THE ASSOCIATION BETWEEN REPORTED DISABILITY RATES AND SOCIAL SECURITY DISABILITY INSURANCE IN HIGH AND LOW UNEMPLOYMENT RATE COUNTIES

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ABSTRACT

The Social Security Disability Insurance Program (SSDI) is designed to insure workers against the threat of severe disabling conditions that prevent them from working. While one would expect that advances in medical treatment and improving overall health would lead to a decline in individuals receiving SSDI, the opposite is true. SSDI rolls have been steadily increasing since 1980. Hence, researchers and policymakers worry that the program has become a long-term uninsurance program that permanently removes individuals from the labor force who might have sought employment in its absence. Using county-year panel data, this study employs a fixed effects specification to test the sensitivity of SSDI receipt rates to reported disability rates and whether the relationship is different depending on high or low unemployment. The analysis shows a statistically significant, positive, yet small correlation between SSDI receipt and reported disabilities in counties with high unemployment compared to counties with low unemployment. These findings largely support the body of research that has connected increases in SSDI receipt during periods of economic recession and suggests that more research is needed into programmatic changes targeted for marginal applicants and beneficiaries.
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INTRODUCTION

While aggregate health in the United States has improved significantly in recent decades, the number of disabled workers receiving benefits from the Social Security Disability Insurance (SSDI) program has increased threefold since 1980, from 2.9 million to 8.9 million in 2013\textsuperscript{1,2}. Despite a general trend away from physically demanding and dangerous work, advances in medical treatments and rehabilitation options, and the passage of the Americans with Disabilities Act-all of which would be expected to lower the number of disabled individuals unable to work-this has not been the case (Autor & Duggan, 2006). Instead, the caseloads continue to rise. Population growth, the aging of the baby boom generation, and increased participation of women in the labor force account for some of this growth, but not all (Pattison & Waldron, 2013). While older workers make up the predominant share of individuals receiving SSDI, the biggest growth in new beneficiaries is among younger workers. Between 1982 and 1992, the share of male beneficiaries age 30-44 grew 75 percent and has remained high.

The decline in the age of new beneficiaries, combined with changes in allowable non-fatal conditions in 1984 has resulted in younger people receiving benefits and staying on the program longer. Without substantive changes to program eligibility, benefits, or financing for the program, the Disability Insurance (DI) trust fund reserves will be depleted in fiscal year 2016 (Social Security and


\textsuperscript{2} Social Security Administration. http://www.ssa.gov/policy/docs/quickfacts/stat_snapshot/
Medicare Board of Trustees, 2013). As a result, researchers have sought to understand the underlying determinants for the increase in the disability rolls and to develop principles for reform.

One explanation for the changing recipient profile is the possibility that workers with disabilities are turning to SSDI during times when they might otherwise seek employment. Observers worry that the design of the program may provide a perverse incentive to do this. Recent research suggests that workers may be exiting the labor force to seek disability insurance during times of economic hardship (Autor & Duggan, 2006; von Wachter, Song & Manchester, 2011). A significant positive correlation has been identified between application rates for SSDI and the unemployment rate (Figure 1). This suggests that in the absence of a robust job market, individuals with some level of disability, who might otherwise seek employment, apply for benefits instead. The trend is particularly strong among low-skilled, low-income workers (von Wachter, Song & Manchester). This group of workers is disproportionately impacted by negative shocks to the economy and the income replacement rate is more generous for low-income workers than higher-income workers, suggesting a greater incentive to leave the labor force during times of economic recession (von Wachter, Song & Manchester). This has fueled concerns that SSDI has become a de facto welfare program; serving more as a “long-term unemployment insurance program for the unemployable” and resulting in a permanent exit from the labor force of potentially millions of individuals who would seek employment in its absence (Autor & Duggan, 2006). Particular focus has been
paid to SSDI during the Great Recession, when the national unemployment rate peaked at 10 percent in October of 2009\(^3\). Researchers and policymakers are seeking to reform the program to maintain its solvency and to preserve its original intent of supporting workers whom have become permanently and totally disabled.

Figure 1: SSDI Applications per 1,000 Adults and U.S. Unemployment Rate, Ages 25-64, 1970-2002

Source: Social Security Administration

One issue that is surprisingly absent from the literature exploring the relationship between economic shifts and SSDI receipt is the extent of disability in the population. The Social Security Administration reports that nearly thirty million individuals- or 1 out of every 6 working age Americans- have a disability (Center for American Progress, 2013). In 2013, SSDI paid out benefits to 8.9 million disabled

\(^3\) Bureau of Labor Statistics. 
workers (SSA Board of Trustees, 2013). As receipt of SSDI is contingent on possessing a severe disability, one would expect that rising rates of SSDI allowances would be the result of a corresponding increase in the rate of disabling conditions.

The present study seeks to understand the relationship between reported rates of disability and the receipt rate of SSDI. To accomplish this, data drawn primarily from the American Community Survey and supplemented by data from the Bureau of Labor Statistics and the Social Security Administration are used to estimate the association of reported disabilities on the SSDI receipt rates for low and high unemployment counties. Using a fixed effects model and controlling for demographic, economic and social factors expected to be associated with both disability rates and the rate of receipt of SSDI, the estimates are allowed to vary for high and low unemployment counties.

