M1 does not Granger cause Ex</td>
<td>11.486</td>
<td>0.003</td>
<td>Unidirectional Causality</td>
</tr>
<tr>
<td>Ex does not Granger cause M1</td>
<td>2.2696</td>
<td>0.321</td>
<td>M1 -&gt; Ex</td>
</tr>
<tr>
<td>M2 does not Granger cause Ex</td>
<td>9.0753</td>
<td>0.011</td>
<td>Bidirectional causality</td>
</tr>
<tr>
<td>Ex does not Granger cause M2</td>
<td>12.753</td>
<td>0.002</td>
<td>M2&lt;-&gt;Ex</td>
</tr>
<tr>
<td>Ex does not Granger cause INT</td>
<td>0.76407</td>
<td>0.682</td>
<td>Unidirectional causality</td>
</tr>
<tr>
<td>INT does not Granger cause Ex</td>
<td>5.0243</td>
<td>0.081</td>
<td>INT -&gt;Ex</td>
</tr>
</tbody>
</table>

Tests for cointegration (Tables 3 and 4) shows that at least three of the variables are cointegrated. The Granger causality test shows that the bidirectional causality exists between M2 and Exchange rate. The test further reveals that there is a unidirectional causality running from Interest rate to Exchange rate, M1 to Exchange, GCPI to M2, M1 to GCPI. Though, there is no causal relationship between M2 and Interest rate, M1 and Interest rate, GCPI and Interest Rate, GCPI and Exchange rate. So, in this current study I find that in Mongolia money aggregate (M1, M2) causes exchange rate and inflation, which is a standard economic phenomenon. This study provides evidence in supporting the fisher effect for Mongolian economy.

1. Conclusion

This paper has empirically examined the Monetarists’ view that money supply has been a key determinant of inflation in Mongolia. I have employed monthly data and applied cointegration using the Johansen approach and application of Granger causality approach to study the interaction between money, prices, exchange rate, and interest rate. This study finds convincing evidence in support of the modified quantity theory of money using time series data from the Mongolian economy for the period 1991-2012. From empirical results from previous section, it is noted to be that the absence of causality is bidirectional meaning that the changes in M2 do not have a role in the changes in the exchange rate. The existence of the bidirectional causality implies that given the extent of significance of the external source’s price (imported good) to Mongolian economy, this result is moderately intuitive as it supports the fact that volatility in the Exchange rate has a significant effect on price level. Moreover, the changes in exchange rate lead to a significant increase in the real money growth. This study finds convincing evidence in support of the modified quantity theory of money using time series data from the Mongolian economy for the period 1991-2012. Empirical results suggest that prices and money move together in the long-run in case of Mongolia. The results suggest that inflation in Mongolia is a monetary phenomenon. This may
occur because of the implementation of weak monetary policy adopted by central bank of Mongolia to achieve the high priority growth objectives. It has been argued that the policies triggered to output growth through money supply only have a short-run effect on output but generate inflation. In this study, unidirectional causality running from interest rate to exchange rate and money aggregate to GCPI has been found. Exchange rate plays a vital role in Mongolia’s level of trade, which is critical to most every free market economy in the world. Also the results here show that the interest rate, inflation and exchange rate are all highly correlated. By manipulating interest rates, central bank influence over both inflation and exchange rate, and changing interest rate impacts inflation and currency values. Therefore, as its shown in Table 5, higher interest rate causes exchange rate to rise or lower interest rate tends to decrease exchange rate. But in case of developing countries, such as Mongolia, political stability and domestic production growth is a crucial determinant of stable exchange rate.

References
DO FINANCIAL CONSTRAINTS REDUCE INVESTMENT IN SOUTH AMERICA’S MANUFACTURING SECTOR? EVIDENCE FROM CHILE AND BRAZIL

Edward Hedke
Adviser: Professor Robert Cumby
Georgetown University

ABSTRACT

There is a well-documented connection between investment and long-run economic growth. Furthermore, it appears that less developed countries achieve the highest returns from new machinery and equipment. Nevertheless, chronic underinvestment is common across Latin America. One explanation is that local firms struggle to secure external financing for capital projects. In this study, I use data from World Bank Enterprise Surveys to test the sensitivity of investment to fluctuations in financial variables among manufacturers in Chile and Brazil. I find that increased debt is associated with higher investment rates for firms with low levels of financial access and depth. In addition, the effects of additional debt are much stronger for this subset of firms than for their high-access and high-depth counterparts. These results support the hypothesis that a sizeable portion of Chilean and Brazilian firms face financial constraints to investment.

1 Introduction

There is a well-documented connection between investment and long-run economic growth. For instance, Robert Solow’s (1956) refinement of the neoclassical growth model places great emphasis on the role of capital accumulation in the economic development process. This relationship has been confirmed more recently by Summers and Heston (1998) and Lucas (1988). Furthermore, it appears that less developed countries achieve the highest returns from investments in new machinery and equipment (de Long and Summers 1993).

Nevertheless, many developing countries suffer from below average investment rates. Indeed, this problem is especially prevalent across Latin America (Jiménez and Podestá 2009). Over the last two decades only Sub-Saharan Africa has posted lower annual investment levels. To make matters worse, Latin America’s performance has worsened over time. In fact, the region’s average investment rates were some five percentage points higher in the 1970s than at present.

Many authors have sought to identify the principal constraints to business investment. In general, the literature can be divided into national-level and firm-level analyses. This paper is firmly rooted in the second category. Furthermore, most authors tend to focus on one of five well-known frictions: 1) macroeconomic conditions; 2) institutions; 3) infrastructure; 4) firm management/technology; and 5) financial access/costs. The present study is concerned with the last of these. Specifically, I use data from World Bank Enterprise Surveys to test the sensitivity of investment to fluctuations in financial variables among manufacturers in Chile and Brazil. I find that increased debt is associated with higher investment rates for firms with low levels of financial access and depth. In addition, the effects of additional debt are much stronger for this subset of firms than for their high-access and high-depth counterparts. These results support the hypothesis that a sizeable portion of Chilean and Brazilian firms face financial constraints to investment.

2 Literature Review

The literature shows a strong link between access to finance and firm performance. Several studies focus on the connection between external finance and firm growth. For instance, Rajan and Zingales (1998) and Demirguc-Kunt and Maksimovic (1998) find that increased access to finance is associated with improvements in sales and profitability. Similarly, Nkurunziza (2010) draws a connection
between credit use and employment growth. Others argue that the cost of borrowing is more important than financial access alone (Ayyagari et al. 2008 and Beck et al. 2006).

Another strand of the literature focuses on the relationship between finance and investment. For example, Ojah et al. (2010) find that the availability of external finance increases the likelihood that East African firms invest in fixed capital. From a financial management perspective, Myers’ (1984) pecking order theory (also called hierarchy of finance theory) is of particular importance. The basic premise is that, due to information asymmetries, firms prefer internal to external finance and when necessary, debt to equity finance. Thus, insufficient cash flow may reduce investment simply because external finance is more expensive than retained earnings.

Bond and Meghir (1994) deserve a good deal of credit for pioneering firm-level empirical analysis of the investment decision making process. In their seminal paper, the authors study the behavior of 626 U.K. manufacturing firms during the period 1971-1986. Their aim is to test the validity of the neoclassical model of investment while incorporating aspects of hierarchy of finance theory. To do so, they construct a model of investment based on the Euler equation and then analyze the parameters’ sensitivity to various financing regimes. For instance, Regime 1 includes firms which paid above average dividends in a given period. The authors assume that such firms generate sufficient net revenue to finance investment internally through retained earnings. Regime 2 covers firms which paid below average dividends. Investment by these firms is thought to be constrained by the availability of internal finance.

The study’s empirical results confirm the authors’ suspicions. Namely, the neoclassical Euler equation is most accurate for the subset of firms classified under Regime 1. Therefore, it seems that firms do prefer some forms of financing over others. For example, the data show that investment rates by firms following Regime 2 are relatively more sensitive to fluctuations in cash flow.

Building upon Bond and Meghir’s (1994) foundation, Bigsten et al. (1999) apply a Euler equation and flexible accelerator model to a panel dataset consisting of 739 observations of firms in Cameroon, Ghana, Kenya, and Zimbabwe in the period 1992-1995. They find that, compared with other parts of the world, the median values of investments to capital are low in these countries while profit rates are high. The authors also find that a significant portion of African firms does not invest at all. Therefore, they perform a logit test to better understand the effects of profits, debt, and other variables on the investment decision. Their results indicate that the profit rate is a significant determinant of the decision to invest even when controlling for such factors as firm size and age. Meanwhile, the effect of size is positive while age is negative.

When considering only firms that invest, the authors find that higher profits have a positive effect on firms’ investment rates. However, the effect is not uniform across size groups. Investment by small firms tends to be much more dependent upon profit rates than is the case for larger firms. The authors suggest that this could be explained by larger firms’ access to cheaper and more abundant sources of outside financing. Importantly, the results are fairly similar under the Euler equation specification. Though these findings are consistent with other studies, the most striking difference is the comparatively low coefficient of profits on the investment function for African firms. The authors hypothesize that this could reflect the negative effect of high macroeconomic instability in the region.

Naude et al. (2000) advance this topic by exploring the behavior of a group of a 61 South African firms located in the country’s North West Province in 1999. Like Bigsten et al. (1999), the authors find that investment rates are relatively low in South Africa while profit rates are high. In addition, the effects of profits on investment rates are similarly low compared to the rest of the world. However, because South Africa has experienced less macroeconomic instability, the authors question whether uncertainty is the primary culprit for low investment rates. Therefore, to ascertain the determinants of investment, they run several probit regressions using the flexible accelerator model. In addition to the model’s standard components, the authors control for firm size, the level of infrastructure investment, and the efficiency level of the firm. Most of their results fall in line with expectations. For instance, they find firms are more likely to invest if they experience an increase in sales. In addition, more efficient firms invest more on average. However, it is a surprise to find a negative coefficient on the cash flow variable. To the authors,
This means credit constraints are even less of a problem for South African firms. They conclude that firm efficiency is most important overall.

This paper contributes to the literature by examining the effects of financial access and depth on investment behavior by Chilean and Brazilian manufacturing firms. I adapt Love’s (2009) firm-level measures of financial access and depth to test their effects on the sensitivity of investment to changes in value added, cash flow, and debt. Specifically, I follow her methodology for constructing two indexes: the access index, which measures firms’ access to finance, and the depth index, which measures firms’ use of credit products (see Variable Definitions in the Appendix). So, whereas Love (2009) uses these scores as dependent variables, I examine their interactions with the main components of the flexible accelerator investment model.

By constructing these indexes, I am able to create two new dummy variables: highaccess and highdepth. These serve as rough equivalents to Bond and Meghir’s (1994) Regime 1 classification. This is done because the firms in this dataset are mostly privately-held small and medium sized enterprises. Thus, it would be impossible to apply their methodology which based the definition of financial constraint on the firm’s dividend payout rate. This strategy mitigates some of the shortcomings found in Bigsten et al. (1999) and Naude et al. (2000). Namely, the use of financial regimes allows for a more precise interpretation of the investment function coefficients. As shown by Gilchrist and Himmelberg (1995), in addition to alleviating financial constraints, cash flow is also a good indicator of future investment opportunities. Thus, dividing firms into constrained and unconstrained groups permits the isolation of these two separate effects.

3 Data Analysis

The data comes from the World Bank Enterprise Surveys conducted in Chile and Brazil in the period 2003-2004. The cross-sectional samples contain 948 and 1,642 observations, respectively. Though the surveys provide insight into a wide range of investment climate issues, this paper focuses on the relationships between firm financial performance and investment behavior. Therefore, the variables of interest are mainly objective measures of sales, profitability, debt, and financial access.

3.1 Survey Results

Overall, Chilean firms tend to score better on both the access index and depth index. For instance, only 32.7% of Chilean firms fall into the low-access category (score of 0 or 1 on the access index). Meanwhile, 40.07% of Brazilian firms fit this description. In a similar fashion, 53.48% of Chilean firms achieve a score of 0, 1, or 2 on the depth index, while the proportion is 64.92% for firms in Brazil.

Tables 1 and 2 provide a comparison of the main financial variables of interest across the two countries. They also show the effects of removing outliers using a standard +/- 3*IQR method. For Chile, this procedure was performed on: absolute measures of change in value added, profits, and debt, in addition to each of the financial ratios. For Brazil, the procedure was repeated on all of the same variables except absolute debt. The remaining observations paint a much more realistic portrait of the average firm.

Overall, there are few major differences between Chilean and Brazilian firms. For instance, both samples show average profit rates in the neighborhood of two times the fixed capital stock. Also, neither country displays a clear trend in terms of change in value added (Chile: -0.01 and Brazil: -0.25).

Investment rates are also similar with Brazilian firms investing slightly more on average (0.14 vs. 0.09). In fact, the only obvious difference is that Chilean firms tend to use much more financial leverage than do their Brazilian counterparts. For Chile, the average ratio of debt to fixed capital is 0.95 while in Brazil it is only 0.20.

In sum, these summary statistics show that Chilean firms are more profitable and face fewer financial constraints than their Brazilian peers. Such differences can be seen in both the index scores and average debt ratios. Surprisingly, firms in Brazil tend to invest more on average. These results may be related to the overall levels of financial development and macroeconomic stability in the two countries. It is also possible that this set of Chilean firms is more creditworthy or more mature than the national average.
3.2 The Model

According to neoclassical theory, firms invest based on expectations of future returns and the user cost of capital. More precisely, managers make immediate adjustments to maximize the present value of discounted future cash flows. Dissatisfied with the practical implications of this last assumption, Eisner and Strotz (1963) develop an alternative theory known as the flexible accelerator model. Under this specification, firms face increasing adjustment costs and thus invest only a fraction of the difference between the desired capital stock and the actual capital stock in a given period. The simplified equation is given by:

\[ I_t = \beta [K^* - K_t] \]  

Where: \( K^* \) is the desired capital stock.

The following provides a summary of its derivation:

First, consider a valuation function of the form:

\[ V_t(K_{t+1}) = \max \{ \Pi(K_t, L_t, I_t) + \beta_{t+1} E_t[V_{t+1}(K_t)] \} \]

Where:

- \( \Pi( . ) \) is the net revenue function, \( K_t \) is the capital stock, \( L_t \) is labor, and \( I_t \) is investment.
- \( E_t( . ) \) is the expectations operator conditional upon information available at the beginning of the period.
- \( \beta_{t+1} \) is the firm’s discount factor.

With a net revenue function defined by:

\[ \Pi = [p_tF(K_t, L_t) - w_tL_t - G(I_t, K_t) - p^I_t I_t] \]

Where:

- \( F(K, L) \) is the production function,
- \( p_t \) is the output price,
- \( w_t \) is the wage rate,
- \( G(I_t, K_t) \) is the cost of adjusting the capital stock,
- \( p^I_t \) is the price of capital goods.

If the cost function in (3) depends only on investment, then the specification simplifies to the flexible accelerator form and it can be shown that:

\[ \Pi_K = rG(I) - G[I(t)] \frac{dI}{dt} \]

Where: \( r \) is the interest rate on default free bonds.

The Eisner and Strotz (1963) accelerator model of investment follows directly from (4).

Once this model is expanded to allow for liquidity constraints and the effects of past borrowing, we are left with the following specification:

\[ \left( \frac{I_t}{K_{t+1}} \right) = \alpha_0 + \alpha_1 (\Delta V/K_{t+1}) + \alpha_2 (C/K)_{t-1} + \alpha_3 (B/K)_{t-1} + \alpha_4 (B/K)^2_{t-1} + u_t \]

Where:

- \( (I_t/K_{t+1}) \) is the investment rate for new machinery and equipment
- \( (\Delta V/K_{t+1}) \) is the ratio of the change in value added to the capital stock
- \( (C/K)_{t-1} \) is the ratio of profits to the capital stock
- \( (B/K)_{t-1} \) is the ratio of long-term debt to the capital stock
In this paper, equation (5) serves as the baseline regression with new interaction terms added at each stage.

3.3 Regression Results

Tables 3 and 4 show the preliminary results of the investment function regressions. In each case, the first column contains the results of the baseline model. All regressions include controls for firm size, age, industry, region/state, and whether the firm is a direct exporter or partially owned by the government or a foreign entity. Surprisingly, these firm characteristics appear to be largely unrelated to investment levels. The one exception is firm age, which is consistently negative and statistically significant. However, the effect is quite small (-0.003 for Chile and -0.006 for Brazil) and therefore not particularly relevant for this analysis. The second column of both tables shows the results when the financial variables are interacted with the highdepth dummy variable. These interaction terms show the difference in the coefficients for firms that use a high number of credit products and those that do not. Meanwhile, the third column of both tables shows the results when the financial variables are interacted with the highaccess dummy variable. Their interpretation follows the previous example.

For Chile, changes in value added appear to have no significant effects on investment rates. Instead, profits seem to be a more important driver of investment. In the baseline regression, the coefficient on profits is 0.0128 and significant at the 1 percent level. Interestingly, column 2 shows that profits are even more important for firms with high financial depth. (The coefficient on highdepth x profits is 0.0140.) This result is unexpected and may indicate that profit rates serve as another proxy for future demand. However, this property does not hold when considering measures of financial access. Column 3 shows that profit rates are not a significant determinant of investment rates when comparing firms with different levels of financial access.

By far, the most important results are related to the effects of debt across the different regimes. In the baseline regression, debt has an economically and statistically significant effect on investment rates (0.0684). However, column 2 shows a sizeable difference in the effects of debt for firms with different levels of financial depth. For high-depth firms, the effect of increased debt is only 0.019 (0.145-0.126). Meanwhile, low-depth firms accrue a much stronger positive benefit from increased debt (0.145). More precisely, the positive effect of debt is 7.6 times greater for low-depth firms. A very similar effect occurs when considering measures of financial access instead of depth. Column 3 shows that high-access firms gain 0.033 from more debt, while low-access firms gain 0.159. The quadratic debt terms further illustrate the diminishing returns from borrowing. In each column, their negative coefficients indicate the concave relationship between debt and investment. Together, these results provide strong evidence that Chilean firms face financial constraints to investment.

The story is a bit different for Brazil. In this case, changes in value added do appear to have a significant effect on investment rates. For instance, the coefficient on the change in value added is 0.0388 in the baseline regression. Like Chile, profits are also a driver of investment. Again, the coefficients are positive which could indicate that high profits signal strong future demand or that firms face external financing constraints. The results contained in column 2 support the conclusion that profits serve as a proxy for future demand rather than as a primary source of financing in the face of external constraints. This is because the effect of profits actually increases with greater financial depth. (The coefficient on the interaction term is 0.0111.) Financial depth also seems to affect how sensitive firms are to changes in value added. Specifically, high-depth firms are more affected by changes to this measure. This is also the case when considering differences in financial access instead of financial depth (column 3).

Debt levels have more ambiguous effects on investment in Brazil than in Chile. In fact, these terms are never significant at the 10 percent threshold. Nevertheless, the signs on the coefficients display the same dynamics as in Chile. Across all three columns, increased debt leads to higher investment levels. And again, the effects are stronger for low-depth and low-access firms. Similarly, the quadratic debt terms display negative coefficients across all three regressions. This suggests that some Brazilian firms also face
financial constraints to investment. That the effects are not significant may be due to the differences in average debt levels across these samples.

4. Conclusion

In this paper, I have used a flexible accelerator model to test the sensitivity of investment to fluctuations in financial variables among South American manufacturing firms. I find evidence to support the hypothesis that a significant portion of firms in Chile and Brazil face financial constraints to investment.

For instance, 32.7 percent of Chilean firms qualify as credit constrained according to the access index. Among these firms, my results indicate that a 10 percentage point increase in the debt-to-capital stock ratio is associated with a 1.59 percentage point increase in the firm’s investment rate. Similarly, when the depth index is used to group firms, 53.5 percent of Chilean firms qualify as constrained. For such firms, a 10 percentage point increase in the debt ratio is associated with an investment rate that is 1.45 percentage points higher. Most importantly, these positive effects of extra debt are 4.8 and 7.6 times greater than for high-access and high-depth firms, respectively. These results illustrate the diminishing returns from borrowing. That is, as firms increase their financial leverage, each additional dollar of debt does less to improve investment rates. According to adjustment costs theory, this is due to rising bankruptcy costs and the additional risk premia charged by lenders.

The results are similar for Brazil. Although none of the coefficients on the debt terms are statistically significant, each displays the correct sign. That is, increased debt is associated with much higher investment rates among financially constrained firms. What is more, extra debt is tied to lower investment among high-depth firms and seems to have practically no effect on high-access firms. In each case, the marginal benefit of added debt is decreasing.

Together these findings suggest that more should be done to promote financial access and use of credit products among South American firms. Indeed, the macro literature shows a strong connection between financial development and long-run economic growth (Levine 1997 and Levine et al. 2000). Specifically, the World Bank (2005) estimates that a doubling of private credit-to-GDP is associated with an almost two percentage point increase in long-term growth rates.

Although policy options abound, three seem particularly well-suited to Chile and Brazil. First, steps could be taken to improve court quality and bankruptcy procedures. Love (2009) shows that the effectiveness of national court systems plays a large role in determining financial access at the firm level in Latin America. Second, since smaller enterprises face greater challenges in accessing external finance, governments might enhance the attractiveness of SME lending through partial credit guarantees. Many countries have begun experimenting with such programs, though their efficacy remains uncertain (International Finance Corporation 2010). Lastly, policy makers could promote the formation of credit bureaus to reduce information asymmetries. Multiple studies find links between credit bureau information sharing and improved access to finance (Brown et al. 2008 and Sorge and Zhang 2007).
Appendix

Variable Definitions

*foreign* equals 1 if non-residents own more than 10% of common equity

*government* equals 1 if government owns any common equity

*exporter* equals 1 if firm exports any portion of output directly

*checking* equals 1 if firm has a checking account

*credit* equals 1 if firm has overdraft, loan, line of credit, or any bank financing for working capital or investment

*constrained* equals 1 if firm meets one of two conditions: (a) the firm has applied for a loan, but has been rejected; or (b) the firm has not applied for a loan for reasons other than “do not need a loan”

*unconstrained* inverse of constrained

*accessindex* categorical variable equal to the sum of checking, credit, and unconstrained
It ranges from 0 to 3 with higher scores indicating greater financial access

*highaccess* equals 1 if firm’s accessindex score equals 2 or 3

*depth* categorical variable that counts the number of credit products in use
It ranges from 0 to 5 with a point added for overdraft, loan or line of credit, bank financing for working capital, bank financing for investment, and issuance of stock.

*highdepth* equals 1 if firm’s depth score equals 3, 4, or 5

investment = investment_t / capital stock_t-1

Δ value added = (value added_t – value added_{t-1}) / capital stock_{t-1}

profits = (profit / capital stock)_{t-1}

debt = (long-term debt / capital stock)_{t-1}

* signifies variable with +/- 3 x IQR outliers removed
Table 1: Summary Statistics: Chile

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ value added</td>
<td>577</td>
<td>5995.84</td>
<td>144045.20</td>
<td>-962.47</td>
<td>3460084.00</td>
</tr>
<tr>
<td>Δ value added*</td>
<td>477</td>
<td>-0.01</td>
<td>1.04</td>
<td>-3.39</td>
<td>3.38</td>
</tr>
<tr>
<td>profits</td>
<td>586</td>
<td>1595.37</td>
<td>38119.12</td>
<td>-2518.44</td>
<td>922760.90</td>
</tr>
<tr>
<td>profits*</td>
<td>531</td>
<td>2.42</td>
<td>4.02</td>
<td>-12.78</td>
<td>17.70</td>
</tr>
<tr>
<td>debt</td>
<td>641</td>
<td>1278.69</td>
<td>32094.17</td>
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* signifies variable with +/- 3 x IQR outliers removed

Table 2: Summary Statistics: Brazil

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<td>45.47</td>
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* signifies variable with +/- 3 x IQR outliers removed
Table 3: Investment Functions: Chile

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<td></td>
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<td>(0.00535)</td>
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Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
Table 4: Investment Functions: Brazil

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Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
References


INFORMAL HIRING, PUBLIC GOODS, AND GOVERNMENT EFFECTIVENESS:
FIRM-LEVEL EVIDENCE FROM BRAZIL

Michael Lopesciolo
Georgetown University

ABSTRACT
This paper looks at the firm-level determinants of informal hiring practices in modern Brazil. Specifically, in addition to traditional factors like overall tax burden and high labor costs, this study looks to test for the significance of the benefits of operating formally, the effectiveness of the local government, and whether an interactive relationship exists between the two. Overall, mixed evidence is found for the significance of several benefits and measures of trust in government in leading to greater formal hiring, but the empirical analysis reveals no interactive relationship. Moreover, the significance of different factors is heavily segmented between small and large firms, with public goods provision and other benefits of formality, bribery, and faith in the legal system being far more important for larger businesses.

Acknowledgements
I would like to primarily thank two individuals: Professor Charles Udomsaph, my thesis advisor, and Professor Anders Olofsgard, the lead professor for my senior thesis seminar. Having had both of these professors for multiple semesters, they are directly responsible for the vast majority of my research skills and economic knowledge. Without them, this paper would not exist. I would also like to thank Professor Arik Levinson for pointing out several key issues with my theoretical methodology at the 12th Carroll Round, along with my discussant and good friend Glenn Russo for providing interesting ideas on how to extend the study. Many thanks as well to my immensely patient friends, who are probably quite tired of hearing about the Brazilian labor market, at this point. Any and all errors are my own.

1 Introduction
Brazil’s rise from its stereotypical split between grotesque wealth and stagnant poverty has been a huge global success story. By and large, the past two decades have been excellent for South America’s powerhouse: stable democratic politics; a consistently growing economy; oil discoveries; innovative social policies, including the famous Bolsa Familia; and the privilege to host the upcoming 2014 World Cup and 2016 Summer Olympics have helped propel Brazil onto the world stage, with rapid and relatively equitable growth as the engine. In spite of this growth, however, the Brazilian labor market remains uniquely frustrating, with high costs, scarce skilled workers - Manpower, an employment agency, reported that 64 percent of Brazilian firms had problems filling vacancies, compared to 40 percent in China and 16 percent in India - and, most unusually, an extremely high degree of informality.1

The size and nature of Brazil’s informal market is unique for a relatively developed economy. 39.8 percent of Brazil’s 2004 gross national income was not formally regulated, compared with 25.4 percent in Argentina, 19.8 percent in Chile, 23.1 percent in India, and 13.1 percent in China.2 Moreover, 87 percent of jobs created in Brazil’s biggest cities between 1992 and 2002 were informal, especially due to reductions in the size of the public sector. This causes problems for individual workers, firms, and the government. The informal sector exists not only in small-scale service industries or in impoverished areas, but also across a wide swath of the economy, including construction, transportation, and

manufacturing. This is not a case of the economy’s most unfortunate being hired under the table to clean houses or fry food: this is more systematic, impacting the macroeconomy across sector and skill level. Limited tax revenues can lead to poor public services and low government effectiveness, further reducing the incentive businesses have to buy into public schemes: this create a vicious cycle, as opposed to a virtuous one of fair taxes and effective government.

Bringing business activity out of the grey and black markets and into the formal sector has thus long been a policy initiative in Brazil. The multifaceted nature of the issue, though, makes diagnosis difficult. Factors exist on the individual-, firm-, and government-level that push businesses to operate partially or entirely informally. The informal sector itself is a collection of varying shades of grey, with multiple unique definitions for what “counts” as informal, making the issue even more complicated. The levers with the potential to reduce overall informality, thus, span the policy spectrum.

This paper looks to add to the literature by examining the factors that correlate with informal hiring in modern Brazil by looking at the attitudes and practices of firm managers, an understudied slice of the issue. These individuals, after all, set up hiring schemes and choose the direction of a business—they are key actors on a plane that government and individuals are not. The quantitative analysis covers a large span of potential causal factors, in line with the multifaceted nature of informality. In addition to well-established determinants—taxes, labor costs, government inspection—this paper seeks to examine political economy factors—such as access to firm-level public goods and overall government effectiveness—that could also impact how firm owners conceive of the business-government relationship that is so key to public policy. Additionally, how these factors break down upon segmenting the data by firm size is something that has not yet been done at an intranational level.

This work will proceed as follows. Section 2 of this paper reviews the existing literature on informality, beginning with a theoretical grounding and then moving into more specific work done in Brazil and other comparable countries. The dataset and variables are explained in Section 3. Section 4 looks at the theoretical model and quantitative methodology. Section 5 presents descriptive statistics to begin inspecting the data. Section 6 features the econometric results of the different sets of regressions, and Section 7 further examines these through robustness tests. Section 8 outlines the shortcomings of the study and provides logical paths to extend the work further. Section 9 concludes.

2 Literature Review

2.1 History of Theories of the Informal Sector

To place this work in historical, theoretical context, here we briefly review the three major theories on the composition of the modern informal sector. Study of the idea of unregulated, informal employment did not begin until the late 1960s. Before that, informality was thought of as a component of an agricultural, non-industrialized economy. Mainstream development economists believed that urbanization and industrial development would lead directly to formal wage employment. However, as post-colonial Africa and import substitution industrialization-based Latin America became more and more urbanized, the flaws in this logic became clear.

In the early 1970s, thus, the burgeoning informal, low-skilled service sector in poor cities caused the development community to reconsider. A 1970 International Labour Office report diagnosing the urban economy in Kenya pointed the finger at high unemployment. The study explained that rural migrants, in hopes of finding higher wages, had moved to the cities in droves, outpacing the growth in the number of formal work opportunities available. Improving the productivity of these workers and slowing

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overall migration were recommended as solutions. The informal sector, thus, represented entrepreneurial behavior as a response to underperforming job opportunities, usually in the form of self-employment.\textsuperscript{6} This was the dominant train of thought for several decades: the urban informal sector was a result of "hyper-urbanization" in the developing world.

These ideas remained the bedrock of the development literature on the informal sector for several decades, until global liberalization in the 1980s pushed the theories further towards the role of government. De Soto (1989) conceptualized the informal mass of the urban service sector as a group of self-employing entrepreneurs, but blamed this not on migratory flows but on dysfunctional government.\textsuperscript{7} By embracing mercantilist principles and devaluing the sanctity of the accumulation of private property, businesses had strong incentives to keep their assets out of the formal system, De Soto argued. Stagnant urban elites fought for policies, such as state monopolies, high barriers to entry, and strict regulation, that hampered the ability of entrepreneurs to productively disrupt the system – at least in the legal, formal sector.

In both cases, the informal worker is often a business owner, rarely has many employees, and is acting out of necessity, either because of insurmountable labor market odds or strangling regulation. These restrictions are relaxed in a third definition, broadly called structuralist, which views the informal economy as being a more dynamic part of the formal system. Roberts (1992) and Beneria (1989), both looking at the structure of the Mexican economy, find that informal businesses are much more than the bottom end of the labor market or the result of insufficient property rights.\textsuperscript{8} Instead, they are part of the overall economy, supplying inexpensive goods and services to formal businesses not out of necessity but out of a complex but mutually beneficial set of economic circumstances. Supply chains and subcontracting are common arrangements. Moreover, the structuralist theory acknowledges that formally registered business might find it prudent to informally hire some or most of their wage earning workers.

All of these factors are at play in the case of modern Brazil: large pools of relatively unproductive labor in large but poor cities, brutally complicated tax and regulatory infrastructure, and a blurry mixture of formal and informal activity. In light of this, this paper’s goal of uncovering firm-level determinants and better understanding managerial attitudes towards informality points towards the complexity of the structuralist model, including the basic factors emphasized by Hart and De Soto but looking outside of those to further explain the interplay between formal managers and informal employees in Brazil. This is also a reason to focus on firm size: microenterprises and wage-paying businesses fall into different schools of theoretical thought.

### 2.2 Relevant Background

Following the fall of the Soviet Union, a flurry of empirical literature sought to examine the burgeoning, chaotic economies in their transition into capitalism, sparking interest in the informal sector. Johnson et al. (1997) compare the development of the underground economy in the states of the former Soviet Union in a bedrock piece of the literature, using cross-county comparisons of official GDP, electricity consumption as a proxy for business activity, tax rates, budget deficits, and other national-level economic factors.\textsuperscript{10} The authors reaffirm the basic theoretical conclusions: heavy taxes and burdensome regulation leads to the growth of the informal sector as a percentage of GDP. Most cross-country analyses agree with these basic principles. Johnson et al. (1998) use similar cross-country data from Latin America to support these findings.


America, the former Soviet Union, and the OECD to examine whether there exist positive incentives—public goods, an effective legal system—to encourage firms to operate formally.\textsuperscript{11} They find that, especially in Latin America and the former Soviet Union, heavy regulation and high levels of corruption increase the informal share of GDP. More interestingly, they find less evidence for tax rates, but taxes become significant when the discretionary authority and level of competence of the tax apparatus is taken into account. Moreover, national-level public goods, such as an accessible, effective legal system, are found to be significant in determining informal activity, opening the door to positive incentives as a factor in individual and firm decision-making. On the firm level, Dabla-Norris et al. (2008) use World Bank Enterprise Survey data from number of developed and developing countries, coming to the conclusion that smaller firms are pushed into informal activity by financial pressures, while larger ones are more impacted by legal and regulatory constraints.\textsuperscript{12}

Renooy (1990) breaks the factors that drive individuals to act informally into two categories: structural (not to be confused with the structuralist theory) and opportunity.\textsuperscript{13} The structural factors are more obvious, including personal financial pressure and institutional constraints. The opportunity factors, however, include not just personal attributes like skills and education but also political and cultural traits. He argues that individuals with less trust in the government, who thus view the gap in opportunity between the formal and informal sector as minimal, are more likely to choose to work informally.

Most analyses at the sub-country level focus on individual worker traits, rather than policy differences in different parts of the country. In one exception, Chaudhuri et al. (2006) looks at state-level data from India, with the aims of deducting differences in the growth rates in the shadow economy within the nation.\textsuperscript{14} The paper finds that key development differences—literacy rates, press freedom—reduce the size of the informal economy by promoting accountable governance. High levels of state economic liberalization also reduce informality. Most interestingly, states where the coalition of party ruling the national parliament featured lower levels of informality, though the authors hypothesize that this is more a result of cooperative transformation of statistics than genuine political economy at work.

Almeida and Carneiro (2009) looks at variation in the enforcement of labor regulation across Brazil, using firm-level data from the 2003 World Bank Enterprise Survey and various city-level characteristics.\textsuperscript{15} The authors conclude that stricter enforcement, proxied by more frequent inspections, leads to lower levels of informal activity but also to higher unemployment and lower overall firm activity, implying that losing access to cheap labor hampers the growth and profitability of Brazilian firms.

Jonasson (2012) also looks at regional variation in informality between Brazilian firms, focusing on holistic government effectiveness as a potential casual factor. Using worker- and municipal-level data from the 2000 Brazilian census, he empirically tests why individual workers decide to operate informally across Brazil.\textsuperscript{16} After controlling for a variety of factors, he finds that overall government effectiveness is indeed significant, finding that bureaucratic resources and local public goods provision significantly reduce individual informality. Jonasson (2011) examines municipality-level informality using similar criteria, reaffirming the basic conclusions and signaling the importance of the sectoral composition of municipal economic activity: intuitively, manufacturing-dominated cities exhibit less informal activity than those where the service sector plays a predominant role.

The impact of firm-level public good provision and the effect of government competence on hiring managers have not been studied at the sub-national level. In light of the studies done, particularly by Jonasson and by Almeida and Carneiro, this paper hopes to add to the literature by providing a firm-level lens to examine the same thematic issues, and then further breaking the results down into different firm-size categories.

3 Data
3.1 Dataset Description
This paper primarily uses data from Brazil’s 2003 World Bank Enterprise Survey, a large-scale collection of firm-level data. The survey collects response from 1,642 manufacturing plants in roughly 400 cities across a diverse set of 13 Brazilian states. Nine distinct industries are surveyed, ranging from food processing and garment weaving to chemical processing and automobile assembly. More than 90 percent of the responses are from firm owners who have only one or two plants in the country, so the characteristics of the plant surveyed can be largely extrapolated to represent the firm as a whole. The responses consist of general information about the plant, facts regarding the manager of the establishment, labor relations, business environment, government relations and regulation, innovation, and firm finance, mixing quantitative measures taken from a firm’s balance sheet with the opinions of the plant manager. Brazilian census data from 2000 is used to obtain literacy and GDP per capita statistics on a municipal level, while several other Brazilian Institute of Geography and Statistics (IBGE) reports give us information on 2003 state-level GDP and agricultural activity.

The survey consists of nearly 150 questions, many of which are broken down into subcomponents and year-by-year panel data. For the purpose of this paper, in addition to some basic facts about the business, three rough categories of data are taken from the survey: traditional factors (relating to tax rates, regulation, and labor costs), formal-sector benefits, and measures of government effectiveness. Methodologically, several of these factors are objective, quantitative figures: firm size, number of inspector visits, use of public goods, cost and wage structure, and so forth. Alternatively, several of the responses used in this paper are based on manager responses to questions asking how large of a problem certain factors (high taxes, low skilled workers, and so forth) are for their business, or how effective they find certain public institutions. These variables will be explained in greater detail in the next section.

3.2 Description of Major Variables
Before beginning descriptive and econometric analysis, we review the specific definitions of the key variables, in order to better place the results into accurate context. Most importantly, defining the specific concept of informality used in this paper’s quantitative analysis is vital, as the various ways of conceptualizing the amorphous idea all produce slightly different policy recommendations. Henley et al. (2007) clarify three different ways that the Brazilian informal sector can be quantified: employer compliance with labor regulations in the form of a signed labor card for each of its workers, individual enrollment in a social security protection scheme, or through measuring the scale of micro-entrepreneurship activity. Each definition has different determinant factors, although the three are obviously related.

The main dependent variable used in this paper is based on the answers to a question posed to firm owners, asking that, given the constraints to higher workers and high costs that it can imply, what percentage of permanent and temporary employees in a typical firm of their size in their industry are “trabalhando sem carteira assinada”–working without a signed worker card. Given that the survey is anonymous, the question’s goal is to approximate the number of informal workers that the responder employs; regardless, it provides an idea of the responder’s perception of the labor market. Specifically, due to the non-linearity of the data and the high concentration of responses at 0 percent, these results are

then grouped into five segments for quantitative analysis: 0 percent, .1 to 10 percent, 11 to 25 percent, 26 to 51 percent, and finally 51 to 100 percent.\(^{18}\)

Although the lines obviously blur together, we look at three groupings of data in our quantitative analysis. First, traditional factors in analyzing the prevalence of the informal economy, including labor or capital intensity, hiring costs, frustrations with taxes, and the risk of being caught operating outside the law. We include two measures to account for the labor intensity of the firm: a ratio of labor costs (salaries, wages, social security, bonuses, and so forth) to total costs, and a ratio of the value of the plant’s Property, Plants, and Equipment to the value of its total assets. Moreover, we also include a measure of how difficult the plant owner finds attracting skilled workers. To incorporate tax-related frustrations, we include responses on how large of an obstacle the plant owner finds tax rates and the tax administration to their business. Last, for inspections, we include a 0-1 binary of whether or not the plant had been visited by municipal, state, or federal tax authorities in the past year, and a sum of all visits by government inspectors, divided by the number of employees to account for size differences between plants.

The benefits of formality we include are all 0-1 binaries: whether the firm has used a government fiscal incentive, exports any of its products, has bid on government procurement contracts in the past three years, belongs to a trade organization, has access to overdraft facilities, utilizes financial loans, or conducts business with more than a handful of financial institutions. All of these are factors that require cooperation with local officials or invite greater oversight into the firm: we assume that all of these factors would be more easily accessible by partially or fully formalized firms.

To measure government effectiveness, we use several 0-1 binary variables, measuring whether the plant manager believes that government officials are fair in their application of regulations, that government services are efficiently provided, and that the firm had any impact on the laws and regulations that significantly impact their industry. Additionally, to proxy for corruption, we include a percentage measure of how much the firm owner expects to pay in bribes to win a government contract.

Last, several firm traits are included to act as controls and add more weight to the core results. The firm’s size (micro, small, medium, or large), industry, and state are all added to the regressions to control for unspecified variation between firms on these categorical lines. Moreover, given that many of the WBES responses are based on the manager’s personal opinions, we also include the firm owner’s gender and their level of education. Last, to control for locational differences, the municipality’s GDP per capita and literacy rate are also included, along with the state’s percentage of GDP that is agricultural in nature.

4 Methodology
4.1 Theoretical Model

To build a basic model, we look to Dabla-Norris et al. (2008) and their theoretical outlining of a firm’s choice to operate formally or informally. This model compares profit maximization in either the formal or informal sector, based on a production function, financial costs of formal activity, and the risk of being reprimanded by public officials. Formally, the two-tracked profit model can be represented as:

\[
\pi_i^f = [a_i f(L) - wL](1 - p)
\]

\[
\pi_i^i = a_i f(L) - wL - C,
\]

where \(\pi_i^f\) and \(\pi_i^i\) represent informal and formal profits for firm \(i\), \(a_i f(L)\) is the firm’s production function, assuming consistent firm-level productivity \(a_i\) and a production function based solely on labor \(L\), a wage rate \(w\), increased costs of formality \(C\), and the chance of being caught \(p\).\(^ {19}\)

\(^{18}\) Unless otherwise specified, this segmentation is used as the dependent variable in all regressions. Alternate groupings were tested as a robustness check.

Using this as a base, which encompasses many of the “traditional factors” described in previous sections, there are several theoretical additions that this paper will seek to test. Given that constraints to capital accumulation are a well-documented downside of informal activity, basing a production function solely on labor is unrealistic. Moreover, this model ignores the potential benefits that formality might provide, along with the fact that an effective government could amplify these benefits. Thus, we alter the models here. For the model estimating informal-sector profits, we add capital to the production function, the cost of capital to the overall calculation, and differentiate the costs of labor and capital:

\[ \pi_i^I = [a_i f(L, K) - (w_i L + r_i K)](1 - p). \]

For the formal profits, we add both government efficiency and formal-sector benefits as potential boosts to profit, along with their interactive impact:

\[ \pi_i^F = a_i f(L, K) - (w_F(C) L - r_F(B, G, BG) K \]

where \( K \) represents capital inputs, \( B \) represents benefits from formality, and \( G \) measures government competence. Essentially, while the costs of formality \( C \) mean that \( w_F > w_i \), we seek to find out if the fact that \( r_f > r_i \), when conceptualized broadly as the costs and other difficulties of accumulating capital are enough to alter firm decisions on informal hiring.

Bringing the model back to the context of the paper, the obvious flaw is that our data looks at the number of works hired informally, rather than a black-and-white split between formality and informality. That said, while this is definitely a constraint, firm profits can be reinterpreted on a marginal basis, and the risk of being caught—and the punishments therein—are logically more severe as each informal worker is added.

With this laid out, this paper fundamentally looks to test the impact of \( B, G, \) and \( BG \) on the profit-maximization decision of a firm weighing the costs and benefits of hiring formally or informally. Whether these factors are significant in the empirical analysis will validate or dismiss these hypotheses.

4.2 Quantitative Methodology

4.2.1 Ordinal Logits

For the empirical analysis, this paper relies primarily on ordinal logit regressions, testing the various independent variables against grouped segments of the responses to the survey question regarding the percentage of workers typically hired informally. Because the data is not spread continuously between 0 and 100 percent, and because extrapolating the dependent outside the 0 to 100 range produces unrealistic results, standard OLS regression is inappropriate.

For each panel of regressions, all independents will be run without controls to begin. From there, firm size, state, and industry effects will all be controlled for in separate regressions, before applying all three during a final, fifth test. Based on the hypothesized interaction between public goods provision and government effectiveness and the results of Dabla-Norris et al. (2008), we will run four separate panels: all independents; all independents, plus a set of interaction variables; all independents and interaction variables, micro and small firms only; and all independent and interaction variables, medium and large firms only.

4.2.2 Principal Component Analysis

Moreover, for benefits of formality and government effectiveness, we also attempt to use principal component analysis (PCA) to create indices. These compiled values are intended to be correlated to each of its components. Although this makes interpreting significance and evaluating economic policy options more difficult, it helps avoid multicollinearity problems induced by the nature of the sets of independent variables.\(^{20}\)

\(^{20}\) Correlation matrices have been redacted due to length constraints.
We conduct PCA on both formality and government effectiveness using the same quantitative procedure: run the `pca` command in Stata, score the index, and then run a correlation matrix between the index and its components to check for value. The benefits of formality index displays positive correlations with all of its components, with the procurement binary as the only bivariate correlation below 0.44. The government effectiveness index, however, only has two values above 0.3 –responses on government and tax effectiveness—and both bribes and opinions on the legal system are correlated negatively with the index. Trying to continue with PCA for this set of variables would be ill advised: the negative correlations would mean that the index does not accurately reflect an overarching concept. As a result, only the government effectiveness index is used in subsequent regression analysis.

5 Descriptive Statistics

In order to better inspect the sample, we examine several panels of basic descriptive statistics before beginning the regression analysis, redacted due to length constraints. The tables showed that the sample relatively evenly distributed in terms of firm size, with some extremely small plants and some very large ones. Small plants generally displayed higher levels of informality. Most respondents engaged in either garment or furniture manufacturing, with capital-intensive industries displaying the least informality. Most firms are located in either the Southeast or South, with wealthier states–with the exception of Rio de Janeiro–displaying less informality. Last, a correlation matrix that inspects the independent variables for proper analysis was ran. Overall, despite the fact that many of these variables are designed to represent the same concept, most pairs of variables are not overly correlated.

6 Results

6.1 Main Regression

Table 1 shows us the primary results of our analysis, with the full set of non-indexed independents run against the five segments of the informality responses. Overall, the results are roughly in line with our basic predictions. The absolute magnitudes of the coefficients are difficult to interpret, as the dependent variable is an artificial construct based on a subjective survey response; nonetheless, the direction and statistical significance of coefficients can be interpreted at roughly face value. Comparing the first five regressions with the second five shows that the results are robust to the swap from individual variables to the benefits of formality index.

Looking at the control factors, only agricultural prevalence is significant in reducing informality, perhaps a reflection on the prevalence of informal hiring in large cities. Among traditional factors, firms that struggle to find skilled workers and firms for whom labor costs represent a large fraction of their overall costs are strongly significantly likely to operate more informally. Frustrations with the tax system as an obstacle to business, additionally, are weakly connected to informal operation. This is all intuitive, but is useful information: even when controlling for industry and firm size, it is labor-intensive firms that lean towards informality, and the connection between reliance on informal labor and frustrations with low-skilled worker is an important one. Tax inspection always appears as negative, but is only significant in one instance. The lack of significance in the tax-related variables is surprising, given the empirical background and nightmarish Brazilian tax system: perhaps because this is measuring internal variation, taxes do more to set a baseline than cause diversity within the Brazilian context.

With regards to the benefits from formality and measures of government effectiveness, the most significant variables are the exporter binary and the number of banks binary, both of which are in the expected direction. Even after controlling for state, industry, and size, exporting firms are more likely to hire formally. Using a large number of banks implies the same. Using a government fiscal incentive is weakly significant in one case and moves in a consistent direction. Frustrations with the legal system are highly significant in impacting informality, as are the prevalence of bribery in public operations. All of these are intuitive. Oddly, loan usage is weakly significant in the unexpected direction. This is possibly because, in a relatively developed country like Brazil, loans represent an inferior financial good. Regardless, this is against our intuition regarding public goods access and formality.
Last, the introduction of industry and state effects have relatively minimal effect on the data, surprising for a country as geographically diverse as Brazil. Most of the individual dummies are insignificant. Firm size, however, is hugely important. In both firm-size regressions, micro and small firms are shown to be significantly more informal at the 1 percent level, and large firms significantly less so at the 5 percent level. This justifies segmentation, as predicted.

6.2 Benefits of Formality and Government Effectiveness Interaction

Next, we take the benefits of formality index and create interaction terms linked with every measure of government effectiveness we have previously included. Before running regressions, we check for multicollinearity between the index, original effectiveness measures, and the interaction terms, and in the process drop the interaction term for belief in firm impact, due to excessively high correlation values. Unfortunately, all interaction panels yield disappointing results. In this context, the existence of an interactive relationship between government effectiveness and benefits of formality seems dubious, despite the individual significance of both sets of factors.

6.3 Micro and Small Firms

In every regression run so far, firm size has been overwhelmingly important as a control. Thus, looking at the sample in separate segments is a logical next step, as such high significance might imply that different factors are at work for different firm sizes. We begin here with micro and small firms—i.e., all firms with 35 or fewer full-time workers. We run the same regressions as in Sections 6.1 and 6.2, removing the now-irrelevant medium and large terms from the plant size controls, although the associated results are redacted due to length constraints.

Many of the same factors remain similarly significant in this regression panel, but some make interesting changes. The level of education of the plant manager is positively correlated with higher informality, an odd feature that runs countercurrent to the broad assertion that higher-skilled or higher-complexity businesses tend to be more formal. The impact of the benefits of formality section is much weaker than in the overall regression. The index is never significant, and loan usage and procurement bids are the only significant variables, both in the unexpected direction. Simple loan usage may be an inferior financial good in Brazil, but the procurement issue is a tricky one to explain, although future regressions show that either controlling for city effects or testing only large firms puts this measure back in. Moreover, the lack of significance in bank usage and exporting is a startling shift from the initial sample: access to these benefits is distinctly less important in hiring when looking at smaller firms.

The government effectiveness measures are more of a mixed bag. Faith in the legal system drops in significance, perhaps evidence of small firms struggling to access the legal system even in the best of scenarios. Belief in firm efficacy in determining industry regulations, however, becomes significant. Contrastingly, bribes drop from being significant at the 1 percent level in nearly every regression previously to being completely insignificant here—perhaps bribery is not as much of an issue among small firms with scarcer resources to exploit.

6.4 Medium and Large Firms

The panel for medium and large plants provides a logical output in light of the holistic sample and examination of small and medium firms. Executive education now becomes significant in the predicted direction, in direct opposition to the impact in the smaller-firm regressions. The significance of tax inspectors and frustrations with the tax administration disappear, although other forms of inspections become weakly significant.

Benefits of formality are vastly more significant here than they were previously. The index remains significant despite full controls being added in. Using a public fiscal incentive becomes significant in the expected direction in all five regressions, despite it being previously insignificant. Bank usage and exporting continues to be significant, as well. Overdraft facilities are significant in the opposite

21 The associated regression tables have been redacted due to length constraints.
direction, but it is possible that for large firms, this represents an inferior financial good rather than a benefit of formal operation.

In terms of government effectiveness, the quality of the legal system and the prevalence of public corruption, proxied through the prevalence of public bribery, are highly significant in increasing informal hiring. Firm size remains highly significant, even when solely comparing firms with between 35 and 100 workers with those with more than 100.

7 Robustness Tests

In some ways, our base regression analysis has already been shown to be relatively resilient: using both individual variables and an index, dividing the sample into smaller categories, and running firm-size, industry, and state dummies all make the previous results more credible. However, there are still several issues that we can address here to assure that our findings are more robust. We look at altering the ordered groups in the ordinal logit, including factors to measure firm performance overall, and running city effects in place of state effects.

Due to length constraints, the full explanations and tables have been redacted from this version. In summary, modifying the specific definition of the ordered groups does not diminish the significance of the results. The results are further significant to the inclusion of firm performance and age. Including city effects in place of state effects and running an Ordinary Least Squares regression lowers the significance in several key variables, such as labor costs, bank usage, and bribery, but does not fundamentally transform the results.

8 Constraints, Avenues for Expansion

8.1 Constraints

Despite the large handful of significant results, some serious methodological constraints do exist with the regression analysis. First and foremost, the central dependent variable struggles both with its technical definition and with its survey response. Similarly, the lack of specific information about worker skill and the requirements of the various positions at the firm lead to problems in the theory. The marginal decisions about the costs and benefits of hiring a worker formally or informally could potentially be different for a minor clerical role than it is for a difficult technical or managerial role. The significance of frustrations with finding skilled workers throughout the regression analysis further underscores this relationship’s importance. The singular focus on Brazil does also cause some problems with external validity.

8.2 Avenues for Expansion

Despite these shortcomings, these results do lay the groundwork well for future examination into firm-level determinants of informality and policy prescriptions therein. The most actionable specific result probably lies in the significance of exporting, even when controlling for firm size, profitability, industry, and state. Through a combination of geographic and lingual isolation and insular ISI policies, Brazil has never been a large exporter. Further examination on the relationship between exporting and informal hiring could be extremely economically beneficial to Brazil. Another avenue for further development is adding partisan politics in as a potentially influential factor. Last, expanding this study into a panel would help determine whether the factors that drive firms towards informality have remained constant over the past several decades, or whether they have shifted as Brazil’s economy has modernized.

9 Conclusion

Traditionally, negative incentives—the high costs of labor contracts, crippling taxes, the fear of being reprimanded—have been the main factors in the study of the informal sector in the developing world. This paper looked not to disprove that, but to identify if positive incentives—public goods that firms operating informally would struggle to access, or faith in bureaucratic competency—were also important in determining whether firms relied on informal labor. Moreover, given that most studies look at national-level economic indicators, turning our attention to internal variation in a diverse country like
Brazil aimed to better understand the marginal aspects of the problem. Ordinal logit analysis on firm-level data on informal hiring revealed several key conclusions. One, several benefits of formal activity—particularly exporting and access to finance—and several evaluations of government effectiveness—especially corruption and access to the legal system—are consistently significant in determining informal activity, even with stringent controls placed on the regressions. Two, the theoretical impact that an effective government bureaucracy could have on how much businesses value public goods does not appear significant in this case. Three, testing small and large firms separately resulted in divergent results; most notably, access to public goods was much more important in determining variation amongst larger firms than smaller ones.

The most important takeaway from this study is the last point. Given that most studies are cross-country, and the most significant factors are assumed to be national-level taxation and regulation, the internal diversity in informality is easy to miss. However, while the impact of informality on any individual's life has some similarities, helping the microentrepreneurs of Hart and De Soto operate legally is very different from altering the structuralist conditions that lead large firms to hire workers under the table. Labor market reform must be multifaceted, with different initiatives aimed at employers and employees, if it is to be successful.

Brazil’s massive informal sector continues to be a drain on an otherwise rising star in the international economic community. Better understanding its continued existence could be a boon to Brazilian policymakers attempting to unlock the full potential lying in Brazil’s labor market.

References


## Appendix

### Table 1 – Main Results

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Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
GENTRY IN THE WINDY CITY: DOES GENTRIFICATION EXPLAIN CHICAGO’S INTEGRATION?

HADI ELZAYN

Abstract. Recent studies have found that residential segregation is declining across nearly all metropolitan areas in the United States, and have concluded that this may herald a new era in which racial preferences matter little. I discuss the importance of such a conclusion — why segregation matters — and then I examine these claims, with a focus on Chicago and its surrounding metropolitan area. First, I confirm broadly a trend of declining segregation, including in Chicago. Then I use a previous author’s model to inform the testing of two possible scenarios: one under which integration represents a shift in preferences, and one under which it is merely a consequence of gentrification processes. Such processes could be a result of shocks to neighborhood preferences, housing stocks, or housing demands, which may encourage agents to accept residence in neighborhoods with ethnic compositions that they do not like for the sake of differing costs of housing and living. While creating integration in a statistical sense, such a form of integration may be displacing the poorest — those most vulnerable to the deleterious effects of segregation— and thus may be neutral or even negative for outcomes. Using evidence from the U.S. Census over years 1980-2010, I examine what drove the decrease in segregation and test these two scenarios, and conclude that there is some evidence that gentrification processes may have occurred. I then consider the implications of this process for the poor, finding that segregation by skill has decreased, indicating that there may have been some positive effects of gentrification. Finally, I consider various robustness checks, assumptions necessary for my results to hold, and interpret my results in light of policy. Please note that this is an abridged version of the final paper. Notably, we omit all tables and figures.

1. Introduction

That segregation is a defining feature of the modern American urban landscape is well-known in academic and journalistic literature, not to mention self-evident after sufficient exploration of large cities. Segregation is prevalent on an ethnic level as well as on a racial level. While segregation is apparent between all races, it is most prominent and sustained in the geographic areas of co-locating whites and blacks. This is the segregation that this paper will focus on, as this is the segregation that has played the largest role in the history of American life.

After the end of the Civil War, slavery was eliminated, but racial prejudice was not. Before the Civil Rights movement, the term segregation referred not only to geographic separation of housing units, but to de jure separation of living spaces and facilities and institutionalized discrimination in all aspects of life. The Civil Rights movement gained ground gradually in the 60’s, and finally won major victories that brought about legal integration through the Fair Housing Act of 1968, which made discriminatory practices illegal in the housing market. Since its peak in the 1970’s, segregation has declined almost universally throughout American cities [Glaeser and Vigdor (2001)]. Glaeser and Vigdor (2012) even go as far as to declare the ‘End of the Segregated Century’. Yet while there may have been a decline in segregation, it remains important to understand why this decline has occurred. Racial segregation in its legal form was undoubtedly a great injustice in itself, but its pernicious effects on outcomes among blacks (and other minorities) are of the most pressing consequence. As I will note below, segregation has been shown to be associated with a number of social pathologies, and while the correlations are strong, the causal mechanisms are not well understood.

It is quite plausible, given the correlation between poverty and many of these associations, that the worst of segregation’s consequences may fall on the poorest. If this is the case, then insofar as society is concerned with improving outcomes, it must be concerned with what sort of integration process occurs, and how it affects the hardest-hit. Casual introspection suggests that the spillover benefits of ameliorating social pathologies will be huge for all involved, not just for the poor; mitigating the negative externalities of crime and increasing education rates (and thus the skill of the labor force) are two obvious ways in which the well-being of the larger society is tied to that of its least fortunate.
To that end, this paper will examine integration in Chicago from 1980-2010 with the purpose of understanding its relationship to socioeconomic outcomes as well as whether its relationship to gentrification. More concretely, I will examine whether the evidence points to integration being a consequence of a decline in the importance of race-based preferences or whether it seems resultant of nonracial market factors incentivizing richer whites to move into poorer Black neighborhoods. I will also associate changes in income, rent, and other variables with racial changes. In doing so, I hope to shed light on exactly how the city’s composition has changed and provide interpretative context to decreasing segregation rates.

I choose to focus on Chicago for several reasons: it is one of the most segregated cities in the United States as well as the third largest; it has seen some of the largest disparities of income by race, as well as one of the largest public housing programs; and it is historically important to both the Civil Rights movement, having been the site of the largest civil disobedience acts under the name of the Chicago Freedom Movement, and the African-American experience generally. In principal, the methodology I use here could be extended to examine the integration that has occurred across the United States, and in general provides a useful way to evaluate the likely efficacy of reducing segregation in any society which faces racial income disparity similar to that of the United States.

The paper will proceed as follows. In Section 2, I discuss theoretical and empirical arguments as to why segregation matters, and why gentrification may matter; this will make up the motivation for the paper. Additionally, I devote a subsection to discussing approaches previously taken in the literature. In Section 3, I discuss the plan of my empirical analysis, describe my data sources, present confirmation of some previous results and other useful context, and present my models. Section 4 presents my results and analysis. In particular, I am interested in three topics: what movement drove the increase in integration; how it affected poverty and skill spillover potential; and whether there is evidence of decreased importance of racial preferences. Section 5 concludes. Section 6 presents references and Section 7 provides tables and graphs.

2. SEGREGATION AND GENTRIFICATION: LITERATURE AND STYLISTIC FACTS

Before the current era, in which most race-based discriminatory practices have been officially banned by the judicial branch as unconstitutional, segregation was legally enforceable by municipal or larger local authorities in every walk of life from schooling to buses to drinking fountains. Restrictive covenants, particularly on the sale of property, limited where blacks and other minorities could live; even after such discriminatory titles were declared unconstitutional, other practices, such as ‘redlining’ geographic segments where loans could and could not be made conveniently correlated with racial distributions enforced de facto discrimination. While such practices remain extant to some degree, ever-increasing legal protections and rights have allowed further mitigation of their effects; legally, at least, it has become more and more difficult for prejudiced citizens to act on their prejudice without repercussions.

2.1. Theoretical and Empirical Arguments for Why Segregation Matters. The most obvious explanation for the persistence of segregation is one of racial preferences affecting locational decision-making on the parts of whites, blacks, or both. The approach of Schelling 1971 shows that even a small degree of prejudice or ethnocentrism can result in large amounts of segregation. Importantly, if agents want to be in any degree of strict racial majority, then even a strict preference for a relatively high amount of minority presence in neighborhoods can give rise to a highly segregated outcome.

In most datasets, it is quite difficult to engineer research design to differentiate between racial preferences and preferences for or against characteristics correlated with racial distributions, precisely due to how strongly these characteristics are correlated by race. While this may seem like a fine point, it matters greatly as far as how society should approach the question of segregation. If racial segregation is purely a consequence of these sorts of preferences, and thus emerging out of the will of the agents themselves, it is not a priori obvious whether segregation itself is a problem in need of a solution. If different races wish to live alone as a consequence of different distributions of characteristics and preferences, there is no reason to focus on segregation as opposed to viewing issues of crime, poverty, and education as public policy concerns in themselves. But even stripped of moral content, there are reasons for policy to examine segregation closely. The possibility of externalities due to segregation is quite plausible; as suggested below, there are possible costs and possible benefits. Indeed, it is not obvious, without real-world data, that ghettos must in all cases have negative impacts on their residents or society; neither is it obvious that ghettos must in all cases have
positive impacts. In any case, such externalities would imply that the phenomenon should be considered in its effect on society as a whole, not only its effect on individual agents.

Cutler (1997) asks the question, “Are ghettos good or bad?” While such a question would likely be considered self-evident outside the discipline, the above line of reasoning is exactly what spurs Cutler and Vigdor to model the phenomenon carefully, focusing on human capital transmission affected by positive spillovers. The authors abstract segregation into a fixed cost for blacks (equivalent to discrimination), and explore segregated equilibria with an eye towards welfare effects. Under their model, the effect of racial segregation is directly tied to how it affects segregation by skill level. If segregation decreases skill-segregation, it may actually increase welfare for unskilled minorities. If, on the other hand, it increases segregation by skill, it will decrease welfare for the unskilled minorities and may or may not increase welfare for those that are skilled. Of course, this merely defers the question of how segregation affects welfare to the form that segregation takes, and points to the causal mechanism as being the segregation by skill. Real-world examples of both scenarios seem to exist—consider the experience of the Harlem Renaissance versus the experience of the so-called ‘hyperghettos’—and so as usual, empirics must be used to get a substantial answer to the question. Cutler and Vigdor do so, and in order to avoid confound within-city effects from neighborhood sorting, they compare intercity variations in city-wide segregation with average black outcomes, including wage growth, education, rates of teen pregnancy, crime, and others. They use geographic features as instruments in order to isolate causality and avoid the confounding effects that arise if blacks endogenously sort across cities based on their levels of socioeconomic success. They find a strikingly large magnitude to the effect of segregation: eliminating it entirely would eliminate all black-white differences in earnings, high school graduation rates, and idleness. Clearly, this result (and other literature omitted for the sake of brevity) suggest real and strong negative effects caused by segregation.

2.2. Previous Approaches to gentrification. Gentrification and segregation have both been considered in the Economic Literature, but their treatment has often been distinct. Because gentrification analyses have tended to be couched in terms of somewhat unrealistic comparative statics, the gentrification as a phenomenon has been relatively under-examined compared to the larger topic of segregation and often considered with less of an emphasis on racial classification of agents. Segregation, on the other hand, has been extensively studied.

The approach in Mckinnish (2009), which considers 72 primary metropolitan statistical areas over the years 1990 and 2000, involves accessing restricted data, to which I do not have access, in order to determine the composition of residential inflow in gentrifying neighborhoods. Here, the authors define a gentrifying neighborhood as a census tract whose average income begins in the 1990 bottom quintile, and then increases by $10,000 in 2000. While such a definition of gentrification captures the income portion of gentrification, I will consider neighborhoods to be gentrifying when they are not only gaining average income, but also gaining whites. This seems to best conceptions of the phenomena among those who tend to deal with it.

Guerrieri (2010) focuses on gentrification in both theory and empirics, but do not consider race. They show that in their model of endogenous gentrification, at least one rich-centralized equilibrium exists that, when shocked with population increase, will display a similar pattern in expanding outward and displacing poorer agents towards the periphery. They predict that housing prices should respond much more strongly to shocks in poor neighborhoods (particularly those closest to the rich neighborhood). They then turn to empirics and note that a similar pattern occurs in reality, with poor neighborhoods’ housing prices rising faster than rich neighborhoods in a boom and that indeed, poor neighborhoods closest to the richest neighborhoods appreciate in housing prices the fastest.

2.3. Adapting Glaeser’s Model to Explore Gentrification. Again, the economics literature has tended to analyze gentrification and segregation as separate phenomena. However, many of these models are flexible in interpretation; for some, it is possible to interpret various parameters in segregation models in light of gentrification and vice versa. In particular, I will examine a model from Glaeser (2011), designed to answer questions about segregation, and reinterpret it in light of the phenomenon at hand. While Glaeser explores the model thoroughly in light of segregation, he does not consider gentrification explicitly; with a little bit of thought, however, it is possible to adapt its prediction to this larger framework. As I am not proposing a new model but rather testing the implications of one in this issue, I will not spend too much of the paper focusing on its proofs or mechanics, but I will describe its setup and implications, and describe how it informs my research design as well as to what degree it is empirically translatable.
2.3.1. Model Setup. Consider a city with two neighborhoods of equal size, indexed by $i$. The city is filled by only black agents and white agents, and the white population is in the majority. Define $P$ as the proportion of blacks in the city and $P_i$ as the proportion of blacks in neighborhood $i$. Designate $B_i$ as the number of blacks in neighborhood $i$, $W_i$ as the number of whites in neighborhood $i$, and $K$ as the capacity of each neighborhood. Each agent likes or dislikes (and thus gains or loses utility through living in) neighborhood 1. These tastes are distributed in the population symmetrically around zero with a cumulative density function $F$. White agents living in neighborhood $i$ pay cost $\alpha_w * P_i$, while black agent gain benefits $\alpha_b * P_i$; note these functions are linear. Additionally, blacks are taxed $G$—equivalent to discrimination—to live in neighborhood 1. The rent of neighborhood 2 is normalized to be zero, and $Q$ denotes the rent premium to live in neighborhood 1. $a_w$ and $a_b$ represent the white and black ‘taste’ or preference for neighborhood 1. Utility is the difference between wealth, rent, spillovers, and tastes.

Then define

$$U^1_w = wealth - Q - \alpha_w * P_1 + a_w$$
$$U^2_w = wealth - \alpha_w * P_2$$
$$U^1_b = wealth - Q - G + \alpha_b * P_1 + a_b$$
$$U^2_b = wealth + \alpha_b * P_2$$

The model allows agents to choose locations, and the rent premium is determined as a results of agents’ decisions, but $G$, $\alpha_w$, $\alpha_b$, and the distributions of preference for neighborhood 1 are given.

2.3.2. Equilibrium. An equilibrium is set of locational decisions and a rent premium such that each agent is maximizing utility through his choice. The simplicity in this model allows for an easy description of how the parameters relate to each other: because in the equilibrium, the neighborhood proportions and rents are fixed, the only difference in the utility functions among nonblack agents will be in the taste distribution for neighborhood 1. Mapping agents to their position on the taste distribution provides the following result: in equilibrium, everyone who prefers neighborhood 1 more strongly than the ‘marginal’ nonblack agent (who is indifferent to both neighborhoods) will locate in neighborhood 1, while those that prefer neighborhood 1 less strongly will locate in neighborhood 2. Thus the equilibrium condition is really a function of that marginal agent. Denote the marginal agent’s preference for neighborhood 1 with a star. Then with some work, one can show that the equilibrium requires

$$Q + \alpha_w P^1 - a^*_w = \alpha_w P^2$$
$$Q + G - \alpha_b P^1 - a^*_b = -\alpha_b P^2$$
$$Q = 2\alpha_w (P - P^1) + a^*_w$$
$$= 2\alpha_b (P - P^1) + a^*_b - G$$

Since each agent take the neighborhood compositions to be fixed, and the only variation in preferences comes from the distribution of tastes for neighborhood 1, there must be a marginal nonblack agent and a marginal black agent, both denoted with *, such that everyone whose preference for neighborhood 1 is greater than this agent lives in neighborhood 1 and everyone whose preference is less than this agent lives in neighborhood 2. A similar argument exists for blacks. After some more algebraic manipulation, treating the cumulative distribution of tastes as a cumulative distribution of agents, one can see that in equilibrium:

$$a^*_w = F^{-1}\left(\frac{1 - 2P + P^1}{2(1 - P)}\right)$$
$$a^*_b = F^{-1}\left(\frac{2P - P^1}{2P}\right)$$

Several other conditions are required to ensure stability of the equilibrium, and several assumptions can dictate whether stable equilibria are completely segregated or only partially so; but again, as I am more focused on the empirics of the model, I will not focus on these.
2.3.3. Application. Glaeser discusses several plausible assumptions and their implications for segregation in the real world. Using some manipulation, he shows that a sufficiently wide distribution of preference intensity for neighborhood 1 among the two races implies stability of any equilibrium, and in particular that this condition will be satisfied when demand curves for both neighborhoods are downward sloping. If that condition holds, then \[ \frac{\partial P_1}{\partial \alpha_w} = \frac{\partial P_1}{\partial \alpha_b} < 0 \] and \[ \frac{\partial P_1}{\partial G} < 0. \] These results, of course, fit well with intuition and reality — the greater costs whites pay for proportion of the neighborhood that is black, or that blacks gain from proportion black, the fewer blacks will choose to live in the first neighborhood. Additionally, the greater the discrimination costs that are levied on blacks living in neighborhood 1, the fewer will choose to live there. But more interestingly, through further manipulation of the main variables, Glaeser shows that if the black demand curve for the first neighborhood slopes downward, and the nonblack demand curve for the neighborhood slopes downward as well, then \[ \frac{\partial Q_1}{\partial \alpha_w} > 0. \] In words, this says that the more utility costs that whites pay as a result of a given level of integration, the more that the premium to be living in the nonblack neighborhoods should increase. This insight provides a testable prediction: in principle, it should be possible to examine the premia in rental prices for whiter neighborhoods, and thus ascertain whether there is evidence that \( \alpha_w \) declined or not. A negative answer will point towards gentrification, and lay the impetus at some other factor than declining integration costs; in the context of this model, this will mean a demand shock, and likely consist of \( \alpha_w \) or \( \alpha_b \) changing. One could imagine that, if amenities differ among neighborhoods, such distributions of taste may be correlated with wealth— this point is one way in which such a change could be explained within this model.

Thus, I will examine the price premia of the nonblack neighborhoods. If they have remained the same or increased, then decreased racial preferences can be ruled out. If they have declined, then decreased importance of racial preferences is a possibility. There are real-world complications, of course. One example is the fact that the income distributions have also changed over time. Failing to control for this could lead to a false positive in observing rent premia failing to decline. The number of people in a tract will also affect rents, not to mention various neighborhood amenities. In short, the real world is more complicated than this model. Yet it provides a useful avenue: in the next section I will discuss the specific design in testing the premia, and consider important controls.

3. Empirical Analysis

3.1. Data. Data is drawn from the United States Census, conducted every ten years by the Census Bureau, and the American Community Survey. While aggregate census data does not allow for tracking individuals, it is very useful for understanding long term trends and net flows. The primary unit of analysis is the census tract. A census tract is a contiguous geographic measure containing between 1000 to 8000 people. I aggregate together census tracts that have ever merged or split into one unit, amalgamating their data wherever possible and designating them as modified census tracts in order to maintain continuity across time. Following the literature, I conduct all of my city-wide analysis at the Chicago Metropolitan Statistical Area level. The MSA is defined as including all areas surrounding an urban region where 25% or more of workers commute into the city proper; this provides a more useful definition of the city than the somewhat arbitrary city limits.

Two variables available at the tract level that I draw from the census long form (in addition to income) are what I will refer to as the ‘Poverty’ variables and the ‘Education’ variables. The Poverty values provide a breakdown of number of persons living below the poverty line vs. number of persons living at or above it; these numbers are broken down by race and provide a convenient way of measuring outcomes. The Education variables count persons reaching a given level of educational attainment: given levels include no high school, some high school, high school graduate, some college, and college graduate and above (in the case of the 1980 census) and associate’s degree, bachelor’s degree, and master’s and above (in the case of all others). These numbers are also broken down by race. From the Education variables, I define three categories of skill level (though I later consolidate to two in order to calculate segregation): unskilled includes those who have not completed high school, have completed some high school, have completed some high school, have completed high school; semiskilled includes those who have completed some college or associate’s degrees; skilled includes those who have completed a bachelor’s or more. I define an enclave as a neighborhood that has a greater proportion of a given race than some fixed cutoff. Except for robustness checks, I will use 80% as that cutoff. Some parts of the most recent
census have not yet been released, meaning that some of my variables will be limited to the period 1980-2000 rather than 1980-2010.

3.2. Research Design. In the next section, I first describe some empirical facts about the distributions of the black and nonblack populations in Chicago. Then I move on to my primary question: I am interested in whether this observed process of integration is truly a manifestation of decreased importance of racial preferences, or whether it is in fact a consequence of gentrification. Such hypotheses would display tell-tale signs that allow me to differentiate between them. Glaeser’s model above gives a possible test to provide evidence supporting one or the other.

Now even under the first scenario, where racial preferences lose importance, there is no reason to expect an immediately integrated society; transaction costs, particularly large in changing residence, mean that the status quo will be preferred by agents to incurring those costs (if there is no benefit or harm derived from segregation), and as famously shown by Schelling (1971) even a small amount of (prejudicial or ethnocentric) racial preference can keep segregation levels high. What is expected, however, is that new location choices should display no racial preference. In this case, focusing on changes in black and nonblack populations should provide a reasonably accurate proxy for moves into the neighborhood. (While there is the possibility of differential birth rates affecting population growth and distribution, these effects should be small when controlling for total population size; in addition, in my robustness checks I break up the population composition by age in addition to race, which allows me to focus on the population that could not have been born in between census. This may miss population growth in the form of young children; however, as a final robustness check I repeat the analysis for only those who are adults, which should properly standardize the comparison.) To this end, I will look at neighborhood change, rather than levels, as my variables of interest. Formally, this scenario means that there is some shift over time which approaches $\alpha_b = \alpha_w = 0$.

Under the second scenario, gentrification is what drives the apparent increase in integration. For the purpose of this paper, gentrification will be conceptualized as a phenomenon in which richer whites move into poorer black neighborhoods because shocks to housing stocks, demand for housing, or neighborhood preferences, rather than changes in spillover costs/benefits $\alpha_w$ and $\alpha_b$. I give the regressions and rationales behind them in this subsection, and present and analyze the results in the next subsection.

First, I examine the changing population in order to understand to what degree neighborhoods gained or lost income and black population. One way to do this is to examine the change in log population by percentage black. A set up of

1. \[ \Delta \ln \text{black} = \beta_0 + \beta_1 \text{lagged percent black} + \epsilon \]
2. \[ \Delta \ln \text{white} = \beta_0 + \beta_1 \text{lagged percent black} + \epsilon \]

will give basic associative results. These results are not good estimations of causality, but are useful in understanding the average change of different segments of the city. Additionally I add controls for the lagged logarithm of average gross rent, lagged logarithm of average black and nonblack incomes, and the lagged logarithm of total population.

Next, I compare associations of within period gains and losses in black and nonblack populations. In particular I am concerned with these changes among tracts that are majority black as of the observation or are ever majority black (i.e. tracts that gain or lose black majority. I also consider this for black enclaves, defined at the 80 percent cutoffs, and in fact find very similar results.) To do this, I consider:

3. \[ \Delta \text{black} = \beta_0 + \beta_1 \Delta \text{Nonblack} + \epsilon \]

with controls for lagged logarithm of gross average rent, lagged logarithm of average black and nonblack incomes, and the lagged logarithm of total population.

Finally, I examine the rent premia as specified from Glaeser’s model. To do so, I run the following regression:

4. \[ \text{Average Household Rent} = \beta_0 + \beta_1 \text{percent white} + \epsilon \]

and include controls for total population, housing per person, and average income. (I also try a similar model using the logarithm of average household rent.) However, for both models, I run each year separately. If all outside factors were controlled for, $\beta_1$ would represent the rent premium for being in whiter neighborhoods. Now, these associations may contain omitted variable bias if I have failed include enough controls; I will
further address this in the robustness section. Additionally, I consider the possibility that the rent premia may be different among differing income levels, and repeat the regression for each quartile of income alone.

In the next section I present the empirical results. After that, I present some more empirical facts about the distribution in particular how segregation indices of educational attainment and poverty level changed, to give context and interpret the results.

4. Empirical Results and Analysis

4.1. Stylized Facts about Chicago Population Changes and Gentrification. There are two main indices used to measure segregation: the dissimilarity index and the isolation index. I will focus on the dissimilarity index: I choose this measurement in particular as it is the most widely used measurement to calculate segregation in both the economics literature as well as other disciplines with an interest in the subject, including sociology, political science and urban planning. The dissimilarity index is also desirable in that it has several nice properties, chief among them its ease of interpretation: 0 represents complete integration and 1 represents complete segregation; one can think of the dissimilarity index as a ‘percent segregated’ (when multiplied by 100). The dissimilarity index is calculated as

\[ DSRI_{city} = \frac{1}{2} \sum \left| \frac{\text{black}_i}{\text{black}_{total}} - \frac{\text{white}_i}{\text{white}_{total}} \right| \]

where \( i \) identifies each neighborhood in the city. A conceptual interpretation of the index is that it measures the proportion of the black population (or whichever minority population is being considered) that would have to be moved from their current location in order to create a ‘perfectly’ integrated city, where perfectly integrated is defined by having each neighborhood containing the same racial mix as the city as a whole.

Below, Figure 2 compares the dissimilarity of Chicago, New York, and Los Angeles (as metropolitan standard areas) according to the census data over the years 1980-2010. These are the three largest cities in the United States, and have been so for the extent of the time period I examine and before. Chicago is represented by the red circles, New York by the blue, and the green represent Los Angeles. Evidently, Chicago has a stunningly high segregation index, higher than either of the other two (also deeply segregated) cities; and while all three decline, concordant with the general pattern Glaeser and Vigdor found, Chicago segregation declines the least, and levels remains high in all three cities.

As visible in Table 7, Chicago’s segregation level has fallen significantly, though it remains very high. It drops from an astounding 0.87 in 1980 to a high but lower 0.72 in 2010. (The trend is similar, though the indices are lower, when DSRI is computed for blacks-nonblacks.) Clearly, Chicago is an interesting case; further work will have to identify whether analyzing it will prove to be using an outlier and an exception or shedding light on a broader phenomenon.

4.1.1. Where is the decrease in segregation coming from? One obvious question to ask, after establishing that segregation has at least modestly decreased, is: where is this decrease coming from? Are black populations growing in previously white neighborhoods, or white populations growing in previously black neighborhoods, or both? This matters, of course, because gentrification is much more likely to take the guise of white populations growing in black neighborhoods, while a decrease in preferences should result in growth of black and white populations in their opposite enclaves. One convenient aspect of the segregation index that I am using is that it is sums additively over the neighborhoods in question. As Equation ?? indicates, the index is the sum of terms. Thus it is possible to fix geographic regions of the city and consider their contribution to the total index. To exploit this, I fix and then examine the census tracts in 1980 who are either white or black enclaves (as defined above). Those who are neither black nor white enclaves I designate as mixed. Then I can decompose equation ?? into

\[ DSRI_{city} = \sum_{i \in \mathcal{B}} \left| \frac{\text{black}_i}{\text{black}_{total}} - \frac{\text{white}_i}{\text{white}_{total}} \right| + \sum_{i \in \mathcal{W}} \left| \frac{\text{black}_i}{\text{black}_{total}} - \frac{\text{white}_i}{\text{white}_{total}} \right| + \sum_{i \in \mathcal{M}} \left| \frac{\text{black}_i}{\text{black}_{total}} - \frac{\text{white}_i}{\text{white}_{total}} \right| \]

where \( \mathcal{B}, \mathcal{W}, \) and \( \mathcal{M} \) represent the set of white Enclaves, black Enclaves, and mixed neighborhoods respectively. I define Neighborhood 1 to be the union of tracts of white enclaves, Neighborhood 2 to be the union of tracts of black enclaves, and Neighborhood 3 to be the union of tracts of mixed tracts. Then the first series is Neighborhood 1’s contribution to the total segregation index, the second series is Neighborhood 2’s contribution, and the third is that of Neighborhood 3. As populations shift over time, these relative contributions will change: Figure ?? plots these changes. What is interesting is that while the total segregation index is
decreasing, the contribution of Neighborhood 1 decreases significantly from 1980 to 1990 but then stagnates or rises, while the contribution of Neighborhood 2 declines consistently. This means that the black enclaves are responsible for less and less segregation as time goes on, meaning they are becoming more integrated; this can mean that either they are losing blacks or gaining whites (or both). The white enclaves, on the other hand, must have gained whites or lost blacks (after 1990) in order for this pattern to make sense.

4.1.2. Regression Results and Analysis. I begin with regression ??, whose dependent variable is the change in log of white population. The following table presents coefficients on the included variables, as well as added controls (and year fixed effects, not listed but included in the regression). The most important result is that there seems to be a consistency to $\beta_1$, the coefficient of lagged percentage black. It is negative, with a magnitude between $-0.08$ and $-0.13$. The implications of this are that controlling for average rent, black and white incomes, an total population size, blacker neighborhoods gained less whites (or lost more whites). The next table, provided on page ?? provides results of regression ?? again. I find a negative and significant coefficient on lagged percent black, varying in magnitude between $-0.99$ and $-0.70$; including all the controls puts it at about $-0.75$. This has a similar interpretation to the last regression: blacker neighborhoods, even after controlling for various factors that might affect population growth, lost more blacks. Thus together, the regressions indicate blacker neighborhoods lost more blacks and more whites. Given Chicago’s loss in black population (see Appendix), this is not entirely surprising. While these results do not comprise a smoking gun for gentrification, they do not point towards the reintegration hypothesis. Table 5 on page ?? compares the association in white population versus change in Black population for tracts that were majority black. These compare changes in number of persons directly, and so can be interpreted as follows: for every 1 white gained, on average, about 1.2 blacks were lost. This interpretation is again associative and not causal. It is possible that blacks left majority tracts during these years and were replaced by whites in a 5 to 4 ratio. However, the results are also supportive of the gentrification interpretation. Table ?? on page ?? performs similar analysis, only this time including all tract-years of tracts which were ever black majority. Here there is a slightly weaker relationship— on the order of $-0.75$ to $-0.9$. This suggests that the association between decline in blacks with gains in whites was strongest on average in the years that neighborhoods flipped from white to black. This is a more interesting fact than it may seem at first blush; in fact the counterfactual would be possible if ‘reverse tipping’—black flight— was a significant component. (I discuss some of my results on white and black flight in the appendix. Succinctly, there are no instances of true black flight, as defined by a switch from a black enclave to a white enclave, in my dataset. There are, however, 7 tracts which switched from white enclaves to black enclaves at various points in the dataset. Since this is a rather small number of the total tracts, it seems that at least in Chicago’s case, there either was not enough mixing to create a lot of white flight, or it may exist more commonly on a more localized level, i.e. the block level.) Finally I move on to examining the rent premium question discussed in section ??, Table 5 on page ?? describes the regression of the logarithm of average rent on percent white, by year. The coefficients are positive and highly significant, and range from around 0.3 to 0.45. Of course, without including controls, this regression does not really measure the rent premia of being in a white neighborhood as much as the correlation of rent and whiteness, which is in turn correlated to income. Thus I add controls for log population and log average white income to the regressions; these results are presented in table ?? on page???. Because my race-specific income data begins in 1990, I have to omit the 1980 regression. Over the period 1990-2010, however, the coefficients on percentage white remain highly significant and positive, increasing from .23 to .31 to .56. If this coefficient in this regression can be taken to be an effective proxy for the rent premium, then this regression says that rent premiums increased over the period of integration. By Glaeser’s model, then, this implies white externalities paid for living with blacks have not decreased, but even increased.

4.2. Segregation of Poverty and Educational Attainment Levels. The above section shows that most of the increase in integration came from the black enclaves. The immediately preceding analysis shows that there is evidence that some gentrification was going on, as among those tracts, white gains were associated with black losses, and the rent premium for living in a white neighborhood has only gone up, not down. Thus, there is evidence that gentrification may be responsible for at least some of the observed integration over this period. However, this is not enough to say whether outcomes have improved or not. First, I consider changes in economic segregation. To examine this, I treat poor black and nonpoor blacks as separate populations, and calculate a segregation index for them alone. If the proposed mechanism of positive spillovers affecting
outcomes is valid, then there is good reason to suspect that lower economic segregation will benefit the poor, at least insofar as their development of human capital goes. If racial preference is still extant, then it makes sense that knowledge transmission will move primarily along networks of the same race, so for the moment I will consider economic segregation among blacks only. Figure 4 displays the changes.

The most obvious qualitative difference between these two series is that the overall level of black economic segregation is much lower than the level of black-white racial segregation. This is no surprise, of course; if both racial preference and consumption preferences play a role in determining people’s location choices, then segregation should be higher when both race and income vary. What is interesting, however, is the direction that the series moves in: between 1980 and 1990 it jumps from .344 to .383, an increase of 11.3 percent, only to return to .350 in 2000 (an 8.6 percent drop over the 2000 figure). These are fairly large jumps, in percentage terms, but on a total scale from 0 to 1, such changes do not appear to be extremely economically significant. Overall, the level of Poor-Nonpoor segregation has not changed much as segregation has increased. This could is consistent with several scenarios. First, because there is evidence that for rent premium on whiter neighborhoods, it is possible that the poor are being priced out, but are moving to other black enclaves, and this is decreasing segregation. It is also possible that black departures from the MSA are decreasing the segregation index: algebraic manipulation of each term contributing to the segregation index shows that removing a number of people from the city as a whole will decrease that term’s contribution to the segregation index, and either poor or non poor departures could cause this. Perhaps more important than pure economic segregation is segregation of education levels; if spillovers from educated peers or mentors can contribute to human capital development, policy makers might be just as concerned with segregation of knowledge. Indeed, it is often the case that economic segregation is being used as a proxy for this larger factor. As discussed in Subsection ??, the census records educational attainment by race, and I have used this to construct a segregation index between educated and uneducated members of the population. While the labor literature tends to be focused on labor force skill, I have not differentiated between those employed, unemployed, or retired, nor do I consider years on the job, which is often a large component of the determination of skill level. This choice may be misleading if the only valuable education is that which increase labor force skill, but in any case education is a fundamental requirement for human capital development.Moreover, the literature concerned broadly with segregation, education, poverty, and outcomes, suggest that educational attainment may be related to the incidence of various social indicators. The degree of educational segregation could thus act along several channels: first and directly, spillover effects resulting from more educated peers can help distribute the knowledge necessary to build human capital among the adult population. Second, it is well known that the probability of attending and completing education beyond the primary and secondary level is affected by the availability of role models who have completed such a path. Finally, more educated parents may be correlated with better imputation of knowledge to their children as well as more stable households, which may affect health outcomes as well as delinquency rates. Thus there is good reason to surmise that low skill segregation is desirable in terms of reducing poverty. Figure 5 below extends figure 4 by adding a plot for educational segregation. Skill segregation has declined from .393 in 1980 to .318 in 1990 to .306 in 2000, a total decline of .087 or roughly 22 percent. The absolute drop seems like it is an economically significant drop. In any case the qualitative trend is clearly that increased racial integration and possible gentrification did not coincide with increased skill segregation.

Both these results point to the possibility that gentrification of neighborhoods may have pushed the poor black population to neighborhoods with lower concentrations of poverty and higher concentration of skills within the black population. The results are also consistent with poor, unskilled blacks being pushed out of the city altogether. In either case, there is no denying that displacement may wreak significantly deleterious on individual’s lives, and the experience of any one individual impacted by gentrification may be tragic. But gentrification does not seem to have made the poor population as a whole worse off from the viewpoint of these specific types of segregation. It is at least possible that gentrification could drive the poor from concentrated poor neighborhoods to more mixed neighborhoods. While outcomes would need to be corroborated, such a scenario could be a silver lining.

4.3. Robustness. This paper has argued that integration in Chicago may have stemmed from gentrification rather than the abandonment of racial preferences; if each of the results are taken at face value, then this paper provides worthwhile evidence towards that conclusion. However, there are several causes for concern to be followed up on in further work. One important caveat to this work stems from the possibility of omitted
variable bias, particularly in regressions involving rent premia. As discussed above, I find that there does exist a premium to being in whiter neighborhoods. I control for income and population size; controlling for population is particularly useful in that if tastes for neighborhood amenities are correlated with income, a reasonable proposition, this may avoid the issue of confound amenity premia with racial premia. However, there are several other potentially problematic variables. The supply of housing relative to available demand is important; in particular it is possible that the relative shortage of housing would raise the rent premia on white neighborhoods. Such a phenomenon would also provide an impetus for gentrification. Qualitatively, however, blacks located in inner city neighborhoods are likely to be in denser housing situations, and this may mitigate to some degree the possibility of the white rent premia being subsumed by relative housing insufficiency. This deserves further exploration, however. Another possibly important variable that I have not included is the distance to a central business district. If whites live closer to such a district, and transportation costs are important, then such a measure would be inversely correlated with tract percentage white. Such a correlation could mean that the observed rent premia are really just prices to pay for living closer to the center of the city. While this too, deserves further exploration, one comforting fact that can be glimpsed from the geography of the city is that there is not an overwhelming concentrations of whites near the city. Figure 6 provides a chloropleth map of the fraction of each tract that is of a particular race. Visual inspection shows that no one race occupies exclusively the area nearest to the central business district. There may be some degree to which the whitest neighborhoods are blacker than the blackest neighborhoods, however, and visual inspection is not a terribly reliable method, therefore this is an important avenue to consider.

5. Conclusion

In this paper, I have examined data from Chicago an the eye towards the question of whether gentrification explains Chicago integration or whether there is evidence that racial preferences are of less importance than they once were. Based on the data, I have shown that there is evidence that points to the gentrification hypothesis. First, most of the integration which occurred due to previously Black neighborhoods becoming more white rather than white neighborhoods becoming more black. Third, there exists a relationship in Black majority tracts, whereby forever white that moved in, 1.2 blacks moved out. Furthermore, the rent premium for living in a white neighborhood has increased, not decreased. Caution is required when interpreting these results, however, due to the possibility of omitted variable bias.

The ramifications of gentrification do not seem entirely clear. On the one hand, it does seem there has been some degree of displacement as a consequence of rising rents, which may have resulted in distress for those displaced. However, the results are segregation between the Black poor and non poor has not increased; neither has the segregation between educated and non-educated blacks– in fact it even decreased to a nontrivial extent. Thus the poor as a whole group do not seem to be worse off as a result of gentrification.

Several directions for further research seem potentially fruitful. Initially, this particular study could be repeated with greater attention to robustness to omitted variable bias as well as to using different sorts of variables and cutoffs. Ideally, the rent premium could be derived theoretically in a way that was not so dependent on the model used. In another direction, it is worth considering what makes gentrification happen what, across the cities of the U.S. and beyond, seem to be the conditions necessary for gentrification to occur? Finally, is there a clear-cut effect of gentrification on the people in the neighborhood that gentrify, as well as those displaced? All these questions and more could further our understanding of city dynamics. Even more importantly, they could point the direction towards useful policy measures, whether that means encouraging further integration through gentrification, discouraging gentrification, or taking a non-interventionist attitude. Cracking this puzzle would prove a grand step forward in the study of urban systems and has the potential to greatly improve the welfare of the world’s large and growing urban population. This methodology seems to be useful in understanding inter and intra city movements; further study of gentrification seems merited.

References


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THE IMPACT OF TRADE LIBERALIZATION ON INCOME INEQUALITY: A CROSS-COUNTRY ANALYSIS

Sara Marcus
Dartmouth College

ABSTRACT

This study evaluates the relationship between trade liberalization policy and income inequality. Using variation in trade policy created by the General Agreement on Tariffs and Trade (GATT) Uruguay Round of negotiations, I conduct a cross-country comparison between liberalizers and non-liberalizers. To do so, I create a difference-in-difference regression that measures the impact of trade liberalization on changes in Gini coefficients, an aggregate measure of country-level income inequality. Among developed countries, I find that trade liberalization is associated with a relative increase in income inequality. Among developing countries, however, I find no significant difference in trends in income inequality between liberalizers and non-liberalizers. This finding differs from recent studies documenting the increase in skill premium following trade liberalization in developing countries, and suggests an alternative long-run trend among liberalizers.

1 Introduction

In 2013, trade openness continues to be at the forefront of strategic policy to promote growth and increase welfare across countries of all sizes and income levels. This international liberal economic order first emerged among wealthier western nations following World War II, with the creation of international economic institutions such as the International Monetary Fund and the General Agreement on Tariffs and Trade (GATT). It was not until more recent decades, however, that developing countries joined this era of increased trade and openness. There now exists a broad consensus among economists and policymakers alike that increased trade is correlated with economic growth. However, is GDP growth the best measure of economic welfare? How do we know which groups actually benefit from trade-related growth? This paper seeks to explore the relationship between trade liberalization policy and income inequality to better capture the distributional impact of trade. If all of the benefits are accrued to the top of the income distribution, trade’s relationship with income inequality measures will reflect that reality. I am particularly concerned with the nature of this relationship in developing countries, to whom developed countries and international institutions continue to prescribe trade liberalization policy as a mechanism for poverty relief. Do such policy prescriptions have a positive impact in reducing income inequality?

In order to capture this relationship, this paper uses the Uruguay Round of GATT negotiations as a source of variation in trade liberalization policy, following the methodology of Estevadeordal and Taylor’s (2008) work on the impact of trade policy on changes in GDP growth rates. I conduct a cross-country analysis and examine the impact on countries’ Gini coefficients, an aggregate measure of income inequality. Using a difference-in-difference regression, I find that trade liberalization is not associated with a significant change in income inequality among developing countries in either the positive or negative direction. Developed countries that liberalized during the Uruguay Round, however, did see a significantly larger rise in inequality compared with those that did not liberalize. While trade theory can explain rising inequality in developed countries following trade liberalization, the mechanisms behind the ambiguous impact in developing countries are more difficult to identify.

The paper proceeds as follows: Section 2 provides a theoretical framework for the relationship between trade liberalization and income inequality, and examines relevant literature to contextualize the contributions of this paper. Section 3 describes the variables of interest, their data sources, and the methodology used in this study. Section 4 reports empirical results along with robustness checks. Section 5 provides a discussion of these results. Section 6 concludes.
2 Literature Review

The relationship between trade openness and income inequality is explored extensively in economics literature. The importance of income distribution as an economic indicator has been recognized by Çelick and Basdas (2010), who argue that in the long term, governments must be concerned with the interaction of economic and social development. Within this context, income equality is one of the most important indicators for social justice. Despite concern for this indicator, however, the literature is severely lacking in consensus about the way in which it responds to trade liberalization.

Much of this debate stems from the discord between trade theory and empirical evidence on the impact of trade liberalization on income inequality in developing countries. The Stolper-Samuelson (1941) theorem of international trade predicts that trade liberalization should lead to decreased inequality in developing countries due to the relative abundance of unskilled labor compared with developed countries. When developing countries liberalize, they will have a comparative advantage in sectors that rely heavily on unskilled labor. The relative prices of such goods will therefore rise, increasing demand for unskilled workers and raising their relative wage. This will narrow the wage gap and reduce inequality. In developed countries, the opposite will be the case; relative prices of goods that require skilled labor will rise, widening the gap between skilled and unskilled wages.

While empirical evidence does point to rising inequality following trade liberalization in developed countries, the evidence for the impact in developing countries does not likewise follow trade theory. Many economists find that the Stolper-Samuelson prediction does not hold true, and developing countries generally see rising inequality as a result of trade liberalization. Beyer, Rojas, and Vergara (1999) argue that this was the case in Chile, where they found a positive relationship between the volume of trade and the wage gap between skilled and unskilled workers following a round of trade liberalization in the 1970s. Hanson and Harrison (1999) found a similar increase in the skilled-unskilled wage gap in Mexico, resulting from the country’s sweeping trade liberalization measures in the 1980s. Pavcnik and Goldberg (2007) conduct a survey of the literature on this subject, and find that the majority of studies looking at the impact of trade on the skill premium conclude that increased trade does, in fact, lead to rising inequality in developing countries.

How can such findings be explained, given the contradictory prediction of the Stolper-Samuelson theorem? Alongside the aforementioned empirical findings, there exists a growing body of literature on the mechanisms by which trade openness may lead to rising inequality in developing countries. Feenstra and Hanson (1997) argue that while sectors in which developing countries have a comparative advantage may use relatively large amounts of unskilled labor from a developed country’s perspective, the reverse would be true from the perspective of the developing country. Consequently, relative demand for skilled labor increases in both regions as a result of trade, thereby increasing inequality. Atolia (2007) reconciles rising wage inequality in Latin America with the Stolper-Samuelson theory by arguing that trade liberalization can lead to a short-run rise in inequality, while ultimately contributing to its long term decline. This occurs because adjustment costs slow down the release of capital in the import-competitive sector. Meanwhile, tariff cuts on intermediate inputs create a strong incentive for immediate capital accumulation in other sectors. This asymmetry in contraction and expansion facilitates a short-run capital accumulation, boosting the relative wage of skilled labor due to capital-skill complementarity. Atolia argues that this trend can last for ten to twenty years, after which the import-competing sector should fully contract and the Stolper-Samuelson prediction should hold. Topalova (2010) also looks at the issue of sectoral rigidity, and argues that a variety of labor market frictions contribute to factor immobility in all sectors. These frictions tend to be amplified in developing countries, where labor regulations prevent sectoral mobility and economic constraints limit geographic mobility. Consequently, industries that intensively use unskilled labor are unable to adequately expand, and the wage gap cannot contract. While this growing body of literature does not reach a consensus as to the causal mechanisms linking trade openness with an increase in the wage gap, the studies do provide a number of viable explanations.

In contrast to much of the literature surveyed by Pavcnik and Goldberg (2007) that uses the wage gap as a measure of inequality, I am interested in looking at a more aggregate measure of
income inequality: the Gini coefficient (see Appendix A for an explanation of Gini coefficients and how they are calculated). This approach requires a cross-country study because Gini coefficients are measured at the country level. Pavcnik and Goldberg’s paper notes the dearth of empirical research looking at cross-country comparisons and long-term trends in this arena, which they attribute to ambiguities involved in measuring inequality. However, a recent contribution to the data on inequality (Solt 2009) has significantly improved our ability to compare Ginis across years and across countries. I am therefore interested in making use of this new data to examine whether trade liberalization has a similar impact on the Gini coefficient as a measure of inequality as it does on the skill premium.

I am not the first to use Gini coefficients as the dependent variable in measuring the impact of trade openness. However, previous studies that do so find far less conclusive results than those that use the wage gap as a measure of inequality. Mah (2003) found that an increase in trade volume in Korea had no significant impact on the country’s Gini coefficient, and hence had little impact on income inequality. Bergh and Nilsson (2010) use cross-country panel data and find a positive effect of trade liberalization on income inequality. However, they separate countries into developed and developing and find a stronger relationship between openness and inequality in relatively rich countries. Çelick and Basdas (2010) break down countries even further into three groups: developed, developing, and “miracle” countries. They find that trade openness is associated with higher Gini coefficients only in developing countries, and lower Ginis in both developed and miracle countries. These results not only conflict with those of Bergh and Nilsson, but also run contrary to the Stolper-Samuelson prediction. Given the small number and inconsistent findings of these studies, this paper will contribute to the literature by using a unique approach to assess the impact of trade policy on movement in Gini coefficients. This approach is described in the following section.