If the results of this analysis reveal that economic factors do not play a role in the application and receipt of SSDI, then we would expect a positive trend between disability rates and SSDI receipt irrespective of the strength of the labor market. If economic factors do play a role in the decision to seek benefits, however, we would expect the relationship between disability and SSDI receipt to be different depending on whether the economy is strong or weak. While a number of studies have examined the association between economic conditions and SSDI application rates, few have provided estimates for SSDI receipt and economic recession and no recent papers have explored the relationship of reported disability prevalence and
SSDI receipt in areas of high and low unemployment. The results of this study will provide important insight into this relationship and will contribute to the dialogue on the growth of SSDI.

The rest of this paper is organized as follows: First, I will provide an explanation of the SSDI program and relevant changes in recent decades while discussing related background literature. I then explain the data and methodology used for this study, followed by a presentation and discussion of the results. I conclude with a discussion about the implications of my findings as it contributes to the existing body of research and areas for future exploration.
BACKGROUND

The Social Security Disability Insurance Program insures workers against the threat of income loss due to a disability. In 2013, about 90% of workers aged 21-64 were covered by SSDI, defined as individuals who contribute to social security taxes in their working years\(^4\). To be eligible for benefits, an individual must have worked for at least 5 out of the previous 10 years. In addition, an individual must have a medically determinable physical or mental illness that prevents them from engaging in “substantial gainful activity”\(^5\), defined in 2013 as being unable to earn $1,040 a month (Center for American Progress, 2013).

The SSDI program began in 1956 to insure workers aged 50-65 possessing a disability that was of indefinite duration or expected to result in death (Lindner & Burdick, 2013). In the following three decades, the narrow scope of SSDI was expanded significantly. In 1960, workers under the age of 50 were included as eligible beneficiaries and, in 1965; the definition of disability was relaxed to mean any disabling conditions expected to last for at least 12 months. In 1973, Medicare eligibility was extended to DI beneficiaries after 24 months of disability, increasing both the attractiveness of applying for benefits and the federal outlays for the program. In 2005, DI beneficiaries made up 15.4% of all Medicare recipients and $15.1B of Medicare expenditures (Autor & Duggan, 2006).

Liberalization of Screening Process

The most significant changes to the DI program, however, occurred in 1984, when Congress changed the disability screening process (Autor & Duggan, 2006). Prior to 1984, disability was determined by a verifiable, objective medical condition or impairment. While these listed impairments are still primary determinants for eligibility, Congress instructed the Social Security Administration (SSA) to consider an applicant’s reported pain and discomfort, as well as mental illness, in the determination process. Additionally, individuals who reported multiple nonsevere impairments could be considered disabled, even if none of the specific ailments on their own would constitute a disability (Autor & Duggan, 2006). The 1984 regulations also provided for the applicant’s health care provider to play a significant role in the determination of disability, whereas SSA’s internal medical examination had historically carried the most weight. While it could be argued that an individual’s physician possesses the fullest picture of an individual’s history and condition, some have suggested that local physicians are more subjective in their recommendations and are more likely to make a determination of disability if they view the applicant’s employment potential as weak (Autor & Duggan, 2006; Black, Daniel & Sanders, 2002). These changes resulted in a dramatic shift away from awards based solely on objective medical factors. In the years prior to the 1984 reforms, 82% of awards relied exclusively on medical factors; in 2000, this number had plunged to 40% of awards (Autor & Duggan, 2006).
The shift away from objective medical factors to more subjective physical and mental impairments that are harder to classify, combined with the added emphasis on the consideration of an applicant’s ability to function in a job setting, has meant an increased reliance on subjective criteria and the likelihood that economic swings in the labor force will impact applications and receipt of SSDI (Autor & Duggan, 2003, 2006; Rupp, 1995; von Wachter, Song & Manchester, 2011).

Disability Determination Process

The disability determination process for applicants is a five-stage procedure. The first stage rejects applicants with too high earnings, while applicants with no severe impairment are rejected in stage 2 (Lindner & Burdick, 2013). Applicants with a condition that is listed as a specifically allowed medical impairment are awarded at stage 3. For applicants with a health condition that is not explicitly listed, their capacity to engage in past relevant work is evaluated by a caseworker in stage 4 (Lindner & Burdick). If it is determined that the individual cannot perform past work, their residual work capacity is evaluated in stage 5. Rejected applicants at any stage can appeal the decision and request reconsideration (Autor & Duggan, 2006; Lindner & Burdick, 2013). While only a small share of initial appeals is awarded benefits upon reconsideration, applicants can further appeal the decision to an administrative law judge, where the majority of denials are reversed (60% in 2005) (Lindner & Burdick).
LITERATURE REVIEW

SSDI Applications and Economic Conditions

The present study examines the receipt of SSDI and not applications to the program, however, the determination process has been used in past studies to identify connections with economic trends and so it is useful to highlight here. Rupp (2012) found a positive correlation between applications and awards and economic recessions, although the association was stronger for applications. Rupp suggests this likely demonstrates that the determination process is successful in screening out marginal applications. Lindner and Burdick (2013) found that both rejections and allowances of applications during stages 2, 4 and 5 are positively correlated with high unemployment, pointing to a rise in “conditional applicants” for whom applying for SSDI is more attractive than trying to find a job. The number of applications that were determined at stage 3, however, was largely unchanged as a result of changes in the business cycle, suggesting that those with disabilities listed as a qualifying medical condition are not influenced by economic conditions (Lindner & Burdick). Using data from the Disability Research File, the researchers employ a state and time fixed effects model to explore the relationship between the unemployment rate and applicant characteristics. Their results suggest that individuals with moderate disabilities apply at increased rates when the

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6 Autor and Duggan coined this term in their 2003 study, defining “conditional applicants” as those individuals possessing a health impairment that may qualify them for DI but who would not apply for benefits as long as they are employed.
unemployment rate is high and that conditional applicants account for almost all of the increased applications during economic recessions (Lindner & Burdick).

Autor and Duggan (2006) point out that the 1984 “liberalization” of the screening process has resulted in employment factors being a consideration in 4 out of the five stages. They posit that these changes in the screening process have resulted not only in an increased share in the total DI application pool consisting of conditional applicants, but also in an increased proportion of allowed beneficiaries (Autor & Duggan). In contrast with other research attributing the majority of DI growth to demographic factors, Autor and Duggan claim that aging and health are relatively minor considerations in the growth of SSDI when compared to changes in the screening process and the rise in the income replacement rate. It is the policy changes, they say, that explain growth; not an increase in the incidence of disabling illness (Autor & Duggan).

Contributing to the argument that economic conditions are increasingly a factor in SSDI applications, Autor and Duggan demonstrate in their 2003 study that DI application rates among less educated and lower-income workers are more elastic during times of economic recession. Using state level data from the Current Population Survey and SSA administrative data, their findings suggest that the deterioration of the labor market for low-skilled workers, combined with the increased progressivity of SSDI benefits, have lowered the opportunity cost for
otherwise work-capable individuals with medical impairments to seek SSDI instead of trying to find employment (Autor & Duggan, 2003).

Much of the research on disability insurance and labor market conditions has built on the work of John Bound’s 1989 paper on the health and earnings of rejected disability applicants. To examine the claim that SSDI has large disincentive effects on working, Bound reviewed data on rejected applicants to explore what he considers the upper bound of labor force participation that could be expected of beneficiaries (Bound, 1989)⁷. While his findings that less than half of DI beneficiaries would work in its absence have been questioned in more recent research, his methodology of studying the characteristics of rejected applicants has been replicated or built upon in numerous studies (see von Wachter, Song & Manchester, 2011; Autor & Duggan 2003, 2006).

Von Wachter, Song and Manchester (2011) demonstrated that rejected applicants have characteristics that are statistically significantly different from allowed beneficiaries. Following Bound’s (1989) methodology, the study found that rejected applicants have a weak attachment to the labor market and are more likely to be nonwhite, low-skilled and have lower mortality rates than the majority of beneficiaries (von Wachter, Song & Manchester). While Bound's research was limited to men aged 45-64, von Wachter, Song and Manchester extended their analysis to include male applicants 30-44, citing the increasing proportion of

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⁷ Bound used data from the 1972 Survey of Disabled and Non-Disabled Adults and the 1978 Survey of Disability and Work, conducted by the U.S. Census Bureau for the Social Security Administration
younger individuals applying for benefits since Bound’s original paper. In 2007, this younger cohort made up 30% of new beneficiaries and more than half of rejected applicants (von Wachter, Song & Manchester). Replicating Bound’s analysis, they found similar results for older men in terms of labor force attachment; however, their findings for younger men suggest that those applications on the margin would likely have sought employment in the absence of the program (von Wachter, Song & Manchester). The rising share of younger individuals applying for and receiving DI is cause for concern in light of these findings. Von Wachter, Song and Manchester report additional evidence that is consistent with the concept that an increasing proportion of applicants are motivated by economic factors, including a decline in average earnings of new beneficiaries over non-applicants and declines in employment rates of rejected applicants.

**Labor Market Changes**

The U.S. economy has experienced a persistent decline in labor force participation since 2000 (Aaronson, Fallick, Figura, Pingle & Wascher, 2006). Following four decades of a general increasing trend in labor force participation rates, Stephanie Aaronson and her team used state level data to analyze what they call the “nearly unprecedented” decline in labor force participation after a peak in the first quarter of 2000 (Aaronson et al., 2006). The labor force participation rate is defined as the percentage of non-institutionalized working-age individuals who are working or actively looking for work (Bureau of Labor Statistics). Unemployed individuals are captured by the labor force participation rate, while discouraged
workers, those who have exited the labor force and given up looking for work, are not. The labor force participation rate can provide insight into the availability of job opportunities and the unemployment rate provides a more immediate proxy for the robustness of the economy; both are useful in the discussion about SSDI receipt in relation to economic conditions. The results reported by Aaronson et al. (2006) find a role for both cyclical (business cycle fluctuations) and structural factors (policy changes, demographics) as likely contributors to the decline in labor force participation. The authors also cite other studies with similar findings. For instance, a study by Chinhui Juhn documented that the decline in real wages for low-skilled workers explained nearly the entire decline in the labor force participation for low skilled men in the 1970s and 80s (Juhn 1992). Also relevant to the present analysis, Aaronson et al. (2006) credit the increased generosity of SSDI benefits as a partial explanation for rising SSDI receipt rates, given that reported work-limiting disabilities have been stable. Taken together, the evidence suggests that there is an increase in the proportion of disabled individuals receiving benefits, not an increase in the proportion of work-limiting disabilities (Aaronson et al, 2006).