3. Data and Methodology

In order to measure the relationship between trade policy and income inequality, I employ the methodology used by Estevadeordal and Taylor (2008), who exploit the variation in trade policy caused by the Uruguay Round of the GATT. The authors make use of this event to examine the relationship between trade policy and change in GDP growth. While I am concerned with changes in income inequality as opposed to GDP growth, I use their methodology and substitute the change in Gini coefficient for the dependent variable.

The Uruguay Round spanned from 1984-1996, and came to be known as the “Great Liberalization” because of its far-reaching impact among countries who previously had enormous barriers to trade. Many of these were developing countries, who were opening themselves up to world markets for the first time. However, many countries did not adopt the Uruguay Round trade liberalization measures. This creates a source of variation in trade policy, from which I construct a difference-in-difference equation; countries that liberalized are the “treatment” group and those that did not are the “control” group. There are two time periods used in this regression; period 1 is 1975-1989 and period 2 is 1990-2005. The length of the periods corrects for lags in policy implementation and short-run output fluctuations.

It is important to note that the outcome variable is the change in the Gini coefficient. I am thus asking the question of whether or not the countries that liberalized saw a larger change in their Gini than non-liberalizing countries. Estevadeordal and Taylor comment that this methodology leads to a cleaner empirical design; when differences are used, omitted variable bias from time-invariant characteristics become irrelevant. Differencing therefore eliminates country-specific fixed effects from the equation. This does, however, assume that the adoption of the Uruguay Round liberalization policies was exogenous. However, Estevadeordal and Taylor conduct extensive work to refute contentions of endogeneity, and this issue will be explored again in my robustness checks.

3.1 Variables and Data

The dependent variable is the change in average Gini coefficient between the 15-year period prior to the Uruguay Round of negotiations and the 15-year period after reforms. For each country included in the sample, I averaged their Gini coefficients for 1975-1989 and 1990-2005 and then calculated the difference. In order to obtain data on Ginis I used Solt’s (2009) database, which standardizes the World Income Inequality Database (SWIID). Gini coefficients are not often used in
empirical research because prior to Solt’s work, it proved difficult to find comparable Ginis across
countries and years due to the variety of methods of calculating the measure. Solt used a custom
missing-data algorithm to correct for this problem and standardize the World Income Inequality
Database. His standardization re-calculates each Gini to represent net income inequality. Ginis are
calculated as percentages, with zero signifying perfect equality and 100 signifying perfect inequality.

The independent variable is a simple discrete (zero-one) treatment for openness. This variable
is defined by Estevadeordal and Taylor (2008), who researched the extent to which countries adopted
Uruguay round trade liberalization measures. They created a list of “liberalizers” and “non-
liberalizers”, which will be used in this paper. My dataset includes 72 countries, which are also
identified as either developing or developed countries according to Estevadeordal and Taylor’s
distinction.¹

The controls are a combination of variables used in Estevadeordal and Taylor’s difference-in-
difference regression as well as Bergh and Nilsson’s (2010) regression, which uses Gini as the
dependent variable. The first control is real GDP per capita, which I obtain from the Penn World
Table database (version 7.1) The second control is institutional quality. I measure this using a
composite score of legal and property rights obtained from the Economic Freedom in the World 2005
database. My third control is a measure of human capital, calculated as total years of schooling by
Barro and Lee (2010). The first three controls are all measured in differences, using the same
technique as the dependent variable. The final control is a measure of corruption, obtained from
Transparency International’s Corruptions Perception Index (CPI). Due to insufficient CPI data for
pre-reform years, this control was not measured in differences. Rather, the variable was included as a
level value for the earliest year with adequate data, 2001.

3.2 Empirical Specification

My baseline specification is the following:

\[ \Delta \text{Gini}_i = \alpha + \beta_1 \text{Liberalizer}_i + \beta_2 \Delta \text{RealGDPpercap}_i + \beta_3 \Delta \text{InstitutionalQuality}_i + \beta_4 \Delta \text{HumanCapital}_i + \beta_5 \text{CorruptionPerception} + \epsilon_i, \]

where \( \text{Liberalizer}_i \) = 1 if the country adopted Uruguay Round liberalization reforms, and 0 if they did
not adopt reforms. The coefficient of interest is therefore the estimate for \( \beta_1 \), which reflects whether
countries that liberalized saw their Gini coefficients change by a different magnitude than non-
liberalizers. In a secondary specification I introduce an interaction term between the liberalizer
indicator and a dummy variable for developing countries. This specification provides a more adequate
test of the Stolper-Samuelson theorem, which predicts differential outcomes for developing and non-
developing countries. This specification is as follows:

\[ \Delta \text{Gini}_i = \alpha + \beta_1 \text{Liberalizer}_i + \beta_2 \text{Developing}_i + \beta_3 \text{Liberalizer}_i \times \text{Developing}_i + \beta_4 \Delta \text{RealGDPpercap}_i + \beta_5 \Delta \text{InstitutionalQuality}_i + \beta_6 \Delta \text{HumanCapital}_i + \beta_7 \text{CorruptionPerception} + \epsilon_i, \]

where \( \beta_1 \) represents the impact of liberalization on developed countries, and \( \beta_3 \) represents the
difference in impact between developing and developed countries.

4 Empirical Results

¹ Liberalizers: Austria, Turkey*, Australia, New Zealand, Argentina*, Bolivia*, Brazil*, Chile*, Colombia*, Costa
Nonliberalizers: United States, United Kingdom, Belgium, Denmark, France, Germany, Italy, Luxemborg, Netherlands, Norway,
Sweden, Switzerland, Canada, Japan, Finland, Greece, Iceland, Ireland, Spain, South Africa*, Oman*, Unit. Arab Em.*, Hong
(*=developing country).
Table 1 reports descriptive statistics for the variables of interest. It is interesting to note that the average change in Gini between the two time periods is positive. On average, countries in the sample saw an increase in inequality between the time periods 1975-1989 and 1990-2005. My question of interest is therefore whether or not countries that liberalized saw a greater or smaller rise in inequality than the countries that did not liberalize.

The results of equation (1) are found in Table 2. In column (1) I regress the change in Gini coefficient on the dummy variable Liberalizer, and find a positive coefficient of 0.707. This suggests that countries that liberalized, on average, saw their Gini coefficient rise by 0.7 percentage points more than countries that did not liberalize. However, this estimate is not statistically significant at any conventional significance levels. The finding thus cannot be interpreted as causal. Columns (2) through (5) include controls for GDP per capita, institutional quality, human capital, and corruption perception. The coefficient on Liberalized remains positive until the addition of the corruption control, but statistically insignificant.

According to the Stolper-Samuelson theorem, these findings should not be surprising. Trade liberalization should have a heterogeneous impact on countries, depending on their factor endowments. Developing countries, with their relative abundance of unskilled labor, should see relative declining inequality as they begin exporting goods that use this factor intensively. Non-developing countries should see a relative rise in inequality as they begin exporting goods that use large amounts of skilled labor.

Table 1. Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
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Table 2. The Effect of Trade Liberalization on Change in Gini Coefficient

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<td>(1.858)</td>
<td>(1.767)</td>
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<td>(1.749)</td>
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<td>(0.525)</td>
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<td>(1.703)</td>
<td>(2.054)</td>
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<tr>
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<td>0.008</td>
<td>0.021</td>
<td>0.126</td>
<td>0.081</td>
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</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3. The Effect of Trade Liberalization on Change in Gini Coefficient in Developing Versus Developed Countries (Excluded Group: Developed Countries)
The specifications in Table 3 test for heterogeneous treatment effects by introducing an interaction term between Liberalizer and a dummy variable for developing countries. The coefficient on the liberalizer indicator now represents the effect of liberalization on developed countries only. In column (1) we see a positive coefficient of 2.91, significant at the 5% level, suggesting that developed countries that liberalized saw their Gini coefficients rise by 2.91 percentage points more than developed countries that did not liberalize. The inclusion of controls in columns (2) through (5) does not change the sign of this estimate, nor does it substantially change its magnitude. However, the human capital control does reduce the significance of the coefficient estimate, and slightly reduces its magnitude. A positive change in human capital is associated with a smaller rise in Gini, which reflects the fact that a more educated population is likely to have a larger middle class. Liberalizers therefore saw smaller rises in human capital, which may in part be responsible for their higher Gini coefficients. However, the coefficient on the liberalizer indicator remains positive and significant at the 10 percent level. Therefore, even with the inclusion of controls, trade liberalization is associated with a 2.39 larger percentage point rise in income inequality among developed countries.

The specifications in Table 3 also allow us to see the difference in the impact of liberalization between developing and developed countries. The coefficient on the interaction term (Liberalizer*Developing) reflects this difference. In each specification the estimate is negative, suggesting that the relationship between trade liberalization and inequality is less positive in developing countries. However, this relationship does not become significant until column (5), when all controls are included. Our most rigorous specification therefore tells us that the relationship between trade liberalization and income inequality is not necessarily positive in developing countries, as it is in developed countries.

In order to more directly capture the impact in developing countries, Table 4 conducts the same specifications, but with a dummy for developed countries. Developing countries are now the excluded group, and the coefficient on the liberalizer indicator reflects the direct impact among this cohort of countries. Although the coefficient in column (1) is positive, the estimate is not statistically significant at any conventional significance levels. As controls are added into the regression, the sign of the estimate becomes negative and continues to lack statistical significance. The data therefore does not indicate a significant relationship between trade liberalization and Gini coefficients among developing countries.

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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
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<td>Liberalizer Indicator</td>
<td>2.910**</td>
<td>2.939**</td>
<td>3.099**</td>
<td>2.179*</td>
<td>2.393*</td>
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<tr>
<td></td>
<td>(1.159)</td>
<td>(1.182)</td>
<td>(1.292)</td>
<td>(1.277)</td>
<td>(1.288)</td>
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<tr>
<td>Developing</td>
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<td>-1.231</td>
<td>-0.470</td>
<td>0.133</td>
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<td></td>
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<td>(1.223)</td>
<td>(1.289)</td>
<td>(1.561)</td>
<td>(1.167)</td>
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<td>-2.185</td>
<td>-1.441</td>
<td>-3.388**</td>
</tr>
<tr>
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<td>(1.737)</td>
<td>(1.785)</td>
<td>(1.654)</td>
<td>(1.571)</td>
<td>(1.680)</td>
</tr>
<tr>
<td>Change in ln(GDP) per capita</td>
<td>0.604</td>
<td>1.333</td>
<td>1.016</td>
<td>-0.201</td>
<td>-0.227</td>
</tr>
<tr>
<td></td>
<td>(1.848)</td>
<td>(1.934)</td>
<td>(1.922)</td>
<td>(1.770)</td>
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</tr>
<tr>
<td>Change in Institutional Quality</td>
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<td>0.371</td>
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</tr>
<tr>
<td></td>
<td>(0.651)</td>
<td>(0.703)</td>
<td>(0.516)</td>
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<tr>
<td></td>
<td>(0.615)</td>
<td>(0.490)</td>
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</tr>
<tr>
<td>Corruption Perception Index</td>
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<td></td>
<td></td>
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<td>-0.227</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td>(0.191)</td>
</tr>
<tr>
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<td>70</td>
<td>68</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.053</td>
<td>0.052</td>
<td>0.062</td>
<td>0.135</td>
<td>0.116</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. The Effect of Trade Liberalization on Change in Gini Coefficient in Developing Versus Developed Countries
4.1 Robustness Checks

The empirical methodology in this paper is a difference-in-difference approach, which relies upon a critical assumption to maintain its validity: the trends in the dependent variable prior to the time of treatment must be similar for those who liberalized and those who did not liberalize. Did trends in Gini coefficients of the liberalizers vary from trends in among the non-liberalizers prior to reforms? If so, the treatment can no longer be seen as exogenous.

To test this, I regress the change in Gini coefficient between 1975 and 1989, the 15-year period prior to reforms, on the variable Liberalized. The results are shown in Table 5. Column (1) reports results for the entire sample whereas columns (2) and (3) include an interaction with the developing and developed country dummy, respectively. The latter two columns test whether pre-trends in Gini coefficients varied systematically between liberalizers and non-liberalizers among either developed or developing countries. The coefficients on the liberalizer indicator in all specifications are statistically insignificant, thus confirming that there is no correlation between previous trends in Gini coefficients and the treatment variable. This upholds the contention that trade liberalization during the Uruguay Round was exogenous to the model for the sample as a whole, as well as for developing and developed country sub-groups.

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td>1.231</td>
<td>0.470</td>
<td>-0.133</td>
</tr>
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<td>(1.160)</td>
<td>(1.223)</td>
<td>(1.289)</td>
<td>(1.561)</td>
<td>(1.167)</td>
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<tr>
<td>Liberalizer*Developed</td>
<td>1.693</td>
<td>2.148</td>
<td>2.185</td>
<td>1.441</td>
<td>3.388**</td>
</tr>
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<td>(1.654)</td>
<td>(1.571)</td>
<td>(1.680)</td>
</tr>
<tr>
<td>Change in ln(GDP) per capita</td>
<td>0.604</td>
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<td>(1.934)</td>
<td>(1.922)</td>
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<td>Change in Institutional Quality</td>
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<td>(0.651)</td>
<td>(0.703)</td>
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<tr>
<td>Change in Human Capital</td>
<td>-1.126*</td>
<td>-0.746</td>
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<tr>
<td></td>
<td>(0.615)</td>
<td>(0.490)</td>
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<tr>
<td>Corruption Perceptions Index</td>
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<td></td>
<td>(0.191)</td>
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<td>55</td>
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<td>R-squared</td>
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<td>0.052</td>
<td>0.062</td>
<td>0.135</td>
<td>0.116</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

(Excluded Group: Developing Countries)
To further prove that the results of the main regression are not driven by differences in preexisting trends in income inequality between liberalizers and non-liberalizers, I reexamine the relationship between liberalization and change in Gini using a different calculation of the dependent variable. Rather than taking the difference between the average Gini coefficients over the two time periods, I calculate the post-reforms change in Gini, and subtract out the pre-reform change. This approach differences out any preexisting differences in Gini movement. Table 6 reports the results from this regression. Column (1) regresses the dependent variable on the sample as a whole, whereas columns (2) and (3) introduce interaction terms with developing and developed country dummy variables, respectively.

Table 6. Pre-Trends Differenced out

<table>
<thead>
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<td>65</td>
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</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The results in Table 6 confirm our previous findings. The coefficient on the liberalizer indicator in column (2) reflects the difference in Gini movement between developed country liberalizers and non-liberalizers. The positive and statistically significant coefficient suggests that developed country liberalizers saw a larger increase in Gini coefficient than developed country non-

Table 5. Pre-Trends

<table>
<thead>
<tr>
<th>VARIABLES</th>
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</table>

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The insignificant coefficient on the liberalizer indicator in column (3) again suggests that this relationship does not exist among developing countries. The results in Table 6 therefore indicate that the previous findings were not driven by differences in preexisting inequality trends.

5 Discussion

I find that my data on the relationship between trade liberalization and Gini coefficients in developed countries confirm the prediction of the Stolper-Samuelson theorem; as countries with abundant skilled labor open up to trade, the top of the income distribution benefits most. Following the Uruguay Round of GATT negotiations, developed countries that liberalized saw their Gini coefficients rise by 2.93 percentage points more than developed countries that did not liberalize.

The results for developing countries are less conclusive. As discussed in Section 2, the Stolper-Samuelson theorem predicts that income inequality should fall in developing countries that liberalize, relative to those that do not liberalize. The results in Table 4 do not confirm this prediction, as the estimates are statistically insignificant. However, my prior hypothesis for this study was that we should see significant increases in inequality among developing liberalizers, given the results of many recent studies that relate trade openness to the gap between skilled and unskilled wages. My results do not fall in line with this conclusion.

I see two possible explanations for the deviation of my results from those surveyed in Pavcnik and Goldberg’s (2007) paper. The first is that perhaps the Gini coefficient is too aggregate of a measure to capture the impact of trade openness. It is conceivable that the relationship between trade liberalization and inequality is not apparent at the country-level of analysis. A second explanation is that my results reflect long-term trends in inequality, as opposed to studies examining the wage gap, which may be driven by short-run fluctuations. While I cannot confirm the Stolper-Samuelson prediction of declining inequality, perhaps my results suggest a movement towards a long-term equilibrium in which inequality is reduced through trade liberalization. If this were the case, my findings would fall in line with Atolia’s (2007) explanation of rising inequality; he argues that sectoral rigidity prevents industries from adequately adapting to tariff cuts in the short-term. After a period of ten to twenty years, however, industries should adjust and inequality should thereby fall. My results may therefore reflect a movement away from short-run rises in inequality towards a long-term equilibrium.

I suspect that my results stem from a combination of these two explanations, as well as a third consideration, which is the heterogeneous impact of trade liberalization. A host of other domestic factors likely impact the way in which inequality responds to trade openness, particularly when measured at the country-level. As such, cross-country comparisons may not adequately capture the nature of trade’s impact.

A number of weaknesses of this study may have also impacted the results. The use of country-level data required a small sample, which may have reduced the precision of coefficient estimates. Additionally, I used a discrete treatment variable to measure trade liberalization. This does not reflect the wide spectrum of trade liberalization adoption across countries. Further research should create similar specifications, but use a continuous measure of trade liberalization. Finally, following the methodology of Estevadeordal and Taylor (2008), I included developed countries that likely did not liberalize during the Uruguay Round because they already had relatively low tariffs. This may have biased upwards my findings for developed countries.

6 Conclusion

The results of this study indicate that at the country-level, income inequality is not significantly impacted by trade liberalization in developing countries. In developed countries, however, trade liberalization is associated with a relative increase in inequality. The latter finding confirms both the prediction of the Stolper-Samuelson theorem as well as recent literature. My results for developing countries, however, confirm neither. While I do not find a significant decline in income inequality as the Stolper-Samuelson theorem would predict, I also do not confirm recent literature on the positive relationship between trade openness and the skill premium. If we believe that my use of the Gini coefficient over a fifteen year period reflects the long-term impact of trade liberalization, the policy implications of this finding are important. The literature surveyed by Pavcnik and Goldberg (2007) conveyed a bleak outlook for impoverished populations in developing countries.
facing widespread tariff declines. From a policymaker’s perspective, this may advocate for a more critical look at the use of trade liberalization policy as a mechanism to alleviate poverty. My results, on the other hand, suggest that this outlook may not, in fact, be so bleak; if developing countries do not see a significant rise in their Gini coefficient in the long-term, increases in inequality may only be temporary, as industries take time and resources to adjust to the new economic landscape. Policymakers in developing countries must therefore weigh the short-run costs of trade liberalization measures against the potential long-term gains as they formulate their trade policy going forward.

Appendix: Gini Coefficients

In order to understand the meaning behind a Gini coefficient, one must first understand the Lorenz curve (see Figure A). This curve diagrams the relationship between shares of the population and their associated share of total income earned. In a society with perfect equality, the Lorenz curve would be a 45-degree line because each share of the population would be earning an equivalent share of the total income. In a society with perfect inequality, the Lorenz curve would be a perfect right angle, because the richest 1% of the population would be earning 100% of the total income. For most countries, the Lorenz curve falls somewhere in between, as is the case in Figure A.

From the Lorenz curve, one can calculate a Gini coefficient by taking the area between the line of perfect equality and the Lorenz curve, and dividing it by the total area of the triangle. In other words: \( \text{Gini Coefficient} = \frac{\text{Area } A}{\text{Area } A + B} \). This gives a value between 0 or 1, which gets reported as a percentage value between 0 and 100 in the data used for this paper (The World Bank, GINI Index).

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LOW-WAGE WORK AND THE GREAT RECESSION: APPLICATION OF THE ‘INSTITUTIONAL INCLUSIVITY’ MODEL

Emily L. Oehlsen  
*Georgetown University*

**ABSTRACT**

I investigate low-wage work—earnings below a threshold of two-thirds of national median hourly wages—during the period of the Great Recession in Europe. I review scholarship on income inequality and low-wage work from the mid-twentieth century to the present, taking care to elucidate the definition of low-wage work, its place within the literature on income inequality, and alternative measures of income inequality passed over in favor of low-wage work. Moreover, I illustrate the changing landscape of low-wage work during the Great Recession, using descriptive statistics and econometric analysis based on the European Union Statistics on Income and Living Standards database. Finally, I evaluate the predominant theory within literature on low-wage work, the institutional inclusivity model, and posit new determinants of low-wage work during the Great Recession. As one of the first, detailed analyses of low-wage work during the Great Recession, this paper makes a substantial contribution to the literature—revising incidences of low-wage work, conceptualizing and exploring its relationship to the recent macroeconomic environment, and calling attention to the importance of low-wage work as it relates to persistent inequality and national labor market institutions.

**Acknowledgements**

I would like to thank my generous advisors, Professors George Shambaugh and Anders Olofsgard, for their time and energy. I would also like to thank the Georgetown Office of Fellowships, Awards, and Research for the opportunity to conduct research for this thesis during the summer of 2012 under the auspices of the Lisa Joy Raines Endowed Undergraduate Research Fellowship. I am very grateful to the Amsterdam Institute for Advanced Labor Studies at the University of Amsterdam for the opportunity to work on this thesis as a guest researcher for the 2012-2013 academic year. Finally, I am forever indebted to two mentors who have helped to shape me as a researcher and as a person: Professors Matthew Carnes, SJ and Ken Mayhew.
TRADE FLOWS AND REAL EXCHANGE RATE VOLATILITY IN THE BALTICS: DOES IT REALLY MATTER FOR COMPETITIVENESS?

Igors Pašuks and Eduards Sidorovičs
Supervisor: Morten Hansen
Stockholm School of Economics in Riga

ABSTRACT

The following thesis devotes itself to a dynamic analysis of how real exchange rate (RER) volatility affects bilateral trade flows in the Baltic States. The scope and topic of the research are relevant, as real exchange rate fluctuations can adversely affect a country’s terms of trade and its ability to compete successfully on an international level even in the case of fixed exchange rates. Furthermore, Estonia’s recent accession to the EMU and the ambiguity of the existence of the so-called “Rose Effect” would serve as an important backbone in order to assess and speculate about the potential economic implications on the Latvian economy after its planned accession to EMU in 2014. Given the following arguments and the absence of prior empirical research in the region, the main aim of this paper is to examine the industry-level effect of real exchange rate volatility on the trade flows of the Baltic states during a period of 2000-2012 using a dynamic autoregressive model with an integrated bounds-test feature. These tests allowed the authors to decipher whether a short-term or a long-term effect exists as well as assess the economic significance of RER volatility on trade. In addition to this, significant emphasis was placed upon determining the industry-specific effects and comparing the results both on a country and industry level. The obtained results largely confirm the high level of ambiguity associated to the direction as well as the magnitude of RER volatility on trade. Yet significant effects for industries with higher intra-industry trade and trade diversification are observable, which would call for potential policy action in mitigating the effect of RER volatility on these industries.

1 Introduction

It has long been perceived as a general rule that different exchange rate arrangements, such as exchange rate pegs or currency unions, provide a country with a unanimous increase in trade and a severe decrease in its exchange rate volatility. Nevertheless, the recent economic downturn has put this argument under severe questioning as many countries in Europe (including the Baltics) have faced elevated real exchange rate volatility, eventually translating into deteriorated competitiveness and trade flows. These observations can also cast doubt on whether the countries’ efforts to sustain competitiveness solely by means of managing price competitiveness, productivity and non-price factors may lead to the necessary increase, as the price and volume setting behavior of local companies engaged in foreign trade is often overlooked (Clark et al. [2004]). As a result, the still prevailing issue of real exchange rate volatility does not achieve the deserved attention despite the widely documented evidence in this field of research.

Developments in the theories of international economics have shown that exchange rate volatility (in particular, that of real exchange rate) plays an important role in the volume and price setting behavior of the companies, which has been supported by numerous empirical findings both on an aggregated and individual company level (Chowdhury [1993], Dell’Ariccia [1998], Clark [2004], Rogoff & Obstfeld [2003], etc.). For instance, lower volatility may lead to greater certainty for risk-averse firms as well as provide notable cost savings for firms that face a non-linear cost schedule (De Grauwe [1988]). However, there may be circumstances when companies would have significant costs associated, for instance, with
their exit from foreign markets (Dixit [1989]) or when they can even view elevated volatility as an opportunity for excess profits (Gagnon [1998]), leading to perverse incentives to increase trade at times of elevated volatility. Furthermore, the abovementioned studies provide no account for industry specific effects and do not show whether these effects are transitory or persistent (Auboin & Ruta [2011]), which could uncover the importance of the above and other factors in the adjustment path of trade.

Recent research has immersed mainly with the purpose of addressing the prevailing issue of aggregation bias, with major contributions from Bahmani Oskooee et al. (2006, 2008, 2012), Wesseh & Niu (2012), Johanssen (n.d.) and Caglayan (2008). These studies also take into account that given the stickiness and low responsiveness of prices in the short term, which may stem from contractual obligations or the corporate inertia in adjusting their prices systematically, short-term fluctuations in nominal exchange rate translate into real changes with a significant time lag. Understanding these effects is important, as Cheong et al. (2005) suggest that there is a significant long-term trade-off between quantity and price adjustments depending on the initial response of prices to volatility. Both instruments are being systematically utilized to avoid uncertainty in exchange rates, thus leading to varying degrees of effects across different industries.

Notwithstanding the extensive evidence supporting the existence of the link between exchange rate volatility on trade, a consistent and clear-cut effect remains largely unexplored. A great deal of polemic surrounds the assumptions of the models as well as the issues related to estimating the true effect of exchange rate uncertainty (Mckenzie [1999], Bahmani-Oskooee [2007], Ozturk [2006], and Cote [1994]). In this paper the authors shall investigate the causality between the volatility of the real exchange rate of the three Baltic States with respect to the trade flows of their main partners using dynamic short- and long-run econometric estimation tools over the period of 2000-2012. As a consequence, the authors will strive to find an answer to the following research question: “How do the changes in real exchange rate volatility influence the bilateral trade flows of the Baltic States with respect to their main trading partners?” In order to provide an extensive answer to the question, the authors shall look at whether exchange rate volatility exhibits any short term effects on the trade flows and whether these effects tend to persist in the long term. The authors would also seek to compare different volatility estimation methods and test how stable are these models over the course of the study period.

What particularly interests the authors in the study is the magnitude or economic significance of this relationship as well as studying the differences across the major tradable product groups and possible structural changes over time. Therefore, since prior research has raised elevated interest in studying industry-level data, which would allow to disentangle the effects according to the specifics of each industry, the authors will seek to find the answer to a sub-question, which is stated as follows: “How does the pattern of the effects of exchange rate variability vary across different industries and product groups?”

As suggested by De Grauwe (1988), if the results are supportive of a persistent long-term effect, such findings would have widespread policy implications both on the national and industry level. This is because potentially high levels on sensitivity on volatility may induce further real exchange rate management by the government (via stabilization of inflation) or a more subtle use of hedging instruments by companies. As a matter of fact, Estonia has recently joined the EMU by dropping its kroona and so is heading Latvia in a pursuit to introduce the euro in the beginning of 2014. While prior research indicates that membership of the EU can be associated with a significant increase in trade and reduction of exchange rate volatility (Baldwin [2005], de Grauwe & Schnabl [2008]) there also are significant opponents to these results concerning the vulnerability of the union to external shocks (Cavelaars [2001]; Barrel, Davis & Pomeranz [2009]). Therefore the Estonian case and empirical results would serve as a backbone in order to assess and speculate about the potential economic implications on the Latvian economy after introducing the euro.

Furthermore, despite a comparatively long history of the theories based on the topic and the multitude of empirical research conducted over time, the authors find an insignificant amount of empirical studies focusing particularly on the Baltics, such as the works by Bitâns & Kaužēns (2004) and Cociu (2007). Usually the Baltic States are estimated as part of a broader dataset, thus the results for the Baltics
are not reported (such as in Clark et. al [2004], Johanssen [n.d.]) due to low data availability. The following research will be unique in that it will be the first comprehensive study aimed particularly at the Baltics and will contribute to the existing research with industry specific as well as aggregate results from this region. The novelty of this research is not only confirmed by the use of a fully disaggregated dataset, but also by the use of the recent developments in times series analysis and cointegration tests (e.g., the bounds testing approach), leading to greater reliability and predictability of the obtained results.

The remainder of this paper is organized as follows. In Section 2, the authors shall immerse in the theoretical underpinnings of the issue of external competitiveness and discuss the validity of RER volatility as an important driver to price competitiveness. Section 3 presents an overview of the developments and recent occurrences in the Baltic foreign trade and investigates the literature available on the region. Sections 4 and 5 present the data and methodology employed in the research. Section 6 examines the results of regressions and the estimated industry-level effects in the Baltics. Sections 7 and 8 would engage in a critical discussion of the results and potential caveats that might surround them, while Section 9 concludes.

2 The Baltic Case

In the following section, the authors will immerse into a critical analysis of trade development in the Baltic States, taking a look at the peculiarities of each country in their path to trade liberalization. We also examine Latvia’s ongoing aspirations to join the Eurozone and the potential benefits, given the Estonian experience. Furthermore, the analysis shall touch upon the recent empirical contributions on exchange rate volatility and its determinants and seek to establish a clearer account of the obtained effect and patterns of the Baltic trade.

2.1 The Economic Background

In their quest to achieve economic stability and promote international trade, the Baltic countries faced a multitude of challenges, including lack of own currency, absence of trade agreements and incompliance to the current market conjuncture. Studies by Larson & Wikstrom (2002) provide a comparative study of the different phases of development as well as the outcome of different trade policies undertaken by the Baltic States in the period towards the accession to the European Union (EU). Both papers agree that all three countries, even though being geographically, historically and culturally linked, have undertaken different paths of transition and integration into the world trade, which has had a direct effect on the countries’ trade structure, vulnerability to internal and external shocks as well as competitiveness levels.

The first years of the peg saw a massive surge in the countries’ real exchange rates as a result of price corrections and the gradual equalization of the purchasing power parities with their main trading partners, which came largely due to the highly undervalued exchange rates. As part of their exchange rate stabilization policies, all three countries opted for a peg, yet each country went for slightly different options: Estonia, with its proximity to Scandinavia and dependence on trade opted for the German mark (DEM), while Lithuania entered a currency board with the US dollar, in the hope it would help stabilize its large dependence on the trade with Russia. The main points for such a move were “that a fixed peg would commit the government to stabilize the economy, anchor inflation expectation for price- and wage-setters and allow a remonetisation of the economy” (Nerlich [2002]). Latvia took a more sensible step by pegging its currency to the SDR currency basket, which included the abovementioned currencies, which allowed it to mitigate severe exchange rate fluctuations given that the euro was not the only implicit anchor.
However, in the years between 2005 and 2009 all three countries experienced particularly high levels of inflation partially as a result of the Balassa-Samuelsson effect (Swedbank [2011], Mihaljek & Klau [2009]), which in combination with a fixed exchange rate to the euro quickly drew down the competitiveness levels of all three countries (Latvia was even at risk of being devalued in 2009), with the monthly RER volatility levels being significantly higher, spurring up to unprecedented levels in 2008-2009. Estonia, being the most prudent of the three economies and better aligned with the EU in terms of trade integration and having fulfilled the necessary criteria, was able to successfully exploit the time gap and join the EMU. Since then, its exports have soared dramatically, with the trade balance rising to an astonishing 8 percent of GDP in 2012 (Eurostat, 2012). Latvia and Lithuania were similarly successful to curb their imports and stabilize their balances, while their turn to join the EMU is yet to come.

The abovementioned occurrences raise a number of questions towards the efficiency of currency pegs as an efficient means of curbing RER volatility. The issue of choosing an appropriate currency arrangement for small open economies is extremely cumbersome (Ngouana [2012]), especially given that a recent study by Rogoff (2003) shows that countries with flexible exchange rates tend to outperform fixed exchange rates by a significant margin both on output stability and exchange rate volatility. Baldwin (2005) and Clark (2004), for example, postulate that the decreased costs of currency exchange can potentially be outweighed by the additional volatility with respect to other currencies, which could in turn lead to ever-increasing inflation differentials among countries and contribute towards lower exchange rate volatility. Therefore, the effect of volatility should not necessarily be viewed from the point of view of the choice of an appropriate exchange rate regime.

Similar considerations surround the ongoing debate on the potential trade effects and benefits of Latvia’s accession of the EMU in 2014 as well as the possible accession of Lithuania in 2015-2016. In the case of Latvia, the main propagation of the advantages and the so called Rose effect (see Baldwin [2005]) on trade is driven by the Bank of Latvia. According to Rutkaste (2012a, 2012b), the immediate advantages arising from lower trade costs as well as transaction costs for currency exchange (which would be an important relief, given that 60 percent of Latvian trade is denominated in euro) would contribute towards even tighter trade with the EU. While looking at the Estonian case, the imminent effect on trade is noticeable (a 38 percent increase in total trade over just one year), yet a large part of the change was accounted by a rapid growth in imports and thus a deteriorating trade balance, which has grown consistently ever since (Baltic Export, 2011). Presumably, these effects could have been accounted by the elevated and varying inflation levels that the country experienced (in the vicinity of 6 percent in 2011), which could be a reason why the country still had slightly higher exchange rate volatility relative to its Baltic peers.

A more comprehensive review of the effects of euro adoption and the peg of the lats to the euro on the trade flows was carried out by Bitâns & Kaužēns (2004). According to their estimates on the elasticity of trade flows to exchange rate volatility using the gravity model, the immediate short-term effect following the peg to euro would account for a 0.6 percent increase in exports in the first two years, thereby exerting empirical support for the negative relationship in the years before EU accession. However, they also mention that a mitigating effect on trade can also be anticipated, primarily stemming from the large structural fluctuations of the euro to other freely floating currencies (such as the U.S. dollar, the Swedish kronor or the Russian rouble). The regression results obtained by the authors suggest that the effect on trade for Latvia “is not likely to be too pronounced as well as one cannot expect a full elimination of RER volatility with its main trade partners” (Bitâns & Kaužēns p.10).
3 Methodology

3.1 Model Specification

In this paper, the authors shall attempt to empirically estimate the relationship between exchange rate volatility and trade flows for the Baltic countries with regards to their main trade partners. In order to achieve greater reliability and interpretability of results, the authors shall run the standard model of trade on sectoral data between the Baltics and their major trade partners and seek to answer the hypotheses set prior to the empirical research.

An important feature in the research design of this paper is the fact that the authors not only seek to estimate the short run effects of exchange rate volatility, but also whether these short-run fluctuations exert a long-run effect upon the trade flows. For this purpose, we shall employ the general methodological approach developed by Pesaran et al. (2001). In order to develop the logic behind using the aforementioned methodology and discuss its benefits, as a starting point the authors shall use the one developed by Gotur (1985), which is specified as follows:

\[
\ln VX_t = \delta_0 + \delta_1 \ln Y_t + \delta_2 \ln RER_t + \delta_3 \ln V_t + \epsilon_t \\
\ln VM_t = \delta_0 + \delta_1 \ln Y_t + \delta_2 \ln RER_t + \delta_3 \ln V_t + \epsilon_t
\] (1)

The model represents a simple standard long-term model of international trade (with \( \ln VX_t \) and \( \ln VM_t \) representing either volume or value of imports and exports), where \( Y_t \) measures the real economic activity of the country and is represented by its production index (or, alternatively, its GDP), \( \text{RER}_t \) incorporates the bilateral real exchange rate of the two countries (PPI-based, discussed in previous chapter), while \( V_t \) is a measure of its exchange rate volatility. An important requirement for the validity of long-run level models is to ensure that the variables are cointegrated and share a common long-term trend. The most commonly used techniques for testing cointegration are the two-step approaches developed by Engle & Granger (1987) and Johanssen (1991), which require a significant amount of pretesting and variable alteration in order to ensure that the variables are integrated of level one (I(1)). As noted by Pesaran et. al (2001) and De Vita & Abbott (2004) such pre-testing could be “potentially harmful by introducing further uncertainty into the regressions and weaker interpretability of the regression coefficients” (p.2).

The former authors propose a completely new methodology that eliminates the necessity to run separate cointegration tests, irrespective of whether the variables are integrated of level zero (I(0)), level one (I(1)), etc. Using a self-constructed test statistic based on the standard F-statistic, they could test the significance of the long-term coefficients in a simple unrestricted short-run error correction model (ECM) as well as prove that the model and test statistic are consistent even if all regressors are I(0). Therefore, this approach eliminates the need for pre-testing the level variables using conventional cointegration testing methods, nor even to make any a priori assumptions about their level of integration.

Following these considerations and the methodology employed by Bahmani-Oskooee & Harvey (2012), Cermeno et al. (2009) and Presley & Niu (2012), regressions (1) and (2) will be integrated into the model in combination with the error correction term, which would allow to test which proportion of the deviations are accounted for the short-run adjustments to equilibrium:

\[
\Delta \ln VX_t = \\
\alpha_0 + \sum_{j=1}^{m_1} \beta_j \Delta \ln VX_{t-1} + \sum_{j=0}^{n_2} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{n_3} \delta_j \Delta \ln \text{RER}_{t-j} + \sum_{j=0}^{n_4} \mu_j \Delta \ln \text{VOL}_{t-j} + C_0 + C_1 t + \\
\theta_1 \ln VX_{t-1} + \theta_2 \ln Y_{t-1} + \theta_3 \ln \text{RER}_{t-1} + \theta_4 \ln \text{VOL}_{t-1} + \omega_1 B r_t + \epsilon_t
\] (3)

\[
\Delta \ln VM_t = \\
\alpha_0 + \sum_{j=1}^{m_1} \beta_j \Delta \ln VM_{t-1} + \sum_{j=0}^{n_2} \gamma_j \Delta Y_{t-j} + \sum_{j=0}^{n_3} \delta_j \Delta \ln \text{RER}_{t-j} + \sum_{j=0}^{n_4} \mu_j \Delta \ln \text{VOL}_{t-j} + C_0 + C_1 t + \\
\theta_5 \ln VM_{t-1} + \theta_6 \ln Y_{t-1} + \theta_7 \ln \text{RER}_{t-1} + \theta_8 \ln \text{VOL}_{t-1} + \omega_1 B r_t + \epsilon_t
\] (4)
One can immediately note that the level variables are taken with a lagged term, which is pivotal in order to avoid the risk of autocorrelation. The bounds-testing coefficients are represented by $\theta$, and if the joint F-tests show significant results (above the upper level boundary), this implies that short-term real exchange rate shocks will have a significant long-term effect on the trade flows. $C_0$ and $C_t$ represent the drift and trend components of the regression, while $B_t$ represents the dummy variables for break dates. As mentioned previously, the bounds-test F-statistic is different to the conventional test-statistic in that it provides critical value bounds, which allow classifying the order of integration (either $I(0)$ or $I(1)$) of the variables or show inconclusive results if the values fall within these bounds. The test statistic boundary tables are provided by Pesaran et al. (2001), which shall be used over the course of the research. One significant drawback of this method is the situation when the test statistic falls between the bound values, since the authors would have to take additional steps to determine the long run relationship: the level variables shall be estimated separately and grouped into an error correction term $z_t$ (Johannsen method), which we will test whether it is significantly negative and thus corrects the deviations from equilibrium.

The appropriate lag length for short run coefficients shall be determined using Akaike’s Information Criterion (AIC). In order to avoid excessively long pre-testing for the lag lengths the authors have set up a maximum of 5 lags for all fundamental variables and 12 lags for exchange rate volatility until which an optimal lag specification is chosen. This is done not only because the regressions in Bahmani-Oskooee & Harvey (2012b) do not include more than 4 lags, but also taking 12 lags would be a reasonable assumption given that companies cannot quickly adjust their export/import quantities due to their agreements. A time frame of 1 year should presumably fit well with this adjustment period.

All the variables will be tested for stationarity using the Dickey-Fuller (D-F) test statistic. As noted by Presley & Niu (2012), an important assumption of the model is that the variables are not cointegrated among themselves, stemming from the fact that the level variables are assumed to have a long-run relationship with either $VX_t$ or $VM_t$. In order to test the assumption, the authors shall use the cumulative sum of residuals (CUSUM) method, which will be plotted against the 5% significance level boundary. If the residuals stay within the boundaries, then there is a strong and stable relationship between the variables over the long-term.

The final data cluster consists of 450 individual industry datasets with approximately 155 monthly observations in each, and nearly 70,000 monthly observations in total.

### 3.2 Volatility Estimation Methods

Since the models also require stationarity for real exchange rate volatility, the authors shall solve the issue by employing one of the widely used ARIMA, ARCH & GARCH estimation techniques, as proposed by Engle (1982), and Bollerslev (1986). Given the argumentations provided in Section 2, as the prime technique the authors shall employ the GARCH($p$, $q$) estimation technique exactly as it appears in its original version:

$$y_k = \sigma_k \varepsilon_k$$

$$\sigma_k^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{k-j}^2 + \sum_{i=1}^{p} \alpha_i y_{k-i}^2$$

As mentioned previously, GARCH supplements the more simplistic ARCH procedure by solving for potential computational problems arising from the high order of the polynomial. In the case when $q$ is zero, the model is reduced to a simple ARCH model. It takes into account the orders of both $\sigma_k^2$ (the volatility of RER) and $y_k^2$ (in this case, the moving average of RER), implying that large (small) values several periods ago would also be followed by large (small) values in the forthcoming periods (also called volatility clustering), which leads to persistency in the conditional volatility over time (refer to Section 2 for a more detailed comparison). Given the persistent issue of the asymptotic complexity of GARCH coefficient estimation, which leads to frequent problems with regards to obtaining the correct coefficients,
the authors shall employ three different estimation methods (LADE, GMLE, QMLE) in order to verify the correctness of the coefficient estimates and evade imprecision in estimates.

In order to amplify the robustness of the results of the regressions, it is imperative that other volatility estimation methods be used. For that reason, the models will be re-run using the popular and rather simplistic 12-month moving average standard deviation (MASD), which is specified as follows:

$$V_t = \left[ \frac{1}{T} \sum_t \left( \frac{RER_{t+12,t} - RER_{t,t}}{RER_{t,t}} \right)^2 \right]^{1/2}$$  (7)

Despite being a relatively crude measure of estimating true exchange rate volatility, it allows the authors to verify whether the ARCH/GARCH method is actually superior to more conventional methods. As a decision rule, we shall employ the methodology used by Bahmani-Oskooee & Ardalan (2006):

$$AIC(A1:A2) = LL_1 - LL_2 - (K_1 - K_2)$$  (8)

$$SBC(A1:A2) = LL_1 - LL_2 - (K_1 - K_2)\ln(n)$$  (9)

AIC and SBC stand for Akaike Information Criterion and Schwarz Bayesian Criterion, where essentially the authors will look at the differences between the maximized log-likelihood values of the two regressions ($LL_1, LL_2$), the number of regressors ($K$) and the number of observations ($n$). If the difference is positive across both measures, then GARCH is considered a better measure, while the reverse would be true if the difference is negative.

4 Discussion of Results

The results obtained from the regressions overall suggest that the effect varies on a case by case basis for each country (see Table 6 for an overview for the obtained results for hypotheses), implying that each industry and each country pair has a different susceptibility to exchange rate fluctuations and can have their internal mechanisms to counteract or reinforce the effects or RER volatility regardless of the currency arrangements that these countries have with each other. The results confirm the notion by Cote (1994), Huchet-Bourdon & Korinek (2012), & Clark et al. (2004) that the difference in the effects across industries stems from a number of industry-specific factors and assumptions, which in turn determine the risk profile of each company and thus their likelihood to adjust for RER fluctuations. A further step for the authors is to determine what are the likely drivers that have led to the ample ambiguity obtained in the regressions both in the short-run and in the long run. Following careful examination of the data, previous research literature (whose effects are line with this paper) and additional industry-specific analysis conducted in order to provide solid grounding for these arguments, strong parallels with obtained effects can be drawn from the points of view of industry structures, market concentration and product differentiation, adjustment costs and the presence of intra-industry trade. Additionally, the authors shall embark upon the discussion of the varying effects found for all three Baltic states and seek to understand the underlying arguments for such inconsistency in results.

<table>
<thead>
<tr>
<th>Hyp.</th>
<th>Latvia</th>
<th>Estonia</th>
<th>Lithuania</th>
<th>Total</th>
</tr>
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<tbody>
<tr>
<td>H1</td>
<td>Partial support (4, 16, 18)</td>
<td>Partial support (13, 17, 21)</td>
<td>Partial support (8, 10, 21)</td>
<td>Partial support</td>
</tr>
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<td></td>
<td>Partial support (with EE and DE in imports, with EE and LT in exports)</td>
<td>Partial support (with RU in value imports, with SE and FI in quantity import; with DE and FI in quantity export)</td>
<td>Partial support (PL, DE and NL in value import, NL in value export, and LV for all exports)</td>
<td>Partial support</td>
</tr>
<tr>
<td>H2</td>
<td>Partial support (for intermediate – export to PL, imports from EE, DE, capital goods – imports)</td>
<td>Partial support (for intermediate goods- export to RU; for capital – export to DE)</td>
<td>Partial support (for intermediate goods 65% of the cases); no support for capital goods</td>
<td>Partial support</td>
</tr>
<tr>
<td>H3</td>
<td></td>
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</table>
Baldwin (2005) suggests that under imperfect competition, increasing returns to scale for the companies and higher product differentiation are the primary factor for volatility affecting companies. The argument stems from the fact that the lower the industry concentration and the more differentiated the goods that are traded in each industry, the average company is much smaller than for the industries with larger concentration (industries with capital requirements or notable entry barriers, such as Metallurgy, Heavy Machinery, Mining, etc.). Thus, they are less apt to hedge their real exposure. Furthermore, as suggested by Broda & Romalis (2003), in less concentrated industries the products are more differentiated, therefore they should be more affected by exchange rate volatility than homogenous goods. The authors have attempted to examine the presence of this phenomenon by calculating proxies for market concentration for all the industries (omitted in this shortened version) and comparing them to the significant effects obtained in the regressions (for convenience purposes only the results for value equations are reported). Indeed, by comparing the results for both import and export with the calculated Herfindahl Index1, reasonable support can be found for the export equations (both quantity and value). More frequent significance with the trading partners (in at least three of five cases) occurs in the industries whose market concentration is significantly below 0.15, which indicates highly non-concentrated industries. This occurs in industries such as leather for all countries and high support in Latvia (e.g., wood, apparel, chemicals), Estonia (computers, metals, machinery, transport, agriculture, etc.) and Lithuania (wood, minerals, petroleum, etc.) individually. According to Rauch (1999), the heterogeneity and the differences of the products imply that the goods will be less prone to be sold through organized exchanges, brokers or wholesalers. Instead, buyers for the products are found through a rather costly search process in order to establish networks and advertising. Since smaller companies are structurally similar and may face similar cost schedules, after these costs are sunk, RER volatility will adversely affect the profitability of the firms and reduce the amount they will trade. While certainly this correlation is not fully consistent across all industries (for instance Petroleum for Estonia and Lithuania and Pharmaceuticals for Latvia and Lithuania), they nevertheless allow judge that industries with a higher number of companies (which in the majority of cases are very small and structurally very similar) are more exposed to swings in the exchange rate.

Meanwhile, positive results were found for many of the short run-coefficients in export quantity equations, indicating that corporates (largely within the intermediate and capital goods sectors) increase their trade following short run fluctuations. As a result, since smaller companies tend to have steeper indifference curves in their risk-profit schedule (de Grauwe, 1988), in the event of increased volatility risk, risk-averse companies would be so afraid of losing their revenues, so they would be inclined to increase their exports (their expected marginal utility from exports rises due to a convex utility schedule). Since the minimum threshold to keep the company afloat remains relatively high (due to the mentioned sunk costs [Dixit (1989), Krugman (1988) and the costs of renegotiating contracts or transaction costs (Gagnon, 1998)]. As put by Johanssen (n.d.) and De Vita & Abbott (2004), these positive effects are particularly common for capital and intermediate goods (also found in the regressions results for exports), as at the same time higher volatility provides profit opportunities for new companies to enter the market.

---

1 Herfindahl Index is commonly utilized as a consistent proxy for market concentration and trade differentiation and is calculated by summing the squares of the market shares of the companies in the industries.
Subsequently, an immediate response from the existing companies would be to increase trade volume in the short-run by lowering their prices. The following arguments may largely explain the positive effects on trade, yet for some industries with low concentration they still remain negative (e.g., minerals, computer electronics and machinery for LT, LV and EE respectively) which may stem from other factors such as risk-averseness, imperfect hedging opportunities (highly likely for the case of the Baltics) or differing cost structures.

As for the long-run effects, differences in the level of exposure in different industries are not solely dependent upon the short-term dynamics within the industry, but also technological differences come into play as production factors become flexible. Kumar (1992) argues that an increase in RER volatility can be compared to adverse technological shocks, especially for industries where intra-industry trade is high. Due to elevated exchange rate exposure, the cost of production factors rises significantly in relation to the foreign competitors in the industry (thereby making it less rentable to compete in the trade with other players within the industry) as well as comparative advantage is reduced, thus economies of trading countries will become less specialized and intra-industry trade will decrease, thereby creating trade diversion towards inter-industry trade (Auboin & Ruta [2011]). Broda & Romalis (2009) state that for the industries with a higher share of intra-industry trade, elevated exchange rate volatility leads to trade diversion towards inter-industry trade (lower Grubel-Lloyd index) over the long-term and, since this effect takes time to adjust, it is persistent only in the long-term. An examination of these effects in the regressions, using the industry-specific Grubel-Lloyd index (omitted in this shortened version), shows support for the argument that a higher share of intra-industry trade leads to a greater susceptibility to RER volatility, yet the effect is consistent only across a few industries for export (leather, wood, electrical equipment and aggregated industries) and import (electrical equipment, capital goods, durables, textile and wood). Furthermore, the effect is especially pronounced for Estonia’s exports, thereby confirming the notion put forward in one of the previous sections that meaning that most of these goods serve as intermediate goods for a wide range of final products that are produced by companies in the same or different industry (implying higher intra-industry trade).