In a number of studies examining economic conditions and the possible impact on SSDI receipt, manufacturing is used as a proxy for economic restructuring during recessions (Rupp, 1995; von Wachter, Song & Manchester, 2011). Examining the impact on specific sectors during periods of high unemployment can provide insight into potential long-term shifts and the association of increased applications to SSDI. Black, Daniel and Sanders (2002) found that permanent job creation or
destruction is more significantly correlated with growth in SSDI than temporary economic shocks. The researchers describe the high opportunity costs associated with applying for benefits, including the loss of income during the application process as a result of eligibility requirements, and the long and sometimes challenging process until a disability determination is reached as a disincentive for disabled individuals who may be able to find work (Black, Daniel & Sanders, 2002). Black, Daniel and Sanders (2002) used the change in value of coal reserves to instrument for county earnings in states highly dependent on the coal industry and found a strong and statistically significant impact on earnings and SSDI payments. Their analysis predicted that a 10 percent decrease in earnings in the county was associated with a 3.6 percent increase in SSDI receipt (Black, Daniel & Sanders). While caution is warranted with respect to whether these results can be generalized to other regions, the researchers employed the same methodology using the steel industry in the largest steel-producing states as an instrument and their results were quite similar to estimates from the coal-producing regions (Black, Daniel & Sanders).

**Demographic changes**

Research is conflicting on the magnitude of the role demographic changes have played in the growth of the disability rolls, but they are undeniably a factor. The aging of the baby boom generation into age groups that are more disability-prone and the increased participation of women in the labor force have changed the composition of the working-age population since the program’s inception (Pattison
In a recent 2013 study, David Pattison and Hilary Waldron examined demographic factors in the years 1970-2008 and found that population growth, the aging of the population, and female labor force participation accounted for 90% of the increase in the disability incidence rate- the number of exposed workers becoming newly entitled to benefits in any given year (Pattison & Waldron, 2013). Pattison and Waldron identify three factors as the determinants of new disability entitlements: the number of individuals in the working-age population; the proportion of those workers who are disability-insured, and; the proportion of disability-insured workers who become entitled (i.e. seek out and begin receiving SSDI benefits). It is this third factor that is of primary interest to this study. Those who become entitled are those who are either newly disabled or those for whom their disability becomes work limiting.

They draw a sharp contrast with Autor and Duggan’s work, which focused on disability prevalence, measured by the number of exposed workers receiving disability in any given year, which accounts for both movement on to the disability rolls and exits from the program (Autor & Duggan, 2003). Pattison and Waldron (2013) only examined, therefore, new awards and do not look at length of stay. Both are important determinants to overall caseload growth and program cost (Rupp, 1995).

Pattison and Waldron’s (2013) method is useful to tell a story about long-term program growth over the 38-year period of the study, but the age / sex
adjustment is expected to be less of an influence in the present study, which uses data from 2005 to 2012. Female labor force participation, while increasing dramatically from 45.2% in 1965 to 75.3% in 2005\(^8\), has leveled off and is not anticipated to significantly affect the SSDI prevalence rates in this current data set. On the other hand, the present study examines a period of time where baby boomers are entering the most disability-prone age cohorts. The leading edge of baby boomers will be 59 years old at the beginning of the study and 66 at its finish, while the youngest boomers are 41 in 2005 and 48 in 2012 (U.S. Census Bureau). As more boomers move into at-risk age cohorts, disability incidence can be expected to grow as a share of the insured, working-age population. While Pattison and Waldron (2013) acknowledge that economic factors and unemployment rates are likely to affect the incidence rate, they choose to leave out data from the beginning of the recession to avoid the large effects and concentrate their focus on long-term trends. In contrast, this study examines a shorter period of time, beginning with the period directly before the recession and terminating in 2012 with the most recently available data.

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\(^8\) These figures represent female labor force participation during “prime earning years”, ages 25-54. Total labor force participation of females aged 16 and older was 40% in 1966 and 60% in 2008 (Pattison & Waldron, 2013)
CONCEPTUAL FRAMEWORK

I hypothesize that county-level SSDI is positively correlated with county disability rates and that the relationship will be stronger in counties with high unemployment versus low unemployment. As noted in the literature review section, economic factors, such as labor market opportunities and income replacement rates, play a role in the opportunity costs concerning any individuals decision to pursue SSDI benefits or not. Demographic factors, such as age, sex, and skill level, and social factors, such as marital status, also clearly impact rates of participation in SSDI. My model accounts for the economic, demographic and social characteristics of counties, which are diagrammed in Figure 2.

Economic Characteristics

Participation in SSDI is correlated with economic conditions. A robust economy, with low unemployment and diverse job market opportunities, is more likely to keep individuals on the margins in the labor force (Autor & Duggan, 2006). In contrast, declining labor force participation, high unemployment, and the disappearance of formerly robust employment sectors, like construction and manufacturing, likely draw those individuals with disabilities out of the labor force (Black, Daniel & Sanders, 2002; Aaronson et al., 2006; Rupp, 2012). Consistent with existing literature, my model includes control variables for the construction and manufacturing sector.
Income will also play a role in decisions to apply for SSDI. The benefit formula for SSDI is progressive, meaning that lower income individuals will see more of their pre-DI income replaced than higher-income individuals (Autor & Duggan, 2006). The generosity of benefits may induce some low-income individuals with disabilities to exit the labor force and apply for SSDI. Income level is also associated with skill and education level of individuals. Low-income individuals are more likely to be low skilled and less educated. Worsening economic conditions disproportionately impact this subset of workers and therefore it is likely that low-income workers would exit the labor force at higher rates than other workers in a weak economy (Aaronson et al., 2006).

**Demographic Composition**

As noted in the literature review section, the aging of the baby boom and the increase in female labor force participation has contributed to the overall growth of SSDI participation and expenditures (Pattison & Waldron, 2013). Older individuals are more likely to be disabled; they also make up the largest share of SSDI recipients. The aging of the baby boom generation means that increasingly large numbers of people are entering disability-prone age cohorts. Female labor force participation has leveled off in the past decade after several decades of significant increases (Autor & Duggan, 2006). Men, however, still participate in the labor force at higher rates than women, and are therefore more likely than women to be insured against the threat of disability.
Health status can be viewed as an important indicator for the prevalence of disability. Individuals in consistently poor health and those who experience a decline in health are more likely to apply for SSDI than individuals who report being in good health (Bound 1999). While health is undeniably correlated with the prevalence of disability, finding a simple, accurate measure of health is difficult. This study uses county level obesity rates as a proxy for health.

Social Characteristics

Marital Status

If an individual is married, they are more likely to have economic stability in the event of a disability and may therefore apply for SSDI at lower rates than single disabled individuals. Households that contain more than one individual of working age have more flexibility in responding to both labor market shocks and the onset of medical impairments. Marital status, while not a perfect measure of every household with two working age adults, is plausibly correlated with receipt of SSDI and is included in the model.

Educational Attainment

Individuals who are less educated are more likely to earn lower wages and are most at risk of losing a job in a weak economy (Aaronson, 2006). Additionally, individuals with lower levels of education are more likely to work in physically demanding jobs, increasing their risk of developing musculoskeletal conditions and experiencing pain that may limit their capacity to continue to work. Therefore, I
expect educational attainment to be correlated both with unemployment rates and disability rates.

An important advantage of using county level fixed effects is that it controls for changes that occur at the national level, such as disability program rules and policy implications that influence counties similarly, as well as accounting for permanent differences across counties.

**Figure 2. Conceptual Framework of Factors that Affect Receipt of SSDI**

- **Social Factors:**
  - Marital Status
  - Educational Attainment

- **Demographic Factors:**
  - Age
  - Sex
  - Race
  - Health
  - Disability

- **Economic Factors:**
  - **Unemployment Rate**
  - Labor Force Participation
  - Income
  - Employment Sector
  - Poverty
DATA & METHODS

Data

This study combines county level data for all 50 states and the District of Columbia from several sources including the Bureau of Labor Statistics, the Social Security Administration, the Centers for Disease Control and the National County Health Rankings and Roadmap. The majority of variables, however, were obtained from the American Community Survey (ACS) 3-year estimates.

American Community Survey

The ACS is conducted by the U.S. Census Bureau to gather timely information about small geographic areas (i.e., census tracts and block groups) and small population groups. It uses a series of monthly samples (300,000 households) to produce annually updated data that are used as supplements to the decennial census. Data from the ACS is a frequently used tool for policy analysts as a result of the depth and breadth of the information about households it collects and the ACS’ rigorous design and methodology\(^9\).

\(^9\) ACS non-response rate averages 4.6%, an exceedingly low rate for the size and scope of the survey. To improve the non-response rate, ACS employs three data collection methods; mail response, telephone interview and personal interview. See https://www.census.gov/people/disability/files/2008ACS_disability.pdf for more information on sampling and survey non-response.
Monthly data are compiled into 1-year, 3-year and 5-year estimates\textsuperscript{10}. Among these estimates, the 3-year series are the most suitable for the present study. The 1-year estimates are not available for all counties, only those with populations larger than 65,000\textsuperscript{11}. It would have been untenable to restrict the study sample in that way, as it would result in a loss of information about three-quarters of the country, including all information about rural counties. While the 5-year estimates are available for all counties, a tradeoff occurs because data smoothing techniques are used for these estimates, which results in a loss of information. The ACS 3-year estimates are available for over 1800 counties consisting of 20,000 inhabitants or more.

The observation period for this study begins in 2005, when the ACS was fully implemented, and extends to 2012, the year for which the most recent data is available\textsuperscript{12}. A change to disability questions in 2008 modified the availability of 3-year estimates for the disability measure\textsuperscript{13}. Therefore, the years included in this sample are the 3-year estimates for 2005-2007, 2008-2010 and 2009-2011\textsuperscript{14}.

\textsuperscript{10} U.S. Census Bureau. American Community Survey Design and Methodology. \url{https://www.census.gov/acs/www/Downloads/survey_methodology/acs_design_methodology.pdf}
\textsuperscript{11} Census Bureau does produce internal statistics including all counties, however the sampling that occurs in smaller counties results in standard errors that make statistical analysis on the one-year data difficult. Therefore, Census only publishes one-year data for counties with a large enough population to result in standard errors that make the coefficients meaningful. The 3-year estimates are therefore the result of 36 months of continuous sampling, resulting in meaningful data analysis for counties with 20,000 or more; the 5-year estimates are 60 months of ongoing sampling so that even the smallest counties will contain statistically meaningful data. See ACS Design & Methodology Section for more detailed explanation of how the survey is constructed and administered: \url{https://www.census.gov/acs/www/methodology/methodology_main/}
\textsuperscript{12} The Social Security Administration publishes annual data in June of the following year
\textsuperscript{13} Census Bureau changed the questions related to disability on the 2008 ACS, yielding a general downward effect on the estimates of disability prevalence compared to previous estimates. Census bureau does not combine data sets that include pre- and post- 2008 disability data. Further detail on
Comparability of Variables Across Data Sources

Given that some variables in the study were created using annual data from sources other than the ACS, it was necessary to make some adjustments to achieve comparability. Specifically, data collected from the Bureau of Labor Statistics and the Social Security Administration were transformed into 3-year moving averages and matched with the estimates of reported disability and control estimates from the 2007, 2010, and 2011 ACS data sets.