The comparison also reveals that, while volatility is more significant in the industries with higher intra-industry trade in the long-run, for some partners (Russia, Poland) the direction appears to be the reverse: lower intra-industry (and thus higher inter-industry) trade leads to more susceptibility in the long-run by exchange rate volatility. Bahmani-Oskooee & Wang (2007) and Bahmani-Oskooee & Harvey (2012) provide an interpretation for these contradicting results, postulating that if exchange rates tend to adjust to the swings in exchange rate, the losses from an exporter in the long-run will be offset by a higher export if the exports are priced in foreign currency. As a matter of fact, there will be some offsetting effect to the input costs as well, therefore companies operating with multiple currencies are “naturally” hedged against volatility and thus are insensitive to RER fluctuations. This notion is certainly true in the case of Baltics for the partners given that the mentioned countries have a floating exchange rate regime with the Baltic States (except for Sweden, whose effects resemble those of a fixed exchange rate regime), thus for the industries with higher intra-industry trade the effect appears to be statistically insignificant and significant results are only found in industries with higher inter-industry trade. Since for other country pairs the exchange rate is fixed, there are no fluctuations other than those of relative prices. Thus, there is no offsetting from exchange rate fluctuations, hence input costs are directly exposed to exchange rate fluctuations and thus affect industries with a higher share of intra-industry trade.

Another issue which poses some questioning following the tests for structural breaks is the fact that the Baltic States (in particular, Estonia) did not experience at least a similar effect to the Rose effect, i.e., when trade increases due to lower exchange rate volatility as a result of a country’s to peg to the Euro or the actual adoption of it. The contributions by de Grauw & Schnabl (2008), Baldwin (2005) & Rogoff & Obstfeld (2001) find support for the strong welfare effects stemming from increased trade volumes. While on a more aggregate MIG industry level (Capital and Durable goods for Lithuania, Intermediate and Total goods for Estonia and Durable goods for Latvia) one can encounter some commonalities in terms of the time of a break right before the peg or currency area, for other country pairs it has remained unnoticed or even dawned by the repercussions of the economic crisis in the beginning of 2009. On the
individual industry side, the effects appear to be relatively mixed and highly country-specific with varying directions of effects. This leads to question whether there has actually been a swift structural change because of lower exchange rate volatility in the trade composition of the Baltic States following their pegs.

Harms & Hoffmann (2009), Rogoff (2003), suggest that the immediate effect of a peg or a monetary arrangement can be negligible and may not lead to trade diversion immediately due to the fact that the peg itself is anticipated and does not occur in an instant manner. For instance, supposing Lithuania enters into a peg with the euro on January 1st, 2002, even if it pegs the currency according to the latest available exchange rate, the peg itself will be anticipated by the central bank months before the actual peg date and in most of the cases, and thus the bank is aware of the approximate range in which the exchange rate would end up fixed. Since the announcement to peg a currency would become public, this would bring about intense action by producers who would seek to set contracts at some expected exchange rate (determined by consensus or personal estimates) after the peg date, thereby smoothening the change in trade flows in the dates around the actual peg date. The following argument holds for Estonia as well, since approximately six months before the accession 75 percent of Estonian companies had already taken measures to prepare for the changeover of the currency (renegotiating contracts, adjusting payment and transfer systems), which may imply that the positive effect upon trade had already taken place before the date of accession (Eurobarometer, 2010).

The abovementioned arguments explain the insignificance of the coefficients for structural breaks, yet uncertainty arises about the potential drivers of the obtained negative effect for several industries. The reasons for this may be manifold. For the case of Estonia, for instance the significant negative effect may be the result of elevated inflation and volatility in relative that the country experienced throughout 2011 (between 5.0 and 5.5 percent), with the rates not receding until now and still remaining above 4 percent. As a result, the varying price differentials induced additional uncertainty for several industries in Estonia, which may have lead the scale down of foreign operations of these companies. The trade effects for Lithuania and Latvia, as mentioned previously, can be significantly skewed following the economic downturn and lead to the overall average volume of trade not being substantially higher than before the peg, even despite the fact that trade may in fact had increased before the turmoil.

Nonetheless, it is the results for Estonia that deserve more attention from a policy perspective, given the persistently negative effect on trade for several industries following the EMU accession. For the industries with a negative post-EMU dummy variable, by examining closer the development of industry-specific volatility with the partners of Estonia, it can be seen that volatility remains relatively high after EMU accession because of the surging inflation in the country in 2011 and 2012 in comparison to the pre-crisis period. While it can be presumed that in the long-run the price levels would stabilize and dampen RER volatility levels, it may be suggestive that volatility would still pertain in the short-run, and there thus may be no additional or even negative effect arising from a common currency area, unless the country takes anticipated precautionary measures to curb the levels of inflation.

5 Concluding Remarks

This paper attempts to reconcile the ambiguity in results prevalent in existing research on RER volatility and extend the analysis to the Baltic States. The goal to determine the trade adjustment patterns within different industries and seek to answer the research question of how RER volatility affects trade flows of the Baltic states, and in particular how it varies across different industries. A landmark Autoregressive Distributed Lag model with a bounds test feature developed by Pesaran et al. (2001) was employed for the five largest trade partners of each country in individual time series regressions for thirty industries was carried out and compared with previous findings in other countries as well as a thorough theoretical account of the peculiarities in the Baltic states was also made.
Past empirical research has predominantly placed focus on the short-term effects of volatility, whilst finding no consistent effect of volatility on trade across multiple industries. A great deal of polemic surrounds the assumptions of the models as well as the adjustment paths across different currency settings, given that under floating exchange rates the effect can be the opposite to what can be encountered in the countries with a fixed exchange rate regime (Rogoff (2003), Huchet-Bourdon & Korinek (2011)). Nevertheless, even though the results obtained over the course appeared to resemble the notions by the previous works, several important findings are worth mentioning. Whilst only partial support was found for persistent negative short-term effect (unambiguous effects across the majority of partners in several industries for Lithuania), estimated coefficients in the remaining regressions appeared to vary significantly even within the same industry. There was also no specific adjustment path for the industries.

The effects for major tradable categories for the Baltic countries (following the studies by Johanssen [n.d.], Calgayan [2008], Bahmani-Oskooee & Wang [2007]) were also tested in this research, allowing to the authors to compare the effects by the nature of the goods. In general, only partial support was found to the stated hypotheses that durable goods have a more persistent effects than non-durables and that capital goods are more susceptible to volatility than intermediate goods. The degree of market concentration and product differentiation within each of the industry have been found to be consistent in estimating these differences in the magnitude and the direction of the effect of volatility on trade.

According to the contributions of Bahmani-Oskooee et. al (2006, 2008,2009,2012) and De Vita & Abbott (2004), relatively mixed results are obtained regarding the notion that short-term RER volatility may have a long-run forcing effect upon trade. By using the bounds-test procedure for cointegration, the authors have revealed that even despite a fixed currency arrangement with the majority of the partners in the sample, the estimated effects appear to be significant and cointegrated in approximately 21 and 17 percent of the cases in import/export regressions respectively, thereby counterfeiting the results found in previous literature. Nevertheless, the relationship has been found to be generally unstable for the majority of cointegrated industry and with varying signs for the effects. Such ambiguity can be explained by the presence of several industry-specific factors, such as corporate sentiment, structural composition, degree of risk diversification and differentiation, hysteresis effects, etc. Particularly strong interpretation of the obtained results was achieved with respect to the degree of intra-industry trade, namely, according to Kumar (1992) and Broda & Romalis (2003) for countries with a fixed exchange rate regime industries with a high degree of intra-industry trade are more affected by RER volatility, whereas for floating exchange rate regimes the effect appears to be the reverse.

Following the widespread debate on which measure of exchange rate volatility would provide the most appropriate proxy for exchange rate uncertainty and thus capture the true effects upon trade, regressions for two alternative uncertainty proxies (12m MASD and GARCH) were run and the models were tested for fit in order to find the most appropriate measure for the Baltics. The main aim of the tests were to examine the hypothesis that GARCH is theoretically more appropriate to capture the fluctuations in exchange rates due to its statistical properties. The findings suggest that neither of the two measures shows statistical superiority over the other across imports/exports or quantity/value equations across all three countries and their partners. However, consistent with their statistical properties, the authors found support that GARCH-estimated volatility provides a better account for industries with a high degree of seasonality, while MASD provides a better fit for the industries for which RER volatility is more persistent and trend-like in the long-term.
Additionally, further analysis into the effects of EMU accession for Estonia and the introduction of an exchange rate peg for Latvia and Lithuania was carried out in order to re-assess the notions of Rose (1999), Rogoff (2003), Baldwin (2005), etc. that the introduction of a currency arrangements shows a positive effect in terms of promoting growth in trade. The estimated tests of a presence of a structural break, nevertheless indicate that the exact impact upon trade growth is uncertain, with a notable fraction of industries for Lithuania and Estonia showing a negative effect upon trade growth. While for Latvia and Lithuania the insignificant or negative effects may be characterized by structural changes in the aftermath of the economic downturn, for Estonia the largely insignificant effects come due to the prior anticipation, leading to a lower subsequent effect on trade. Such contradictory findings can have strong policy implications for Lithuania and Latvia who are on the verge of potential accession to the EMU and may face similarly high RER volatility following the transition to the EMU.

Overall, from the results the authors conclude that there is no universal solution for all industries on how to improve one country’s trade by altering exchange rate volatility, especially for such small countries as Baltic States. It seems that the introduction of the fixed exchange rate (or currency union) regime has not played an important role in the minimization of volatility for multiple industries even when relative prices is the only thing that fluctuates, the countries become more dependent on the external supply and demand shocks, which would make the countries’ terms of trade fluctuate at an even greater range and make the issue of sustaining long-run competitiveness an even less executable task.

References


PURCHASING POWER PARITY AND THE BRAZILIAN EXCHANGE RATE: LINEAR EVIDENCES FROM UNIVARIATE TIME SERIES

Nicolas Powidayko
University of Brasilia

1. Introduction

Exchange rate misalignment consists of a macroeconomic distortion, which customarily occupies a privileged position on the international economic agenda. Therefore, it is not surprising that recently the Group of Twenty has fiercely criticized policymakers that have unilaterally weakened their national currencies in order to artificially boost exports and strengthen their domestic output. By doing so, the Group of Twenty has signaled that the international community shall avoid the beggar-thy-neighbor competitive devaluations that amplified the Great Depression in the 1930s. Thenceforth, multiple techniques and theories have emerged to handle these issues and challenges academically.

One powerful voice behind the Group of Twenty’s past declarations was the Brazilian Finance Minister Guido Mantega, who first warned global leaders in September 2010 that the world might then be sliding into a kind of currency war. Mr. Mantega was naturally concerned with the Brazilian currency, which sharply appreciated due to the commodities boom of mid 2000s that drove a large inflow of money towards Brazil. The Economist’s Big Mac index evidences that the Brazilian real has appreciated since 2001, breaking the parity level between 2005 and 2006 and peaking 50 percent of overvaluation in 2010. Thereafter the real has softly declined, though it is still highly appreciated (roughly 30 percent).

In this context, one economist might consider whether there is any reliable evidence suggesting that the Brazilian exchange rate is truly misaligned. Or perhaps the real is regressing to its parity level throughout time. This is the question this article aims to answer. It is crucial to emphasize beforehand that drawing a conclusive diagnostic regarding the real or advising policy makers about exchange rate management extend this paper’s proposals. Further research is also indeed encouraged. This article’s worth lies at employing updated and state-of-the-art methodology to appraise econometric evidences of the PPP theory’s validity to Brazil.

The Purchasing Power Parity theory states that price levels around the world are all equivalents when converted into one single currency denominator. The exchange rates assume thus a nominal significance, being solely an instrument to stabilize external and internal price levels. Imagine for instance an inflationary hike in Brazil. In accordance to the PPP theory, the nominal exchange rate would devalue in response to the rising price level, thus preserving the purchasing power of the Brazilian citizen. Though simplistic, this theory entails a high interdependence among the evolution of exchange rate and price levels around the globe, says Rogoff (1996).

The building block of the PPP theory is the Law of One Price, which states that equivalent goods shall be sold for the same price in different countries when converted to a mutual denominator through their nominal exchange rates. What causes the Law of One Price to hold is a phenomenon called international goods arbitrage. Imagine, for instant, that a commodity price is falling in Brazil comparing to the other trade partners. Smart trades shall buy the commodity in Brazil and sell it in other markets, profiting from the price gap. Naturally the traders’ movement will pressure upward the price of that commodity in Brazil, gradually closing the gap. Such international goods arbitrage guarantee that prices all around the globe are equivalents when converted to one mutual currency.

This rest of this study is divided in three sections. Section 2 outlines the data and index selection to test the Parity hypothesis as well as the design of a proxy for protectionism. Given the methodology and the data, Section 3 reports the detailed empirical outcomes. Conclusively, Section 4

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1 I am indebted to Professors Geovana Bertussi, Maria Eduarda Tanurri-Pianto and Mauricio de Paula Pinto, from University of Brasilia’s Department of Economics, for their helpful suggestions, critics and comments, emphasizing though that responsibility for the forthcoming pages is solely mine. Database facilities from University of Brasilia are gratefully acknowledged.
summarizes the econometric results, highlighting the nexus between the article’s key conclusion with the lessons learned by previous junctures and past generations. Section 4 also leaves some remaining questions for the future.

2. Data

Estimations rely on monthly data between Brazil and the United States, which until April 2009 was Brazil’s largest trading partner. The samples of the pure monetarist model’s estimations encompass solely the price level gap to explain the exchange rate. These estimations range from February 1944, the first monthly producer price index’s release, until October 2012. Structural models are, in turn, more limited. The tests incorporating trade protectionism, proxied by the import duty effective revenue, start from January 1986, the initial data of the Brazilian total amount of import duty revenue.

The data is described below. It is mostly gathered from IPEAD data [www.ipeadara.gov.br](http://www.ipeadara.gov.br), and in excel form on the author’s personal website, with the link below: [www.nicolaspowidayko.wordpress.com/2013/03/purchasing-power-parity-and-the-brazilian-exchange-rate-data.xlsx](http://www.nicolaspowidayko.wordpress.com/2013/03/purchasing-power-parity-and-the-brazilian-exchange-rate-data.xlsx).

None of the data was seasonally adjusted. The foreign price levels were normalized in accordance with the domestic price level due to the de facto monetary stabilization that followed the real plan’s release in June 1994, so \( P_{\text{CPI}} = P_{\text{PPI}} = P_{\text{PPI}} = 100 \) in August 1994.

- \( S_t \): Nominal exchange-rate R$/US$, average selling rate, issued by the Central Bank of Brazil (Banco Central do Brasil, BCB);
- \( \Delta P_{\text{CPI}} \): Brazilian Consumer Price Index (Índice de Preços ao Consumidor, IPC) until 1990 from the Fundação Instituto de Pesquisas Econômicas (FIPE) and thenceforth from the Fundação Getúlio Vargas (FGV);
- \( P_{\text{CPI}} \): Brazilian Consumer Price Level, based on the Brazilian Consumer Price Index (IPC), from FGV. FGV normalized the data so \( P_{\text{CPI}} = 100 \);
- \( \Delta P_{\text{PPI}} \): Brazilian Producer Price Index (Índice de Preços ao Atacado, IPA), from FGV;
- \( P_{\text{PPI}} \): Brazilian Producer Price Level, based on the Brazilian Producer Price Index (IPA), from FGV. FGV normalized the data so \( P_{\text{PPI}} = 100 \);
- \( \Delta P_{\text{CPI}_t} \): United States’ Consumer Price Index (CPI), by the US Bureau of Labor Statistics (BLS);
- \( P_{\text{CPI}_t} \): United States’ Consumer Price Level, based on the its Consumer Price Index (CPI), by the US BLS. The author normalized the data so \( P_{\text{CPI}} = 100 \);
- \( \Delta P_{\text{PPI}_t} \): United States’ Producer Price Index (PPI), also issued by the US BLS;
- \( P_{\text{PPI}_t} \): United States’ Producer Price Level, based on the its Producer Price Index (PPI), by the US BLS. The author normalized the data so \( P_{\text{PPI}} = 100 \);
- \( M \): Brazil’s total import in US$, from the Ministry of Development, Industry and Foreign Trade (Ministério do Desenvolvimento, Indústria e Comércio Exterior, MDIC);
- \( T_M \): Brazil’s total gross import’s revenue in R$, issue by the Federal Revenue Office (Receita Federal, RF);

The real exchange rate \( R \) is computed through the equation below:

\[
R_t = S_t \frac{P_{\text{PPI}}^*}{P_{\text{PPI}}^*} 
\]

(01)

Where \( S_t \) is the nominal exchange rate RS/US$, \( P \) the Brazilian price level, \( P^* \) the US price level and \( \rho \) the index chosen – either consumer-based or producer-based.

Of course, equation 1 may be calculated in the natural logarithm base, by just replacing the country \( i \) by the period \( t \):

\[
q_t \equiv s_t + \left( p_{\text{PPI}}^* - p_{\text{PPI}}^* \right) 
\]

(02)

Where \( q_t \) is the natural logarithm of \( R_t \), \( s_t \) of \( S_t \), \( p_{\text{PPI}}^* \) of \( P_{\text{PPI}}^* \) and \( p_{\text{PPI}}^* \) of \( P_{\text{PPI}}^* \).
Figure 1 describes the evolution of the import duty effective revenue $\tau$, a proxy for trade protectionism, from early 1986 to late 2012. The graphic shows a relatively stable period between 1986 and 1994, in which $\tau$ oscillated between a 6 to 10 percent leeway; a hike following the real plan from 1994 until 1999, when Brazil left the crawling-peg system; a downfall from 1999 to 2006; and another hike, though modest, since 2006. The import duty effective revenue is calculated through Skiendziel’s (2008) proposed methodology, as below:

$$\tau = \frac{T_M / s_t}{M}$$

where $T_M$ is Brazil’s total gross import’s revenue in R$, $s_t$ the average selling nominal exchange rate R$/US$ and $M$ the Brazilian total import in US$ for each given period $t$.

![Figure 1: Evolution of the import duty effective revenue](image)

Source: IPEAdata (RF, MDIC, BCB).

3. Estimation

Section 3 is divided as identification and leg structure selection, residual’s diagnostic, ADF and DF-GLS unit root tests, and cointegration.

3.1. Identification and leg structure

It was estimated through the graphic analysis of the autocorrelation and partial autocorrelation that the maximum number of legs tested functions for the whole sample without the variable import duty effective revenue, from February 1944 to October 2012, is 20. For the total sample including the import duty effective revenue, from January 1986 to October 2012, it returns 16. The $\rho_{max}$ for the first subsample, ranging from February 1944 to December 1985, is 18. For the second subsample, January 1986 to July 1994, it is 12. For the third subsample, from August 1994 to December 1998, it is 10 legs. Lastly, the $\rho_{max}$ for the fourth subsample, ranging from January 1999 to October 2012, is 13.

Evaluating the autocorrelation and partial autocorrelation functions of the natural logarithms of the real exchange rates both at consumer and producer prices level and either including or not the trade protectionism proxy, the overall result supports the estimation of the four real exchange rates as autoregressive processes (AR) at the level base and as autoregressive moving-average processes (ARMA) at the first difference, as showcased on Figures 04 and 05.

<table>
<thead>
<tr>
<th>Sample</th>
<th>q(PPI/IPA)</th>
<th>$q^*(PPI/IPA)$</th>
<th>q(CPI/IPC)</th>
<th>$q^*(CPI/IPC)$</th>
</tr>
</thead>
</table>


1944.02 to 1984.12  AR(2)   -   AR(1)   -
1985.01 to 1994.07  AR(1)   AR(1)   AR(1)   AR(1)
1994.08 to 1998.12  AR(2)   AR(1)   AR(1)   AR(1)
1999.01 to 2012.10  AR(2)   AR(2)   AR(2)   AR(2)
1944.02 to 2012.12  AR(2)   AR(2)   AR(2)   AR(2)

<table>
<thead>
<tr>
<th>Sample</th>
<th>q(PPI/IPA)</th>
<th>q*(PPI/IPA)</th>
<th>q(CPI/IPC)</th>
<th>q*(CPI/IPC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to 1984.12</td>
<td>ARMA(1,1)</td>
<td>-</td>
<td>ARMA(1,1)</td>
<td>-</td>
</tr>
<tr>
<td>1985.01 to 1994.07</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1994.08 to 1998.12</td>
<td>ARMA(2,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
</tr>
<tr>
<td>1999.01 to 2012.10</td>
<td>ARMA(2,1)</td>
<td>ARMA(2,1)</td>
<td>ARMA(2,1)</td>
<td>ARMA(2,1)</td>
</tr>
<tr>
<td>1944.02 to 2012.12</td>
<td>ARMA(2,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(3,1)</td>
</tr>
</tbody>
</table>

Figures 4 and 5: Results from the autocorrelation and partial autocorrelation functions of the natural logarithms of the real exchange rates at the level base (figure 04) and at first difference (figure 05). Author’s own estimation.

Even though expected, this outcome elucidates that the errors term is not white noise, because the main property that distinguishes one autoregressive from one moving-average process is exactly the residuals being white noise. The error term not being white noise means that it violates stationarity, homoscedasticity or autocorrelation, or all three. Note that this result is covered at level base, but unleashed at first difference.

To determine whether each real exchange rate follows either an AR or an ARMA process, a Ljung-Box is employed. The Ljung-Box is applied solely to first difference identifications, only once these estimations have pointed toward ARMA processes. The test is then summarized by comparing the Q-stat together with the FAC and PFAC data. Each Q-stat exceeding their critical values, outlined in Figure 9 below, culminates with a violation of the null hypothesis of zero autocorrelation, i.e it implies autocorrelation among the residuals, what gainsays the white noise’s properties. Overall the null hypothesis were all rejected but q(PPI/IPA) between January 1985 and July 1994.

<table>
<thead>
<tr>
<th>Degrees of Freedom</th>
<th>10%</th>
<th>5%</th>
<th>1%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>15.99</td>
<td>18.31</td>
<td>23.21</td>
</tr>
<tr>
<td>12</td>
<td>18.55</td>
<td>21.03</td>
<td>26.22</td>
</tr>
<tr>
<td>13</td>
<td>19.81</td>
<td>22.36</td>
<td>27.69</td>
</tr>
<tr>
<td>16</td>
<td>23.54</td>
<td>26.30</td>
<td>32.00</td>
</tr>
<tr>
<td>18</td>
<td>25.99</td>
<td>28.87</td>
<td>34.80</td>
</tr>
<tr>
<td>20</td>
<td>28.41</td>
<td>31.41</td>
<td>37.57</td>
</tr>
</tbody>
</table>
To correctly identify each time series and select their leg structure, the modified version of the identification criteria was employed: the MBIC, MAIC and MHQ. As expected, identification criteria systematically increased as more legs were embed on the time series. On the other hand, the legs of upper orders were all statically insignificant. Three was then the greatest number of legs that were concomitantly statically significant and related to a lower identification criterion. Figure 10 highlights the series identification for each sample period. It is crucial to emphasize beforehand that the identification below is not ultimate, once the failure to reject the null hypotheses of unit root implies that ARMA processes are in fact ARIMA processes.

<table>
<thead>
<tr>
<th>Sample</th>
<th>q(PPI/IPA)</th>
<th>q*(PPI/IPA)</th>
<th>q(CPI/IPC)</th>
<th>q*(CPI/IPC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to 1984.12</td>
<td>ARMA(3,1)</td>
<td>-</td>
<td>ARMA(1,1)</td>
<td>-</td>
</tr>
<tr>
<td>1985.01 to 1994.07</td>
<td>AR(1)</td>
<td>ARMA(2,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
</tr>
<tr>
<td>1994.08 to 1998.12</td>
<td>ARMA(3,1)</td>
<td>ARMA(2,1)</td>
<td>ARMA(3,1)</td>
<td>ARMA(2,1)</td>
</tr>
<tr>
<td>1999.01 to 2012.10</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
</tr>
<tr>
<td>1944.02 to 2012.12</td>
<td>ARMA(3,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(1,1)</td>
<td>ARMA(2,1)</td>
</tr>
</tbody>
</table>

5.2. Error’s term diagnostic

Error’s normality, homoscedasticity and autocorrelation are tested through a Jarque-Bera test, a Breusch-Godfrey test and an ARCH-LM test, respectively. However, each test does not culminate in lack of residuals’ stationarity. Instead, their value relies on conjecturing the error’s terms pathways, possibly evidencing how the residuals behave throughout the sample.

5.2.1. Jarque-Bera test

The Jarque-Bera test reported consistent rejections of null hypotheses of normal distribution to all samples but the real exchange rates given by consumer prices, both with and without the trade protectionism proxy, from January 1986 to July 1997. This period witnessed a speedy convergence of the real exchange rates based on consumer price toward the ones based on producer prices. The samples encompassing the entire period were all rejected. The absence of normality does not imply absence of stationarity though, but simple forecasting methods are indeed challenged.

<table>
<thead>
<tr>
<th>Sample</th>
<th>q(PPI/IPA)</th>
<th>q*(PPI/IPA)</th>
<th>q(CPI/IPC)</th>
<th>q*(CPI/IPC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to 1984.12</td>
<td>37,19 ***</td>
<td>-</td>
<td>138,51 ***</td>
<td>-</td>
</tr>
<tr>
<td>1985.01 to 1994.07</td>
<td>2,37</td>
<td>2,47</td>
<td>7,86 ***</td>
<td>7,54 ***</td>
</tr>
<tr>
<td>1994.08 to 2012.12</td>
<td>18,54 ***</td>
<td>9,17 ***</td>
<td>43,69 ***</td>
<td>20,33 ***</td>
</tr>
</tbody>
</table>
Figures 08: Jarque-Bera test’s outcome indicating presence or absence of error’s term normality. Author’s own estimation.

5.2.2. Breusch-Godfrey and ARCH-LM test

Breusch-Godfrey and ARCH-LM tests did not reject the null hypotheses of absence of errors’ autocorrelation and conditional heteroscedasticity for all the samples and all variables, both with and without the trade protectionism proxy. Results are available upon request.

5.3 ADF and DF-GLS unit root tests

Evaluating the residual terms stationarity is the utmost evidence to either refute or endorse the purchasing power parity hypothesis for any given country. The ADF and the DF-GLS tests were applied to four variables – the real exchange rate based on producer prices not inserting the import duty effective revenue \( \tau (q\text{PPI/IPA}) \); producer prices real exchange rate embedding \( \tau \) (q*(PPI/IPA)); consumer price’s real exchange rate without \( \tau \) (q*(CPI/IPC)); and lastly, the real exchange rate based on consumer prices embedding the proxy \( \tau \) (q*(CPI/IPC)). They range from February 1944 to October 2012, but the two real exchange rates including the proxy \( \tau \) that range from January 1986 to October 2012 are also estimated to four intervals: February 1944 to December 1985; January 1986 to July 1994 (inflationary acceleration); August 1994 to December 1998 (crawling-peg regime); and finally from January 1999 to October 2012 (floating-exchange rate system). The unit root tests are conducted both at level base and at first differences, being the real exchange rates already estimated through their logarithm base, an ordinary step in macroeconometrics. The ADF test and the DF-GLS’s equations include one constant and one trend, but deterministic components of each series, i.e. their trend, are removed before employing the ADF test\(^2\).

The outcome describing the t-statistic of the unit root tests are showcased at Figures 09, 10, 11 and 12. Being the reported result larger than its critical value, the null hypothesis of unit root is rejected. The residuals are in turn stationary, corroborating therefore the empirics of the purchasing power parity.

<table>
<thead>
<tr>
<th>Sample</th>
<th>q(PPI/IPA)</th>
<th>q*(PPI/IPA)</th>
<th>q(CPI/IPC)</th>
<th>q*(CPI/IPC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to 1984.12</td>
<td>- 3,86 ***</td>
<td>-</td>
<td>- 2,19</td>
<td>-</td>
</tr>
<tr>
<td>1985.01 to 1994.07</td>
<td>- 1,69</td>
<td>- 1,71</td>
<td>- 1,48</td>
<td>- 1,60</td>
</tr>
<tr>
<td>1994.08 to 1998.12</td>
<td>- 5,91 ***</td>
<td>- 5,29 ***</td>
<td>- 3,10 **</td>
<td>- 3,82 ***</td>
</tr>
<tr>
<td>1999.01 to 2012.10</td>
<td>- 4,27 ***</td>
<td>- 4,19 ***</td>
<td>- 3,89 ***</td>
<td>- 3,90 ***</td>
</tr>
<tr>
<td>1944.02 to 2012.12</td>
<td>- 2,82 *</td>
<td>- 2,32</td>
<td>- 2,79 *</td>
<td>- 1,81</td>
</tr>
</tbody>
</table>

\(^2\) Critical values of the ADF and DF-GLS tests for 10% (*), 5% (**) and 1% (***) of significance are respectively – 2,57, – 2,97 and – 3,44.
### Table 1: Augmented Dickey-Fuller Unit Root Test

<table>
<thead>
<tr>
<th>Sample</th>
<th>$q(PPI/IPA)$</th>
<th>$q^*(PPI/IPA)$</th>
<th>$q(CPI/IPC)$</th>
<th>$q^*(CPI/IPC)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to</td>
<td>- 19.91 ***</td>
<td>-</td>
<td>- 20.68 ***</td>
<td>-</td>
</tr>
<tr>
<td>1984.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1985.01 to</td>
<td>- 8.44 ***</td>
<td>- 9.36 ***</td>
<td>- 8.41 ***</td>
<td>- 8.39 ***</td>
</tr>
<tr>
<td>1994.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1994.08 to</td>
<td>- 2.01 ***</td>
<td>- 5.52 ***</td>
<td>- 9.95 ***</td>
<td>- 5.07 ***</td>
</tr>
<tr>
<td>1998.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1999.01 to</td>
<td>- 9.24 ***</td>
<td>- 9.09 ***</td>
<td>- 8.41 ***</td>
<td>- 8.27 ***</td>
</tr>
<tr>
<td>2012.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1944.02 to</td>
<td>- 24.71 ***</td>
<td>- 14.53 ***</td>
<td>- 20.01 ***</td>
<td>- 9.28 ***</td>
</tr>
<tr>
<td>2012.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figures 09 and 10: Augmented Dickey-Fuller unit root test at level base (figure 09) and at its first difference (figure 10).

### Table 2: DF-GLS Unit Root Test

<table>
<thead>
<tr>
<th>Sample</th>
<th>$q(PPI/IPA)$</th>
<th>$q^*(PPI/IPA)$</th>
<th>$q(CPI/IPC)$</th>
<th>$q^*(CPI/IPC)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to</td>
<td>- 3.82 ***</td>
<td>-</td>
<td>- 1.37</td>
<td>-</td>
</tr>
<tr>
<td>1984.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1985.01 to</td>
<td>- 1.61</td>
<td>- 1.66</td>
<td>- 1.67</td>
<td>- 1.79</td>
</tr>
<tr>
<td>1994.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1994.08 to</td>
<td>- 4.55 ***</td>
<td>- 2.28</td>
<td>- 0.86</td>
<td>- 0.68</td>
</tr>
<tr>
<td>1998.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1999.01 to</td>
<td>- 1.78</td>
<td>- 1.75</td>
<td>- 1.52</td>
<td>- 1.53</td>
</tr>
<tr>
<td>2012.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1944.02 to</td>
<td>- 2.47</td>
<td>- 2.17</td>
<td>- 1.99</td>
<td>- 1.78</td>
</tr>
<tr>
<td>2012.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figures 11 and 12: DF-GLS unit root test at level base (figure 11) and at its first difference (figure 12).

Generally the unit root tests support the PPP hypothesis at the series’ first difference and reject it at the base level, except since 1994 when employing the ADF. These estimations are in...
accordance with several authors such as Sarno and Taylor (2001), Rogoff (1996), Kannebley (2003) and Freixo and Barbosa (2004).

There are indeed some reported conjectures worth mentioning. First, the sample ranging from January 1986 to July 1994 gainsays the previous literature and the PPP theory is rejected for all price indexes and unit root tests, without or with $\tau$, when estimated at the base level. One explanation might be that although the Central Bank’s crawling-peg regime was used to consistently foster the parity, and the exchange rate management was grounded on relative parity (note that this sample’s estimation at first difference all corroborate the PPP hypothesis). Therefore, the fast convergence of the consumer price based real exchange rate toward the produced price based rate was not actually grounded on the absolute PPP level.

Secondly, the entire sample of exchange rates embedding the proxy $\tau$ are rejected both at consumer and producer prices by both ADF and DF-GLS tests, outlining that either $\tau$ is not a suitable proxy for trade protectionism or that the trade policy has a low explanatory power on the PPP hypothesis validation.

A third evaluation is that regardless of $\tau$ and the index selection, from February 1944 and December 1985, the PPP is robustly endorsed when applying first differences. As I mentioned earlier, this might be due to Central Bank’s effort to pursue the parity level, adjusting the nominal exchange rate in line to the PPP. Figure 05 elucidates this phenomenon, showing precisely how the real exchange rates moved continuously and in consonance during those decades, establishing a stationary relationship.

In addition, the real exchange rates based on producer prices show at the first difference more robust statistics than the consumer prices based exchange rate. This result was expected and corroborates the abovementioned tendency of endorsing the PPP more vigorously when consumer prices indexes are chosen.

Hitherto it might be said that the estimation endorses the relative version of the PPP to all samples and tests and using both consumer and producer prices level with and without the trade protectionism proxy, also supports the absolute PPP based on producer prices and without the aforesaid proxy $\tau$ from February 1944 to December 1985 and from August 1994 to December 1999. The inference with the absolute version of the purchasing power parity hypothesis is therefore either inconclusive or it denies the remaining observations. Further analysis is indeed required.

### 5.4. Cointegration analysis

The specification of the autoregressive vector is the first step toward the cointegration analysis. Subsequently, Subsection 5.4.2. showcases the Engle and Granger’s cointegration outcome and afterwards, Subsection 5.4.3. describes the main results from Johansen’s trace and maximum eigenvalue tests. Even though the correction error vector’s and the cointegration vector’s specifications are as interesting as the results, their significances are less valuable to either endorse or reject the purchasing power parity. They are available upon request. Lastly, Subsection 5.4.4 summarizes the cointegration analysis’s key results.

#### 5.4.1. VAR specification

VAR specification is carried out similarly to the series identification that employs the Schwarz, Akaike and Hanna-Quinn modified information criteria. It was also tested with either the inclusion or exclusion of both a constant and a trend. The main results are displayed in Figure 13.

<table>
<thead>
<tr>
<th>Sample</th>
<th>q(PPI/IPA)</th>
<th>q*(PPI/IPA)</th>
<th>q(CPI/IPC)</th>
<th>q*(CPI/IPC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to 1984.12</td>
<td>VAR(2)</td>
<td>-</td>
<td>VAR(2) ^2</td>
<td>-</td>
</tr>
<tr>
<td>1985.01 to 1994.07</td>
<td>VAR(12)</td>
<td>VAR(12) ^2</td>
<td>VAR(12) ^2</td>
<td>VAR(12) ^2</td>
</tr>
<tr>
<td>1994.08 to 1998.12</td>
<td>VAR(1) ^1</td>
<td>VAR(12) ^2</td>
<td>VAR(1) ^1</td>
<td>VAR(12) ^2</td>
</tr>
</tbody>
</table>
1999.01 to 2012.10 & VAR(2) ¹ & VAR(2) & VAR(1) ² & VAR(12) ² \\
1944.02 to 2012.12 & VAR(2) & VAR(2) & VAR(2) ² & VAR(2) ² \\

Figure 13: VAR specification’s main results. Author’s estimation.

* The subscript 1 denotes inclusion of a constant term. The subscript 2 denotes the inclusion of both a constant and a trend terms. Absence of a subscript denotes the exclusion of both a constant and a trend terms.

Identification has shown that all samples have either one, two or twelve lags in the autoregressive vector’s specification. Most VARs with twelve legs are concentrated in the second period, January 1985 to July 1994, and unsurprisingly, a moment of inflationary hike is boosted by inertial determination.

5.4.2. Engle and Granger’s cointegration test

The Engle and Granger’s cointegration test denied the purchasing power parity hypothesis for Brazil to all samples but the first and fourth intervals of the real exchange rate with producer prices and without the import duty effective revenue $\tau$, i.e. from February 1944 to December 1984 and from January 1999 to October 2012. Recalling Subsection 5.3, the period ranging from February 1944 to December 1984 for the variable $q(PPI/IPA)$ was one of the two periods in which the DF-GLS sustained the PPP at base level. Outlined earlier, during this period the Brazilian money authority vigorously chased the PPP level on its operations.

Further attempts to evidence cointegration with modern techniques such as Johansen’s trace and maximum eigenvalue tests are encouraged. However, exceedingly elevated p-values, as shown in Figure 14, are one critical hindrance.

<table>
<thead>
<tr>
<th>Sample</th>
<th>$q(PPI/IPA)$</th>
<th>$q^*(PPI/IPA)$</th>
<th>$q(CPI/IPC)$</th>
<th>$q^*(CPI/IPC)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02 to</td>
<td>0.001 ***</td>
<td>-</td>
<td>0.979</td>
<td>-</td>
</tr>
<tr>
<td>1984.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1985.01 to</td>
<td>0.721</td>
<td>0.974</td>
<td>0.975</td>
<td>0.940</td>
</tr>
<tr>
<td>1994.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1994.08 to</td>
<td>0.247</td>
<td>0.392</td>
<td>0.876</td>
<td>0.987</td>
</tr>
<tr>
<td>1998.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1999.01 to</td>
<td>0.081 *</td>
<td>0.699</td>
<td>0.693</td>
<td>0.898</td>
</tr>
<tr>
<td>2012.10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1944.02 to</td>
<td>0.993</td>
<td>0.960</td>
<td>0.808</td>
<td>0.286</td>
</tr>
<tr>
<td>2012.12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 14: P-values of Engle and Granger’s cointegration test. Author’s own estimations.

5.4.3. Johansen’s trace and maximum eigenvalue tests

Generally speaking, Johansen’s tests reject the presence of cointegration in all samples based on producer prices indexes except for the complete sample, and acknowledges cointegration in all sample based on consumer prices indexes. This outcome is displayed in Tables 15 to 18, being one table for each variable. The outcome is reinforced by the p-values of both trace and maximum eigenvalue tests for each sample, with the top result being the trace test p-value and the bottom the eigenvalue test p-value. They are interpreted as follows. Should the p-value be significant (lower than
0.10), it means that the null hypothesis of the X cointegration vectors is rejected. There is so far no evidence of cointegration. Cointegration is only endorsed when the p-value is not significant, once the null hypothesis of X cointegration vectors is not rejected, as is the case of two cointegration vectors for the sample February 1944 to December 1984 displayed in Figure 15.

In case of conflict between the trace and the maximum eigenvalue results, the maximum eigenvalue test, which is more robust, is instead recommended.

<table>
<thead>
<tr>
<th>Sample</th>
<th>0</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02</td>
<td>0.000</td>
<td>0.000</td>
<td>0.850</td>
</tr>
<tr>
<td>1984.12</td>
<td>0.000</td>
<td>0.000</td>
<td>0.891</td>
</tr>
<tr>
<td>1985.01</td>
<td>0.000</td>
<td>0.054</td>
<td>0.422</td>
</tr>
<tr>
<td>1994.07</td>
<td>0.000</td>
<td>0.064</td>
<td>0.422</td>
</tr>
<tr>
<td>1994.08</td>
<td>0.000</td>
<td>0.122</td>
<td>0.267</td>
</tr>
<tr>
<td>1998.12</td>
<td>0.000</td>
<td>0.129</td>
<td>0.280</td>
</tr>
<tr>
<td>1999.01</td>
<td>0.013</td>
<td>0.071</td>
<td>0.215</td>
</tr>
<tr>
<td>2012.10</td>
<td>0.054</td>
<td>0.070</td>
<td>0.229</td>
</tr>
<tr>
<td>1944.02</td>
<td>0.000</td>
<td>0.026</td>
<td>0.886</td>
</tr>
<tr>
<td>2012.12</td>
<td>0.000</td>
<td>0.026</td>
<td>0.887</td>
</tr>
</tbody>
</table>

Figures 15 and 16: P-values of Johansen’s tests for producer prices based real exchange rates with (figure 15) without (figure 16) the import duty effective revenue. Author’s own estimation.

Figures 15 and 16 underline the presence of two cointegration vectors in most samples based on producer prices indexes. There is one sample with solely one vector in Figure 15 as well as two samples with three cointegration vectors in Figure 16, which embeds the import duty effective revenue. There is therefore an inclination to support variables cointegration when employing producer prices.

On the other hand, outcomes are tremendously negative when employing consumer prices based indexes (CPI and IPC), as indicated in Figures 17 and 18. Solely one cointegration vector was uncovered in all the subsamples, from January 1999 to October 2012, encompassing the trade protectionism proxy.

<table>
<thead>
<tr>
<th>Sample</th>
<th>0</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1944.02</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>1984.12</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>1985.01</td>
<td>0.000</td>
<td>0.000</td>
<td>0.018</td>
</tr>
<tr>
<td>1994.07</td>
<td>0.000</td>
<td>0.000</td>
<td>0.018</td>
</tr>
<tr>
<td>1994.08</td>
<td>0.000</td>
<td>0.000</td>
<td>0.046</td>
</tr>
</tbody>
</table>
One piece of good news is that there is evidence of cointegration on the complete samples, ranging from February 1944 to October 2012. This result consists in a major indication that the PPP is not valid in the short-term, but is instead a long-run anchor, as portrayed by Rogoff (1996).

Figures 17 and 18: P-values of Johansen’s tests consumer prices based real exchange rates with (figure 17) without (figure 18) the import duty effective revenue. Author’s own estimation.

Figure 19: Johansen’s tests results compiled

### 5.4.4. Overall results

Johansen endows the Engle and Granger’s naïve test, which consistently reject cointegration among the nominal exchange rate and the price levels, either with or without the import duty effective revenue. Consequently, both the trace and the maximum eigenvalue tests recognize cointegration vector among those variables for all sample and subsamples based on producer price indexes and for the complete samples based on consumer price indexes. This result clashes with the foregoing unit root tests when carried out at the base level. Highlighted in Subsection 5.3, the DF-GLS endorsed the presence of unit roots essentially for all samples and subsamples. Nonetheless, the ADF weakly rejected the unit roots for the entire samples without the import duty effective revenue, while it was not able to reject them with such proxy. The overall result is indeed positive, because the Johansen’s methodology endorses purchasing power parity for Brazil as an long run anchor when based on consumer price indexes and both as a short and long run benchmark when computed by producer price indexes.

### 6 Final remarks
Purchasing power parity is a theoretical and empirical proposition, which advocates that price levels around the world are equivalent when converted into one single currency denominator. It proposes a relationship between price levels and the nominal exchange rates, implying that they shall move in harmony somehow.

This paper’s value lies in empirically reviewing PPP, with special attention to papers appraising the Brazilian currency experience, and straightforwardly testing the PPP through unit root tests and cointegration analysis. Further research is encouraged, specifically on unit root tests enabling multiple and endogenous structural breaks as well as on nonlinear models.

Generally the unit root tests support the PPP hypothesis at the series’ first difference and reject it at the base level, except since 1994 when employing the ADF. These estimations are in accordance with several authors, such as Sarno and Taylor (2001), Rogoff (1996), Kannebley (2003), Freixo & Barbosa (2004). In addition, the entire sample of exchange rates embedding the proxy τ are rejected both at consumer and producer prices by both ADF and DF-GLS tests, outlining either that τ is not a suitable proxy for trade protectionism or that the trade policy has a low explanatory power on the PPP hypothesis validation.

Johansen endows the Engle and Granger’s naïve test, which consistently reject cointegration among the nominal exchange rate and the price levels, either with or without the import duty effective revenue. Consequently, both the trace and the maximum eigenvalue tests recognize cointegration vector among those variables for all sample and subsamples based on producer price indexes and for the complete samples based on consumer price indexes.

The overall result is indeed positive, because the Johansen’s methodology endorses purchasing power parity for Brazil as an long run anchor when based on consumer price indices, both as a short and long run benchmark when computed by producer price indexes.

References


The hot-hand and gambler's fallacies are two cognitive fallacies that arise due to the existence of "streaks"—repeated outcomes in successive events. Previous studies have attempted to model the theoretical effects of the two fallacies. This paper adds to the existing literature by testing the models for empirical accuracy using a randomized controlled experiment. Participants are asked to bet on coin flips with the option of purchasing a demonstratively useless prediction, in order to isolate the hot-hand and gambler's fallacies. Results show that participants systematically err in their belief of continuation (hot-hand), with minor support for their belief in reversal (gambler's fallacy).
A RE-EXAMINATION OF THE YIELD SPREAD AS A FORECASTING VARIABLE

Rosa C. Hayes
Wesleyan University

ABSTRACT

Since Kessel (1965), it has been well documented in macroeconomic literature that the spread between long- and short-term government bond yields is a strong predictor of a country’s future economic growth. In addition, recent research suggests that the yield spread’s predictive power began to decline in the mid-1980s and attributes this decline to increasing monetary regime credibility in the latter part of the twentieth century. This paper revisits the statistical relationship between the yield spread and the future economic growth rate by using post-WWII data on OECD countries, which is more comprehensive in terms of geographic and temporal coverage than before. The paper uncovers two new empirical regularities. First, though I confirm that the yield spread is a strong predictor of future economic growth in many countries, there is enormous heterogeneity in its predictive ability across countries as it turns out to be a highly unreliable predictor of growth in some countries (e.g. Norway, Korea, Japan). Second, in contrast to earlier findings, I find neither that the spread’s predictive power has been declining in the post-WWII era nor that increasing monetary regime credibility is in any way systematically related to the spread’s predictive power. Rather, I observe that periods of generally declining volatility (e.g. the Great Moderation period between 1986-2006), not monetary credibility per se, are associated with diminished forecasting capability.
BIDDING DECISIONS IN PAY-PER-BID AUCTIONS WITH A BUY PRICE OPTION

Glenn Russo Jr.1

Georgetown University

ABSTRACT

I examine a type of online auction called a *penny auction*, which has exploded in popularity since its recent introduction. A penny auction is an auction in which every bid increases the price of an item for sale by a small, fixed amount while the bidder incurs a relatively high bidding fee for each bid cast. I build on the work of Hinnosaar (2010) to incorporate a buy price, or Buy It Now (BIN), option into a theoretical auction model. Unlike other literature, my retail price remains fixed and bidding fees are not deducted from it. This solves some tractability issues encountered in related projects. I determine that any auction can be completely solved and that the end price can be predicted with some probability. Using this result I determine the expected revenue for the auction retailer. I find that penny auctions can be profitable for the seller and that high prices can be reached in most auctions. Finally, I propose extensions to my model and questions for future research.

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1 Introduction

In recent years, a type of internet-based pay-per-bid auction, called a *penny auction*, has grown in popularity amassing fans and critics. The auction is one in which players pay a fixed fee per bid to raise the price by $0.01 at a time, hence the prefix “penny.” Each bid also extends the time of the auction by a fixed amount; thus the auction can be thought of as a multi-period game with an indeterminate end. On most penny auction websites, the bidding fee is relatively large, somewhere between $0.50 and $1.00. Because of the bidding fees, participating in a penny auction can result in sizeable losses for the non-winners. Some critics have likened these auctions to a form of gambling, which may have some truth to it. Despite criticism, the unique format of a penny auction provides a fascinating economic experiment to study bidder behavior.

A relatively new development in this industry is the addition of a retail buy price option, commonly known as a Buy It Now option (BIN). Auction websites provide the opportunity for the bidder to obtain the item for retail price while the auction continues or after it ends. By this mechanism, a clear array of choices is presented to the player each period: bid, don’t bid, or buy the item and exit the auction. No author has successfully adapted the standard, multi-period penny auction model as characterized by Hinnosaar (2010) to include a BIN price. The most complete attempt to model the BIN option was Xu (2012) who proposed a model of an all-pay auction with a retail price option in order to explore the effect of the BIN feature.

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1 Email: gmr22@georgetown.edu; Department of Economics, Georgetown University, Washington, D.C.

2 Notice that this prevents the use of jump bidding as a signaling mechanism, that is bidding a high number relative to the current auction price to deter competitors, making it harder for players to indicate their seriousness. See Avery (1998) for a discussion of jump bidding and its effectiveness.


4 In fact, some of the literature on penny auctions posit a utility premium, similar to that derived from gambling activity, as a way of accounting for participation in penny auctions at higher price levels.
I attempt to complement the findings of Hinnosaar (2010) and Xu (2012). Specifically, I alter Hinnosaar’s (2010) model to consider an auction with a BIN option. Determining the theoretical equilibrium strategies for bidders in this type of auction will be the purpose of this paper. My paper is intended to answer the following questions: 1) What are the equilibrium strategies for the current highest bidder and the non-highest bidder? 2) When would a bidder select the BIN option over choosing to continue to play the auction game? 3) At what point will the auction end and with what probability? 4) What is the expected revenue for the seller in any auction?

The following is a brief outline of the paper. Section 2 will review recent literature. Section 3 will present my model. Section 4 will explore the auction dynamics for auctions with two players and then auctions with more than two players. Particular focus will be paid to the equilibrium strategies for bidders in each round of bidding. Section 5 will briefly outline some observations on the limits of possible prices achieved and a method for calculating expected revenue in any auction. Section 6 will conclude.

My research adds to the limited collection of working papers on penny auction theory and provides an updated model for considering bidder behavior on these websites including a BIN option. This paper defines equilibrium strategies for all players in any penny auction with a BIN option and proves that any auction can be solved using these strategies. Bidder behavior is altered by the availability of a BIN option. I also show the probability of an auction ending at a specific price p, and the formula to determine the expected revenue for the seller. I find that penny auctions can be profitable for the seller and that high prices are reached with positive probability in most cases. Finally, I propose extensions to my model and questions for future research.

2 Literature Review

Penny auctions compose a relatively unexamined area in auction theory and relevant literature remains scarce, mainly in the form of working papers. The first significant model of penny auctions was developed by Augenblick (2009) who considered a pay-per-bid auction modeling time as discrete periods where only one bid is accepted per a period. If multiple players bid per period, a winner is chosen at random but only that player whose bid was accepted incurs the bidding fee. Platt, Price, and Tappen (2010) proposed an alternative model for penny auctions that differed from Augenblick’s (2009) by allowing for variable-length bidding periods and a shifting pool of bidders. In this case as well, only one bidder can bid per round.

Hinnosaar (2010), the main foundation for my paper, built upon Augenblick’s work by modifying the discrete-period model to allow for multiple bids to be simultaneously counted each round; the highest bidder is then chosen at random from among the accepted bids. This extension allows for a more complete estimation of the possible ending price. It also better captures the experience of a player who, in the quick-paced world of internet bidding, would experience a number of bids, split-seconds apart, as a single discrete bidding period with a random outcome. Hinnosaar employed a backwards induction methodology to determine a Subgame Perfect Nash Equilibrium for auctions involving two bidders and more than two bidders. He found a wide variance in possible ending prices dependent on factors as simple as whether the number of predicted periods left in the auction is even or odd. My analysis also yields similar results regarding the variance in ending prices and existence of equilibrium strategies.

All the above models do not include a BIN option, but there have been some efforts to examine BIN dynamics. The first attempt at introducing BIN prices into this sort of auction was Anderson and Ødegaard (2011). They examined two channels for purchase, a retail channel and an auction channel. They then considered a BIN modification in which the losing bid amount paid by non-winners in the all-pay auction can be deducted from the retail price in the retail channel. For example, if the retail price is R and the bidder submitted and paid a losing bid x, the price to buy the item in the retail channel is reduced to $R - x$. Many BIN options on real penny auction sites take a similar form.

Following this research, Xu (2012) proposed a model of an all-pay auction with a BIN option for the losers, based on the work of Anderson and Ødegaard (2011). He utilized a private valuation framework with a continuous distribution and also simplified the auction to a single period as well. However, he only considered a single, sequential channel through which buyers first participate in the
auction and then losers can choose to BIN if they so wish. He also deducted losing bids from the posted retail price, like Anderson and Ødegaard (2011). Xu determined an optimal starting retail price, according to his model, by which the seller can achieve the maximum revenue.

Extending this research to a multi-period model of pay-per-bid auctions has proven challenging. Wang and Xu (2012) attempted to tackle this problem in an appendix to their paper. They found that the addition of a BIN option to the Hinnosaar penny auction model is too difficult an endeavor if we assume that bidding costs are deducted from the BIN price as in Xu (2012). Deduction of accumulated bidding fees is a common feature on penny auction sites, but including the dynamics of a multi-period auction and a variable BIN price makes analysis highly complicated. Each bidder would be heterogeneous since bidding costs are likely not incurred at the same rate. I seek to address this by changing the model such that the retail price \( R \) is fixed and does not move depending on past bidding behavior. This small change in rules provides a mathematically tractable way to explore the penny auction dynamics with a buy price option.

My model has the modest goal of providing an improved groundwork upon which to base any further theoretical research into penny auctions by being the first to successfully integrate a BIN option into the multiple-bid framework. I will make the same basic rationality assumptions as Hinnosaar (2010); however my model comes closer to reality by integrating the retail BIN option and improving the understanding of consumer behavior in this type of auction. Almost all major penny auction sites offer this feature and I hope that my research will improve our understanding of how a buy-price option affects economic behavior in pay-per-bid auctions.

3 Model

I use a model based on the work of Hinnosaar (2010). Consider a pay-per-bid auction with defined bidding periods, \( t \in \{0, 1, \ldots\} \). A bidder incurs a fixed cost \( C \) to submit a bid to raise the price by fixed amount \( \varepsilon > 0 \), a small positive number. The auction begins at an initial price \( P_0 \). I assume a common valuation framework with value \( V \). There is a starting pool of \( N \) bidders who are risk neutral. In period \( t > 0 \), that is once the first bid is cast, one bidder is the current highest bidder. I will refer to him as the leader. Therefore once the auction begins there are \( N - 1 \) non-leaders. We assume the leader cannot bid in the round because he is already the highest bidder.

Each period, non-leaders decide simultaneously whether to bid or not. Let \( K \) be the number of non-leaders who choose to bid in a round. When at least one bid is cast, the auction is extended to period \( t + 1 \), and the auction price increases by \( K \cdot \varepsilon \). If only one player bids, then he automatically becomes the leader in the next period. If \( K > 1 \), then the leader is chosen at random with probability \( \frac{1}{K} \), but all bidders still incur the bidding fee.\(^5\) When no player chooses to bid in period \( t \) the auction ends and the current leader pays the current price, denoted \( P_t \). All of the auction parameters and rules are known by all players, all bidders know who the current leader is, and all players observe previous bids.

Each period, the seller also offers bidders the choice to pay a fixed retail price \( R > 0 \) to obtain the item and exit of the auction. This is commonly referred to as a Buy It Now (BIN) option.\(^6\) I assume that there is sufficient supply of the item at auction to make this system feasible. Because the retail price \( R \) is fixed, it is the same in every round. Therefore in period \( t \) the bidder faces three choices: to bid, not bid, or buy the item outright at price \( R \).

For this paper, we assume that \( v \geq r \). This limits the study to consumers that value the item at least at retail, but are participating in the penny auction for the chance to get it for less. I rule out any consumers who would not buy the item at full retail price. Therefore, we can easily assume that all

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\(^5\) This assumption reflects split-second bidding in real internet penny auctions. Realistically, there are not multiple bids per period in the age of instantaneous bidding; however human players would perceive discrete simultaneous bidding periods given the limits to data transfer and reaction times, making the leader in each period appear randomly chosen. This stylization also simplifies the model.

\(^6\) This paper also could be seen in a different light as modeling the availability of the retail market outside of the penny auction that always exist whether or not the website offers a BIN function. Consumers always have a choice to drop out of the auction and purchase the item somewhere else. I do not explicitly consider this here, but I believe the extension to follow directly.
players in the auction have already committed to buying the item so that when the auction ends, all losing players must buy the item at full retail price \( R \) from the seller for some positive payoff.\(^7\)

Given that each round is independent, all past bidding costs are sunk. This makes play in each round contingent only upon future bidding costs and probability of winning based on current conditions, i.e. history does not matter.\(^8\) By far, this is the most striking and useful assumption in my model.

Additionally, players do not discount future costs. I justify this by noting that penny auctions take place in the course of a few hours or days, not months and years, making the discount rate negligible. Time costs are also not a factor for the same reason; the amount of time spent bidding is limited.\(^9\) Given the instantaneous, internet-based nature of the auctions, transaction costs are negligible.

To ease the analysis, I will use the following normalizations to put all variables in terms of the fixed auction price increment \( \varepsilon \):

\[
v = \frac{V - P_0}{\varepsilon} \quad c = \frac{C}{\varepsilon} \quad r = \frac{R}{\varepsilon} \quad p_t = \frac{P_t - P_0}{\varepsilon}
\]

In my model, \( P_0 = 0 \). I will use these normalized values for the rest of the paper unless otherwise noted.

A penny auction is fully characterized by \( (N, v, c, r) \). To designate the possible outcomes of the auction, we will use the following notation. There is a chance that no one bids in the first period, which I denote as \( Q_0 \). In this case the auction never begins and all choose to BIN. Conditional on the object being sold, there is a probability \( Q(p) \) that the auction ends with exactly \( p \) bids cast. The unconditional probability that the item is sold via auction after \( p \) bids is \( \bar{Q}(p) \), such that \( \bar{Q}(0) = Q_0 \) and \( \bar{Q}(p) = Q_p (1 - Q_0) \). The unconditional probability is the overall chance that the auction ends at price \( p \) taking into account all bidding paths, even the chance that the auction never begins.

We can use current price \( p_t \) to solve for a Subgame Perfect Nash Equilibrium (SPNE). This strategy profile can be fully characterized by \( q(p_t) \in [0,1] \) where \( q(p_t) \) is the probability of a non-leader submitting a bid at price \( p_t \).

### 4 Auction Dynamics

To begin, I make a simple assumption that the value and the retail price are both greater than 1 plus the bidding fee.

**Assumption 1.** Assume \( v > c + 1 \) and \( r > c + 1 \).

This assumption simply ignores irrelevant cases in which the value of the item is not high enough for an auction to begin. Since \( c \) is the bare minimum amount of money spent bidding, if \( v \) were any lower no bids would be cast. In the same vein, if it cost less to buy the item at retail than to begin bidding in the auction, no one would ever bid.

We can denote a SPNE by a vector \( q = (q(0), q(1), ...) \), where \( q(p) \) is the non-leaders’ individual probability of bidding at price \( p \). I will write the leader’s continuation value as \( v^*(p) \) and the non-leaders’ continuation value as \( v(p) \). Continuation value is the expected value of the equilibrium payoff in the next round. Remember that continuation values do not include the sunk past bidding costs, only the future payoffs.

The first step in analyzing the auction is finding the maximum price that can be reached given the fixed retail price \( r \). I define a new variable. Let \( \bar{r} = (r - c) \) such that \( r = \bar{r} + c \). By Assumption 1, we know that \( \bar{r} > 0 \). It can be proven that no player will choose to bid at \( \bar{r} \) or above in Lemma 1.

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\(^7\) In the model, I will assume the auction retailer is the only seller of the item being sold in order to avoid transaction costs, time costs, preferences, different market prices, etc. from other sellers. However, this theoretically could be changed to assume that the auction and retail channels are separate without any practical differences in bidder strategy. The expected profit for the seller, however, would change. See Anderson and Ødegaard (2011) for related analysis.

\(^8\) This assumption is troublesome given Augenblick’s observation that though economically true, players rarely see previous bidding fees and wasted time as sunk. He and other authors have attempted to approximate both time costs as well as a “regret” term that grows (either linearly or geometrically). That may be a feasible extension of this research in the future.

\(^9\) That is not to say that these factors would not be useful to include in this model. They are excluded in the interest of simplicity and could be fodder for future extensions of this research.
Lemma 1. No player will place a bid at any price \( p \geq r \) in equilibrium. In other words \( q(p) = 0, \forall p \geq r \).

Proof. Omitted for space.

It is important to note that Lemma 1 does not depend on the value of \( v \), which could be \( \leq r \).

Intuitively, at any price equal to or above the final limit price of \( r \) there is no incentive to ever bid, whether the non-leader exercises the BIN option in the current period or not. The bidder may choose to wait it out till the end of the auction and not press the BIN button immediately, but will never see value in attempting to become the highest bidder. Practically, it is a moot point since the auction will end that period given \( q(p) = 0, \forall p \geq r \).

If the player chooses to wait, he will not be waiting long; he will be forced to BIN at the end of the period.

We can draw the following corollaries immediately:

Corollary 1.1. The upper bound of realized prices is \( r + N - 2 \).

Proof. If \( r > 1 \), then the last price bidders will bid with positive probability is \( r - 1 \). If all \( N - 1 \) non-leaders bid then the price could plausibly increase to,

\[
(r - 1) + (N - 1) = r + N - 2
\]

Corollary 1.2. There exists a point in time \( \tau \leq r \) at which the auction has ended with certainty. In any equilibrium, the game is finite.

Proof. I will give a sketch of the logic. This corollary follows from the fact that the price must increase by at least 1 for every period the auction does not end. The maximum number of bidding periods can be found by assuming that price goes up by 1 and only 1 each period until the price reaches \( r - 1 \) and \( t = r - 1 \). At this point there can only be one more bidding period until the price reaches \( r \) and bidding stops. The more important conclusion from this is that the auction is finite.

Corollary 1.3. At \( t = \tau \) the auction has ended with certainty and there is a strictly dominating strategy to not bid at prices \( p \geq r \). Therefore we can solve for SPNE using backwards induction.

4.1 Two-Player Game

First, let us consider a version of the game where \( N = 2 \). Each player alternates bidding with the other since at every \( t > 0 \), one player is leader and one is the non-leader. We can solve this simple game by backwards induction. First, I will make a simplifying assumption to deal with situations in which a player is indifferent between bidding and not bidding. This assumption will hold only for this analysis of the \( N = 2 \) case.

Assumption 2. I assume that when indifferent between bidding and not bidding, a player will choose to bid.

To begin, I will sketch the intuitive logic of solving this two-player game in reverse, beginning from the point \( p = r \). We know that \( \forall p \geq r, q(p) = 0 \). So the game ends instantly at price \( p = r \) or above.

At this price, the current leader will receive his value minus the auction price, which is \( (r - c) \), and the non-leader will buy the item at retail and thus gain his value minus the retail price. The non-leader would rather walk away than raise the price to \( r + 1 \) and pay an additional bidding fee, as the equations show. Specifically the payoffs at \( p = r \) are:

\[
v^*(p) = v - r = v - r + c \quad \text{and} \quad v(p) = v - r
\]

Then consider the period prior when \( p = r - 1 \). The non-leader has a decision whether to bid or not bid. By bidding, the payoff is

\[
v^*(p + 1) - c = v^*(p) - c = v - r - c = v - r
\]

Not bidding, the auction ends that period leaving payoff \( v - r \). The logic is similar. Since in this case \( v^*(p + 1) = v(p) \), the non-leader is indifferent. We assume the non-leader will bid given Assumption 2.
Next, consider when $p = \bar{r} - 2$. By bidding, the non-leader becomes a leader, who then will be outbid next round given the non-leader will bid. So the payoffs appear to be

$$v^*(p + 1) - c = v^*(\bar{r} - 1) - c = (v - r) - c \quad v(p) = v - r$$

In this case the non-leader will not bid since it is better to remain a non-leader, that is $q(\bar{r} - 2) = 0$. Continuing this process, we can see that the outcome of the game simply depends on the whether $\bar{r}$ is odd or even.

Formally we can define the unique SPNE derived from this logic in Proposition 1.

**Proposition 1.** Consider an auction in which $N = 2$. There is a unique SPNE with strategies such that,

$$q(p) = \begin{cases} 
0 & \text{when } \bar{r} - p \text{ is even} \\
1 & \text{when } \bar{r} - p \text{ is odd}
\end{cases}$$

for $p > 0$

and $q(0)$ is determined by:

$$q(0) = \begin{cases} 
0 & \text{when } \bar{r} \text{ is even} \\
2l & \text{when } \bar{r} \text{ is odd and } r < 3c + 1 \\
i + c + 1 & \text{when } \bar{r} \text{ is odd and } r > 3c + 1 \\
1 & \text{when } \bar{r} \text{ odd}
\end{cases}$$

**Proof.** See Appendix A.

We can draw a few simple conclusions from our analysis of the two-player version of the pay-per-bid auction. First, the outcome of the auction depends on whether $\bar{r}$ is odd or even. If $\bar{r}$ is even, then the auction will never begin; no one will want to be the first bidder. If $\bar{r}$ is odd, then under certain conditions, both will bid, and the player selected as the non-leader will bid again to win at $p = 3$.

The condition $r > 3c + 1$ is realistic since in most cases $r > 3c + 1$ so both players will submit a bid at $t = 0$. If we assume $r > 3c + 1$, then the equilibrium collapses to:

$$q(0) = \begin{cases} 
0 & \text{when } \bar{r} \text{ even} \\
1 & \text{when } \bar{r} \text{ odd}
\end{cases}$$

The equilibrium determined here also mirrors a dollar auction as described by Shubik (1971), which makes sense since the all-pay auction and penny auction share certain similarities. This resemblance also intuitively reminds us of how penny auctions, like dollar auctions, can reach irrationally high prices in reality.

My final observation is that results follow the results of Hinnosaar (2010) closely. As we found earlier with Lemma 1, the introduction of a BIN retail price eliminates the role of the valuation model as well in the two player case. While Hinnosaar found that $v$ was the key variable, I find that $r$ plays the main role in determining strategies. Substituting $v$ for $r$, the results are comparable.

**4.2 Game with More Than Two Players**

Next I consider a game in which $N > 2$, which will build upon the results in the preceding section. The rules of the game are the same, however for each round with $p > 0$ there are multiple non-leaders simultaneously choosing to bid or not. Note that in the first period, $t = 0$, there will be $N$ non-leaders. In all following periods there are $N - 1$ non-leaders. I denote the number of non-leaders in any round by $\mathcal{N}$.

Continuing with the assumption that all bidders have a common, known value for the item, I will look for a symmetric equilibrium solution to this game. In each period, the game will be in one of four states, designated S1, S2, S3a, S3b, which are characterized by $q(p)$, $v(p)$, and $v^*(p)$.

The first state, S1, is one in which no player would choose to bid and corresponds to the following equations.

**State 1 (S1)** In which, no player bids and the auction ends. All BIN.

$$q(p) = 0$$

$$v^*(p) = v - p$$

$$v(p) = v - r \geq v^*(p + 1) - c$$
In S1, the auction ends, so the leader would expect to pay \( p \) for the item. Other players will, of course, purchase the item at retail, having lost the game. Since players know no one will bid, including themselves, they will all BIN this period. This equilibrium state occurs in instances where it is better to just buy the item at retail then engage in another round of bidding.

The second state to consider is the opposite case where all non-leaders will bid with certainty.

**State 2 (S2)** *In which, all non-leaders choose to bid and the auction continues with certainty.*

\[
q(p) = 1 \\
\nu^*(p) = v(p + N) \\
\nu(p) = \frac{1}{N} v^*(p + N) + \frac{N - 1}{N} v(p + N) - c \geq \max \{v(p + N - 1), v - r\}
\]

In S2, the price will increase by \( N \) since every non-leader will bid. The leader will certainly become a non-leader in the next round. This is reflected in the leader’s continuation value. A non-leader must value bidding more than both the BIN option or waiting and remaining a non-leader at the price \( p + N - 1 \) where every non-leader bids except him. Each non-leader who bids in the current round has an equal chance of becoming leader in the next round, since when more than one bidder bids simultaneously, the leader is chosen at random.

The third and fourth states both consider a case in which \( q(p) \in (0, 1) \) and the non-leader plays with a mixed strategy. In S3a, those non-leaders that do not bid in the current round choose to wait until the next round as a non-leader and do not BIN. In S3b, those non-leaders who do not bid in the current round will choose to BIN instead.

In some cases players could be indifferent between waiting and BIN. In this case two equilibriums are possible. The non-uniqueness of the equilibria presented here will be discussed in further detail below. The important point is that it is possible for players in an auction to have more than one equilibrium strategy set. With that in mind, I proceed to the third and fourth states.

**State 3, case a (S3a)** *In which, non-leaders play a mixed strategy and non-bidders do not BIN.*

\[
0 < q(p) < 1 \\
\nu^*(p) = (1 - q)N (v - p) + \sum_{k=1}^{R-1} \binom{N}{k} q^k (1 - q)^{R-k} v(p + K) \\
\nu(p) = \sum_{k=0}^{R-1} \binom{N - 1}{k} q^k (1 - q)^{R-1-k} \left[ \frac{1}{K + 1} \nu^*(p + K + 1) + \frac{K}{K + 1} v(p + K + 1) \right] - c \\
= (1 - q)^R (v - r) + \sum_{k=1}^{R-1} \binom{N - 1}{k} q^k (1 - q)^{R-1-k} v(p + K) \geq v - r
\]

**State 3, case b (S3b)** *In which, non-leaders play a mixed strategy and non-bidders BIN.*

\[
0 < q(p) < 1 \\
\nu^*(p) = (1 - q)N (v - p) + \sum_{k=1}^{R-1} \binom{N}{k} q^k (1 - q)^{R-k} v(p + K) \\
\nu(p) = \sum_{k=0}^{R-1} \binom{N - 1}{k} q^k (1 - q)^{R-1-k} \left[ \frac{1}{K + 1} \nu^*(p + K + 1) + \frac{K}{K + 1} v(p + K + 1) \right] - c = v - r \\
\geq (1 - q)^R (v - r) + \sum_{k=1}^{R-1} \binom{N - 1}{k} q^k (1 - q)^{R-1-k} v(p + K)
\]

In S3a and S3b, the leader has a chance of no one bidding and the auction ending, and a chance that at least one non-leader bids and the leader becomes a non-leader at price \( p + K \), where \( K \) is the number of players who bid in the round. The probability of each price occurring is factored into the summation term in the leaders continuation value. Recall that the leader in each round of an auction does not face a decision, so the value of \( \nu^*(p) \) only depends on the actions of the other bidders.
For the non-leader, she has a more complicated decision. Recall that three actions are available to the non-leader: bid, not bid and wait, or not bid and BIN. In S3a or S3b, the conditions for mixed strategy consist of the ‘bid’ action in equilibrium with some form of ‘not bid,’ either wait or BIN. The action taken, of course, depends on the payoffs in the given period. The mixed strategy state, S3, is split into a and b in order to account for the possibilities that the waiting payoff may be greater, less than, or equal to the BIN payoff.

We can make some quick observations about these four states:

i. The definition of \((1 - q)\) as the probability of not bidding is correct, though complicated. In S3a, it represents the probability of not bidding while remaining in the auction. In S3b, it represents the probability of BIN and exiting the game.

ii. Each round, \(N\) could change if some players BIN, while others remain in the auction. Each state may have a new \(N\) especially when \(N\) is high and state S3b is reached with a mixed strategy. This adds uncertainty in future rounds concerning the number of non-leaders in the auction. In cases where \(N\) varies in each round, the outcome can only be predicted with positive but not certain probability.

A key takeaway is that a penny auction of this form is fully explained by these four states. Every price must fall into one or more of these states, and so at each price level, an equilibrium can be predicted. Proposition 2, below, confirms this statement.

**Proposition 2.** In every pay-per-bid auction, there exists a SPNE \(q \in [0,1]\) such that the probability of a non-leader bidding, \(q(p)\), and the corresponding continuation value functions are recursively characterized as S1, S2, or S3 at each price, \(p \geq 0\). This SPNE is not necessarily unique.

**Proof.** For \(N = 2\), this special case is covered in Proposition 1.

For the rest of the proof we draw directly from Hinnosaar (2010) who uses the following logic to justify his equilibrium findings. I will go through the logic briefly here and I encourage the reader to refer to Theorem 2 in Hinnosaar (2010) for more detail.

The equations above describe how to find the equilibrium \(q\). The states, S1, S2, S3a and S3b are such that there are no profitable one-stage deviations. To prove existence we must show that there exists at least one \(q\) that satisfies at least one of the state conditions. Nash (1951) Theorem 2, and the extension by Cheng, Reeves, Vorobeychik, and Wellman (2004), proves that this finite game has at least one symmetric equilibrium in either mixed or pure strategies. Therefore, there exists at least one \(q\) that satisfies a state above.

That the equilibrium is not unique can be proven by example. Proof omitted for space.

**5 Revenue**

Now that I have characterized the equilibrium of the auction fully in each state, we can begin to delve into the revenue dynamics. Let us consider for a moment the level of prices reached in this type of auction.

As the equations in Section 4 show, the probability of a non-leader casting a bid affects the possible price levels reached. Price will increase based on how many bids are submitted in each round and it is possible to calculate what price can be reached with positive probability in any auction.

To begin, I will show the simple fact that there cannot be two adjacent price levels \(p, p - 1\) \(\leq \bar{r} - 1\) at which all players would pass. The obvious reason is that the auction would end with certainty on the first of the pair of price levels when no one bids and never reach the second. But we can mathematically show that two adjacent price levels with \(q(p) = 0\) is an impossibility. We follow the lead of Hinnosaar (2010) in the following lemma.

**Lemma 2.** In any SPNE, there is no \(\hat{p} \in \{2, \ldots, \bar{r} - 1\}\) such that \(q(\hat{p} - 1) = q(\hat{p}) = 0\).

**Proof.** Omitted for space.

As a quick corollary, this also means that specifically, \(q(\bar{r} - 2) > 0\). However, it does not preclude adjacent passing prices at the price levels \(\bar{r} - 1\) and \(\bar{r}\). We then can ask how high prices might
rise in an auction. Proposition 3 states that high prices can be reached with positive probability in this auction model.

**Proposition 3.** Call the highest price that can be reached with positive probability \( \bar{p} \).

(i) For \( N > 2 \), \( r - 1 \leq \bar{p} \leq r + N - 2 \).

(ii) For \( N > 4 \), \( r + N - 3 \leq \bar{p} \leq r + N - 2 \).

Proof. See Appendix A.

This result holds for all games with a sufficient number of players. Therefore, with complete knowledge, we can determine the maximum possible price in each case within 1 unit. The addition of mixed strategy actions in each round allows for positive probability to be attached to much higher prices. The fact that prices may reach as high as \( r + N - 2 \) based upon the variables of \( r, N \), and \( c \). means that before the auction even begins, we can determine to what price it might stretch. In fact, with enough knowledge, we can calculate the probability that the auction will end at any specific price before the first bid is cast.

### 5.1 Expected Revenue

To determine the expected revenue of a specific auction, we must first determine the probability of it ending at each incremental price. Obviously, the length of the auction partly determines its possible revenue. Remember that I denote the unconditional probability of the auction ending at price \( p \), as \( Q(p) \); that is, the absolute probability not conditioned on the auction beginning. The process of calculating \( Q(p) \) is complicated because every possible bidding path must be accounted for. Even in a simple auction with only three players the terms increase rapidly at low price levels. An example of \( Q(p) \) is shown below.

\[
Q(3) = (1 - q_3)^2 \\
\cdot \left[ (q_0^2) + (3 \cdot q_0 \cdot (1 - q_0) \cdot 2 \cdot q_2 \cdot (1 - q_2)) \\
+ (3 \cdot q_0 \cdot (1 - q_0)^2 \cdot (q_1^2 + 2 \cdot q_1 \cdot (1 - q_1) \cdot 2 \cdot q_2 \cdot (1 - q_2))) \right]
\]

The equations are bulky, but the basic idea is that the probability of an auction ending at price \( p \) is the chance that no one bids in the current round multiplied by the combined probability that the bids from previous rounds exactly reach the price \( p \). With these results we can determine the probability of any round being the last, given \( q(p) \) and \( N \).

Remember that in this model, the market is closed so the auction retailer is the only seller of this item at retail. Of course, in reality losing bidders could choose to go elsewhere to purchase the item and there would be no way, except through empirically observed averages, to determine what fraction of losing bidders would buy from the seller.

We can use the values of \( Q(p) \) to determine the total expected revenue of an auction. The expected revenue will be denoted, \( E[\omega] \) and is determined by the following equation:

\[
E[\omega] = \sum_{p=0}^{r} Q(p) \cdot [p \cdot (c \cdot p) + (r \cdot N)]
\]

That is the probability that the auction ends at each price \( p \) times the revenue accumulated at each round (price paid when the auction ends, the total sum of bidding fees up to that point, and the BIN revenue from all losing bidders). Note that at \( p = 0 \), \( N = N \) but at all other prices \( N = (N - 1) \) since the auction has begun and there is a leader. The revenue variable \( \omega \) is also normalized by nature of the other variables in the formula. Non-normalized revenue would be found by multiplying \( \omega \) by \( \epsilon \), that is,

\[
\Omega = \omega \cdot \epsilon
\]

For an example, let us consider the simple case in which \( N = 3 \), \( v = 6 \), \( r = 6 \), and \( c = 2 \). Note that I continue to use normalized values, i.e. \( c = c / \epsilon = 2 \). In this case, given in Table 5, we can see that the auction extends to a maximum price of 4. In equilibrium, \( Q(p) \) varies between rounds and, as expected, the sum of all \( Q(p) \) is equal to 1. With the proper knowledge of the number of players and their common valuation, it is possible to calculate the equilibrium values of \( q(p) \) and \( Q(p) \).
Once evaluating the value of $\tilde{Q}(p)$, we can easily determine the expected revenue of this auction using the formula for $E[\omega]$ given above. By substitution we obtain

$$E[\omega] = \sum_{p=0}^{4} \tilde{Q}(p) \cdot [p + (c \cdot p) + (r \cdot N)]$$

$$= [0.1740 \cdot (6 \cdot 3)] + [0.4130 \cdot (1 + (2 \cdot 1) + (6 \cdot 2))] + [0.0817 \cdot (2 + (2 \cdot 2) + (6 \cdot 2))]$$

$$+ [0.2496 \cdot (3 + (2 \cdot 3) + (6 \cdot 2))] + [0.0817 \cdot (4 + (2 \cdot 4) + (6 \cdot 2))]$$

$$= 18.18$$

We can see quickly that in this model the seller stands to make a profit even on small items. Assume that the seller buys the items at retail price. Here a quick expected profit calculation yields,

$$E[\pi] = E[\omega] - r \cdot N = 18.18 - 18 = 18.18$$

In non-normalized units, $\Pi = \pi \cdot \epsilon = 18.18 \epsilon$.

For purposes of discussion, I will momentarily drop the assumption in our model that players must exercise the BIN option when losing an auction. In this updated model, only the winning player would receive the item paying the ending price $p$. All other players would pay their respective bidding fees but no additional money and walk away to perhaps purchase the product at another retail location.

Using the same example auction, the expected revenue is $E[\omega] = 4.956$, or less than the retail price. If we assume that the penny auction retailer is not buying at wholesale and obtains the item at full retail price, then the auction would be a losing venture. With this simple example, it is easy to see that penny auction sites have an incentive to have customers purchase the product through them and not leave to go elsewhere after losing. Sites might accomplish this by offering discounts, bidding credits, and loyalty programs.

6 Conclusion

This paper has attempted to incorporate a BIN option into the basic penny auction model presented by Hinnosaar (2010) to yield useable results and a framework for future research. Beginning with the simple $N = 2$ case, I have shown using a backwards induction technique there exists a unique SPNE strategy set for bidders in any auction in my model. Similarly in $N > 2$ case, a solution is presented in the form of various states. Given the circumstances of each round, the states presented can be used to predict bidder behavior using a backwards induction to solve from the limit price $r$, which I calculated above. An example of this process is given in Table 5.

I also presented a general method for calculating the probability, denoted $\tilde{Q}(p)$, that any auction ends at a specific price $p$, and used this value to determine expected revenue, $E[\omega]$.

From this research, I can conclude that the actual calculations of probability and continuation values for bidders in a penny auction are doable, but complicated. The examples presented in this paper employ low values for $N$ and $r$ in the interest of simplicity; in reality, those normalized values are much higher and would increase the number of terms in the calculations exponentially. Clearly, a penny auction is a complicated game that would benefit from learning and sophistication, which aligns with the empirical findings of Wang and Xu (2012). Studies have found that misestimating key variables by small margins can alter the outcome of auctions significantly.

Finally, I prove that penny auctions with a BIN option are finite games with at least one equilibrium strategy set for all players, solvable through a backwards induction process. This conclusion is key for motivating future research, since it proves it is possible to build from this model to further explore the intricacies of auction dynamics and compare models to empirical results. I find that high prices are reached with positive probability in most penny auction games when the number of players is sufficiently large. This complements well the findings of Hinnosaar (2010).

My results in this paper raise questions for future research. Specifically the addition of a term that models utility derived from participating in the auction, a gambling enjoyment term, could account for higher achieved prices beyond the limits established in my analysis. On the other hand, a term might be added to account for time cost, which may increase linearly or exponentially to model the cost of
continuing to stay in and bid in the auction. Similarly, a regret term has been posited by some authors as another drag on utility in extended bidding wars.

Overall, this paper builds a more complete foundation upon which to analyze penny auctions. The addition of a BIN option better approximates the real options available to bidders. Building from this theoretical basis may yield better results for future research on this new way of auctioning off goods.

Appendix A: Proofs

**Proposition 1.** *Proof.* We know that when \( \bar{r} - p \) is even, then \( p = \bar{r} - 2i, i \in \mathbb{Z}^+_0 \). When \( \bar{r} - p \) is even, then \( p = \bar{r} - (2i + 1), i \in \mathbb{Z}^+_0 \). Given Lemma 1, \( q(p) = 0 \) for all \( p \geq \bar{r} \).

Now at \( p = \bar{r} - 1 \), the non-leader bidding gives \( v - (p + 1) - c = v - \bar{r} - c = v - r \). At this price we know the auction will end from the lemma. Not bidding, the auction will end in the current period, and the non-leader will pay \( v - r \) for the item. Given Assumption 2, \( q(\bar{r} - 1) = 1 \).

This is the basis case for induction when \( i = 0 \), where \( \bar{r} - 2i = \bar{r} \) and \( \bar{r} - (2i + 1) = \bar{r} - 1 \). Assume that for some \( i \), the proposition is true. I will show that it holds for \( i + 1 \).

Consider the even case. Let \( p = \bar{r} - 2(i + 1) \). Then \( p + 1 = \bar{r} - 2i \). I have shown that \( q(\bar{r} - (2i + 1)) = 1 \), so if the non-leader does not bid, he should expect to be outbid next period. In that case, \( p + 1 = \bar{r} - 2i \). We have assumed that \( q(\bar{r} - 2i) = 0 \), so bidding will stop at this point.

Next consider the case that \( q(\bar{r} - 2(i + 1)) = 0 \), so the non-leader never bid. We know \( v - r + 2i + 2 > v - r \). So \( q(\bar{r} - 2(i + 1)) = 1 \). We have shown that \( q(\bar{r} - 2(i + 1)) = 0 \), so the auction will end at price \( p + 1 \).

Finally, I must consider the case in which \( t \) and \( p = 0 \), where both players are simultaneously considering submitting a first bid. First consider when \( \bar{r} \) is even. Let \( \bar{r} = 2i + 2 \). Then when a bid is placed, \( p + 1 = \bar{r} - (2i + 1) = 1 \). Because \( q(\bar{r} - 2i) = 1 \), bidding would continue to \( p + 2 = \bar{r} - 2i \) at which point the auction will end. It is key to remember that if two bids are graded simultaneously, the price increases to \( p + 2 \) and the leader is chosen at random. The following payoff matrix describes the first-period game:

<table>
<thead>
<tr>
<th>Bid</th>
<th>Not Bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v - r + 1 - \frac{1}{2}c, v - r + 1 - \frac{1}{2}c )</td>
<td>( v - r - c, v - r + 2i )</td>
</tr>
<tr>
<td>( v - r + 2i, v - r - c )</td>
<td>( v - r, v - r )</td>
</tr>
</tbody>
</table>

In this case, it is clear to see that Not Bid is the strictly dominant strategy in all cases. It is plainly evident for when one player chooses not to bid, the other also chooses not to bid with payoffs \( v - r > v - r - c \). Mathematically we can show that when one player bids, the other player invariably chooses to not bid with payoff \( v - r + 2i > v - r + 1 - \frac{1}{2}c \), which is true since \( i > \frac{1}{2}c \).

Next consider the more complicated case of when \( \bar{r} \) is odd. Let \( \bar{r} = 2i + 1 \). If a bid is submitted, \( p + 1 = \bar{r} - 2i \). At this price the auction would end since \( q(\bar{r} - 2i) = 0 \). If both submit bids, the price rises to \( p + 2 = \bar{r} - (2i - 1) \). Because \( q(\bar{r} - 2(i + 1)) = 1 \), the randomly chosen non-leader would bid a second time and raise the price to \( p + 3 = \bar{r} - 2i + 2 \). At this price the auction would end. The payoff matrix is as follows:

<table>
<thead>
<tr>
<th>Bid</th>
<th>Not Bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v - r + i - c - 1, v - r + i - c - 1 )</td>
<td>( v - r + 2i, v - r )</td>
</tr>
<tr>
<td>( v - r, v - r + 2i )</td>
<td>( v - r, v - r )</td>
</tr>
</tbody>
</table>
The indifference point is found at $i > c + 1$. Given $i = \frac{r - 1}{2}$, then we can write this equation as:

$$
\frac{r - 1}{2} > c + 1 \Rightarrow r > 3c + 1
$$

If $r > 3c + 1$, then bidding is the dominant strategy for both players in the first round of the auction. The non-leader will submit a bid after that, and the auction will end at $p = 3$.

If $r < 3c + 1$, then there exist two asymmetric pure-strategy Nash equilibria in which one player bids and the other does not: (B, NB), (NB, B). There is also a symmetric Mixed Strategy Nash Equilibrium (MSNE) in this case where both players bid with probability $q \in (0,1)$, where $q$ is defined:

$$
q(v - r + i - c - 1) + (1 - q)(v - r + 2i) = v - r
$$

$$
q(0) = \frac{2i}{i + c + 1} = \frac{r - (c + 1)}{r + (c + 1)} \in (0,1)
$$

### Proposition 3. Proof:

(i) First, I will show that $\bar{r} - 1 \leq \bar{p} \leq \bar{r} + N - 2$.

By Corollary 1.1, we know that $\bar{p} \leq \bar{r} + N - 2$.

Since $\bar{p}$ is the highest possible price and higher prices are never reached, $q(\bar{p}) = 0$. Then $v^*(\bar{p} + 1) - c \leq v - r$. Because the auction ends at $\bar{p} + 1$ with certainty, then $v^*(\bar{p} + 1) = v - \bar{p} - 1$. So,

$$
v - \bar{p} - 1 - c \leq v - r \quad \Rightarrow \quad \bar{r} - 1 \leq \bar{p}
$$

Therefore, I have shown that $\bar{r} - 1 \leq \bar{p} \leq \bar{r} + N - 2$.

(ii) Second, I will show that $\bar{r} + N - 3 \leq \bar{p} \leq \bar{r} + N - 2$ for $N > 4$.

By Corollary 1.1, we know that $\bar{p} \leq \bar{r} + N - 2$. We must show that $\bar{p} \geq \bar{r} + N - 3$. Suppose, for sake of contradiction, that $\bar{p} < \bar{r} + N - 3$.

If $\bar{p}$ is a reachable price then $Q(\bar{p} - N + 1) > 0$ and $q(\bar{p} - N + 1) > 0$, since up to $N - 1$ bidders might bid.

**Case A:** $q(\bar{p} - N + 1) < 1$.

This would mean that $Q(p) > 0$ for all $p \in \{\bar{p} - N + 1, \ldots, \bar{p}\}$. Then specifically $Q(\bar{r} - 2) > 0$ since $\bar{r} - 2 < \bar{r} - 1 \leq \bar{p}$ and $\bar{p} - N + 1 < \bar{r} - 2$ by assumption. Given Lemma 2, $q(\bar{r} - 2) > 0$.

If $N - 1$ non-leaders bid at $p = \bar{r} - 2$ then the price would rise to $\bar{r} + N - 3$. This is a contradiction of the assumption that $\bar{p} < \bar{r} + N - 3$.

**Case B:** $q(\bar{p} - N + 1) = 1$.

At this price all non-leaders will bid and the price with rise to $\bar{p}$ with certainty. Then we can write the equilibrium as,

$$
\frac{1}{N - 1} v^*(\bar{p}) + \frac{N - 2}{N - 1} v(\bar{p}) - c \geq v(\bar{p} - 1)
$$

Since $\bar{p} > \bar{r}$, the auction will end with certainty at this price and so we can write, $v^*(\bar{p}) = v - \bar{p}$, $v(\bar{p}) = v - r$, and $v(\bar{p} - 1) \geq v - r$. Then simplifying the equation above,

$$
v - \bar{p} + (N - 2)(v - r) - (N - 1)c \geq v(\bar{p} - 1)(N - 1) \geq (N - 1)(v - r)
$$

$$
\bar{r} \geq \bar{p} + (N - 2)c
$$

Consider the term $(N - 2)c$. We know that $c \geq 1$, since it is a normalized value. That makes $(N - 2)c \geq (N - 2)$. We also know that $p \geq \bar{r} - 1$.

Putting these facts together, we can see that for all $N > 4$,

$$
\bar{r} \geq \bar{p} + (N - 2)c \geq \bar{r} - 1 + (N - 2) \geq \bar{r} + 1
$$

which is false. So by contradiction, $\bar{p} \geq \bar{r} + N - 3$.

**QED**

### Table 5: Equilibrium for auction with $N = 3$, $v = 6$, $r = 6$, $c = 2$

<table>
<thead>
<tr>
<th>$p$</th>
<th>$q(p)$</th>
<th>$v^*(p)$</th>
<th>$v$</th>
<th>$\bar{Q}(p)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.4417</td>
<td>0</td>
<td>0</td>
<td>0.1740</td>
</tr>
</tbody>
</table>
References
Platt, B. C., Price, J., & Tappen, H. “The Role of Risk Preferences in Pay-to-Bid Auctions.”
This paper describes an Anchored Sentiment-regime Dependant Natural Expectations (ASDNE) theory of asset bubble dynamics. The author proposes that ASDNE provides a significant addition to the asset bubble literature in two respects: i) ASDNE can solve the “underreaction puzzle”; that is, why underreactionary post-earnings-announcement drift persists during overreactionary asset bubble events; and ii) ASDNE supports a “leaning-against-the-wind” approach to central bank bubble management by providing theoretical evidence that the current “mop-up-after” consensus creates financial instability.

1 Introduction

When fear takes over, or when greed takes over, people act just as irrationally as they have in the past – Warren Buffet 2008

1.1 Asset Bubbles and Monetary Policy

The creation of a new macro-prudential monetary policy paradigm grounded in a detailed analysis of asset bubble dynamics is one of the most important unresolved tasks in post “Great Recession” economics. Under the current consensus, policy makers should not use interest rates to intervene in asset prices by identifying and bursting bubbles, as this presumes either: i) that the market mechanism does not cause asset prices to reflect fundamental values, contrary to the Efficient Markets Hypothesis (EMH); or ii) that the central bank can better estimate fundamental values than the market, which presumes that market participants are subject to an irrationality to which policy makers are inexplicably immune. Instead, central banks should act only ex-post by managing the financial fallout from collapsing bubbles.

However, in light of the rollercoaster experience of the last decade, the “mop-up-after” strategy requires re-evaluation. First, there is evidence that market participants are, in fact, subject to deterministic behavioral biases whose effects on asset prices are not corrected for by the market mechanism. Whether this is due to “bubble riding” behavior by those aware of the biases (Abreu & Brunnermeier 2003), or a genuine ignorance of behavioral finance among investors, there appears to be room for cautious central bank intervention. This paper aims to support this viewpoint and facilitate the task of constructing a new monetary policy paradigm by adding to our understanding of the behavioral heuristics underlying asset bubble dynamics.

Second, even if the inefficacy of pre-emptive policy is accepted, the ex-post “mopping-up” also needs to be reviewed, as the previous decade has often been characterized as a process of sequential bubble formation. Within this narrative, the low-interest rate environment established as a response to the dot-com crash led to a U.S. housing bubble, and, in turn, the Quantitative Easing response to the bursting of that bubble is conjectured to have inflated further as-yet un-popped bubbles in assets as diverse as farmland, HY bonds and Hong Kong Real Estate. While this paper finds the sequential bubble story to be lacking in certain respects, it provides theoretical evidence for a link between low interest rates and the size of bubbles.

1.2 Paper Outline
Empirical studies on asset prices have demonstrated two persistent stylized facts. First, they display overreactionary bubble dynamics over the long-run (OR): the best performing stocks over a three year period regularly reverse their gains and underperform against the worst performing stocks over the following period three year period. Paradoxically, however (at least *prima facie*), there is also short-run underreactionary post-earnings-announcement drift (UR): the best performing stocks over a three month period tend to gain momentum and continue to outperform over the following three month period, even during bubble periods.

This paper uses the reductionist method of behavioral economics to combine and explain these two phenomena in a consistent theoretical framework. Section 2.1 outlines the precise theoretical definitions of each of the phenomena and summarises their empirical evidence. Sections 2.2 and 2.3 provide a brief summary of the previous attempts at modelling OR and UR through the rational expectations and behavioural finance frameworks and identify the conceptual and empirical holes in both of these accounts. Sections 3.1, 3.2 and 3.3 detail a model of Sentiment-regime Dependent Natural Expectations which can generate asset bubbles and OR. Section 3.4 describes a model of analyst/investor interaction in which UR is generated independently of OR by an anchoring process, such that the two phenomena do not pose a contradiction. Section 3.5 presents the results of a simulation study proving that ASDNE generates both UR and OR and exploring the influence of monetary policy on bubble formation. Finally, Section 4 concludes by examining potential extensions of ASDNE to better represent true asset price dynamics, especially with regard to “crash” events.

2 Literature Review

2.1 Under and Over-reaction in Asset Prices: Empirical Evidence

Asset bubbles\(^1\) have been a recurrent phenomenon throughout the history of economics, observed in nearly all geographic regions and financial systems, and even in controlled laboratory experiments (Haruvy, Lahav, Noussair 2007). OR is closely associated with these traditional bubble phenomena: there is a tendency for asset prices to overshoot their fundamental value following a string of consistently positive (or negative) earnings announcements. Having overreacted, the asset then underperforms (or outperforms) the index over the next three to five years as the price either gradually or sharply reverts back to the underlying value of the stock (De Bondt & Thaler 1985, Zarowin 1989). We can formally write OR as:

\[ E(r_{t+1} \cdots r_{t+20}|z_t > 0, \ldots, z_{t-j} > 0) < E(r_{t+1} \cdots r_{t+20}|z_t < 0, \ldots, z_{t-j} < 0) \]  

That is, the expected cumulative return over the next five years \(r_{t+1} \cdots r_{t+20}\) following a string of positive earnings surprises \(z_t > 0\) is less than the expected return following a string of negative earnings shocks. This can be understood as the tendency for bubbles to inflate and deflate.

The second pattern, UR, is the tendency for asset prices to incorporate new information slowly, which manifests as post-earnings announcement drift, or positive autocorrelations between excess index returns over a twelve month horizon (Cutler, Poterba, and Summers 1991). Bernard (1992) connects this to information shocks: over a two-month period the cumulative risk-adjusted return of stocks with the highest unexpected earnings shocks (measured as an SUE) is 4.2 percent higher than for those with the lowest shocks. We can write UR as:

\[ E(r_{t+1}|z_t > 0) > E(r_{t+1}|z_t < 0) \]  

\(^1\) While the precise definition of an asset bubble is contentious, they are typically characterised either by a Ponzi structure with a potentially persistent premium in the asset price for the option to resell at a higher price on a later date (Harrison & Kreps 1978) or by “excess asset price volatility” beyond that attributable to fluctuations in the fundamentals (Lansing 2007).
That is, the expected return in the period following a positive earnings shock is higher than the expected return in the period following a negative earnings shock.

Importantly, Ikenberry, Lakonishok & Vermaelen (1995) show that UR is still observable after stock splits, which tend to follow a string of positive news, and Michaely, Thaler, Womack (1995) find evidence of UR after dividend omissions, which tend to follow a string of negative news. There is, therefore, evidence of the presence of UR during both positive and negative bubble periods - we call this the “underreaction puzzle”

2.2 Bubbles in an RE framework

In an influential early paper, Tirole (1982) demonstrated using a finite time backward induction argument that a population consisting only of agents with rational expectations will never inflate a bubble. This result does not hold for assets with a potentially infinite maturity horizon, but rational bubbles can still only arise in that asset-class under either: i) the unrealistic assumption that the price-dividend ratio rises in perpetuity; or ii) the uninformative assumption that the crash is due to an exogenous stochastic process (Blanchard & Watson 1982).

However, if we assume that the asset price is already following a bubble equilibrium path \( p = p(t) \) for reasons external to the rational traders, then by relaxing either the assumption that traders take a loss if the bubble bursts (Allen & Gorton 1993) or that every trader knows the exact exogenous bursting time (Abreu & Brunnermeier 2003) we can generate the conclusion that that rational agents will not immediately pop bubbles once they have begun to inflate. In the former model, rational traders speculate using borrowed funds with no penalty for default, such that the expected value of purchasing an asset is positive at any price as long as there is some chance of reselling the asset at a higher price in the future. In the latter, they “ride the bubble” until the hazard rate of bursting given their signal regarding the exogenous crash date is greater than the benefit gained by holding on to the asset for one more period.

2.3 The Bubble Trajectory and Agent Heuristics

One core question, then, relates to the mechanism by which asset prices enter onto a bubble trajectory \( p = p(t) \). The ideal model used to answer this question should apply a parsimonious and empirically justifiable theory to generate both UR and OR. It is widely recognized that such a theory will be psychological in nature: even Abreu & Brunnermeier’s model of rational behavior during bubble periods explicitly assumes that “the price \( p = e^{\sigma t} \) is kept above its fundamental value by irrationally exuberant behavioral traders” (p. 179).

Most behavioral finance models of asset bubbles reduce the two economic phenomena to an application of one or more of the heuristics discovered by Tversky and Kahneman (1974). In one of the best-known examples, rising sentiment causes agents to form “new era” or “new economy” beliefs after periods of rapid technological progress, such as the internet revolution (Shiller 2000). In the language of behavioral finance, the representative heuristic causes them to extrapolate the rapid dividend growth rates associated with such progress from a short sample of data, producing OR. As well as being psychologically parsimonious and justifiable, this theory fits the criteria of empirical validity: the incorporation of a sentiment shock into a DSGE framework can explain 96 percent of stock market volatility and 25-45 percent of business cycle fluctuations (Miao, Wang, Xu 2012(2)). Additionally, as irrational agents are unaware of the presence of an asset bubble and so raise their dividend expectations, this theory has the advantage of being consistent with the co-movement between bubbles and consumption.