Dependent Variable

The dependent variable is the county level SSDI caseload, measured as the percentage of the civilian non-institutionalized working-age population receiving SSDI benefits. Annual program enrollment figures were obtained from the Social Security Administration OASDI county level data for the years 2005 through 2012. I use annual values for approximately 1,800 counties in the United States, including the District of Columbia. The SSDI percentage is calculated by dividing the number of disabled workers receiving SSDI by the total county population.

Key Explanatory Variable

The key explanatory variable is the number of persons with self-reported disabling conditions as a share of the county civilian non-institutionalized population. These estimates were obtained from the ACS. As noted earlier, the

the changes to the measurement of disability can be found here:  

14 Years are coded as 2007, 2010 and 2011
wording of the disability questions in the ACS changed on the 2008 survey. The Census Bureau does not recommend combining data from before and after the 2008 change, therefore, the estimates were normalized in order to retain the 2007 data set in the analysis\textsuperscript{15}.

\textit{Control Variables}

The study employs control variables from two domains: economic and demographic. The economic measure is primarily the county unemployment rate gathered from the Bureau of Labor Statistics (BLS); a dummy variable for high unemployment rate, where the value 1 indicates unemployment rates exceeding 10\%. The BLS publishes unemployment rates on a monthly basis and compiles annual county-level data for multiple measures of economic conditions\textsuperscript{16}.

The poverty rate is also used as an economic control. It is measured as the percentage of the county population with individual or family incomes below the poverty level. Poverty status is determined by comparing total income received in the previous 12 months to the adjusted poverty thresholds set by the Census Bureau for that year (U.S. Census Bureau, 2012). These data are gathered from the ACS. Two measures of the local labor market were also drawn from the ACS. The size of the construction sector is measured as the percentage of the county population that is

\textsuperscript{15} The raw disability data was made into a multiple of the national rate, or normalized, so that data from 2007 3-year estimate and data from 2010 and 2011 3-year estimates could be interpreted in the same way.

employed in the construction sector. The size of the manufacturing sector is similarly constructed. The ACS is also the source of the final economic control variable, a continuous variable that captures the percentage of the county population that earns less than $25,000 in income per year.

There are eight demographic control variables drawn from the ACS for each county: percent male, percent black, percent Hispanic, percent elderly (ages 65 and older), percent ages 55-64, percent of the population aged 25 and older without a high school diploma, percent of the population aged 25 or older with a high school diploma, as highest level of educational attainment; and percent of households with a married couple. The final demographic variable is percent obese. The Centers for Disease Control (CDC) defines obesity in adults as Body Mass Index greater to or equal to 30 (CDC, 2013). For years 2010 and 2011, these estimates were obtained from the County Health Rankings and Roadmaps data set, which is the result of collaboration between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute\textsuperscript{17}. The County Health Rankings data are based on obesity rates from the National Diabetes Surveillance System at the Centers for Disease Control. Obesity rates were not available through the County Health Rankings and Roadmaps for 2007, so data for that year was obtained from the Centers for Disease Control\textsuperscript{18}. Obesity rates for years 2010-2012 were obtained

\textsuperscript{17}http://www.countyhealthrankings.org/ranking-methods
\textsuperscript{18}Obesity rates at CDC were available from 2002-2009, resulting in two incomplete measures of obesity for the time span of the present study. The estimates were standardized ($z$-scores) to reduce the potential of inaccuracies resulting from using data from two separate datasets, although inaccuracies should be minimized as both originated from CDC.
from the County Health Rankings and Roadmaps. See footnote (19) for an explanation of how the two data sets were compiled.

Unlike the disability questions used in the ACS, there were no changes in the way any of the control variables were measured. As a result, 3-year estimates for 2007 were not available for controls, but 3-year estimates for each year from 2008-2012 were available. Footnote (20) describes how this incongruence in the overlapping datasets was addressed\(^{19}\).

**Methods**

I estimate the following model, with the county-year as the unit of analysis:

\[
\text{SSDI}_{it} = \beta_0 + \beta_1 \text{Disability}_{it} + \beta_2 \text{UnemploymentRate}_{it} + \beta_3 \text{Disability} \times \text{UnemploymentRate}_{it} + \beta_4 \text{Poverty}_{it} + \beta_5 \text{Income25K}_{it} + \beta_6 \text{Male}_{it} + \beta_7 \text{Elderly}_{it} + \beta_8 \text{Black}_{it} + \beta_9 \text{Hispanic}_{it} + \beta_{10} \text{Obese}_{it} + \beta_{11} \text{Construction}_{it} + \beta_{12} \text{Manufacture}_{it} + \beta_{13} \text{NoHSgrad}_{it} + \beta_{14} \text{HSgrad}_{it} + \beta_{15} \text{Age5564}_{it} + \alpha_{it} + \mu_{it},
\]

Where \( i \) represents the county index, \( t \) is the year index, \( \alpha \) represents time-invariant characteristics, and \( \mu_{it} \) is the error term.

\(^{19}\) Missing data in 2007 for control variables was imputed using data from ACS 3-year estimates from 2008-2012. Variables were individually graphed to identify whether the imputed estimate should be representative of a trend or the mean.
The key independent variable, reported disability rates, and the control variables were lagged by one year in order to avoid reverse causality\textsuperscript{20}. There is precedent for lagged variables in the SSDI research (Rupp, 1995; Bound, 1999). As a result of the disability determination process, which can take several years if an appeal is involved, we may not expect to see a corresponding increase in SSDI until a year or two following an increase in reported disabilities. Similarly, the projected effect of an economic downturn may not result in a corresponding spike in SSDI applications and awards until one or two years later.