Fuster et al. (2011) provide a mathematical formulation of this Shillerian process called Natural Expectations (NE). In NE, the conventional preference for econometrically parsimonious models leads to a misspecification of dividend growth rate lag structures. If the fundamentals follow a hump-shaped dynamic, this leads to an under-estimation of the degree of long-term mean-reversion in levels and hence OR. However, while their basic argument is compelling, the authors’ claim that their idea is

\[\text{2 albeit in an arguably over-specified model}\]
reinforced by Shillerian “new era” beliefs does not quite hold water. They do not model an association between strings of positive shocks and OR, which means that they predict OR both as a response to all new information and over all time horizons, contrary to the empirical evidence.

Vishny, Shleifer & Barberis (VSB/1998) provide an alternative model that solves many of the deficiencies of NE. They also use the representative heuristic to generate OR, but combine it with conservatism to (partially) explain UR. The VSB model uses a Bayesian regime-switching mechanism where investors infer either trending earnings or mean-reversion from perceived patterns in white noise data. The former belief causes periods of OR, while the latter causes periods of UR. However, by relying on distinct conservative and trend-chasing attitude regimes their theory falls short of the ideal model: during bubble episodes it predicts short-term OR to additional shocks, which is again contradicted by the empirical evidence. As such, the VSB model does not fully solve the underreaction puzzle.

3 Anchored Sentiment-regime Dependent Natural Expectations Model

3.1 Set-up

The VSB model cannot solve the underreaction puzzle because it makes the common error of treating the heuristics of representativeness and conservatism as binary opposing attitudes. Agents are always either over or under reacting, but never both, and so cannot underreact during bubble episodes. However, heuristics are integral parts of the apparatus by which we perceive and make sense of the world (Kahneman 2011), and it therefore makes little conceptual sense to limit their use to one at a time. To remedy this mistake, we introduce the Anchored Sentiment-regime Dependent Natural Expectations (ASDNE) model, which treats representativeness and conservatism as distinct ‘always-on’ mechanisms. For the former, we use an extended “sentiment-regime dependent” theory of Natural Expectations (SDNE) in which the level of irrationality is dependent on a function of the length of the string of same sign shocks (the “run”); and for the latter we create an anchoring effect by applying adaptive expectations to the interaction between producers and consumers of financial research.

ASDNE models a division of labor between a representative research analyst and a representative investor, where the former produces dividend forecasts and the latter provides capital. Their interaction generates the price of a representative Lucas-tree domestic equity asset in each period $t$ via a five-stage process (Fig. 1):

i) The asset produces dividends whose growth rate is described by an AR(40) mean equation and an EGARCH(1,1) variance equation;

ii) The analyst uses the vector of past dividends $D_{t-1}$ to produce a vector of growth rate forecasts $F_t$, subject to an SDNE structure;

iii) Additionally, the analyst faces a linear asymmetric loss-function, and so attaches a persistent “optimism bias” to each forecast, creating an optimal forecast vector $\hat{F}_t$;

iv) The investor observes an estimate of the optimism bias at $t-1$ and uses an adaptive expectations rule to update an “optimism adjustment”. They adjust down each element in $\hat{F}_t$ by this term to produce an adjusted forecast vector $F_{t%}$.

v) Finally, they assemble the adjusted forecasts into an estimate of the fundamental value of the asset $A_{t%}$, which is equivalent to the asset price under the no arbitrage condition.

During this process OR is generated by the SDNE structure of the analyst’s forecasts, and UR is generated by the interaction of the “optimism adjustment” and “optimism bias” terms.
3.2 Assumptions Regarding the Underlying Dividend-Growth Dynamics

Letting $D_t$ be the real dividend paid out by the asset in period $t$, and $d_t$ the log of the real dividend, we assume that the distribution of the dividend growth rate $d_t$ in period $t + h$ conditional on all past dividends $d_h$ is given by:

$$
\partial d_{t+h} | \partial d_t \sim N \left( \partial d_{t+h}, h_{t+h} \right)
$$

First, for the mean equation, I follow Fuster et al. (2011) in assuming that the true data generating process for $d_t$ follows a hump-shaped dynamic with short-run momentum and partial long-run mean reversion (Fig. 2: RE). Such a dynamic can be justified by supposing that aggregate dividends are determined primarily by technology growth following an implementation cycle with fixed-costs (Shleifer 1986). We suppose that the implementation of technological advances is clustered to coincide with business cycle expectations: above trend growth rates are therefore typically followed by further above trend growth rates in the short-run, but then followed by below trend growth rates over the medium-run as all prior innovations have already been implemented and firms begin to make new ones. For NOS, Fuster et al. estimate that this dynamic is described by an AR(40) such that:

$$
\partial d_t = \alpha + \rho(L) \partial d_t + z_t
$$

Where $\rho(L) = (\rho_0 L + \ldots + \rho_{40} L^{40})$ and $z_t$ is a mean zero earnings shock.

Second, for the variance equation, I estimate that $h_t$ is a EGARCH (1,1):

$$
\ln h_t = \alpha_0 + \alpha_1 \ln h_{t-1} + \alpha_2 \left[ \frac{|z_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + \alpha_3 \frac{|z_{t-1}|}{\sqrt{h_{t-1}}}
$$

$\alpha_1$ measures the persistence of the variance, $\alpha_2$ measures the symmetric effect of the size of the previous earnings shock on the variance of dividend growth, and $\alpha_3$ measures the asymmetry with respect to positive and negative shocks. Negative shocks generate more future expected variance than positive shocks, and larger shocks more variance than smaller shocks.

Again, an implementation cycle framework can explain the impact of negative shocks on the variance of dividend growth. With fixed-cost implementations, the cause of a large negative shock to earnings would be a breakdown in business cycle co-ordination. This could reasonably be expected to increase uncertainty in the next period by increasing the range of possible outcomes. For example, it could trigger a “stone-age expectations equilibrium” (Shleifer [1986]), in which no agents expect other agents to implement their technologies and so expect aggregate demand to be high enough to cover their fixed-cost investment, and so no technologies are implemented.

3.3 OR: Sentiment-regime Dependent Natural Expectations

OR in ASDNE is generated by Fuster et. al’s Natural Expectations (NE) theory of the representative heuristic (or the tendency to extrapolate from small samples of data). Under the mean equation assumptions in Section 3.2, short sample $AR(p < 20)$ models of dividend growth rates predict a more persistent effect of earnings shocks on future dividends than the true $AR(40)$. Fig. 2 demonstrates this: under the true $AR(40)$, a 1 percent earnings shock at time $t$ increases expected

<table>
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<tr>
<th>Agent</th>
<th>Psychological Mechanism</th>
<th>Consequence</th>
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<tr>
<td>Analyst</td>
<td>Irrational Exuberance: Sentiment-regime Dependent Natural Expectations</td>
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<tr>
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<td>Conservatism: Adaptive Expectations</td>
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dividends at time $t + 40$ by just 0.3 percent, but under an AR(1) expectations rise by 1.25 percent. If analysts apply the parsimonious econometric models of NE they will therefore have “excess optimism in good times and excess pessimism in bad times” (Fuster et al. 2011), in accordance with Shiller’s theory of Irrational Exuberance.

Figure 2 – Estimated impulse function for earnings (in levels), for an AR($\rho$) at time $t+h$ compared with RE [AR(40)]. $\rho$ decreases as the length of the run of same sign shocks increases.

In order to connect NE to the empirical phenomenon of OR following “runs”, we could mimic the VSB framework by modeling a representative research analyst who uses either an AR(1) or AR(40) estimation of the mean equation based on the observed length of the string of same sign shocks. Empirically, this follows from Bergman & Roychowdhury’s (2008) finding that “[fund] managers [tend] to be more optimistic about the future when past market returns have been high over sustained periods”. In normal business conditions the analyst would apply RE, and so correctly expect the long-term mean-reversion, but during a run they would apply NE and so overreact.

However, in order to make the representative heuristic an ‘always-on’ mechanism, we extend the model by having the analyst use an AR($\rho$) expectation where $\rho$ decreases as the length of the run of same sign shocks increases. This means that they are always irrational to some lesser or greater extent, but become progressively more irrational the longer the run continues, as lower order AR imply greater persistence in the effect of the earnings shock on dividends (Fig. 2). We call this “Sentiment-regime Dependent Natural Expectations”. Letting $F_{t-1}(\partial d_t)$ be the dynamic forecast at $t-1$ of dividend growth in period $t$, SDNE is described by the set of equations:

$$F_{t-1}(\partial d_t) = \alpha + \mathbf{I}' \mathbf{\rho} \partial \mathbf{d}_t; \text{ where}$$

$$\mathbf{I} = \begin{pmatrix} I_1 \\ M \\ I_{40} \end{pmatrix}; \quad \mathbf{\rho} = \begin{pmatrix} \rho_1 & 0 & L & 0 \\ 0 & \rho_2 & L & 0 \\ M & M & O & M \\ 0 & 0 & K & \rho_{40} \end{pmatrix}; \quad \partial \mathbf{d}_t = \begin{pmatrix} \partial d_{t-1} \\ \partial d_{t-40} \end{pmatrix}; \text{ and}$$

$$I_n = \begin{cases} 1 & \text{if } q_i < f(n) \\ 0 & \text{else} \end{cases} \quad \forall n \neq 1, n = 1, \ldots, 39$$

We set $I_1 = 1$ and $I_{40} = 0$ to make the model an AR($\rho$); $1 \leq \rho \leq 39$. 

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We set $I_1 = 1$ and $I_{40} = 0$ to make the model an AR($\rho$); $1 \leq \rho \leq 39$.
Like in the VSB model, \( q_t \) is a function of the length of the run. However, there has recently been an increased focus on the role of sentiment in irrationality following Shiller (2000), with a close connection being drawn between the representative heuristic and the over-confidence phenomenon (Fuster et al. 2011). For example, Bergman & Roychowdhury (2008) also demonstrate that the error in analysts’ long-term estimates of earnings growth is positively associated with the University of Michigan Consumer Sentiment index. \( q_t \) should therefore be interpreted as an indicator of sentiment rather than simply of the length of the run; this variable represents conviction in a “new era” economy.

Unlike the VSB model, however, we do not treat analysts as Bayesian in their updating of this variable following new information. NE represents a deviation from RE, and irrational deviations from RE are typically to reduce cognition costs (Kahneman 2011); it therefore seems unlikely that a cognitively expensive model of reasoning such as Bayesianism could drive the deviation. Instead, I use a simple linear equation:

\[
\begin{align*}
q_t &= \sum_{i=1}^{m} \left( \partial d_{t-i} - F_{t-i} \left( \partial d_{t-i} \right) \right) \\
\end{align*}
\]

where \( m \) is the “look-back” period of sentiment. Irrationality under SDNE is therefore temporary, and will fade out as time passes or if prediction errors with an opposite sign to \( q_t \) are observed, causing the bubble to deflate. As such, this mechanism describes “quiet” bubble deflations (or market corrections), although it can be extended to incorporate crash events using an Abreu & Brunnermeier framework.

3.4 UR: Investor Anchoring of Optimism Bias Estimates

Rational Exuberance

In their empirical analysis of long-term analyst forecast errors Bergman & Roychowdhury (2008) find that “analyst estimates are, on average, optimistic [by] 0.48 percent of price per share”. There are three reasons for the existence of such a bias. First, analysts are often partly incentivized to act in a sales role. For research analysts in buy-side long-only equity funds this incentive is via inflows into their portfolio and larger management fees, while for sell-side analysts the incentive is via increased trading desk revenues: Haruvy et al. (2007) experimentally demonstrated that over-optimism about stock prices encourages trade volume. Second, favorable stock ratings improve relations with the researched company and so provide access to valuable meeting with company management: Chen and Matsumoto (2006) found that “analysts receive relatively more management provided information following the issuance of more favorable recommendations”. Third, for sell-side analysts a negative forecast could itself cause asset prices to fall, which could sour relations with buy-side clients holding the stock, who may blame their losses on the sell-side firm.

To model this, I assume that forecasts face an asymmetric linex loss-function:

\[
C(\varepsilon) = b \left( e^{a\varepsilon} - a\varepsilon - 1 \right); \quad \text{where} \quad \varepsilon_t = \partial d_t - \hat{F}_{t-1} \left( \partial d_t \right)
\]

We can use this to derive the optimal predictor (Appendix C):

\[\text{it is worth noting that our tendency to associate bubbles with crashes rather than “quiet” deflation appears to be due to the availability heuristic: crashes are more easily observed than real value erosion through inflation. However, Shiller (2000) demonstrated that the latter process is equally as common. For example, the real value of the S&P Composite Index fell by 56% between 1966 and 1974 without a nominal crash.}

\[\text{However, the $1.4bn Spitzer settlement in 2003 reduced this motivation. The Dodd-Frank act also explicitly acts to remove this incentive by legislating the independence of research from sales and trading.}\]
\[
\hat{F}_{t-1}(\partial d_{t+1}) = F_{t-1}(\partial d_{t+1}^h) + \frac{\alpha}{2} h_{t+1}^h
\]

As a simplifying assumption, both for our model and analyst cognition, we suppose that analysts use the optimal forecast vector:

\[
\hat{F}_t = \begin{pmatrix}
F_{t-1}(\partial d_t) \\
M \\
F_{t-1}(\partial d_{t+40})
\end{pmatrix} + \begin{pmatrix}
\frac{\alpha}{2} \left( h_t = \exp \left[ \alpha_0 + \alpha_1 \ln h_{t-1} + \alpha_3 \frac{z_{t-1}}{\sqrt{h_{t-1}}} \right] \right) = OB_{t-1,t} \\
M \\
OB_{t-1,t+40} = OB_{t-1,t}
\end{pmatrix}
\]

Such that at any given \(t-1\) the same value optimism bias is added to every forecast \(F_{t-1}(\partial d_{t+1})\).

As an EGARCH(1,1) displays asymmetry, we know that the optimism bias will fluctuate with the business cycle, becoming larger following a negative earnings shock and smaller following a positive earnings shock. For the empirical basis of such a fluctuation, I point toward the historical evidence. In an article from late 2007, in the midst of the credit crunch, just 7 percent of stocks were given “sell” ratings by analysts despite a 38 percent fall in the benchmark Dow Jones index over the next 12 months, and Bloomberg reported that the ratio of “sell” ratings was at an all-time low. This appears to be because all three of the above effects are amplified when there is greater uncertainty regarding the growth of the firm: a study by Chen and Cheng (2003) found that analysts’ ratings have a larger effect on stocks with a high variance of returns than a lower variance.

**Conservatism**

UR in ASDNE is a manifestation of psychological conservatism or “the slow updating of models in the face of new evidence” (VSB 1968). To manifest this bias I suppose that investors receiving research revise down each dividend forecast from the optimal forecast vector by an “optimism adjustment” to account for the optimism bias, which updates in accordance with an adaptive expectations rule. As a result of the adaptive expectations, the investor is anchored to his prior estimation of the optimism bias and so tracks its true value slowly, generating UR at the asset price level.

First, we let:

\[
\hat{p}_t^0 = \begin{pmatrix}
\frac{\hat{p}_0}{F_{t-1}(\partial d_t)} \\
M \\
\frac{\hat{p}_0}{F_{t-1}(\partial d_{t+40})}
\end{pmatrix} = \begin{pmatrix}
\delta_t^c \\
M \\
\delta_t^c
\end{pmatrix}
\]

\(\delta_t^c\) is the optimism adjustment term reflecting the investors’ expectation of the optimism bias added to each forecast at time \(t-1\). We next note that using the responsiveness of the forecasts to shocks the investor can observe a best estimate of the value of the optimism bias in the previous period, under the assumption that the optimism bias is consistent across all forecasts and that the investor knows the approximate coefficients on the first and second lag of the AR(\(p\)) forecast model\(^5\):

---

\(^5\) These could be approximated using a simple excel spreadsheet rather than requiring sophisticated statistical software.
\[
\hat{F}_t (\hat{d}_{t+1}) - \hat{F}_{t-1} (\hat{d}_{t+1}) = \omega z_t + (\delta_{t+1} - \delta_t) \\
\hat{F}_t(\hat{d}_{t+2}) - \hat{F}_{t-1} (\hat{d}_{t+2}) = \sigma z_t + (\delta_{t+2} - \delta_t) 
\]

(9)

\[
\partial d_i - \hat{F}_{t-1} (\hat{d}_{t+1}) = z_t - \delta_t
\]

We then use Rescorla-Wagner type adaptive expectations to anchor the optimism adjustment term (Glimcher 2011):

\[
\delta^c_{t+1} = (1 - \beta) \delta^c_t + \beta \delta_t
\]

(10)

The coefficient $\beta$ is the learning rate where low $\beta$ investors are more conservative and vice-versa.

This anchoring process has two effects: i) investors are only able to base their estimation of the optimism bias on one-period old data, which slows down the rate at which information is transmitted through the economy; and ii) low values of $\beta$ slow down the rate at which information is incorporated into asset prices.

3.5 Simulation Study

To analyze the dynamics of asset prices in the ASDNE model, we suppose that the investor assembles the adjusted dividend growth forecast vector $\hat{P}^0_t$ into a PV estimate by using a DCF rule that assumes a constant dividend growth from period $t+40$ onwards. We define:

\[
A[\hat{P}^0_t] = \sum_{j=0}^{40} \gamma^j D_{t-1} \prod_{j=0}^{40} \left(1 + \beta^0_{t-1} (\partial d_{t+j})\right) + \frac{\gamma^{40} D_{t-1} \prod_{j=0}^{40} \left(1 + \beta^0_{t-1} (\partial d_{t+j})\right)}{1 - \gamma - \beta (\partial d_{t+40})}
\]

(11)

We then simulate ten years of prices for a theoretical “US economy asset” using quarterly historical data for US Real Private Net Operating Surplus (NOS) between 1947q1 and 2012q3, and compare these to the RE benchmark. We perform two statistical tests to prove that the ASDNE model produces OR and UR as expected. For OR, we expect ASDNE generated prices to exhibit larger peaks and troughs than RE generated ones due to the formation of bubbles following strings of same sign shocks. As expected, we find statistically significant evidence that ASDNE produces ($\approx 50\%$) more variance than RE. Next, for UR, we expect fewer sharp kinks in the ASDNE price series than the RE benchmark, as this implies more periods in which price changes are followed by changes of the same sign. To test for this, we examine the total sum of squared second differences, which is a measure of the smoothness of the series (Fig. 8). Again, our expectations are met: ASDNE is more than a third smoother than RE. These test results hold for both the full ten year simulation and the shorter sample of bubble periods 2005q1 to 2011q4, demonstrating that ASDNE can solving the underreaction puzzle by producing OR and UR simultaneously.

<table>
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<th>Expectation Model</th>
<th>Detrended SD</th>
<th>Second Difference TSS</th>
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6 applying the Gordon Growth model; see Copeland & Weston (1988)

7 Net Operating Surplus is a measure of aggregate earnings; we use this series rather than a “real” asset due to the large number of observations (263 vs. 99 for the S&P 500), because it is seasonally adjusted, and because of the absence of any periods of negative earnings which would complicate a log transformation

8 Using US Real Private Net Operating Surplus data
The current consensus on asset bubble management is to “mop-up” after bubbles crash by providing liquidity into the market. This prevents actual GDP growth from falling below its long-run potential by counteracting the wealth drag effect on aggregate demand (Blanchard et al. 2012). However, ASDNE suggests that this consensus is misguided. As bubbles are characterized by over-optimistic expectations about distant dividend growth rates (Fig. 12), it follows that low interest rates increase the ratio of the bubble component of the asset price to the fundamental value of the asset.

We can demonstrate this by comparing two identical asset price simulations in all respects but the interest rate. With lower interest rates of \( r = 0.05 \) versus \( r = 0.1 \) the series exhibits both a larger positive bubble in 2006, and a larger negative bubble in 2009 (Fig. 6).

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<table>
<thead>
<tr>
<th></th>
<th>RE (2002q3-2012q3)</th>
<th>ASDNE (2002q3-2012q3)</th>
<th>RE (2005q1-2011q1)</th>
<th>ASDNE (2005q1-2011q1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RE (2002q3-2012q3)</td>
<td>1243.4</td>
<td>36857250</td>
<td></td>
<td></td>
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<tr>
<td>ASDNE (2002q3-2012q3)</td>
<td>1883.0</td>
<td>22127078</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RE (2005q1-2011q1)</td>
<td>1016.2</td>
<td>31274510</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ASDNE (2005q1-2011q1)</td>
<td>1459.4</td>
<td>15383556</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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9 we define the bubble component of an asset as the difference between the SDNE asset price and the rational RE asset price, divided by the rational RE asset price.
This provides a strong theoretical case against the current “mop-up-after” response. If we assume that both positive and negative bubbles have a cumulatively adverse effect on the real economy\footnote{which is plausible because both types of bubble represent market inefficiencies}, then the overall policy response under this consensus by the time any bubble reverses will be lower interest rates\footnote{ceteris paribus, relative to the baseline case of no asset bubble}. However, with imperfectly correlated asset prices, we know that the probability of a run of earnings shocks approaches one as the number of assets in the economy approaches infinity, and we can therefore always expect a bubble in at least one asset. As a result, if policy makers lower interest rates to manage the financial fallout from one crashing bubble then they will almost certainly increase the size of another. In turn, the damage caused by the popping of this subsequent bubble will be greater than it would have been in the absence of the monetary stimulus, and, if the consensus is upheld, will require that monetary policy remain loose or be eased further, affecting further assets. By using ASDNE we can therefore see that, while it is not the ultimate cause of asset bubbles, an ex-post “mop-up” policy response does risk perpetuating a bubble-friendly low interest rate environment.

This, in the author’s opinion, provides a compelling case for a “leaning-against-the-wind” response as opposed to the current “mop-up-after” consensus. There is as of yet no means by which policy makers can observe bubbles directly, but they can observe the conditions which cause asset bubbles to form, and there is therefore room to disrupt them ex-ante by using prudential policy to break runs of same sign shocks and meter irrational exuberance or pessimism. This seems to be preferable to acting ex-post with the risk of causing further financial instability.

4.2 Conclusion

This paper described an Anchored Sentiment-regime Dependent Natural Expectations theory of asset bubbles and post-earnings announcement drift. In ASDNE, asset bubbles (OR) are generated by a shift towards natural expectations and away from rational expectations following strings of same sign shocks, while post-earnings announcement drift (UR) is independently generated by the anchored interaction between a representative research analyst and investor. Finally, using a simulation of US economy asset prices under ASDNE we proved that the model can solve the “underreaction puzzle”.

References


A CRITICAL EVALUATION OF THE SIGNIFICANCE OF ROUND NUMBERS IN EUROPEAN EQUITY MARKETS IN LIGHT OF THE PREDICTIONS FROM BENFORD’S LAW

Lim Kai Jie Shawn  
*University College London*

Mohandass Kalaichelvan  
*Dartmouth College*

**ABSTRACT**

In this study, we test the hypothesis that psychological barriers exist in five European Equity Market indices [ATX, CAC, DAX, FTSE, SMI]. We employ both traditional methodology that assumes a uniform distribution of M-Values and a modified approach that accounts for the fact that digits might be distributed in accordance with Benford’s law. In addition, we test the validity of the various assumptions employed in these tests using a Monte Carlo Simulation and Kuiper’s Modified Kolmogorov-Smirnov Goodness of Fit Test. We find evidence for barriers in one index [SMI] at the 1000 level under the assumption of uniformity but no significant evidence of barriers at the 100 level and at the 1000 level in the remaining indices. We also find evidence to substantiate the criticism of the use of the uniformity assumption for tests at the 1000 level in favour of a distribution consistent with Benford’s Law but do not reach a different conclusion when tests are performed without the implicit use of that uniformity assumption. In addition, we find possible evidence of price clustering around round numbers at the 1000 level in two indices [CAC, DAX] even after adjusting for the expected concentration within the region due to Benford-specific effects.

**Keywords:** Benford’s Law; psychological barriers in stock prices; significance of round numbers in stock prices;

**JEL Codes:** C12, C15, G02, G14, G15

1 Introduction

Since the creation of the first stock exchange and the subsequent trading of stocks became widespread, the movement of stock prices has been of interest to a vast group of people. The region around round numbers, in particular, has long captivated the interest of market commentators with conventional wisdom asserting that round numbers act as regions of natural support and resistance, or function as “psychological barriers” as it has come to be known.

Such a bold assertion can hardly remain without academic interest and a raft of papers have emerged in attempts to assess the validity of such claims. As with most tests on controversial issues, the empirical evidence is mixed. One reason for this phenomenon is the lack of agreement on the appropriate methodology to use in testing for the presence of barriers. The early papers on the topic of psychological barriers employed tests based on the assumption that the digits of stock prices should be uniformly distributed. This assumption is fairly intuitive and can be explained by appealing to examples that illustrate the idea that a stock price is an arbitrarily scaled random figure that by itself should have no attributes that would determine its relative frequency of occurrence. For example, there should be no reason for a stock price with ending digits of 32 to occur more frequently than, for example, a stock price with ending digits of 53. Over a long period of time, what we should expect to see is, on average, a stock index closing with ending digits of 32 as frequently as it does with ending digits of 53. This same line of reasoning is then applied to regions around round numbers to assert that in the absence of barriers round numbers should occur with similar frequency to numbers in other regions and the digits of stock prices should hence be uniformly distributed. Tests were then conducted around this assumption of uniformity to test for evidence of non-uniformity that could be attributed to deviations in the region of round numbers and this was then use to support the hypothesis.
that psychological barriers exist at round numbers. Based on such a methodology, a number of papers in the 1990s found evidence of barriers around round numbers in a number of major equity markets around the world.

However, there exists another group of academics that criticise the uniformity assumption based on a much less intuitive mathematical concept known as Benford’s Law. Benford’s Law asserts that the distribution of digits in natural phenomenon tends to follow a specific distribution due to a number of reasons and the predictions from this concept imply that the distribution of digits in stock prices should not be uniformly distributed. Modified tests have been proposed to account for this effect and the conclusion from most studies that take this into account has been that barriers do not exist in round numbers.

In this study, we attempt to contribute to the debate on the significance of round numbers by considering both approaches over a recent time period and a number of significant stock indices within the European equity markets. Through the series of tests that we employ, we critically examine the significance of round numbers as potential regions of resistance in five European equity indices based on different assumptions for the distribution of M-values. Beyond presenting the result and implications from tests based on different assumptions, we also examine the empirical validity of the underlying assumptions of these tests by modelling and testing their fit to the available data to provide a more holistic approach to the assessment of the results obtained.

2 Background

2.1 The significance of round numbers

When we refer to “the significance of round numbers”, we are simply referring to the regions around the 00 region of a stock index (i.e. at the 100, 200, 300, 400,..., 1000, 2000, etc. level) and whether stock prices tend to move in a different manner when it enters the proximity of these regions. The importance of round numbers as a natural region of support and resistance has its roots in Technical Analysis. Technical Analysis of Stock Trends by Edwards, Maggee and Basetti (2007) presents the following analysis on the significance of round numbers:

“There are certain other levels that may, at times, evidently produce considerable Resistance or Support without any reference to a previous “vested interest.” We have in mind the “round” Figures 20, 30, 50, 75, 100, etc. In setting a goal for taking profits when we buy a stock, it is natural for us to think in terms of such round prices… In fact, any time an issue gets out into new all-time high ground, where there is nothing in its chart history to indicate otherwise, it is a fairly safe bet that Resistance will appear at the round figures.”

A region of support is a level or area on the chart under the market where buying interest is sufficiently strong to overcome selling pressure and a region of resistance is a level or area on the chart over the market where selling interest is sufficiently strong to overcome buying pressure (Murphy [1999]). If psychological barriers around round numbers exist, then what we would expect is evidence to show that price levels around round numbers tend to provide support in a downtrend and resistance in an uptrend.

2.2 Proposed explanations for the significance of round numbers

There is a range of plausible reasons that has been suggested for the potential existence of psychological barriers around round numbers. Explanations form technical analysts often rest on the assertion that people use round numbers as natural points to take profits or cut losses. This common anchor point is then used as a part of the investment decision-making process of many individuals, which then manifests itself as overhanging supply or demand around those regions that cause the phenomenon of support and resistance around these points to be observed.

Beyond simple thought experiments, other explanations have also been offered that often appeal to research from behavioural finance or business theory. Some concepts often quoted as possible reasons include the importance of odd pricing (Schindler and Kirby [1997]) coordination within a limited price set (Harris [1991]) and bounded rationality (Sonnemans [2006]). However, while all these reasons and thought experiments provide explanations of why psychological barriers
may exists, none of them provide a reason for why psychological barriers must necessarily be present, and the presence or absence of psychological barriers in European equity markets remains fundamentally an empirical and not a theoretical question.

2.3 Objectives and significance of study

There are three main objectives of this research paper. Firstly, we aim to present empirical evidence from tests on the significance of round numbers in the stock indices of five major European markets using the traditional approach to the testing of barriers based on the methodology from Donaldson and Kim (1993). This study provides an updated investigation over a recent time period as well as results for some previously untested European markets.

Next, we move to investigate the key criticism of the traditional approach of testing for barriers, that of the uniformity assumption. We evaluate the robustness of our earlier results by comparison with a Monte Carlo simulation with results drawn from cyclical permutations of returns as presented in De Ceuster et al (1997). By construction, this simulation would exhibit no psychological barriers and this approach is hence often regarded by critics of the uniformity assumption as a more appropriate approach to test for the presence of barriers that would not lead to the erroneous conclusion of the presence of barriers due only to an expected distribution of digits in a manner consistent with Benford’s Law. We present the empirical results from this test to help provide a more complete picture of the significance of round numbers in these European markets.

Finally, we extend the approach adopted by present studies in this area through a direct investigation of the empirical validity of criticisms based on Benford’s Law. We test, by means of Kuiper’s modified Kolmogorov-Smirnov Goodness-of-Fit Test the fit of a distribution of M-values based on Benford’s law to the distribution of M-values found in the five European stock indices. This enables us to examine the appropriateness of criticisms of the uniformity assumption based on Benford’s law. Thus, we provide a more comprehensive picture of the results obtained from the various tests.

2.4 M-Values

In empirical studies on psychological barriers, the analysis is often restricted to two digits to isolate effects at the 1000 or 100 level. These two digit values are known as M-Values, with $M_{1000}$ denoting the two digits for tests of barriers at the 1000 level and $M_{100}$ denoting the two digits for tests of barriers at the 100 level. To illustrate the calculation of M-values with an example, if a stock closes at 2430.5, then $M_{1000} = 43$ and $M_{100} = 30$. If psychological barriers exist at the 100 level, what we would expect to see is the index closing less frequently at the 100, 200, 300, .., 1100, 2100, 3200, etc. level and hence the $M_{100}$ value of 00 and the $M_{100}$ values in that immediate region occurring less frequently.

Mathematically, M-values can be expressed with the following equations:

$$M_{100}^{t} = \lfloor P_t \rfloor \mod 100.$$  And

$$M_{1000}^{t} = \lfloor 100 \times 10^{\left(\log_{10} P_t \right) \mod 1} \rfloor \mod 100.$$

Where $\lfloor P_t \rfloor$ is the integer part of $P_t$ and mod 100 denotes reduction modulo 100.

2.5 Benford’s Law

The law of anomalous numbers (now more commonly known as Benford’s Law) states that for commonly observed empirical data, regularities should occur in the First Significant Digits (FSDs) of the data. Benford (1938) proposes that for the FSDs $\{1, ..., 9\}$, the frequency observed of the each digit $D_t \in \{1, ..., 9\}$ should be approximately \( \log_{10} (1 + \frac{1}{D_t}) \). For example, the frequency at which we should observe a FSD of 1 = \( \log_{10} (1 + \frac{1}{1}) \) = 0.301. Stated in a probabilistic manner, Benford’s Law dictates that:

$$P(D_1 = k) = \log_{10} [1 + \left(\frac{1}{k}\right)]; k = 1, ..., 9$$
This result has been established via combinatorial arguments (Cohen [1976]) as well as other statistical derivations [Hill, 1995]. Arguments for the use of Benford’s Law have been put forth in areas such as fraud detection (Nigrini [1996]) as well as in tests of auction prices (Giles [2007]) and other areas of statistical analysis (Judge and Schechter [2009]).

2.5.1 Implications for tests on the significance of round numbers

The conventional approach to tests on the significance of round numbers in stock prices relies on the critical assumption of uniformity in the distribution of M-values. De Ceuster et al (1997) proposed the first criticism of this assumption based on Benford’s Law and showed using a test based on cyclical permutations of returns that there was no evidence for psychological barriers in the DJIA as had been previously suggested by Donaldson and Kim (1993). Intuitively, if Benford’s Law holds, M-values cannot be uniformly distributed as we would expect to see 1s occurring with a different frequency than 5s, for example, and tests based on a uniform distribution of M-values are likely to recover significant differences due to the distribution of frequencies according to a manner consistent with Benford’s Law which would be wrongly attributed to the presence of psychological barriers.

2.5.2 Application of Benford’s Law to M-values

The general form of Benford’s Law gives a realistic model for the distribution of the digits of stock indices. Although Benford’s Law is stated for FSDs, the joint distribution for second and higher significant digits is invariant to scale (Pinkham [1961]) and can be stated in the following manner:

$$P(D_1 = d_1, \ldots , D_k = d_k) = \log_{10}[1 + \sum_{i=1}^{k} (d_i \times 10^{k-i})^{-1}],$$

For $d_i \in \{1,2,\ldots,9\}$ and $d_j \in \{0,1,2,\ldots,9\}, j>1$.

De Ceuster et al (1997) derived the limit distribution of M-values, which we state here and have applied in parts of this paper:

$$\lim_{t \to \infty} P(M_t^{1000} = k) = \sum_{i=1}^{9} \log_{10}\left(\frac{i \times 10^2 + k + 1}{i \times 10^2 + k}\right)$$

And

$$\lim_{t \to \infty} P(M_t^{100} = k) = \lim_{n \to \infty} \sum_{i=1}^{9} \sum_{j=0}^{9} \ldots \sum_{n-i-1=0}^{9} \log_{10}\left(\frac{\sum_{r=1}^{n-i} i_r \times 10^{n-r+1} + k + 1}{\sum_{r=1}^{n-i} i_r \times 10^{n-r+1} + k}\right) = \frac{1}{100}$$

Hence, based on results derived from Benford’s Law, we see that the expected frequencies are non-uniform for $M^{1000}$ but uniform for $M^{100}$ values, consistent with the intuition that the n-th significant digit in an arbitrarily scaled random number is closer to being uniformly distributed when n tends to be large.

3 Methodology

3.1 Tests on the distribution of M-Values

The first test evaluates evidence for the significance of certain regions of numbers by testing the distribution of M-Values using a Chi-Squared-Goodness-of-Fit test. In the absence of barriers, the traditional assumption is that we can expect M-Values to approximately follow a uniform distribution over a long time period. The $X^2$ test is hence conducted to evaluate the fit of the M-values to a uniform distribution.

The M-values are aggregated into ten disjunct categories centred on the 00 round number region, i.e. 96-05, 06-15, \ldots , 76-85, 86-95 and the frequency of occurrence of M-values for each category is recorded. The expected number of M-values in each category if it followed a uniform distribution is calculated as follows:
Where $E_i$ is the expected number of observations in category $I$ where $I = 1, 2, \ldots, 10$ and $N$ represents the total number of observed M-Values.

A $X^2$ test with the following hypotheses is then conducted:

$H_0$: The M-Values follow a uniform distribution
$H_1$: The M-Values do not follow a uniform distribution

The $X^2$ statistic is calculated as follows:

$$X^2 = \sum_{i=1}^{10} \frac{(O_i - E_i)^2}{E_i}$$

The number of degrees of freedom for each test is 9. The results of the tests are reported in Table 2.

### 3.2 Tests on the behaviour of prices around round numbers

The Chi-Squared-Goodness-of-Fit test reveals some information on the distribution of M-values and has the potential to provide evidence for the possible presence of barriers. However, proof of a non-uniform distribution of M-values is, at best, a necessary but not sufficient result for the proof of the presence of barriers around round numbers. One primary limitation of the uniformity test is its inability to isolate which regions differ as well as the lack of information on directionality which makes it impossible to conclude if the M-values exhibit evidence of price clustering or price barriers and whether that occurs around the round number region. In order to obtain information on directionality, we conduct tests using a regression model, the Barrier Proximity Test from Donaldson and Kim (1993).

#### 3.2.1 Barrier proximity test

The barrier proximity test evaluates the presence of barriers through the use of a simple ordinary least squares regression. A vector $F(M)$ is created with a length of 100, which registers the relative frequency of M-Values occurring in each region. If the M-Values are uniformly distributed, then we would expect each M-value to have a relative frequency of 1. We adopt the specification used in Koedijk and Stork (1997) as it yields results that are more interpretable with non-overlapping categories than the specification employed in Donaldson and Kim (1993).

The regression is then run with the following specification:

$$F(M) = C + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \varepsilon$$

Where $C$ represents a constant term and $\varepsilon$ the error term and $D_i$ represents dummy variables, where the dummy variables are defined as follows:

- $D_1 = 1$ for $M = \{98, \ldots, 02\}$ and $D_1 = 0$ for $M = \{03, \ldots, 97\}$
- $D_2 = 1$ for $M = \{92, \ldots, 97\}, \{03, \ldots, 08\}$ and $D_2 = 0$ for $M = \{98, \ldots, 02\}, \{09, \ldots, 91\}$
- $D_3 = 1$ for $M = \{85, \ldots, 91\}, \{09, \ldots, 15\}$ and $D_3 = 0$ for $M = \{92, \ldots, 08\}, \{16, \ldots, 84\}$

Where $\{a, b\}$ represents the set of values inclusive of and between $a$ and $b$. For example, $\{98, \ldots, 02\}$ represents the set of values $\{98, 99, 00, 01, 02\}$.

The results of the Barrier Proximity Test are presented in Tables 3 and 4. If there are no barriers, we would expect a significant constant value at 1 and all the $\beta$ values to be close to zero and not statistically significant. A significant and negative $\beta$ value would represent evidence for price
barriers in that category (under the assumption that prices are uniformly distributed) while a positive \( \beta \) value would suggest evidence of price clustering within that region.

### 3.3 Cyclical permutation of returns

We adopt a bootstrap approach to generate a price series that, by construction, would contain no price barriers. This set-up consists of shuffling returns \( \bar{R}_t, t = 2, \ldots, T \), then computing the index values recursively from the following equations:

\[
\bar{P}_1 = \bar{P}_1 \\
\bar{P}_t = \bar{P}_{t-1} \exp (R_t), \quad t = 2, \ldots, T
\]

Let \( R = (R_2, \ldots, R_T) \) be the vector of actual returns over the period. Returns are calculated using the following equation:

\[
R_t = \ln \left( \frac{P_t}{P_{t-1}} \right), \quad t = 2, \ldots, T
\]

Returns are generated using cyclical permutations of \( R \). A cyclical permutation of \( R \) is any \( (R_t, R_{t+1}, \ldots, R_T, R_2, R_3, \ldots, R_{t-1}) \) and we conduct the simulation for all possible cyclical permutations of \( R \). The advantage of using a simulation based on cyclical permutations is that it allows us to simulate price paths with the same starting and ending value. Next, it allows us to consider calendar effects and preserves high volatility clusters and other anomalies in the observed stock index and hence provides the ‘closest’ approximation to the actual data generating process (De Ceuster et al, [1997]). The simulated data series is employed in tests in Section 3.4.1 and 3.5.

### 3.4 Criticisms of the uniformity assumption

In this section, we perform two types of tests, we use a Chi-Squared Goodness of Fit Test based on the results from the Monte Carlo Simulation to evaluate the validity of the uniformity assumption and we use Kuiper’s modified Kolmogorov-Smirnov test to test the fit of Benford’s Law as an alternative hypothesis for the distribution of \( M \)-values.

#### 3.4.1 Uniformity tests

For each price obtained from the simulation we calculate the corresponding \( M^{1000} \) and \( M^{100} \) value and each run thus gives an empirical frequency distribution of \( M \)-values. In this section we test the assumption of uniformity of the simulated runs using the Chi-Square-Goodness-of-Fit-Test as specified in Section 3.1. This allows us to test the uniformity assumption on a simulated price series that by construction does not contain price barriers at round numbers. If the \( M \)-values from the simulated price series consistently show deviations from a uniform distribution as well, we can conclude that the uniformity assumption for the observed price series is not valid and conclusions of the presence of price barriers based on evidence of deviations from a uniform distribution are hence invalid as well. Tables 7 and 8 report the results of these uniformity tests.

#### 3.4.2 Kuiper’s modified Kolmogorov-Smirnov Goodness of Fit Test [KST]

In this section, we test whether the observed data exhibits characteristics consistent with the predictions from Benford’s Law. Stated formally, we investigate whether the empirical data has characteristics consistent with the limit distributions for the \( M \)-values as stated in Section 2.4.2 (included in the full paper). The Chi-Squared-Goodness-of-Fit test is not employed for this investigation as it has been shown to exhibit low statistical power in tests for Benford’s Law when used with small samples. The Kolmogorov-Smirnov Goodness of Fit Test and other common non-parametric tests such as the Cramér-von Mises test have also been deemed to be unsuitable for this investigation due to the “circular” nature of \( M \)-values (Giles [2007]). What we mean when we refer to the “circular” nature of \( M \)-values is the fact that 99, for example, is very close to and not very far from 00 as would be the case for a unidirectional linear data set. We employ the KST because it recognizes the ordinality and circularity of the data and does not depend on the choice of origin. One
additional feature of this test that is particularly useful is the fact that the null distribution of the test statistic is invariant to the hypothesised distribution, for all N.

The KST is conducted with the following hypotheses:

H₀: The M-values are distributed in a manner consistent with the limit values derived from Benford’s Law
H₁: The M-values are not distributed in a manner consistent with the limit values derived from Benford’s Law

The statistic for this test, the $V_N$ statistic, is calculated using the following equation:

$$V_N = \max_x [F_e(x) - F_b(x)] + \max_x [F_b(x) - F_e(x)]$$

Where $F_e(x)$ is the empirical CDF and $F_b(x)$ is the CDF based on a distribution that follows Benford’s Law.

The critical values for the null distribution of the transformed statistic are then calculated as follows:

$$V_N^* = V_N(N^{0.5} + 0.155 + 0.24N^{-0.5})$$

Studies that employ the use of the KST normally use the critical values tabulated by Stephens (1970) in evaluating the results of the test. However, the results of Stephens (1970) have been shown to be too conservative once Benford-specific values are derived and hence we employ the values presented in Morrow (2010) instead. These critical values have been derived from an application of the central limit theorem to a multivariate Bernoulli variable that corresponds to a random variable that exactly satisfies Benford’s Law. It thus yields critical values that have been shown to be more appropriate for tests of Benford’s Law than those presented in Stephens (1970). The results of the KST are presented in Table 9.

3.5 Testing the presence of psychological barriers without the uniformity assumption

We follow the methodology proposed by De Ceuster et al. (1997) for the testing of barriers in a way that does not rely on an assumption of a uniform distribution of M-values. This is done by comparing the observed frequency of M-values around regions of potential psychological barriers with the corresponding frequency in the simulated stock indices from the Monte Carlo simulation.

Let $\omega$ be a set of M-values representing the region around a round number. We consider the following regions for a set-up similar to that used in section 3.2.1:

$$\omega = \{00, 98, ..., 02, 96, ..., 05, 90, ..., 09\}$$

For a given choice of $\omega$, the stock index $P_t$ is considered to be in the region of a barrier if $M_t \in \omega$, i.e. if $I_\omega(M_t) = 1$, where $I_\omega$ is the indicator function of $\omega$. Let $\tau$ denote the relative amount of time spent by an index in the neighbourhood of a psychological barrier as indicated by its relative frequency, then:

$$\tau = \sum_{t=1}^{T} \frac{I_\omega(M_t)}{T}$$

Tables 10 and 11 report the value of $\tau$ for each $\omega$ and each type of M-value. A small $\tau$ lends support to the psychological barrier hypothesis for each $\omega$ selected. We formally test the hypothesis by comparing the percentage of $\tau$ calculated for the simulated stock indices that are smaller than or equal to the corresponding $\tau$ statistic calculated from the observed prices of each stock index. These percentages that are reported in Tables 10 and 11 are essentially left tail percentages and can be
interpreted in an analogous way to p-values from normal statistical tests. This one-sided test is similar to the type of test employed in Section 3.2.1 but does not use uniformity as a benchmark.

4 Results and discussion

4.1 Data
In this study, we examine a ten year period from January 2001 to December 2011 for five European Stock Indices [FTSE, CAC, DAX, ATX, SMI] and obtained data on the daily closing prices of each index. The presence of psychological barriers is more likely to manifest itself in indices that are closely watched by participants and that are actively traded on a daily basis, hence these indices were chosen based on their importance in the European markets. In addition, as we are investigating the presence of barriers at the 100 and 1000 level, only indices with a sufficiently large range were considered in our shortlist and a summary of the data for these five indices can be found in Table 1.

4.1.1 Summary of markets investigated
Table 1: Key Statistics of Markets Investigated

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Market</th>
<th>Low</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATX</td>
<td>Austria</td>
<td>1003.72</td>
<td>4981.87</td>
</tr>
<tr>
<td>CAC</td>
<td>France</td>
<td>2403.04</td>
<td>6168.15</td>
</tr>
<tr>
<td>DAX</td>
<td>Germany</td>
<td>2202.96</td>
<td>8105.69</td>
</tr>
<tr>
<td>FTSE</td>
<td>United Kingdom</td>
<td>3287.00</td>
<td>6732.40</td>
</tr>
<tr>
<td>SMI</td>
<td>Switzerland</td>
<td>3675.40</td>
<td>9531.50</td>
</tr>
</tbody>
</table>

4.2 Test on the distribution of M-values
Table 2: $X^2$-Statistics for $M^{100}$ and $M^{1000}$ values

<table>
<thead>
<tr>
<th>Symbol</th>
<th>$X^2$-Statistic [$M^{100}$]</th>
<th>$X^2$-Statistic [$M^{1000}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTSE</td>
<td>8.774658</td>
<td>90.56731***</td>
</tr>
<tr>
<td>CAC</td>
<td>7.625222</td>
<td>80.98224***</td>
</tr>
<tr>
<td>DAX</td>
<td>4.807487</td>
<td>78.58289***</td>
</tr>
<tr>
<td>ATX</td>
<td>22.89358***</td>
<td>106.3138***</td>
</tr>
<tr>
<td>SMI</td>
<td>6.668103</td>
<td>76.48132***</td>
</tr>
</tbody>
</table>

*** Represents results that are significant at the 99% confidence level

Table 2 reports the results from the Chi-Squared-Goodness-of-Fit-Test. From this test, we see strong evidence to reject the hypothesis that M-values follow a uniform in the $M^{1000}$ values of all the indices and in the $M^{100}$ values of the ATX index. There is not sufficient evidence to reject the hypothesis that the M-values follow a uniform distribution in the $M^{100}$ values of the FTSE, CAC, DAX and SMI index.

4.3 Tests on the behaviour of prices around round numbers

4.3.1 Barrier proximity test
Table 3: Regression of $M^{100}$ Frequencies on $M^{100}$ Value Dummies

<table>
<thead>
<tr>
<th>$M^{100}$</th>
<th>ATX</th>
<th>CAC</th>
<th>DAX</th>
<th>FTSE</th>
<th>SMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables</td>
<td>Freq100$^a$</td>
<td>Freq100</td>
<td>Freq100</td>
<td>Freq100</td>
<td>Freq100</td>
</tr>
<tr>
<td>$D_1^b$</td>
<td>0.1118</td>
<td>-0.0961</td>
<td>-0.0712</td>
<td>-0.0548</td>
<td>0.0036</td>
</tr>
<tr>
<td></td>
<td>(0.0989)</td>
<td>(0.0791)</td>
<td>(0.0824)</td>
<td>(0.0889)</td>
<td>(0.0763)</td>
</tr>
<tr>
<td>$D_2^c$</td>
<td>0.0488</td>
<td>-0.0138</td>
<td>0.0756</td>
<td>0.0742</td>
<td>-0.0173</td>
</tr>
<tr>
<td></td>
<td>(0.0668)</td>
<td>(0.0534)</td>
<td>(0.0556)</td>
<td>(0.0601)</td>
<td>(0.0515)</td>
</tr>
<tr>
<td>$D_3^d$</td>
<td>0.0484</td>
<td>0.0070</td>
<td>0.0251</td>
<td>0.0224</td>
<td>-0.0015</td>
</tr>
<tr>
<td></td>
<td>(0.0626)</td>
<td>(0.0500)</td>
<td>(0.0521)</td>
<td>(0.0563)</td>
<td>(0.0483)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.9818***</td>
<td>1.0055***</td>
<td>0.9910***</td>
<td>0.9907***</td>
<td>1.002***</td>
</tr>
</tbody>
</table>
Table 4: Regression of $M^{1000}$ frequencies on $M^{1000}$ Value Dummies

<table>
<thead>
<tr>
<th>Variables</th>
<th>ATX</th>
<th>CAC</th>
<th>DAX</th>
<th>FTSE</th>
<th>SMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_1^b$</td>
<td>-0.0403</td>
<td>0.2665**</td>
<td>0.4387***</td>
<td>0.1506</td>
<td>-0.2760**</td>
</tr>
<tr>
<td></td>
<td>(0.1454)</td>
<td>(0.1081)</td>
<td>(0.0931)</td>
<td>(0.1229)</td>
<td>(0.1090)</td>
</tr>
<tr>
<td>$D_2^c$</td>
<td>-0.1431</td>
<td>0.1664**</td>
<td>0.2663***</td>
<td>0.0162</td>
<td>-0.3012***</td>
</tr>
<tr>
<td></td>
<td>(0.0982)</td>
<td>(0.0730)</td>
<td>(0.0628)</td>
<td>(0.0830)</td>
<td>(0.0736)</td>
</tr>
<tr>
<td>$D_3^d$</td>
<td>0.2291**</td>
<td>0.0797</td>
<td>0.2146</td>
<td>0.0770</td>
<td>-0.1677**</td>
</tr>
<tr>
<td></td>
<td>(0.0921)</td>
<td>(0.0684)</td>
<td>(0.0589)</td>
<td>(0.0778)</td>
<td>(0.0690)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.9871***</td>
<td>0.9555***</td>
<td>0.9161***</td>
<td>0.9797***</td>
<td>1.0734***</td>
</tr>
<tr>
<td></td>
<td>(0.0378)</td>
<td>(0.0281)</td>
<td>(0.0242)</td>
<td>(0.0319)</td>
<td>(0.02833)</td>
</tr>
</tbody>
</table>

From the Barrier Proximity Test, we see evidence for the presence of barriers at the 1000 level in the SMI and possible evidence of price clustering around round numbers at the 1000 level in the CAC and DAX indices.