\textsuperscript{20} Including SSDI receipt and the percentage of adults who report having a disability in the model pose a threat to reverse causality. To remove this risk, the SSDI variable was lagged by one year, so that any correlation between SSDI receipt is a result of the x variables from the previous year. This also makes sense when considering that the process for applying for and receiving SSDI can take some time, with the average decision taking 6 months and the appeals process taking one or more years. To avoid this reverse causality, the 2005-2007 moving 3-year averages are matched with the 2006-2008 SSDI receipt data, and so on.
DESCRIPTIVE STATISTICS

Table 2 provides descriptive statistics for the dependent, key independent and control variables that are included in the regression analyses. The descriptive statistics illustrate substantial variation in key variables, including county level receipt of SSDI, the disability rate, and the unemployment rate. The average rate for SSDI receipt in a county contained in my sample, measured as the percentage of the civilian, non-institutionalized adult population receiving benefits, is 5.1 percent; the county within the sample with the smallest percentage of SSDI recipients is 0.39 percent and the highest is 16.73 percent. Reported disability rates were even more varied, with the average percentage of the sample population reporting at least one disabling condition being 12.90 percent and ranging from a low of 3.0 percent to a high of 39.6 percent.
RESULTS

The results of my fixed effects analyses are summarized in Table 3. Columns (1), (2), and (3) show results of the OLS regressions that do not contain county and year fixed effects, while columns (4) and (5) illustrate the results of the fixed effects analyses with and without the inclusion of the control variables. The full model of controls with fixed effects is shown in column (5).

For all of these regressions, I estimated robust standard errors to avoid issues with heteroskedasticity. The coefficient for the key independent variable indicates the change in SSDI receipt in the county that is associated with a one percentage point increase in the disability rate in the county, holding constant all other control variables in the model.

The key coefficients in Table 3 for the reported disability rates at the county level indicate a positive, statistically significant relationship between reported disability and receipt of SSDI, when estimated without fixed effects. When control variables and an interaction term for high and low unemployment counties are added in model (3), the key coefficient is still statistically significant at the one percent level, although the magnitude decreases by almost half. When the model is estimated with county and year fixed effects, however, the coefficients for reported disability rates are negative, but quite small in magnitude. The full model in column (5), for instance, which utilizes fixed effects and contains all control variables, shows
a statistically significant coefficient of -0.02 at the 1 percent level. This coefficient indicates that a one percentage point increase in the reported disability rate in the county is associated with a -0.02 decrease in the receipt of SSDI the following year, in low unemployment counties, holding constant county and year fixed effects and the control variables in the model. The coefficient on the interaction term in the full model is 0.04 and is statistically significant at the one percent level, indicating that the relationship between receipt of SSDI and disability rates varies depending on whether the county has high or low unemployment. The full model illustrates that the association between reported disability and SSDI receipt is more positive in counties with high unemployment compared to counties with low unemployment, holding constant county and year fixed effects and the control variables included in the model.

The estimated relationship between a one percentage point change in disability rates and corresponding changes in SSDI appears to be quite small, but the relationship seems to be associated with unemployment rates. The descriptive statistics in Table 2 illustrate that the average disability rate at the county level is 12.9 percent with a standard deviation of 4.36 percentage points. A one percentage point increase in receipt of SSDI, therefore, is a moderate change. Given that the average SSDI rate of receipt is 5.1 percent with a standard deviation of 2.04 percentage points, a -0.02 percent decrease in low unemployment counties and a 0.02 percent increase in SSDI in high unemployment counties are very small shifts in SSDI participation.
DISCUSSION

My empirical analysis confirms the hypothesis that the relationship between SSDI receipt and disabilities is stronger when unemployment is high. Put another way, when county level unemployment rates are high, an increase in the county level disability rates is more closely associated with an increase in the receipt of Disability Insurance. My regression results confirm this hypothesis, although the magnitude is small. A one percentage point increase in the one-year lagged county-level disability rates is associated with a 0.02 percent increase in SSDI receipt in high unemployment counties. While the magnitude of this response is small, it is more than twice as large as the predicted relationship between SSDI receipt and disability rates in low unemployment counties. This suggests that economic conditions play a role in the decision of disabled individuals to seek Disability Insurance.

Of interest, simply regressing SSDI receipt on the one-year lagged disability rates demonstrates a positive significant relationship, where a one percentage point change in disability rates in the previous year is associated with a 0.35 percent change in receipt of SSDI. Without accounting for any control variables, this simple regression would suggest that every three individuals reporting a disability in the county is associated with one new individual receiving SSDI. It is not unsurprising that receipt of SSDI and reported disability are correlated; indeed I expected to find a strong relationship because of the inherent connection between Disability
Insurance and disability. What is surprising is the dramatic drop in magnitude when accounting for unemployment rate, income, education level, age, gender, race, and health, among others. The full model, accounting for all controls and county and time fixed effects, reports a relationship between disability and receipt of SSDI that is much smaller. Even in high unemployment counties, where previous literature has asserted that labor market opportunities provide incentive to apply, the association is weak. This suggests that disability rates explain only a small amount of the variation in the rate of receipt of SSDI. This underscores the fact that Disability Insurance- and the factors contributing to the prevalence of beneficiaries- is complex and varied.