4.4 Testing the uniformity assumption

4.4.1 Monte Carlo simulation (Uniformity tests)

Table 7: Rejection of uniformity test

<table>
<thead>
<tr>
<th>M-Values</th>
<th>Level of Significance</th>
<th>ATX</th>
<th>CAC</th>
<th>DAX</th>
<th>FTSE</th>
<th>SMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M^{100}$</td>
<td>99%</td>
<td>36%</td>
<td>2%</td>
<td>1%</td>
<td>1%</td>
<td>1%</td>
</tr>
<tr>
<td>$M^{1000}$</td>
<td>99%</td>
<td>99%</td>
<td>88%</td>
<td>69%</td>
<td>73%</td>
<td>88%</td>
</tr>
</tbody>
</table>

Table 8: Percentage of simulation statistics greater than observed statistic

<table>
<thead>
<tr>
<th>M-Values</th>
<th>Level of Significance</th>
<th>ATX</th>
<th>CAC</th>
<th>DAX</th>
<th>FTSE</th>
<th>SMI</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M^{100}$</td>
<td>99%</td>
<td>32%</td>
<td>61%</td>
<td>83%</td>
<td>44%</td>
<td>72%</td>
</tr>
<tr>
<td>$M^{1000}$</td>
<td>99%</td>
<td>90%</td>
<td>63%</td>
<td>8%</td>
<td>7%</td>
<td>32%</td>
</tr>
</tbody>
</table>

For the M-values obtained from the Monte Carlo simulation, we see very few rejections of uniformity at the 100 level for four out of five of the indices (CAC, DAX, FTSE, SMI). This is consistent with the expected limit distribution of the M-values according to Benford’s Law [which approaches a uniform distribution at the limit]. The ATX index shows a surprising result, with a significant proportion of the simulations returning M-Values with non-uniform distributions at the 100 level. This could be due to the smaller range of the ATX index and could explain the non-uniform distribution of M-values at the 100 level in the observed prices as well.
At the 1000 level, we see a significant proportion of M-values from the simulation exhibiting characteristics of a non-uniform distribution for all five indices. This is consistent with the expected results if the M-values are indeed distributed according to Benford’s Law, and the results from this simulation provide indirect evidence to support the criticism of the uniformity assumption that traditional tests have been predicated upon.

4.4.2 Kuiper’s modified Kolmogorov-Smirnov Test

From Morrow (2010), the critical values for this test are 1.191 at the 90 percent confidence level, 1.321 at the 95 percent confidence level and 1.579 at the 99 percent confidence level.

Table 9: Kolmogorov-Smirnov Test results

<table>
<thead>
<tr>
<th>Symbol</th>
<th>$\mathcal{V}<em>N$ Statistic [$M</em>{1000}$]</th>
<th>$\mathcal{V}<em>N$ Statistic [$M</em>{100}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTSE</td>
<td>0.50213</td>
<td>0.18416</td>
</tr>
<tr>
<td>CAC</td>
<td>1.03219</td>
<td>0.19798</td>
</tr>
<tr>
<td>DAX</td>
<td>0.95697</td>
<td>0.22499</td>
</tr>
<tr>
<td>ATX</td>
<td>0.54861</td>
<td>0.42490</td>
</tr>
<tr>
<td>SMI</td>
<td>0.91475</td>
<td>0.21206</td>
</tr>
</tbody>
</table>

From this test, we see that there is not sufficient evidence at the 90 percent confidence level to reject the hypothesis that the distribution of M-values conforms to that derived from Benford’s Law in all of the indices at both the $M_{1000}$ and $M_{100}$ values. Hence, we conclude that the criticism of the uniformity assumption applied in earlier tests based on Benford’s law is valid.

4.5 Testing the presence of psychological barriers without the uniformity assumption

Table 10: $\tau$ statistic for each category ($\omega$) for $M_{1000}$ values in each index

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>{0}</th>
<th>{98,…,02}</th>
<th>{96,…,05}</th>
<th>{90,…,09}</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau$(ATX)</td>
<td>0.99</td>
<td>5.47</td>
<td>10.72</td>
<td>21.03</td>
</tr>
<tr>
<td>$\tau$(ATX Simulation) [%]</td>
<td>46.24</td>
<td>79.52</td>
<td>77.54</td>
<td>74.53</td>
</tr>
<tr>
<td>$\tau$(CAC)</td>
<td>1.14</td>
<td>4.55</td>
<td>9.27</td>
<td>19.50</td>
</tr>
<tr>
<td>$\tau$(CAC Simulation) [%]</td>
<td>75.24</td>
<td>11.37</td>
<td>8.10</td>
<td>27.32</td>
</tr>
<tr>
<td>$\tau$(DAX)</td>
<td>0.86</td>
<td>4.60</td>
<td>9.84</td>
<td>20.07</td>
</tr>
<tr>
<td>$\tau$(DAX Simulation) [%]</td>
<td>39.18</td>
<td>13.55</td>
<td>34.80</td>
<td>51.62</td>
</tr>
<tr>
<td>$\tau$(FTSE)</td>
<td>0.90</td>
<td>4.68</td>
<td>10.51</td>
<td>20.84</td>
</tr>
<tr>
<td>$\tau$(FTSE Simulation) [%]</td>
<td>27.57</td>
<td>23.15</td>
<td>82.04</td>
<td>86.11</td>
</tr>
<tr>
<td>$\tau$(SMI)</td>
<td>0.97</td>
<td>5.03</td>
<td>10.49</td>
<td>19.90</td>
</tr>
<tr>
<td>$\tau$(SMI Simulation) [%]</td>
<td>41.77</td>
<td>49.64</td>
<td>79.06</td>
<td>45.51</td>
</tr>
</tbody>
</table>

Table 11: $\tau$ statistic for each category ($\omega$) for $M_{1000}$ values in each index

<table>
<thead>
<tr>
<th>$\omega$</th>
<th>{0}</th>
<th>{98,…,02}</th>
<th>{96,…,05}</th>
<th>{90,…,09}</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau$(ATX)</td>
<td>0.95</td>
<td>4.73</td>
<td>9.10</td>
<td>18.53</td>
</tr>
<tr>
<td>$\tau$(ATX Simulation) [%]</td>
<td>50.39</td>
<td>52.11</td>
<td>48.99</td>
<td>47.78</td>
</tr>
<tr>
<td>$\tau$(CAC)</td>
<td>1.49</td>
<td>6.11</td>
<td>12.15</td>
<td>22.49</td>
</tr>
<tr>
<td>$\tau$(CAC Simulation) [%]</td>
<td>93.85</td>
<td>78.85</td>
<td>79.75</td>
<td>65.68</td>
</tr>
<tr>
<td>$\tau$(DAX)</td>
<td>1.46</td>
<td>6.77</td>
<td>12.76</td>
<td>24.60</td>
</tr>
<tr>
<td>$\tau$(DAX Simulation) [%]</td>
<td>90.05</td>
<td>99.32</td>
<td>98.72</td>
<td>98.04</td>
</tr>
</tbody>
</table>
From the test, we see that all of the indices besides the SMI do not have evidence of psychological barriers when results are compared with the simulated return series at both the 100 and 1000 levels. Only the SMI index shows significant evidence of barriers at the 1000 level. In addition, the results also suggest evidence of price clustering around round numbers in the CAC and DAX indices at the 1000 level even after the expected concentration within the region due to Benford-specific effects are accounted for.

### 5.0 Conclusion

In this study, we test for the significance of round numbers in five European equity markets under different assumptions for the distribution of digits. We find evidence for barriers in one index [SMI] at the 1000 level under the assumption of uniformity but no significant evidence of barriers at the 100 level and at the 1000 level in the remaining indices. This result is consistent with the findings of Dorfleitner and Klein (2009) and in line with the notion that barriers have disappeared in many of these indices after knowledge of their location became widespread. Instead, there seems to be evidence of price clustering around the regions of round numbers in two of these indices [CAC, DAX] at the 1000 level. This could be due to prolonged periods of uncertainty when prices enter the region that manifest itself as a trading range within the region instead of a barrier around the region.

Next, we tested for the appropriateness of the uniformity assumption by comparison with a simulated price series that had no price barriers (by construction). We find evidence that the uniformity assumption is appropriate in most indices [ATX, CAC, DAX, FTSE] at the 100 level, as predicted by the limit distribution for these digits derived from Benford's Law. For the 1000 level, we find results consistent with the predictions from Benford's Law as well that substantiates the argument that the application of the uniformity assumption for tests at the 1000 level is inappropriate in all five indices.

Next, having established that the uniformity assumption is inappropriate for tests at the 1000 level, we investigate whether Benford's Law provides a good alternative model to explain this phenomenon by explicitly testing the empirical fit using Kuiper's Modified Kolmogorov-Smirnov Goodness of Fit Test. For the five indices, we find not sufficient evidence to reject the hypothesis that the observed M-values are distributed according to Benford's Law.

Finally, we re-examine the evidence of the significance of round numbers using a test that does not assume a uniform distribution of M values. We compare the observed frequency distribution of M values with that derived from a Monte Carlo simulation based on cyclical permutations of returns and find evidence of price barriers in one index [SMI] at the 1000 level and possible evidence of price clustering in two indices [CAD, DAX] at the 1000 level. This is consistent with the findings from the tests based on the uniformity assumption. Therefore, while there may be evidence against the use of the uniformity assumption in tests at the 1000 level, the conclusions drawn from a test that implicitly incorporates the predicted outcomes from Benford's Law has not materially changed.

### References


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DO DE NOVO SECONDARY MARKETS AFFECT PRIMARY MARKET INTEREST RATES? A CASE STUDY OF PEER-TO-PEER LENDING*

Michael Reher
Georgetown University

Abstract
What happens to a security’s rate of return in the primary market when a secondary market for that security is created? This question is discussed in the context of a de novo secondary market for peer-to-peer loans using loan data from the peer-to-peer platform Lending Club. Drawing on existing literature on risk and liquidity premiums, a basic model of primary market loan rates is developed and tested against the data using an event analysis. The model suggests that interest rates could either increase or decrease depending on how much risk existed in the primary market loan pool prior to the introduction of the secondary market. Namely, investors with safe portfolios would choose to substitute towards riskier and higher yielding loans, whereas investors with risky portfolios would do the opposite. The data indicate that risk and interest rates rose among safe loans, fell among risky loans, and fell on the whole after Lending Club created a secondary market. These results suggest that, from a regulatory perspective, the decision to permit a financial intermediary to create a secondary market should be informed by the possibility that this innovation could raise risk levels in the primary market.

1 Introduction
In the wake of the 2007 Financial Crisis and subsequent credit crunch, a variety of nontraditional financial intermediaries expanded to fill the funding gap left by risk averse banks seeking to tighten their balance sheets. Unlike banks, many of these so-called “new intermediaries”, which include peer-to-peer lending platforms and crowdsourcing networks, facilitate direct transfers of funds from lenders to borrowers. Accompanying these changes, rumors have circulated that banks may play an obsolete role in post-crisis financial markets.1 Regardless of whether the rumors hold true, though, the advent of these new intermediaries deserves careful thought and analysis. To a certain extent, one can liken the development of such institutions and the loans they originate to the introduction and trading of mortgage-backed securities (MBS). In both cases, financial innovation led to the creation of new assets and markets which smoothed access to credit.2 Moreover, as MBS markets played a pivotal role in the most recent build-up, crash, and reconstruction, these new markets may prove eminently important in years to come.

In particular, the development of secondary trading for peer-to-peer loans resembles, at least remotely, the secondary markets which facilitated MBS turnover. By understanding how the introduction of a secondary peer-to-peer loan market affected the liquidity and risk structure of the underlying loans, one can better develop the kind of macroprudential regulation needed to contain the risks posed by this new market. In addition to furthering our understanding of peer-to-peer lending, such an analysis would also, more broadly, shed light on the dynamics which govern the formation of a de novo secondary market, which is a relatively uncommon event in the financial markets.

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*This piece is an abridged version of the paper presented at the Caroll Round. For the full version of the paper, please send an email to mr532@georgetown.edu.

1In the December 15, 2012 edition of The Economist, a prominent U.K. regulator reportedly suggested that banks could forfeit their sizeable share of the credit market in the future.

2Of course mortgage-backed securities also differ in several key ways from loans originated by, say, peer-to-peer lending platforms. In particular, the payoff structures of the two assets do not bear perfect resemblance, and MBS markets possess a degree of universality lacking in the secondary trading platforms for peer-to-peer loans. Therefore, one should not overstate the similarities between these two assets. However, the fact that both instruments significantly ease access to credit while remaining directly susceptible to loan default is worth noting. In the future, the peer-to-peer loan market may converge in similarity to the MBS market. For information on a typical peer-to-peer platform, visit <https://www.lendingclub.com>.
world. Given the current pace of financial innovation, understanding such dynamics is critical for entrepreneurs and policymakers alike.

This paper contributes to the literature by investigating how the creation of a secondary market for peer-to-peer loans affected interest rates, in particular liquidity and risk premiums, in the primary market. In doing so, it builds on the literature of peer-to-peer lending, much of which to date has focused on the qualities which make one a successful borrower or lender (Freedman and Jin (2008, 2011); Berger and Gleisner (2009); Ravina (2008)). Specifically, this paper innovates by examining peer-to-peer loans in the context of a secondary market and by using data from Lending Club, a dominant player in the industry which has, to the author’s best knowledge, been largely excluded from studies of peer-to-peer lending. Drawing on established methods of measuring liquidity and risk premiums (Sarr and Lybek (2002); McCulloch (1975)), this paper aims to identify the different channels through which the development of secondary trading affects primary market interest rates. In doing so, it highlights a more general link between primary and secondary markets, following a line of studies which has accomplished this task outside the context of peer-to-peer lending (Vickrey and Wright (2010)).

Before proceeding, it is important to briefly touch on the mechanics of the peer-to-peer loan market. Peer-to-peer lending platforms are a relatively new institution for channeling funds from lenders to household borrowers. In recent years, the successes of platforms like Lending Club and Prosper have elevated peer-to-peer loans to a prominent place in post-crisis discussions of credit markets. These platforms directly link lenders and borrowers by allowing the lenders to “shop” from among a variety of online borrower profiles. While borrower profiles generally include statistics such as debt-to-income ratio and FICO range, lenders’ inability to further screen often-anonymous borrowers raises the issue of adverse selection. Moreover, because peer-to-peer loans are usually unsecured, lenders could face high losses in the case of default. These risks have allowed lenders to earn returns of up to 10%, a significant premium relative to many other markets.

In October 2008, Lending Club received SEC approval to establish a secondary market for its loans, and Prosper followed suit in July 2009. Both platforms partner with the brokerage firm FOLIOfn to facilitate secondary trades online. Since Lending Club and Prosper are the dominant players in the U.S. peer-to-peer industry, and since their loans are relatively similar in size and nature, the time gap between their establishment of secondary markets would allow for an interesting analysis of how this development might have affected interest rates in the primary market for each platform. Unfortunately, because Prosper shut down its operations while under SEC review from October 2008 to July 2009, the scarcity of Prosper loan data in this period inhibits the kind of difference-in-difference exercise between the firms which would be ideal. Instead, analysis is focused primarily on Lending Club. In some sense, this situation represents a blessing in disguise, since it directs the focus to a firm which has, to this point, been largely left out of academic literature. In doing so, it invites future studies to broaden the discussion of peer-to-peer lending by including data from a variety of platforms in addition to Prosper, which has to date been the data provider of choice (Freedman and Jin (2008, 2011); Rigbi (2008); Ravina (2008)). Moreover, as will be discussed below, Lending Club’s business model allows for a particularly interesting analysis of the interplay between liquidity and risk premiums.

According to the liquidity premium theory of interest rates, the establishment of a secondary market should reduce rates across loans of all maturities on the primary market. On the other hand, given the availability of a secondary market, primary lenders may have less incentive to select good borrowers, since lenders could potentially liquidate risky loans before default or maturity. In this light, the secondary market might increase the underlying risk in the pool of peer-to-peer loans, implying an increase in the risk premium. Therefore, the interest rate effect of a secondary peer-to-peer market could potentially be positive, zero, or negative. One nuance to Lending Club’s business strategy requires amending the basic model mentioned above. Specifically, Lending Club itself sets interest rates unlike Prosper, which uses an auction-based system. It can be shown that this subtlety could theoretically introduce more credit risk to the loan pool, pushing up interest rates via the risk premium. In particular, this effect would occur when the loan pool contained relatively little risk prior to the secondary market’s creation. On the other hand, if the loan pool already had sufficient risk, then risk levels and interest rates could potentially fall. Empirically, I will test these hypotheses by using the techniques of an event analysis to compare interest rates and risk levels before and after the introduction of the de novo secondary market.

2 Model

When Lending Club unveiled its online trading platform in October 2008, it established the first secondary market for U.S. peer-to-peer loans. In this sense, the development of the trading platform represented more than a firm-specific business strategy; it marked the de novo formation of a secondary market for

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3For example, the December 15, 2012 edition of The Economist mentioned that peer-to-peer platforms might capture an increasing share of the consumer credit market by making funds available to subprime borrowers.

4“High” losses are meant relative to loan size, which often does not exceed $10,000.
an asset which beforehand did not exist outside the primary exchange. The creation of a secondary market occurs relatively infrequently and often has economic effects which feed back into the primary market. In particular, establishing a secondary market injects an asset with liquidity, defined by Allen and Gale (2007) as the degree to which an asset can be transformed into consumption at any given time. All else equal, this positive liquidity shock should increase an asset’s value, since it gives investors the opportunity to transform the asset’s expected cash flow into current purchasing power. At the same time, though, the option of selling a poor investment on the secondary market might reduce investors’ incentive to screen for good risks on the primary market. Consequently, a stream of bad risks may be introduced into the primary market, depressing the asset’s value via adverse selection. Therefore, establishing an aftermarket could have an uncertain net effect on equilibrium prices in the primary market. In the context of peer-to-peer loans, the potential for such uncertainty is real and deserves investigation. This paper contributes to our understanding of the relationship between primary and secondary markets by evaluating how the de novo formation of an aftermarket for peer-to-peer loans affected prices and interest rates in the primary exchange.

Using the simple formulation described in Mishkin (2009), write the nominal interest rate on a peer-to-peer loan as

\[ i = r + \pi^e + \text{lp}(l) + \text{rp}(\sigma) \]

where \( i, r, \pi^e, \text{lp}(\cdot), l, \text{rp}(\cdot), \) and \( \sigma \) denote, respectively, the nominal loan rate, the real rate of interest, expected inflation, the liquidity premium, the liquidity level, the risk premium, and the risk level. Note that the goal of this model is to develop a basic, but reasonable intuition as to how loan rates might respond to the expected inflation, the liquidity premium, the liquidity level, the risk premium, and the risk level. Note that since interest rates vary inversely with prices, this is roughly equivalent to saying that demand is decreasing in price while supply is increasing in price. In other words, on the demand side peer loans are ordinary goods and, on the supply side, they exhibit increasing marginal costs. Moreover, as suggested in the literature, it is reasonable to have \( \partial q^d/\partial l \geq 0 \) and \( \partial q^d/\partial \sigma \leq 0 \). That is, lender demand increases in loan liquidity and decreases in loan risk.

Before proceeding, I will mention two aspects of Lending Club’s business strategy which make this analysis unique. First, during the period of analysis, all loans had a thirty-six month time horizon. In the model, this means that \( t = 36 \) is fixed, and so \( \sigma = \sigma(c, t) \). Secondly, unlike Prosper, Lending Club has not used an auction mechanism for determining loan rates. Instead, the company itself set interest rates using a formula based on loan size and borrower credit quality. Specifically, Lending Club uses FICO credit scores and “a combination of several indicators of credit risk from the borrowers credit report and loan application” to divide borrowers into seven grades, each with five sub-grades, for a total of thirty-five classes of risk. Borrowers are then shifted between classes based on the amount of funds requested. The final interest rate is determined by adding a base rate to a premium based on the borrower’s risk class.\(^5\) Lastly, borrowers with FICO scores below 660, debt-to-income ratios of 35% or more, or credit histories of less than thirty-six months are automatically denied access to funds. With respect to the model, this nuance means that, for a given credit level, equilibrium interest rates depend not only on loan demand and supply, but also, and perhaps most importantly, on the rate established by Lending Club. Since this rate depends on

\(^5\)This base rate was 5.05% as of January 2013.
credit quality and increases in the default risk of a particular loan, we may write \( i = i^L(\sigma) \).

Suppose that, prior to the introduction of the secondary market, the initial equilibrium is characterized by

\[
D = q^D(i_0, l_0, \sigma_0) \\
S = q^S(i_0) \\
i = i_0 = i^L(\sigma_0)
\]

For notational simplicity, I omit \( \pi^e \) from the argument of the demand and supply functions and treat it as a constant, since expected inflation will not play a significant role in this simple exposition. Note that, at least in relative terms, \( l_0 \) must be small, since the absence of a secondary market means that loans cannot be liquidated before maturity. Now, suppose that the opening of a secondary market imposes a liquidity shock which raises \( l \) to some \( l^* \), where \( l^* > l_0 \). All else equal, this shock will increase loan demand across all interest rates and risk levels. Figure 1 illustrates this effect in \((q, i)\) space, with the initial shock described by Arrow 1. If one were to extend the analysis to three-dimensional \((q, i, l)\) space and let \( l_0 = 0 \), this shock is effectively a movement along the demand plane out of the page and into positive \( l \) space.

However, as evident in Figure 1, this shock places the market out of equilibrium: at the initial interest rate, demand exceeds supply. To make the model slightly more realistic, let \( i, l, \) and \( \sigma \) denote the average interest rate, liquidity level, and risk level in the pool of loans, and let \( q \) denote the quantity of loans corresponding to those values of \( i, l, \) and \( \sigma \). This clarification reconciles the fact that, in reality, the loan pool may contain a wide spectrum of interest rates, face values, liquidity, and risk, and so an analysis by graph must focus on the mean values, or central tendency, of the pool. Returning to Figure 1, if liquidity and expected inflation are held constant, the only variable in this simple model which can adjust to bring the market into equilibrium is \( \sigma \). Moreover, \( \sigma \) is the only variable which can endogenously shift the Lending Club rate schedule such that there is a mutual intersection of the supply, demand, and rate schedule curves. Whether \( \sigma \) increases or decreases depends on the investor’s risk preferences and the composition of his portfolio.

On the one hand, with the option of selling loans on the secondary market, lenders can at least partially
hedge themselves against losses from non-performing loans. As a result, they can afford to diversify into higher yielding risks; essentially, the additional loan liquidity makes investors willing to confront the potential adverse selection in the peer-to-peer market. As lenders substitute towards riskier borrowers, $\sigma$ increases and the demand curve shifts in. At the same time, because Lending Club’s interest rate is a function of risk, $i(\sigma)$ moves up. If loan supply is treated as exogenous with respect to risk and liquidity, then the new equilibrium is at $(q^*, i^*, l^*, \sigma^*)$, where $q^* < q_0$, $i^* > i_0$, $l^* > l_0$, and $\sigma^* > \sigma_0$. This scenario is illustrated in Figure 2, where Arrow 1 indicates the initial shock and Arrow 2 indicates the readjustments which bring the market into equilibrium.

On the other hand, it could be that an investor’s pre-shock portfolio was risky enough such that, even after the liquidity shock, it benefits him little to increase the portfolio’s underlying level of risk. In other words, at the new liquidity level and with the same level of risk, the investor’s marginal return to risk, in terms of utility, is relatively small or perhaps even negative. Moreover, because the liquidity shock increased loan desirability, the investor and like-minded peers would be willing to receive a lower interest rate across loans. This willingness can be seen in the lower interest rate associated with the post-shock intersection of demand and supply curves in Figure 1. Put differently, the positive demand shock associated with the de novo secondary market forces investors to accept a lower rate of return. However, because of Lending Club’s rate setting mechanism, the only way that interest rates can come down is through a reduction in risk. Therefore, if investors do not adjust their portfolio risk upwards, competition with other investors forces them to accept a lower rate of return, which occurs through a substitution to less risky loans. In the final equilibrium, $q^* > q_0$, $i^* < i_0$, $l^* > l_0$, and $\sigma^* < \sigma_0$. This scenario can be illustrated by reversing the arrows in Figure 2.

This discussion begs the question of what determines whether risk increases or decreases to bring the system into equilibrium. In short, the answer depends on how strongly the investor’s interest rate schedule responds to an increase in risk when compared to the response of Lending Club’s rate setting schedule. Mathematically, we must compare $\partial i^D/\partial \sigma$ and $di^L/d\sigma$, where $i^D = i^D(q^D, l, \sigma)$ represents the inverse demand curve and $i^L = i^L(\sigma)$ is Lending Club’s rate setting function. In particular, if $\partial i^D/\partial \sigma \leq di^L/d\sigma$, then the market will converge to an equilibrium with average risk level $\sigma^*$ such that $\sigma^* < \sigma_0$. In other words,
average loan risk will decrease. On the other hand, if \( \partial i^D / \partial \sigma > di^L / d\sigma \), then the market may converge to an equilibrium where \( \sigma^* > \sigma_0 \).

To see this, observe that the market will be in equilibrium if and only if the triangle \( A \) in Figure 1 has zero area. Since \( A \) has area equal to \( \frac{1}{2}(q^D(i^L, \cdot) - q^S(i^L))(i^L - i^M) \), where \( i^M \) is the rate associated with the intersection of \( q^S \) and \( q^D \), a sufficient condition for the area to vanish is that \( q^D(i^L, \cdot) - q^S(i^L) \) converges to 0 as \( \sigma \) converges to \( \sigma^* \). Moreover, this condition is also necessary. Otherwise, one could have a situation where \( i^M \) equals \( i^L \) but \( q^D(i^L, \cdot) \neq q^S(i^L) \) and hence \( q^D(i^M, \cdot) \neq q^S(i^M) \), a contradiction since, by definition, \( i^M \) is the rate at which \( q^D(i^M, \cdot) = q^S(i^M) \). It follows that \( A \) has zero area if and only if \( q^D(i^L, \cdot) - q^S(i^L) \) converges to 0 as \( \sigma \) converges to \( \sigma^* \). In other words, we need \( q^D(i^L, \cdot) = q^S(i^L) \) for a market equilibrium.

To understand the conditions under which \( q^D(i^L, \cdot) - q^S(i^L) \) converges to 0 as \( \sigma \) converges to \( \sigma^* \), I define a function \( \Delta : \sigma \to \mathbb{R} \) where \( \Delta(\sigma) = q^D(i^L(\sigma), l, \sigma) - q^S(i^L(\sigma)) \). Differentiating with respect to \( \sigma \) gives

\[
\frac{d\Delta}{d\sigma} = \frac{\partial q^D(i^L(\sigma), l, \sigma)}{\partial \sigma} - \frac{dq^S(i^L(\sigma))}{d\sigma} = \frac{\partial q^D}{\partial i^L} \frac{di^L}{d\sigma} + \frac{\partial q^D}{\partial \sigma} - \frac{dq^S}{di^S} \frac{di^L}{d\sigma}
\]

Taking the total differential of \( q^D \) holding \( q \) and \( l \) constant and then rearranging terms gives

\[
\frac{\partial i^D}{\partial \sigma} = -\frac{\partial q^D}{\partial q^D} \frac{\partial q^D}{\partial \sigma}
\]

So by substitution one has

\[
\frac{d\Delta}{d\sigma} = \frac{\partial q^D}{\partial i^L} \frac{di^L}{d\sigma} - \frac{\partial q^D}{\partial \sigma} - \frac{dq^S}{di^S} \frac{di^L}{d\sigma} = \frac{\partial q^D}{\partial i^L} \left( \frac{di^L}{d\sigma} - \frac{\partial q^D}{\partial \sigma} \right) - \frac{dq^S}{di^S} \frac{di^L}{d\sigma} + \frac{dq^S}{di^S} \frac{di^L}{d\sigma}
\]

As indicated by the sign pattern above, \( \partial q^D / \partial i^L > 0 \), \( dq^S / di^S < 0 \), and \( di^L / d\sigma > 0 \), meaning that the second term is always positive whereas the first term is positive if \( di^L / d\sigma > \partial q^D / \partial \sigma \) and negative if \( di^L / d\sigma < \partial q^D / \partial \sigma \). Therefore, if \( di^L / d\sigma \geq \partial q^D / \partial \sigma \), then \( d\Delta / d\sigma \) is guaranteed to be positive. On the other hand, if \( di^L / d\sigma < \partial q^D / \partial \sigma \), then \( d\Delta / d\sigma \) could be negative. Keeping in mind an equilibrium requires that \( \Delta \to 0 \) as \( \sigma \to \sigma^* \), if \( d\Delta / d\sigma > 0 \), then \( \sigma \) must decrease to bring the market into equilibrium. Likewise, if \( d\Delta / d\sigma < 0 \), then \( \sigma \) must increase.

Taken together, these remarks imply that \( di^L / d\sigma \geq \partial q^D / \partial \sigma \) guarantees that \( \sigma^* < \sigma_0 \) whereas \( di^L / d\sigma < \partial q^D / \partial \sigma \) could, depending on the elasticity of loan supply, lead to an outcome with \( \sigma^* > \sigma_0 \). Specifically, with inelastic loan supply, \( dq^S / di^S \) will be close to 0 and so \( di^L / d\sigma < \partial q^D / \partial \sigma \) implies \( d\Delta / d\sigma < 0 \) and thus \( \sigma^* > \sigma_0 \). In the fact, given the general tightening of U.S. credit markets which coincided with the secondary market’s creation in late 2008, one may reasonably suppose that borrowers had relatively little influence over the interest rate they received, thus corresponding to inelastic supply. Moreover, given that borrowers on peer-to-peer lending platforms might have previously been rejected by credit-tightening banks, they would have had less power to bid down rates on peer loans, and so supply inelasticity would appropriately characterize peer-to-peer markets.

Generally speaking, therefore, low values of \( \partial i^D / \partial \sigma \) correspond to decreases in average risk and interest rates, while high values \( \partial i^D / \partial \sigma \) are associated with the opposite. This result supports the intuitive description of investor decision-making mentioned earlier. Namely, we can think of \( i^D \) as a kind of utility received from a particular investment in the sense that a higher rate of return will, all else equal, increase investor welfare. Therefore, if investors are willing to shoulder more risk at the new liquidity level, then we may say the marginal utility from the added risk, proxied by \( \partial i^D / \partial \sigma \), is positive and nontrivial. In other words,

\[6\text{I use the notation } q^D(i, \cdot) \text{ as a reminder that, in this simple framework, } q^D \text{ is also a function of } l \text{ and } \sigma, \text{ whereas } q^S \text{ is only a function of } i. \text{ Soon, we will consider the case where } q^S \text{ also depends on } \sigma. \]

\[7\text{Although I defined some of these expressions earlier without the use of strict inequalities, I will proceed with the use of strict inequalities since it simplifies the language and does not alter the substance of the discussion.} \]

\[8\text{“Low” and “High” are meant relative to the magnitude of } di^L / d\sigma. \]
\(\partial i^D/\partial \sigma\) will be large enough such that the market sees an increase in average loan risk and interest rates. Conversely, if investors have little utility to gain from increasing portfolio risk, corresponding to a relatively small value of \(\partial i^D/\partial \sigma\), then they will substitute towards safer, lower interest rate loans. On the aggregate level, a low \(\partial i^D/\partial \sigma\) implies that the market converges to an equilibrium with lower risk and interest rates,\(^9\)

In Figure 3, I graphically propose a functional form for \(i^L(\sigma)\) and \(i^D(\sigma, \cdot)\). Namely, \(i^L(\sigma)\) is increasing and linear while \(i^D(\sigma, \cdot)\) is increasing and concave. That both functions increase in \(\sigma\) should not cause alarm, as Lending Club's rate schedule incrementally raises interest rates as credit quality decreases, and investors generally demand a higher rate of return on risky assets. Moreover, the linear nature of \(i^L(\sigma)\) seems reasonable, as Lending Club assigns all loans a base rate which it then raises in increments per unit reduction in credit grade. A truly linear function would require that these increments be of equal size. In reality, the increments vary slightly by risk, and so \(i^L(\sigma)\) is actually somewhat concave. However, the 0.96 coefficient of correlation between increment size and credit grade indicates that \(i^L(\sigma)\) has relatively constant slope, and so the idea that it behaves similar to a linear function is not unrealistic. Lastly, the concavity of \(i^D(\sigma, \cdot)\) implies not only that investors value safe loans, but that they value them at an increasing rate. Specifically, for high values of \(\sigma\), concavity means that \(\partial i^D/\partial \sigma\) is close to 0. That is, if investors switch from a high risk loan to a slightly safer one, they are only willing to let the risk premium fall by a small amount. On the other hand, for low levels of \(\sigma\), concavity implies that \(\partial i^D/\partial \sigma\) will be large. Intuitively, this means that as investors substitute towards a riskless loan, they will accept a large reduction in risk premium. In other words, because lenders prize low risk loans, they are willing to pay increasingly more for them. If such risk aversion indeed characterizes the peer-to-peer market, then supposing \(i^D(\sigma, \cdot)\) is concave would seem reasonable. Moreover, given the likely presence of adverse selection suggested by the literature, the potential for risk among peer-to-peer loans is real and significant.\(^10\)

Returning to the model, observe that an equilibrium risk level must correspond to the intersection of \(i^L(\sigma)\) and \(i^D(\sigma, \cdot)\) in Figure 6. Now, given that the de novo secondary market should introduce a liquidity shock lowering desired interest rates across risk levels, \(i^D(\sigma, \cdot)\) shifts down, as indicated by Arrow 1 in Figure 3. Using Figure 3, observe that the market could have been in either a high (H) or low (L) risk state before the shock, depending on which intersection dictated the pre-shock equilibrium. If the market initially occupied a low risk state \(L_0\), then the liquidity shock forces the system to \(L^*\), which has higher risk and interest rates. Conversely, if the market began at \(H_0\), the shock moves it to a state of lower risk and interest rates at \(H^*\). These outcomes make sense given the slope of \(i^D(\sigma, \cdot)\) at high and low levels of risk. Namely, for \(\sigma\) sufficiently small, \(\partial i^D/\partial \sigma > \partial i^L/\partial \sigma\) and so, in light of the previous discussion, \(\sigma^* > \sigma_0\) and \(i^* > i_0\). On the other hand, for \(\sigma\) large enough, \(\partial i^D/\partial \sigma < \partial i^L/\partial \sigma\), and so the system converges to a lower risk, lower interest rate equilibrium. These results allow for a more refined hypothesis about the secondary market effects. In particular, they imply that lenders with safe portfolios will substitute towards higher risk and interest rates, while lenders with risky portfolios will do the opposite. The net effect of these two processes will determine whether the market sees an aggregate increase or decrease in risk and interest rates.

In sum, this study aims to contribute to the literature in two respects. One, it analyzes the interest rate effects of a de novo secondary market. Specifically, it uses established empirical methods to assess how interest rates, in particular risk premiums, in the primary market might have changed due to the liquidity now afforded by the secondary market. Two, it adds to the growing discussion of peer-to-peer lending by investigating how the option of secondary trading could affect decision-making by market participants.

### 3 Data, Empirical Strategy, and Results

Based on the simple model of interest rates developed above, one might expect primary market interest rates to rise in response to the establishment of a secondary market for peer-to-peer loans if low risk portfolios

\(^9\)In the full version of this paper, I discuss the case where the loan supply curve differs based on the riskiness of the borrower. However, the results of that discussion do not significantly alter the model presented here.

\(^10\)Before proceeding, it should be noted that the functional forms proposed in Figure 3 are not meant to robustly describe the behavior of \(i^L\) or \(i^D\). Indeed, such a thorough characterization would deserve its own paper. Rather, these conjectures serve as a reasonable premise on which to formulate a hypothesis for the question at hand, which asks whether the de novo secondary market affected primary market interest rates. As such, any conclusions derived from this model serve as, at best, a judicious guess to be tested against the data. Nonetheless, to the extent that this simple model adequately describes the market, it can provide important insight into the market mechanisms at play, giving the empirical results a practical and economic interpretation.
Figure 3: Post-shock equilibria in $(\sigma, i)$ space

dominate the primary market, and one might expect rates to fall if high risk portfolios prevail. Specifically, the de novo secondary market should boost loan demand via a positive liquidity shock. In response, lenders could engage the market’s inherent adverse selection and substitute towards riskier loans, bringing the system into an equilibrium with higher average interest rates than the initial state. Alternatively, if lenders gain little utility from riskier investments, they may drive the system to a lower interest rate equilibrium by substituting towards safer portfolios. The ultimate effect depends largely on how vigorously investors change their interest rate schedules in response to higher risk. This response function, in turn, depends on the underlying risk of the lender’s current portfolio, as investors holding safe loans would ostensibly accept an increase in risk, and thus an increase in risk premium, with greater enthusiasm than their peers already exposed to risky loans. Therefore, a primary market dominated by low risk portfolios would move towards higher risk and interest rates following the introduction of the secondary market. On the other hand, a market comprised of high risk loans would tend in the opposite direction.

Using this framework as a starting point, we should look for two effects: a switch towards new risk levels in the primary market and, correspondingly, a net change in primary market rates. The direction of these changes will depend on aggregate risk in the primary market prior to the creation of the de novo secondary market. In theory, there is also a third effect of interest, which is the initial liquidity shock. However, testing for such a shock would not give particularly interesting results since, given the essential absence of peer-to-peer loan liquidity prior to the secondary market’s creation, the mere ability to trade loans means that the secondary market would have had a positive liquidity effect. As to gauging the size of this positive liquidity shock, the requisite data are not observable, or at least not readily observable, and so the cost of such an endeavor outweighs the benefit. In particular, the liquidity shock’s magnitude would seem to play little role in determining which equilibrium the market converges to, at least based on the simple model presented earlier.

This study uses loan data from Lending Club’s platform as the observed primary market data. The sample runs from June 2007 to January 2013 and contains 99,976 observations. Each observation consists of an issued loan along with a set of loan and borrower characteristics.\textsuperscript{11} Among the most important variables

\textsuperscript{11}For a full list of borrower characteristics, please email mr532@georgetown.edu.
are the borrower’s debt-to-income ratio, length of observable credit history, and FICO score range. In terms of data density, a new loan was issued on almost every day of the sample. While the frequency of loan origination slowed somewhat in the weeks leading up to the creation of a secondary market on October 14, 2008, the data are sufficiently dense to perform the appropriate analysis on the primary market, as most days saw at least one origination.

Table 1: Summary Statistics of the Loan Pool

<table>
<thead>
<tr>
<th>Variables</th>
<th>Full Window</th>
<th>Pre-Event</th>
<th>Post-Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan Rate (all loans)</td>
<td>12.23</td>
<td>11.92</td>
<td>12.36</td>
</tr>
<tr>
<td></td>
<td>(2.46)</td>
<td>(2.52)</td>
<td>(2.43)</td>
</tr>
<tr>
<td>Loan Rate (safe loans)</td>
<td>9.75</td>
<td>9.10</td>
<td>9.97</td>
</tr>
<tr>
<td></td>
<td>(1.29)</td>
<td>(0.96)</td>
<td>(1.32)</td>
</tr>
<tr>
<td>Loan Rate (risky loans)</td>
<td>13.62</td>
<td>13.17</td>
<td>13.83</td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td>(1.91)</td>
<td>(1.66)</td>
</tr>
<tr>
<td>LC Credit Grade (all loans)</td>
<td>12.58</td>
<td>13.78</td>
<td>12.07</td>
</tr>
<tr>
<td></td>
<td>(6.84)</td>
<td>(7.45)</td>
<td>(6.50)</td>
</tr>
<tr>
<td>LC Credit Grade (safe loans)</td>
<td>5.68</td>
<td>5.53</td>
<td>5.73</td>
</tr>
<tr>
<td></td>
<td>(2.20)</td>
<td>(2.20)</td>
<td>(2.21)</td>
</tr>
<tr>
<td>LC Credit Grade (risky loans)</td>
<td>16.43</td>
<td>17.43</td>
<td>15.95</td>
</tr>
<tr>
<td></td>
<td>(5.37)</td>
<td>(5.86)</td>
<td>(5.04)</td>
</tr>
<tr>
<td>Proportion of safe loans</td>
<td>0.36</td>
<td>0.31</td>
<td>0.38</td>
</tr>
<tr>
<td>Loans Issued</td>
<td>1658</td>
<td>496</td>
<td>1162</td>
</tr>
</tbody>
</table>

*The values listed are means, with sample standard deviations in parentheses.
**Each observation in this table is a loan, unlike in the rest of the study where the unit of observation is a day.
***Safe loans have LC Grade \( \leq 9 \), risky loans have LC Grade > 9.

3.1 Empirical Strategy

Estimating the interest rate and credit risk effects of the de novo secondary market requires two unique identification strategies. These strategies rely on the notion that a critical event occurred on October 14, 2008 with the unveiling of a secondary market. This structure allows one to exploit variation in the data from before and after the event date, much in the spirit of a conventional event study or regression discontinuity design. With slight modifications, I use these conventional procedures to estimate the interest rate and credit risk effects of the de novo secondary market.

To identify the interest rate effect, I perform a modified, or pseudo event study treating newly issued loans as the security of interest and the introduction of a secondary market on October 14, 2008 as the event date. Because variation among borrower credit backgrounds means that each loan carries a different rate of interest, I take the average interest rate among all loans issued on a given date as the observed rate of return. Strictly speaking, the contract rate on a peer-to-peer loan is not the rate of return, since the rate of return depends also on default probabilities. However, given that higher interest rates correspond to higher return holding risk constant, one can consider the interest rate on peer-to-peer loans as a type of rate of return. In any case, using the language “rate of return” has an advantage in that it corresponds to the terminology of a conventional event study, which this procedure aims to simulate. However, because securitized auto loans might have experienced significant demand fluctuations around the event date because of the financial crisis, the auto loan rate may capture macroeconomic effects unrelated to the peer-to-peer market. For

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12The FICO score is given over a 5 point interval. Note that FICO scores range from 300 to 850.
13This slowdown in loan origination occurred during a general scaling down of Lending Club’s business activity while pending SEC approval of the company’s secondary trading platform.
14Strictly speaking, the contract rate on a peer-to-peer loan is not the rate of return, since the rate of return depends also on default probabilities. However, given that higher interest rates correspond to higher return holding risk constant, one can consider the interest rate on peer-to-peer loans as a type of rate of return. In any case, using the language “rate of return” has an advantage in that it corresponds to the terminology of a conventional event study, which this procedure aims to simulate.
15The rates for 36 month auto loans are national averages and were compiled by Bankrate.com.
this reason, it may be inappropriate to use auto loan rates as the proxied market return, and so I repeat the process using yields on Moody’s AA, A, and BAA corporate bond indices as the market return. The downside with using these indices, though, is that their breadth may diminish any link to peer-to-peer rates. Moreover, these indices contain bonds of various lengths, most of which exceed three years. This maturity mismatch would further weaken the link to peer-to-peer loans.

For several reasons, this strategy cannot be considered a true event study. Most importantly, the relatively low transaction frequency, or in this case origination frequency, of peer-to-peer loans slows the pace at which information filters into the observed market rate. For example, in 2008, the average stock on the New York Stock Exchange experienced 1,400 trades per day, while Lending Club averaged only fourteen

pace at which information filters into the observed market rate. For example, in 2008, the average stock on relative low transaction frequency, or in this case origination frequency, of peer-to-peer loans slows the mismatch would further weaken the link to peer-to-peer rates.

For this reason, it may be inappropriate to use auto loan rates as the proxied market return, and so I repeat this procedure twice using each of these rates and then a fifth time using only the time trend.

One wonders if these statistics mean that peer-to-peer loans require 100 times as long to absorb information as stocks on the NYSE, which are typically the focus of event studies. In any case, an “event study” of peer-to-peer loans would require an information response window significantly longer than one day, which is a window length often used in conventional event studies. For this reason, the strategy employed here should be considered a pseudo event study. Specifically, I lengthen the response window to 150 days. While a clear downside to lengthening the response window is that other, unrelated information could also affect interest rates during the window, a benefit is that the longer window allows enough transactions to occur so that we can observe the full interest rate impact of the event. Given the very low transaction frequency of newly issued peer-to-peer loans relative to stocks traded on the New York Stock Exchange, this benefit may be well worth the cost.

In the standard market model, the expected rate of return on peer-to-peer loans acts as a linear function of the market interest rate. However, given the lengthy response window, I also include a time trend to avoid confounding genuine changes in market structure with an unrelated, time dependent process. Thus, the expected interest rate on peer-to-peer loans issued at time \( t \) conditional on the market return can be written

\[
E(P2P_t | Market_t, t) = \alpha + \beta Market_t + \gamma t
\]

where the parameters \( \alpha, \beta, \) and \( \gamma \) are constants and will be estimated using Ordinary Least Squares. Also, it should be noted that \( P2P_t \) is defined as the average interest rate for loans issued on day \( t \). It is common to use the three months prior to the event as the window for estimating model parameters. However, because of reduced data density in the month prior to the event date, corresponding to the slowdown in loan origination which preceded the introduction of the secondary market, I use a five month estimation window. While lengthening the estimation window has a drawback in that the estimated model might be outdated by the time of the event, it also has the benefit of increasing the sample size so that the fit becomes less susceptible to outliers. Lastly, recall from above there are four candidates for the proxied market return: the 36 month auto loan rate and Moody’s AA, A, and BAA bond indices. I estimate \( E(P2P_t | Market_t, t) \) four separate times using each of these rates and then a fifth time using only the time trend.

With a traditional event study, one would define the excess interest rate on peer-to-peer loans by

\[
e_t = E[P2P_t | Market_t, t] - P2P_t
\]

Intuitively, \( e_t \) would represent the deviation in interest rates from what we would otherwise expect on day \( t \) given the market’s behavior. Ideally, one would compute \( e_t \) on the event day and interpret this statistic as the interest rate effect of establishing a secondary market. While this strategy would work for an efficient market, the relatively low frequency of loan origination following the event date means that the primary market may have taken more than one day to respond to the shock of the \textit{de novo} secondary market. Since I use a 150 day response window, the natural approach would be to compute the average of \( e_t \) over this period and determine whether it differs significantly from 0. Alternatively, given the lengthy response window, one could also estimate \( E(P2P_t | Market_t, t) \) over the the 150 days before and after the event date and include a binary variable which equals 1 for loans issued after the introduction of the secondary market and 0 otherwise. That is, one would estimate

\[
E(P2P_t | Market_t, t) = \alpha + \beta Market_t + \gamma t + \lambda PostEvent_t
\]

and interpret \( \lambda \) as the interest rate effect of the \textit{de novo} secondary market. Furthermore, since the model implies that the interest rate effect might differ based on portfolio risk, I repeat this procedure twice using only high and low risk loans, where low risk is arbitrarily defined as an A or B grade on Lending Club’s

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16 This statistic came from the NYSE website.

17 See, for instance, Gagnon et al. (2011).
As briefly mentioned above, a significant issue with using such a long response window is that news unrelated to the de novo secondary market might also be moving primary market interest rates, and so pinpointing the desired interest rate effect becomes increasingly difficult. Including a time trend in the market model partially corrects for this by removing any variation due to broad, time-dependent macroeconomic patterns. Moreover, given the peer-to-peer market’s low transaction frequency, any other important event which occurred during the 150 day response window would itself require a lengthy period of time to make its own impact on primary market rates. Thus, there is a natural limit on the ability of such exogenous events to distort interest rates during the response window. Nonetheless, given the general financial upheaval which coincided with the de novo secondary market, one should at least be aware of outside factors which may have shifted peer-to-peer loan rates at this time.

Namely, towards the end of November 2008, the Federal Reserve announced that it would begin large scale purchases of distressed assets, in particular mortgage-backed securities (MBS). To the extent that peer-to-peer loans can substitute for mortgage-backed securities, this announcement could have reduced demand in the peer-to-peer market as investors shifted towards the MBS now being purchased by the Fed. However, supposing that the secondary market introduced a positive liquidity shock which boosted loan demand, a shift towards MBS would then oppose this initial effect. As a result, any observed shifts in primary market interest rates would be smaller than without the Fed’s announcement. In other words, the Fed’s announcement would reduce the magnitude of the point estimates, giving them the interpretation as a lower bound of the secondary market effect. Even so, to eliminate the effect of the Fed’s announcement, I repeat the above procedure using a one month response window.

Lastly, one should take into consideration the fact that the opening of a secondary market on October 14 may not have surprised investors. In fact, Lending Club had already been under SEC review for several weeks regarding the company’s request to establish such a secondary market. Therefore, investors may have already adapted their strategies prior to October 14, and so any interest rate effect of the de novo secondary market may have already been built into the average rate on the primary market. Luckily, this nuance would, if anything, bias the estimates downwards. Thus, the results may be interpreted as a lower bound of the actual interest rate effect of establishing a secondary market.

In the second half of the investigation, which identifies the credit risk effect, I use a regression discontinuity design to compare the average risk in the pool of newly issued loans before and after the event date, much in the spirit of the pseudo event study above. Within this framework, the subset of loans issued before the event date comprise the control group while those loans issued after the event date comprise the treatment group. Define a function \( c(t) \) which describes the average credit risk of loans issued on day \( t \). The idea is that, if indeed something occurred on the event date \( t = t^* \) which substantially affected average credit risk, then \( c(t) \) should exhibit a point of discontinuity at \( t^* \). Practically, one can detect such a point of discontinuity by estimating \( c(t) \) using the treatment and control groups separately and then comparing whether a significant difference in the estimate for \( c(t^*) \) exists between the two models. Such a difference would indicate that \( c(t) \) jumped discontinuously at \( t^* \) with admission to the treatment group. In other words, this would mean that the establishment of a secondary market at \( t^* \) was associated with a different average level of credit risk among newly issued loans.

This method proceeds in several steps. First, one must define the average credit risk \( c \) in the pool of newly issued loans. Then, one must estimate \( c(t) \) using the control and treatment groups. Finally, one must compute and interpret the difference in the two estimates for \( c(t^*) \). As a note of caution, the value of \( c \) we are looking for is really the level of perceived risk in the loan pool, rather than the actual risk. In other words, because investors may not gauge risk perfectly, one must distinguish between an actual shift in loan riskiness and a shift in loan characteristics towards what appears risky in investors’ eyes, but which may not necessarily be so. Therefore, \( c \) is defined in multiple iterations to take into account possible variation in the quality of investor judgment. The first, most robust definition of \( c \) is the probability of loan default or charge-off conditional on both the borrower’s credit and personal background. Specifically, for each loan issued to borrower \( i \),

\[
c_i = \Phi(f(Credit_i, Personal_i))
\]

\footnote{Recall that the credit scale runs from A to G with five sub-grades per letter, giving a total of 35 classes of risk. So an A or B grade on the Lending Club scale would correspond to a credit class of 1 through 10. Also, the definition of low risk as an A or B grade is meant only as an arbitrary starting point from which appropriate adjustments may be made.}
where $\Phi$ is the cumulative standard normal distribution function and $f$ is linear. This equation represents the conventional probit model and will be estimated accordingly. In the second, more basic definition of $c$, I condition only on credit background and omit personal characteristics from the model. In the above specification, the components of the credit term include the borrower’s debt-to-income ratio, FICO range, and the length of available credit history. Note that these variables mirror those which Lending Club includes in its basic credit rating method. The personal term consists of education, employment length, and monthly income. For a complete list of these variables, see Table 1. Lastly, in the third definition of $c$, investors do not determine credit risk themselves, but instead rely on the credit grade generated by Lending Club. Thus, $c$ simply equals the Lending Club credit grade assigned to a particular loan.

For each day in the sample, $c$ is averaged across all loans issued that day. This generates a time series $c_t$ of average credit risk in the pool of newly issued loans. To determine $c(t)$, I fit a linear time trend using Ordinary Least Squares. Specifically,

$$c(t) = E(c_t) = \gamma + \delta t$$

where $\gamma, \delta$ are parameters to be estimated. For similar reasons as with the pseudo event study, I use the five months before and after the event date as the estimation window for $c(t)$. Also, as before, I include a binary variable indicating whether the observation belongs to the post-event, or treatment group. That is, I estimate

$$c(t) = E(c_t) = \gamma + \delta t + \omega_{PostEvent} t$$

and interpret $\omega$ as the estimated risk effect of the secondary market. Moreover, since the model implies that this effect varies based on the riskiness of an investor’s pre-event portfolio, I repeat the procedure for high and low risk loans separately, where, as above, low risk is defined as an A or B on Lending Club’s credit scale. Lastly, as with the pseudo event study, investor foreknowledge of the de novo market might mute the estimated risk effect, since lenders may have already adjusted their portfolio by the time the market was formally introduced. However, as above, this nuance means that we can interpret $\omega$ as a lower bound of the risk effect.

### 3.2 Results

On the whole, interest rates and risk levels for newly issued loans decreased following the introduction of the secondary market. Despite this net downward effect, safe loans actually saw an increase of 1.2% to 1.6% in interest rates as well as a rise in credit risk. Risky loans, on the other hand, experienced decreases in credit risk and a drop of 0.6% in interest rates. As a result of these opposing effects, interest rates decreased by 1.3% while risk of charge-off decreased by 2.9%. Taken together, these empirical results support the hypothesis that safe portfolios would shift towards riskier, higher yielding loans while riskier portfolios would behave in the opposite fashion. The net effect of these two opposing forces would then determine the final equilibrium.

With respect to interest rates, most specifications point to increases for safe loans and decreases for risky loans, leading to a net reduction in interest rates. However, the magnitude and significance of the results vary somewhat by specification. Specifically, Table 2 shows that, in the baseline pseudo event study with a 150 day response window, interest rates fell by between 1.2% and 1.3% regardless of the market rate used. However, Tables 4 and 5 show that the estimate varies by market rate in the low and high risk specifications. At the same time, if one market rate demonstrates a superior ability to describe the behavior of loan rates, then the point estimate produced using that market rate would seem to be most valid. Accordingly, if one determines the optimal rate on the basis of highest adjusted $R^2$, then the net interest rate effect was -1.3% for the entire sample, +1.5% for safe loans, and -0.6% for risky loans. Before proceeding, recall that safe

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19 While Lending Club may take other factors into account when determining credit grades, it explicitly names these three characteristics.

20 Recall, again, that Lending Club credit grades range from A to G, each with 5 subclasses. This makes for a total of 35 categories of risk. In the discussion which follows, the terms “grade” and “score” refer to a loan’s credit quality on this 35-point scale, with a value of 1 corresponding to highest quality and lowest risk.

21 In many cases, the optimal rate was the 36 month auto loan rate, which makes sense given that the auto loans were of the same maturity as peer-to-peer loans. As an additional check, the pseudo event study was reproduced using the spread between the auto loan rate and the peer-to-peer rate as the dependent variable. This alternative method produced similar results to the baseline test, giving significant estimates of between -1.2% and -1.3% for the net interest rate effect.
loans were arbitrarily defined as having a Lending Club score of 10 or less, corresponding to A or B grade loans. However, this definition provided inconclusive results, and so, since it was arbitrary, it was modified so that safe loans are now defined by a score of 9 or less. This new definition produced the results discussed here.

Interestingly, while the signs of the point estimates conform to the hypothesis, their magnitudes might raise some questions. In particular, one might expect the point estimate for the full sample to lie between the estimate for the high and low-risk specifications. However, the full sample estimate is even more negative than that of the high-risk specification. On the one hand, given how an observation is defined in this analysis, such a discrepancy might not be interesting. Namely, each observation represents a daily average of loan rates; in the high and low-risk specifications, this average consists only of high and low-risk loans, respectively. Therefore it would not be appropriate to expect the high and low-risk estimates to sum arithmetically to the full sample estimate. At the same time, though, this discrepancy could also point to more interesting effects, such as a change in the risk composition of the loan pool. Namely, Table 1 indicates that the fraction of low-risk loans in the pool increased from 0.31% to 0.38% after the introduction of a secondary market. Given that each observation represents a daily average of loan rates, the increased proportion of safe loans in the market may have depressed observed interest rates following the event date. On a theoretical note, the increased density of safe loans makes sense in light of the model discussed above. Namely, as illustrated in Figure 3, if high-risk portfolios shift towards safer loans, then we should see an outward shift of the demand curve, corresponding to a higher quantity of loans demanded. That is, as investors substitute towards safety, they demand more loans, leading to a rise in the proportion of low-risk loans in the pool. This effect could, in part, explain why the full sample estimate for the change in loan rates is so negative.

Table 2: Pseudo Event Study, All Loans (Full Response Window)

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1) P2P Loan Rate</th>
<th>(2) P2P Loan Rate</th>
<th>(3) P2P Loan Rate</th>
<th>(4) P2P Loan Rate</th>
<th>(5) P2P Loan Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>0.00937***</td>
<td>0.00858**</td>
<td>0.00896*</td>
<td>0.00904**</td>
<td>0.00885**</td>
</tr>
<tr>
<td></td>
<td>(0.00207)</td>
<td>(0.00216)</td>
<td>(0.00243)</td>
<td>(0.00245)</td>
<td>(0.00230)</td>
</tr>
<tr>
<td>Post-Event?</td>
<td>-1.291**</td>
<td>-1.276**</td>
<td>-1.238**</td>
<td>-1.264**</td>
<td>-1.226**</td>
</tr>
<tr>
<td></td>
<td>(0.362)</td>
<td>(0.362)</td>
<td>(0.430)</td>
<td>(0.467)</td>
<td>(0.576)</td>
</tr>
<tr>
<td>36 Mo. Auto Loan</td>
<td>1.234</td>
<td>1.234</td>
<td>1.234</td>
<td>1.234</td>
<td>1.234</td>
</tr>
<tr>
<td>Moody AA Index</td>
<td>0.030</td>
<td>0.030</td>
<td>0.030</td>
<td>0.030</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>(0.282)</td>
<td>(0.282)</td>
<td>(0.282)</td>
<td>(0.282)</td>
<td>(0.282)</td>
</tr>
<tr>
<td>Moody A Index</td>
<td>0.0396</td>
<td>0.0396</td>
<td>0.0396</td>
<td>0.0396</td>
<td>0.0396</td>
</tr>
<tr>
<td></td>
<td>(0.227)</td>
<td>(0.227)</td>
<td>(0.227)</td>
<td>(0.227)</td>
<td>(0.227)</td>
</tr>
<tr>
<td>Moody BAA Index</td>
<td>-359.2**</td>
<td>-336.3**</td>
<td>-343.3**</td>
<td>-346.6**</td>
<td>-339.0**</td>
</tr>
<tr>
<td></td>
<td>(82.12)</td>
<td>(83.95)</td>
<td>(97.28)</td>
<td>(97.96)</td>
<td>(91.81)</td>
</tr>
<tr>
<td>Constant</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
<td>204</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.086</td>
<td>0.089</td>
<td>0.089</td>
<td>0.089</td>
<td>0.089</td>
</tr>
</tbody>
</table>

Standard errors in parentheses (*** p<0.05, * p<0.10). A note on sample sizes: In the following tables, the sample sizes for the high and low-risk specifications do not sum to the sample size for the full specification which includes all loans. This is because each observation corresponds to a daily average of interest rates for loans issued on that day. For the high and low-risk specifications, this average is only computed using the high and low-risk loans, respectively, that were issued on a given day.

As mentioned earlier, even though a long, 150 day response window probably captures the fullness of the interest rate effect, it may also admit other exogenous information, such as, for example, the Fed’s late November decision to purchase large quantities of mortgage-backed securities. For this reason, I repeat

22It should also be noted that on October 14, Lending Club increased the base rate for A4 and A5 loans by 0.75% and for B1 through G5 loans by 0.5%. The most conservative way to deal with this change in Lending Club’s rate schedule would be to simply subtract 0.5% to 0.75% from the point estimates, giving a +0.75% to +1.0% interest rate effect for safe loans and significantly negative interest rate effects for both risky loans and the full sample. The key is that the signs of the point estimates do not change. Moreover, recall from the hypothesis that \( di/d\sigma \), the slope of the Lending Club rate schedule, should determine the equilibrium. To the extent that this rise in the base rate affected all loan rates within a neighborhood of +0.5% to +0.75%, one might consider this effect a change in the intercept, not the slope, of the Lending Club rate schedule. In this
the event study using a truncated, one month response window. By and large, this second specification supports the results from the baseline study. In particular, if the optimal market rate is again chosen as that providing the highest adjusted $R^2$, then the results indicate net interest rate effects of +0.8% for safe loans, -0.6% for risky loans, and -1.5% for the entire sample. Except for the fact that the risky loan estimate is significant at only 10%, these results reinforce the baseline outcomes. The fact that the estimates are of higher magnitude could mean that the market was still adjusting after one month. Alternatively, it could mean that other news had interfered with loan rates during the interim period, dampening the magnitude of the secondary market’s observed interest rate effect by the end of the five month window. In any case, with reasonable confidence it appears that loan rates rose for low risk loans, fell for high risk loans, and decreased on the whole by 1.3% to 1.5%.

For a full table of results, please email mr532@georgetown.edu.
Before discussing the results of the risk analysis, it helps to recall the different measurements of credit risk. In the first two specifications, I measure credit risk by estimating a loan’s probability of charge-off conditional first on borrower credit and personal characteristics and then, in the second specification, conditional solely on credit background. These probabilities are estimated using a probit model which, all things considered, describes charge-off likelihood relatively well. Specifically, both specifications are significant with $\chi^2$ values of 62.95 for the full model and 41.69 for the partial model.\(^{24}\) The third measurement of credit risk is simply the Lending Club credit grade. As might be expected, there are close links between these three measurements. In fact, one can obtain a simple conversion formula by regressing charge-off probability, as predicted by the full probit model, on the Lending Club grade. This procedure gives the conversion formula $\text{Prob} = 0.081 + 0.006 \times \text{LC grade}$. Using this formula, we can compare results among specifications using the probit measurements and that using the Lending Club grade.

As indicated in Tables 3 through 5, credit risk rose for safe loans and fell for risky loans, leading to a

\(^{24}\)As to the difference between the full and partial models, an $F$-statistic for the joint significance of the personal variables corresponds to a $\chi^2$ of 21.47, indicating that these variables are indeed significant and that their inclusion in the full model is not redundant. For a full summary of the probit models, please email mr532@georgetown.edu
net reduction in risk. In particular, charge-off probabilities fell by around 3% for the full sample. This result is consistent across measurements of credit risk, as the estimated reduction in Lending Club grade converts to a 2.9% fall in charge-off likelihood, which mirrors the results obtained using the full and partial probit measurements. When considering safe and risky loans separately, though, the results prove somewhat less consistent. Specifically, when using Lending Club’s credit grade as the metric, the risk effects were +1.47 units for safe loans and -2.64 units for risky loans, corresponding to a +0.9% and -1.6% change in charge-off probabilities, respectively. On the other hand, the test produced insignificant results for both safe and risky loans when using the full probit model to measure risk. This disparity might reflect lender reliance on the Lending Club grade to gauge risk and make investment decisions, even though this metric is suboptimal relative to the full and partial probit models estimated here. In other words, investors might choose to trust Lending Club’s risk measurements rather than formulating their own models. In this light, credit risk increased among safe loans by around 0.9% and decreased among risky loans by about 1.6%, leading to an aggregate decrease in charge-off probability by 2.9%.

4 Conclusion

Since the introduction of Lending Club’s secondary market for peer-to-peer loans in 2008, peer-to-peer lending has grown exponentially. Loan platforms now operate in a variety of countries, often developing unique business models which, in part, reflect the platform’s legal and economic environment. Lending Club itself has seen impressive growth, averaging 328 new loans per day in 2012 versus only 14 in 2008. At present, peer-to-peer lending still plays a relatively small role in consumer credit markets compared to, say, commercial banks. However the recent, rapid growth in the popularity of peer-to-peer loans suggests that, over the next few years, lending platforms may become increasingly important financial intermediaries. As such, market participants and regulators alike should consider the dynamics which govern borrower and lender decision-making on these platforms. In particular, such dynamics should be understood in light of their potential to cause spillover effects which can shift interest rates in other markets.

This study examined the link between Lending Club’s introduction of a secondary market and interest rates in its primary market. It found that the de novo secondary market came with shifts in risk premiums which lowered the average primary market interest rate by around 1.3%. Correspondingly, risk of loan charge-off fell by around 2.9%. However, these results were not homogenous across risk levels. Namely, risky loans saw reductions in interest rates and risk, whereas safe loans actually experienced increases in both. Intuitively, with the additional liquidity made available by the secondary market, investors with safe portfolios became more willing to engage adverse selection in the peer-to-peer market and shoulder greater risk. On the other hand, investors with risky portfolios were unwilling to do likewise. Yet with increased loan demand stemming from the additional liquidity, this second group of investors faced increased peer competition when purchasing loans. As a result of this competition, they were forced to purchase loans with lower returns and thus lower risk. In this case, lenders with risky portfolios dominated those exposed to little risk, forcing the post secondary market equilibrium to a state with lower interest rates and risk levels than at first.

From a policy perspective, these results should inform a regulatory response to a peer-to-peer platform’s request for establishing a secondary market. Namely, when considering whether to allow a platform to create a secondary market, regulators might factor in the potential for heightened risk levels in the primary market, corresponding to the so-called safe portfolio effect identified in this study. Policymakers should consider the likelihood of such a substitution towards risk, as well as its relative costs or benefits. In general, one might expect a de novo secondary market to reduce primary market interest rates through a fall in the liquidity premium. The case of Lending Club, however, indicates that interest rates may not necessarily behave in this fashion. In fact, risk, rather than liquidity, may play the dominant role in shifting interest rates. True, the presence of Lending Club’s rate-setting mechanism significantly raised the importance of risk in determining the final outcome, and so the results might have — indeed, probably would have — differed in the absence of this mechanism. For instance, the lending platform Prosper has used an auction-based mechanism to determine interest rates, unlike Lending Club’s fixed rate method. This observation sparks a series of questions. Did Prosper’s primary market rates experience any change in response to its de novo secondary

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25 This is computed as \(d(\text{Prob})/d(LC\text{grade}) \times \partial(LC\text{grade})/\partial(\text{PostEvent}) = 0.006 \times -4.864 = -0.029\).
market? Would the results in this study maintain if the secondary market was not introduced during a credit crunch? How would changes in elasticity of loan supply alter the final outcome? Would lending platforms in non-U.S. legal environments experience similar effects in response to a de novo secondary market?

These questions gesture towards further research on peer-to-peer lending platforms and, in particular, secondary trading for peer-to-peer loans. In broader terms, this study also points to further research on the more general topic of de novo secondary markets. Given the current pace of financial innovation, such research will become increasingly relevant, as for each newly developed financial instrument, there exists the potential for sale in an aftermarket. Moreover, such aftermarkets can play important roles in maintaining or threatening financial stability, as evident in the most recent financial crisis. While this study examined secondary market effects within the context of peer-to-peer loans, other studies might place such an analysis in the context of, say, crowdsourcing platforms. Again, while at present these relatively new financial instruments play small roles in the greater financial system, it pays to consider how they might have more substantial impact, for better or worse, at some point in the future.

References


APPENDICES

Carroll Round Proceedings
APPENDIX A:
Twelfth Annual Carroll Round Presentation Schedule

Session 1A
Chair: William Jack (Associate Professor, Georgetown University)

Preston Mui (Georgetown University)
*Household Search and Non Participation*
Discussant: Yi Jie Gwee (London School of Economics)

Yi Jie Gwee (London School of Economics)
*Expansion of Higher Education in the UK: Bane, Boon or Boom?*
Discussant: Stephen McDonald (Georgetown University)

Stephen McDonald (Georgetown University)
*Public Sector Wage Setting and Vacancy Creation: Matching the Business Cycle Facts*
Discussant: Phoebe Kotlikoff (United States Naval Academy)

Phoebe Kotlikoff (United States Naval Academy)
*Estimating the Effects of Pre-College Education on College Performance*
Discussant: Preston Mui (Georgetown University)

Session 1B
Chair: Anna Maria Mayda (Associate Professor, Georgetown University)

Nikola Andreev (American University in Bulgaria)
*Discriminatory European Union Membership: Enlargement Process and Distributional Conflicts*
Discussant: Weiwen Leung (Singapore Management University)

Weiwen Leung (Singapore Management University)
*What Makes a Nobel Prize? The Determinants of National Scientific Research Output and Quality*
Discussant: Ilyas Zhukonov (University of Warwick)

Ilyas Zhukonov (University of Warwick)
*The Effect of EU Enlargement on International Student Mobility*
Discussant: Fabian Trotter (London School of Economics)

Fabian Trotter (London School of Economics)
*Hot and Cold Flushes in Business Cycles - What do Networks have to do with It?*
Discussant: Nikola Andreev (American University in Bulgaria)

Session 2A
Chair: Shareen Joshi (Visiting Assistant Professor, Georgetown University)

Asher Hecht-Bernstein (Columbia University)
*The Effects of China’s Hukou System: Evidence from Population Distributions from 1949-2009*
Discussant: Hannah Hill (Georgetown University)

Hannah Hill (Georgetown University)
*Analysis of East African Farmer Field School Initiative: Which Factors Help Farmers Benefit Most?*
Discussant: Leyla Mocan (Wharton School of Business, University of Pennsylvania)

Leyla Mocan (Wharton School of Business, University of Pennsylvania)
*The Impact of Education on Wages: Analysis of an Education Reform in Turkey*
Discussant: Asher Hecht-Bernstein (Columbia University)

Session 2B
Chair: Charles Udomsaph (Visiting Assistant Professor, Georgetown University)

Edward Hedke (Georgetown University)
*Financial Constraints; Manufacturing Firms in South America*
Discussant: Bayarkhhuu Chinzorigt (American University in Bulgaria)

Bayarkhhuu Chinzorigt (American University in Bulgaria)
APPENDIX A:
Twelfth Annual Carroll Round Presentation Schedule

Modification of The Quantity Theory of Money
Discussant: Michael Lopesciolo (Georgetown University)

Michael Lopesciolo (Georgetown University)
Informal Hiring and Government Effectiveness: Firm-Level Evidence from Brazil
Discussant: Edward Hedke (Georgetown University)

Session 3A
Chair: Anders Olofsgard (Associate Professor, Georgetown University)

Hadi Elzayn (Columbia University)
Integration or Gentrification? Evidence From Chicago
Discussant: Emily Oehlsen (Georgetown University)

Emily Oehlsen (Georgetown University)
Low-wage Work & the Great Recession: Application of the “Institutional Inclusivity” Model
Discussant: Sara Marcus (Dartmouth College)

Sara Marcus (Dartmouth College)
The Impact of Trade Liberalization in Income Inequality: A Cross-Country Analysis
Discussant: Hadi Elzayn (Columbia University)

Session 3B
Chair: Faina Rozental (OECD)

Igors Pasuks & Eduards Sidorovics (Stockholm School of Economics in Riga)
Trade Flows and Real Exchange Rate Volatility in the Baltics: Does it Really Matter for Competitiveness?
Discussant: Nicolas Powidayko (University of Brasilia)

Nicolas Powidayko (University of Brasilia)
Power Purchasing Parity and the Brazilian Exchange Rate: Linear Evidences from Macroeconometric Time Series
Discussant: Alexandra (Sasha) Indarte (Macalester College)

Alexandra (Sasha) Indarte (Macalester College)
Financial and Sovereign Debt Crises in Spain: Fiscal Limits and Spillovers
Discussants: Igors Pasuks & Eduards Sidorovics (Stockholm School of Economics in Riga)

Session 4A
Chair: Arik Levinson (Professor, Georgetown University)

Glenn Russo (Georgetown University)
Bidding Decisions in Pay Per Bid Auctions with a Buy Price Options
Discussant: Rosa Hayes (Wesleyan University)

Rosa Hayes (Wesleyan University)
The Information Content of the Yield Curve: Forecasting Recession and the Effect of Monetary Regime Credibility, and Predicting Recovery After Financial Crises and the Impact of Fiscal and Monetary Policy
Discussant: Albert Chiang (Georgetown University)

Albert Chiang (Georgetown University)
Buying the Hot Hand
Discussant: Glenn Russo (Georgetown University)

Session 4B
Chair: Dan Cao (Assistant Professor, Georgetown University)

Matthew Bailey (University of Warwick)
Asset Bubbles and Post-earnings Announcement Drift in a Anchored Sentiment-regime Dependent Natural Expectations (ASDNE) Framework
Discussant: Mohandass Kalaichelvan (Dartmouth College)
APPENDIX A:
Twelfth Carroll Round Presentation Schedule

Mohandass Kalaichelvan (Dartmouth College) & Shawn Lim (University College London)
A Critical Evaluation of the Significance of Round Numbers in European Equity Markets in Light of the Predictions from Benfords Law
Discussant: Michael Reher (Georgetown University)

Michael Reher (Georgetown University)
Do “De Novo” Secondary Markets Affect Primary Market Interest Rates? A Case Study of Peer-to-Peer Lending
Discussant: Matthew Bailey (University of Warwick)

APPENDIX B:
Past Speakers

First Annual Carroll Round (April 5-7, 2002)
Roger W. Ferguson, Federal Reserve Board of Governors
Donald L. Kohn, Federal Reserve Board of Governors
Lawrence B. Lindsey, Assistant to the President and National Economic Council
Edwin M. Truman, Institute for International Economics
John Williamson, Institute for International Economics

Second Annual Carroll Round (April 11-13, 2003)
R. Glenn Hubbard, Council of Economic Advisers and Columbia University
Donald L. Kohn, Federal Reserve Board of Governors
John Williamson, Institute for International Economics

Third Annual Carroll Round (April 15-18, 2004)
Donald L. Kohn, Federal Reserve Board of Governors
John F. Nash, Jr., Princeton University (1994 Nobel Laureate)
Peter R. Orszag, The Brookings Institution

Fourth Annual Carroll Round (April 22-24, 2005)
Ben S. Bernanke, Federal Reserve Board of Governors
William Easterly, New York University
Maurice Obstfeld, University of California at Berkeley
Edwin M. Truman, Institute for International Economics

Fifth Annual Carroll Round (April 28-30, 2006)
Kemal Dervis, United Nations Development Programme
Thomas C. Schelling, University of Maryland (2005 Nobel Laureate)

Sixth Annual Carroll Round (April 19-22, 2007)
Grant D. Aldonas, Center for Strategic and International Studies
François Bourguignon, Chief Economist and Senior Vice President of the World Bank
Randall Kroszner, Federal Reserve Board of Governors

Seventh Annual Carroll Round (April 17-20, 2008)
Susan C. Athey, Harvard University
Philip I. Levy, American Enterprise Institute
Steven Radelet, Senior Fellow at the Center for Global Development

Eighth Annual Carroll Round (April 16-19, 2009)
Eric S. Maskin, Princeton University (2007 Nobel Laureate)
Nassim Nicholas Taleb, Universa Investments and New York University

Ninth Annual Carroll Round (April 22-25, 2010)
Philip I. Levy, American Enterprise Institute
APPENDIX B:
Past Speakers

Lant Pritchett, Harvard Kennedy School

Tenth Annual Carroll Round (April 14-17, 2011)
Jagdish Bhagwati, Columbia University
Joseph Stiglitz, Columbia University

Eleventh Annual Carroll Round (April 19-22, 2012)
Jonathan Levin, Stanford University
Gene Sperling, Director of the National Economic Council

Twelfth Annual Carroll Round (April 18-21, 2013)
John Taylor, Stanford University
Janet Currie, Princeton University

APPENDIX C:
Former Carroll Round Steering Committees

First Annual Carroll Round
(April 5-7, 2002)
Christopher L. Griffin, chair (SFS ‘02)
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Cullen A. Drescher (COL’04)
Meredith L. Gilbert (COL’04)
Joshua M. Harris (SFS ‘02)
Andrew T. Hayashi (SFS ‘02)
Mark R. Longstreth (SFS ‘04)
Kathryn E. Magee (SFS ‘02)
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J. Brendan Mullen (SFS ‘02)
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Waheed A. Sheikh (SFS ‘04)

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(April 11-13, 2003)
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Maria M. Arhancet (SFS ‘04)
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Michael J. Callen (SFS ‘05)
Eric M. Fischer (SFS ‘03)
Daphney Francois (SFS/GRD ‘04)
Meredith L. Gilbert (COL’04)
Jeffrey M. Harris (COL’03)
Robert S. Katz (COL’04)
Marina Lafferriere (SFS ‘06)
Lu Shi (SFS ‘03)
Stacey H. Tsai (SFS ‘03)
Robert T. Wrobel (SFS ‘03)
Erica C. Yu (COL’05)

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Héber M. Delgado-Medrano (SFS ‘06)
Ryan V. Fraser (SFS ‘04)
Tetyana V. Gaponenko (SFS ‘07)
Yunjung Cindy Jin (SFS ‘05)
Sarah H. Knupp (SFS ‘04)
Robert S. Katz (COL’04)
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Alia F. Malik (SFS ‘04)
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Heber Delgado (SFS ‘06)
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Yasmine Fulena (SFS ’08)
Jen Hardy (SFS ‘06)
Michael Kunkel (SFS ’08)
Yousif Mohammed (SFS ‘06)
Emy Reimao (SFS ‘06)
Tamar Tashjian (SFS ‘06)

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Ian P. Hinsdale (COL’09)
Alexander P. Kostura (SFS ’09)
Jennifer M. Noh (SFS ‘07)
Amy M. Osekowsky (SFS ’07)
Allison E. Phillips (SFS ’07)
Sun Yi (SFS ’07)

Seventh Annual Carroll Round
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Sue Bai (SFS ’08)
Stacey Droms (COL ’08)
Brandon Feldman (COL ’08)
LiJia Gong (SFS ’08)
Kory Katenga (SFS ’10)
Sung Kim (SFS ’08)
Michael Kunkel (SFS ’08)
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Henry T. Gillam (SFS ’10)
Tom J. Han (SFS ’10)
Anna A. Klis (SFS ’10)
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Daniel Y. Lim (SFS ’11)
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Katherine E. Donato (SFS ’10)
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Daniel Y. Lim (SFS ’11)
H. Jess Seok (SFS ’12)
Matthew H. Shapiro (SFS ’11)

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Malin Hu (SFS ’11)
Katrina Koser (SFS ’12)
Nancy Lee (SFS ’11)
Doug Proctor (SFS ’12)
Vivek Sampathkumar (SFS ’11)
Monica Scheid (SFS ’11)
Matthew Shapiro (SFS ’11)

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Doug Proctor (SFS ‘12)
Glenn Russo (COL ‘13)
H. Jess Seok (SFS ‘12)
Anusuya Sivaram (SFS ‘12)
Meredith Strike (SFS ‘14)
Shuo Yan Tan (SFS ‘12)

Twelfth Annual Carroll Round
(April 18-21, 2013)
Glenn Russo, chair (COL ‘13)
Albert Chiang (SFS ‘13)
Meredith Strike (SFS ‘14)
Natalie Nah (SFS ‘15)
Brian Goggin (SFS ‘14)
Heather Hedges (SFS ‘14)
Dawn Chan (SFS ‘14)
Edward Hedke (SFS ‘13)
Elena Malik (SFS ‘14)
Stephen McDonald (SFS ‘13)
Emily Oehlsen (SFS ‘13)

APPENDIX D:
Members of the Advisory Panel

Meredith L. Ballotta, The Chartis Group
Christopher L. Griffin, College of William and Mary
Andrew T. Hayashi, University of Virginia
Mitch Kaneda, Georgetown University
Robert S. Katz, Stanford University
J. Brendan Mullen, American College of Cardiology
Scott E. Pedowitz, Corporate Executive Board
Erica C. Yu, Bureau of Labor Statistics
APPENDIX E:
Past Participants

First Annual Carroll Round (April 5-7, 2002)

<table>
<thead>
<tr>
<th>Name</th>
<th>University</th>
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</thead>
<tbody>
<tr>
<td>Azhar Adbul-Quader</td>
<td>Columbia University</td>
</tr>
<tr>
<td>Santosh Anagol</td>
<td>Stanford University</td>
</tr>
<tr>
<td>William Brady</td>
<td>Georgetown University</td>
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<tr>
<td>Daniel Braun</td>
<td>Oberlin College</td>
</tr>
<tr>
<td>Jacqueline Bueso</td>
<td>University of Pennsylvania</td>
</tr>
<tr>
<td>Karla Campbell</td>
<td>University of Virginia</td>
</tr>
<tr>
<td>Benn Eifert</td>
<td>Stanford University</td>
</tr>
<tr>
<td>Courtney Fretz</td>
<td>University of Pennsylvania</td>
</tr>
<tr>
<td>Carlos Galvez</td>
<td>Stanford University</td>
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<tr>
<td>Aniruddha Gopalakrishnan</td>
<td>Duke University</td>
</tr>
<tr>
<td>Christopher Griffin</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Casey Hanson</td>
<td>Lehigh University</td>
</tr>
<tr>
<td>Joshua Harris</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Andrew Hayashi</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Marco Hernandez</td>
<td>Massachusetts Institute of Technology</td>
</tr>
<tr>
<td>Katia Hristova</td>
<td>Illinois Wesleyan University</td>
</tr>
<tr>
<td>Maria Jelescu</td>
<td>Massachusetts Institute of Technology</td>
</tr>
<tr>
<td>Fadi Kanaan</td>
<td>Yale University</td>
</tr>
<tr>
<td>Avinash Kaza</td>
<td>Stanford University</td>
</tr>
<tr>
<td>Vinay Kumar</td>
<td>Duke University</td>
</tr>
<tr>
<td>Anisha Madan</td>
<td>Illinois Wesleyan University</td>
</tr>
<tr>
<td>Kathryn Magee</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Ryan Michaels</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Jack Moore</td>
<td>Stanford University</td>
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<tr>
<td>Brendan Mullen</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Andrei Muresianu</td>
<td>Brown University</td>
</tr>
<tr>
<td>Scott Orleck</td>
<td>Duke University</td>
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<tr>
<td>Scott Pedowitz</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Jonathan Prin</td>
<td>University of Pennsylvania</td>
</tr>
<tr>
<td>Jeremy Sandford</td>
<td>Illinois Wesleyan University</td>
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<tr>
<td>Deborah Slezak</td>
<td>Illinois Wesleyan University</td>
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<tr>
<td>Conan Wong</td>
<td>Brown University</td>
</tr>
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</table>

Second Annual Carroll Round (April 11-13, 2003)

<table>
<thead>
<tr>
<th>Name</th>
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</thead>
<tbody>
<tr>
<td>Nada Abdelnour</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Amanda Barnett</td>
<td>Emory University</td>
</tr>
<tr>
<td>Andrea Bell</td>
<td>Wellesley College</td>
</tr>
<tr>
<td>Patrick Byrne</td>
<td>University of Colorado</td>
</tr>
<tr>
<td>David Chao</td>
<td>Cornell University</td>
</tr>
<tr>
<td>Sylvia Ciesluk</td>
<td>Lehigh University</td>
</tr>
<tr>
<td>Adam Doverspike</td>
<td>Georgetown University</td>
</tr>
</tbody>
</table>
APPENDIX E:
Past Participants

Benn Eifert
Adam Engberg
Alexandra Fiorillo
Eric Fischer
Zlata Hajro
Samina Jain
Avinash Kaza
Eric Kim
Seth Kundrot
Lada Kyi
Lee Lockwood
Sunil Mulani
Holly Presley
Duncan Roberts
Lu Shi
Shanaz Taber
Jiang Wei
Stanford University
Georgetown University
Connecticut College
Georgetown University
Wellesley College
Georgetown University
Stanford University
The George Washington University
Georgetown University
Rice University
Northwestern University
New York University
Vanderbilt University
University of California at Berkeley
Georgetown University
Barnard College
University of Michigan

Third Annual Carroll Round (April 15-18, 2004)

Jeffrey Arnold
Julia Berazneva
Mehmet Cangul
Richard Carew
Ashley Coleman
Dilyana Dimova
Fernando Galeana
M. Blair Garvey
Meredith Gilbert
Adam Greeney
Asim Gunduz
Marc Hafstead
Andrew Hayashi
Katherine Howitt
Sohini Kar
Josh Lewis
Satish Lohani
Alexis Manning
Sara Menker
Elizabeth Mielke
Stratos Pahis
Alicja Pluta
Adam Raymakers
Caroline Schmutte
Dartmouth College
Mt. Holyoke College
Georgetown University
University of Virginia
Vanderbilt University
Stanford University
Stanford University
Emory University
Georgetown University
Oberlin College
University of Virginia
Northwestern University
University of California at Berkeley
McGill University
Columbia University
McGill University
Illinois-Wesleyan University
Illinois-Wesleyan University
Mt. Holyoke College
Vanderbilt University
Dartmouth College
Georgetown University
Dalhousie University
Dartmouth College
APPENDIX E:  
Past Participants

Matt Sekerke  
Johns Hopkins University
John Soleanico  
Columbia University
Kai Szakmary  
Columbia University
Brandon Wall  
Yale University
Kenneth Ward  
University of Chicago
Susan Work  
Georgetown University

Fourth Annual Carroll Round (April 22-24, 2005)

Lidia Barabash  
Dartmouth College
Jasmina Beganovic  
Georgetown University
Xun Bian  
Illinois-Wesleyan University
Michael Furchtgott  
Columbia University
Michael Gechter  
Pomona College
Kevin B. Goldstein  
Dartmouth College
Michael Haase  
University of Copenhagen
Dennis Huggins  
Georgetown University
Michael Insel  
Claremont McKenna College
Jonathan Kirschner  
Georgetown University
Shiying Lee  
Duke University
James Liao  
Dartmouth College
Brian Lichter  
Washington University
Wee Lee Loh  
Cornell University
Alice Luo  
Duke University
Katharine Mullock  
University of Western Ontario
Jose Mustre del Rio  
The Ohio State University
Leah Nelson  
Georgetown University
Ee Cheng Ong  
Wellesley College
Matthew Phan  
Columbia University
Nina Rendelstein  
Washington University
David Rogier  
Washington University
Ana Maria Romero  
Illinois-Wesleyan University
Nathan Saperia  
Dartmouth College
Bogdan Tereshchenko  
Georgetown University
Olga Timoshenko  
University of Western Ontario
Tom Vogl  
Princeton University
Kenneth Ward  
University of Chicago
Jonathan Wolfson  
Washington University
Suzanne Zurkiya  
Emory University

Fifth Annual Carroll Round (April 28-30, 2006)

Sarah Carroll  
Stanford University
Ruth Coffman  
Georgetown University
APPENDIX E:
Past Participants

Dubravka Colic  
Wellesley College

Pratik Dattani  
University of Warwick

Jennifer Dawson  
Illinois-Wesleyan University

Héber Delgado-Medrano  
Georgetown University

Sherri Haas  
Illinois-Wesleyan University

Jen Hardy  
Georgetown University

Lauren Iacocca  
University of California at Los Angeles

Salifou Issoufou  
University of Wisconsin at Madison

Stella Klemperer  
Brown University

Daniel Kurland  
Dartmouth College

Corinne Low  
Duke University

Shanthi Manian  
Georgetown University

Michael Monteleone  
University of Chicago

John Nesbitt  
Georgetown University

Natasha Nguyen  
University of California at Berkeley

Oyebanke Oneyinka  
Carleton College

Evgeniya Petrova  
Dartmouth College

Emy Reimao  
Georgetown University

Svetoslav Roussanov  
Columbia University

Vikram Shankar  
Georgetown University

Juan Carlos Suarez  
Trinity University

Austin Vedder  
Dartmouth College

David Wiczer  
Carleton College

Geoffrey Yu  
Carleton College

Xiaoti Zhang  
University of Warwick

Sixth Annual Carroll Round (April 19-22, 2007)

Matthew Adler  
Oberlin College

Marion Aouad  
Princeton University

Stephen Brinkmann  
Georgetown University

Erik Eggum  
University of Warwick

Lucia Franzese  
Georgetown University

Tanja Groth  
University of St. Andrews

Ashley Halpin  
Dartmouth College

Nicholas Hartman  
Georgetown University

Adrienna Huffman  
Washington University

Abdulla Humaidan  
University of Warwick

Mohammad Huq  
Georgetown University

Nedko Kyuchukov  
Dartmouth College

Zachary Mahone  
New York University

R. Priya Mathew  
Washington University

Yana Morgulis  
University of Chicago

Jennifer Noh  
Georgetown University
APPENDIX E:
Past Participants

Andrew O'Brien Penney  Georgetown University
Jessica Oliveri  Monash University
Matthew Pech  Dartmouth College
Allison Phillips  Georgetown University
Angelica da Rocha  University of Warwick
Sören Radde  University of Bayreuth
Heleri Rande  New York University
Elena Spatoulas  University of Michigan
Yi Sun  Georgetown University
Bennett Surajat  Carleton College
Freddy Tsai  University of British Columbia
David Wolff  Dartmouth College
Jennifer Xi  Dartmouth College
Cynthia Yim  Princeton University

Seventh Annual Carroll Round (April 17-20, 2008)

Karl Andres  University of Warwick
Cecil Ang  University of Virginia
Alaina Antonucci  The Pennsylvania State University
Sue Bai  Georgetown University
Marinella Boyadzhiev  Oberlin College
Quentin Brummet  Illinois-Wesleyan University
Brendan Cooper  Carleton College
Gerard DiPippo  Dartmouth College
Stacey Droms  Georgetown University
Varun Dutt  Macalaster College
Yasmine Fulena  Georgetown University
Amish Gandhi  University of Warwick
Katherine Gordon  Mt. Holyoke College
Yi Kang  Wesleyan College
Michael Kunkel  Georgetown University
Han Youp Lee  Georgetown University
Claudio LoCascio  Dartmouth College
Olivia Lynch  Georgetown University
Amr Moubarak  The George Washington University
Simone Nitsch  University of Warwick
Saurabh Pant  New York University
Carson Sherwood  University of Western Ontario
Tadashi Shirai  University of Warwick
Dominique Shure  Georgetown University
William Slater  Vanderbilt University
Shyam Sundaram  Brown University
Poh Lin Tan  Princeton University
Dorothy Voorhees  Georgetown University
Kris Walsh  Georgetown University
APPENDIX E:
Past Participants

Monica Yu
Dartmouth College

Eighth Annual Carroll Round (April 16-19, 2009)

Jennifer Cairns
Calvin College
David Childers
Georgetown University
Vaska Dimitrova
American University in Bulgaria
Rebecca Freeman
Smith College
Georg Graetz
London School of Economics and Political Science
Markus Gstoettner
London School of Economics and Political Science
Arpit Gupta
University of Chicago
Frederick Haney
New York University
Rebecca Heide
Georgetown University
Gregory Howard
The University of North Carolina at Chapel Hill
Jacqueline Iwata
The George Washington University
Anders Jensen
London School of Economics and Political Science
William Kafoure
The George Washington University
Elira Kuka
Wellesley College
Daniel Leonard
Georgetown University
Chris Lim
Dartmouth College
Juan Ignacio Elorrieta Maira
University of Chile
Nick Marchio
Macalester College
Hekuran Neziri
American University in Bulgaria
Casey Oswald
Georgetown University
Arjun Pant
Georgetown University
Caitlin Pierce
Dartmouth College
Isra Salim
Macalester College
Keval Sangani
University of Warwick
Pronita Saxena
University of California, Berkeley
Benjamin Simmons
Georgetown University
Maximilian Sirianni
Macalester College
Seitaro Takarabe
Wesleyan University
Fabien Thayamballi
Georgetown University
Rachel Winograd
Dartmouth College
Woan Foong Wong
Oberlin College
Anders Jensen
London School of Economics and Political Science
William Kafoure
The George Washington University
Elira Kuka
Wellesley College
Daniel Leonard
Georgetown University
Chris Lim
Dartmouth College
Juan Ignacio Elorrieta Maira
University of Chile
Nick Marchio
Macalester College
Hekuran Neziri
American University in Bulgaria
Casey Oswald
Georgetown University

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### APPENDIX E: Past Participants

<table>
<thead>
<tr>
<th>Name</th>
<th>Institution</th>
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<tbody>
<tr>
<td>Arjun Pant</td>
<td>Georgetown University</td>
</tr>
<tr>
<td>Caitlin Pierce</td>
<td>Dartmouth College</td>
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<tr>
<td>Isra Salim</td>
<td>Macalester College</td>
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<td>Keval Sangani</td>
<td>University of Warwick</td>
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<td>Pronita Saxena</td>
<td>University of California, Berkeley</td>
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<td>Benjamin Simmons</td>
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<td>Maximilian Sirianni</td>
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<td>Rachel Winograd</td>
<td>Dartmouth College</td>
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<td>Woan Foong Wong</td>
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#### Ninth Annual Carroll Round (April 22-25, 2010)

<table>
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<tr>
<th>Name</th>
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<tbody>
<tr>
<td>Jorge Aponte</td>
<td>Georgetown University</td>
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<tr>
<td>Benjamin Arnold</td>
<td>University of Michigan</td>
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<td>Courtney Blair</td>
<td>Harvard University</td>
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<td>Vera Chau</td>
<td>New York University</td>
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<td>Nick Chantraporn</td>
<td>University of San Francisco</td>
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<tr>
<td>Antonina Davydenko</td>
<td>American University in Bulgaria</td>
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<td>Katherine Donato</td>
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<tr>
<td>Yang Du</td>
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<tr>
<td>Siddharth George</td>
<td>London School of Economics and Political Science</td>
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<tr>
<td>Takuma Habu</td>
<td>University of Warwick</td>
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<tr>
<td>Kelsey Hample</td>
<td>Illinois Wesleyan University</td>
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<tr>
<td>Tom Han</td>
<td>Georgetown University</td>
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<tr>
<td>Rob Harris</td>
<td>University of Warwick</td>
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<tr>
<td>Sarah Hinkfuss</td>
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<td>Peter Hull</td>
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<td>Michael Karno</td>
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<td>Todd Kawakita</td>
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<td>Anna Klis</td>
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<td>Birgit Leimer</td>
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<td>University of Warwick</td>
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<td>In Un Flora Ng</td>
<td>Dartmouth College</td>
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<td>Katherine Ng</td>
<td>University of San Francisco</td>
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<tr>
<td>Hang Qian</td>
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<tr>
<td>Paul Unanue</td>
<td>Princeton University</td>
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<tr>
<td>Ahmad Wahdat</td>
<td>Oberlin College</td>
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<tr>
<td>Ariell Zimran</td>
<td>Georgetown University</td>
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</tbody>
</table>

#### Tenth Annual Carroll Round (April 14-17, 2011)
APPENDIX E:
Past Participants

Dimitri Avramov  
American University in Bulgaria
Daniel Boada  
Harvard College
Gustavo Camilo  
New York University
Daniel Chan  
United States Naval Academy
Meryl Ching  
University of Warwick
Kimberly Conlon  
University of Minnesota
Tess DeLean  
Wellesley College
Max Gelb  
Dartmouth College
Ben Guttman-Kenney  
University of Warwick
Malin Hu  
Georgetown University
Kilian Huber  
London School of Economics and Political Science
Tomas Jagelka  
Dartmouth College
Shorena Kalanadarishvili  
Smith College
Hideto Koizumi  
Soka University of America
Krisjanis Krustins  
Stockholm School of Economics in Riga
Benjamin Langworthy  
Macalester College
Nancy Lee  
Georgetown University
Daniel Lim  
Georgetown University
Van Nguyen  
Washington and Lee University
Nikita Orlov  
University of Warwick
Anselm Rink  
London School of Economics and Political Science
Vivek Sampathkumar  
Georgetown University
Monica Scheid  
Georgetown University
Markus Schwedeler  
Maastricht University
Matthew Shapiro  
Georgetown University
Zane Silina  
Stockholm School of Economics in Riga
Anusuya Sivaram  
Georgetown University
David Thomas  
University of Oxford
Maximilian JC Thormann  
London School of Economics and Political Science

Eleventh Annual Carroll Round (April 19-22, 2012)

Madara Bogdāne  
Stockholm School of Economics at Riga
Paul Byatta  
Harvard College
Nikhil Dugal  
New York University
Vladimir Epuri  
American University in Bulgaria
Samuel Evans  
University of Warwick
Evan Friedman  
Brown University
Fabian Gunzinger  
University of Bern
Taras Ignashchenko  
Lancaster University
Katrina Koser  
Georgetown University
Nhaca Le  
Georgetown University
Wanyi Li  
Macalester College
Elitsa Nacheva  
American University in Bulgaria
Anastasija Oleinika  
Stockholm School of Economics at Riga
Carlo Pizzinelli  
Dartmouth College
Thomas Preston  
University of Warwick

APPENDIX E:  
Past Participants

Doug Proctor  
Georgetown University
Julian Richers  
Columbia University
Christopher Roth  
University of Warwick
Andrea Ruiz  
George Washington University
Kaivan Sattar  
New York University
Mark Schmidt  
Georgetown University
H. Jess Seok  
Georgetown University
Kenichi Shimizu  
Soka University of America
Anusuya Sivaram  
Georgetown University
Shuo Yan Tan  
Georgetown University
Anna Weber  
Georgetown University
Edie Wu  
Dartmouth College
Qianyi Yang  
Macalester College

Twelfth Annual Carroll Round (April 18-21, 2013)

Nikola Andreev  
American University in Bulgaria
Matthew Bailey  
University of Warwick
Albert Chiang  
Georgetown University
Bayarkhuu Chinzorigt  
American University in Bulgaria
Hadi Elzayn  
Columbia University
Yi Jie Gwee  
London School of Economics
Rosa Hayes  
Wesleyan University
Asher Hecht-Bernstein  
Columbia University
Edward Hedke  
Georgetown University
Hannah Hill  
Georgetown University
Sasha Indarte  
Macalaster College
Mohandass Kalaichelvan  
Dartmouth University
Phoebe Kotlikoff  
United States Naval Academy
Weiwen Leung  
Singapore Management University
Shawn Lim  
University College London
Michael Lopesciolo  
Georgetown University
Sara Marcus  
Dartmouth University
Stephen McDonlad  
Georgetown University
Leyla Mocan  
University of Pennsylvania
Preston Mui  
Georgetown University
Emily Oehlsen  
Georgetown University
Igors Pasuks  
Stockholm School of Economics in Riga
Nicolas Powidayko  
University of Brasilia
Michael Reher  
Georgetown University
Glenn Russo  
Georgetown University
Eduards Sidorovics  
Stockholm School of Economics in Riga
Fabian Trottner  
London School of Economics
Ilyas Zhukelenov  
University of Warwick