An additional reason that the relationship between disability and SSDI receipt may not be as strong in this empirical analysis is the loss of data due to data smoothing. Monthly estimates were condensed into a single estimate for a three-year period in order to match with estimates from the American Community Survey. This trade-off was made in order for smaller counties to be included in the analysis, but it resulted in a loss of data and loss of sensitivity to small changes year over year. Future research might expand on this study and choose instead to use the ACS one-year estimates. That analysis, which would be limited necessarily to urban counties, would be an interesting comparison to the present study.

The results from this analysis are consistent with previous literature that suggests an economic influence for the pursuit of SSDI. The present study
contributes to this discussion by including the relationship of disability rates and SSDI in high and low unemployment counties, which is absent in previous research. While prior studies have not necessarily divorced disability rates from SSDI in the context of their research, this paper explicitly explores the impact of economic conditions on the rate of SSDI, in the context of the relationship between disability rates and SSDI receipt rates. The empirical analysis performed in this paper supports the hypothesis that disabled individuals are more likely to seek out SSDI benefits when economic conditions are poor.

One conclusion others have drawn from similar results connecting economic conditions and SSDI applications and allowances is to claim that those who seek benefits are not truly disabled. Applying this concept of malingering—that individuals who respond to economic incentives must not actually be disabled—deserves caution. Black, Daniel and Sanders (2002) warn that the responsiveness to economic shocks cannot inform us about the proportion of individuals who may be gaming the system. Instead, these results can inform us about the proportion of individuals who are on the margins, which provides insight into the proportion of individuals applying for and receiving SSDI who would work if they had the opportunity. People with work-limiting disabilities may be most at risk of losing jobs when the economy turns sour. Additionally, SSDI applicants during times of economic recession are predominantly low-income, less educated, and people of color, which coincides with cohorts of individuals most likely to be impacted by economic downturn (von Wachter, Song & Manchester, 2011). A temporary
program that provides assistance to re-enter the labor market is likely to best serve conditional applicants.

CONCLUSION

This empirical analysis is consistent with previous literature that indicates an association between economic conditions and SSDI. The present study contributes to the existing body of work by examining the relationship between disability rates and SSDI in response to economic conditions. My results suggest that people with disabilities are twice as likely to seek out SSDI benefits when economic conditions are poor, although caution is warranted in this interpretation due to the magnitude of the estimates. If this is the case, this research can inform the discussion on the determinants of growth in the SSDI program. Those who are economically motivated to apply for benefits may be those who are most likely to benefit from a different kind of program. While they possess work-limiting disabilities, they are more likely to want to work if employment opportunities are available.

As policymakers work to address the impending SSDI trust fund exhaustion in 2016, difficult discussions will take place about benefits and eligibility. The present study suggests caution should be employed in interpreting rising SSDI receipt rates in economic downturns.
### Table 1: Variable Descriptions

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable</strong></td>
<td></td>
</tr>
<tr>
<td><strong>SSDI</strong></td>
<td>This continuous variable measures disabled workers receiving SSDI in the county as a percentage of the county population. These estimates are obtained from the Social Security Administration's OASDI County estimates</td>
</tr>
<tr>
<td><strong>Independent Variable of Interest</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Disabled</strong></td>
<td>This continuous variable measures the percentage of the county civilian non-institutionalized population that reports have some form of a disabling condition. These estimates are obtained from the ACS.</td>
</tr>
<tr>
<td><strong>Economic Characteristics</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Unemploymentrate</strong></td>
<td>This continuous variable measures the unemployment rate in the county. These data are gathered from the Bureau of Labor Statistics (BLS).</td>
</tr>
<tr>
<td><strong>HiUR</strong></td>
<td>This dichotomous variable indicates whether or not the unemployment rate in a county exceeds 10%. These data are obtained from the BLS.</td>
</tr>
<tr>
<td><strong>Poverty</strong></td>
<td>This continuous variable measures the percentage of the county population with individual or family incomes below the poverty level. The Census Bureau determines poverty status by comparing total income received in previous 12 months to adjusted poverty thresholds for that time period (U.S. Census Bureau, 2012). These data are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>Construction</strong></td>
<td>This continuous variable measures the percentage of the county population that is employed in the construction sector. These estimates are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>Manufacture</strong></td>
<td>This continuous variable measures the percentage of the county population that is employed in the manufacturing sector. These estimates are obtained from the ACS.</td>
</tr>
<tr>
<td>Variable</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>Income25K</strong></td>
<td>This continuous variable measures the percentage of the county population that earns less than $25,000 in income per year. These data are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>Male</strong></td>
<td>This dichotomous variable indicates the percentage of the county that is male. These data is obtained from the ACS.</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td>This continuous variable measures the percentage of the county that is African American or Black and non-Hispanic. These data are obtained from the ACS.</td>
</tr>
<tr>
<td><strong>Hispanic</strong></td>
<td>This continuous variable measures the percentage of the county that is Hispanic. These estimates are obtained from the ACS.</td>
</tr>
<tr>
<td><strong>Elderly</strong></td>
<td>This continuous variable measures the percentage of the county population that is age 65 and older. These data are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>Age5564</strong></td>
<td>This continuous variable measures the percentage of the county population that is between the ages of 55 and 64. These estimates are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>NoHSgrad</strong></td>
<td>This continuous variable measures the percentage of the county population aged 25 and older without a high school diploma. These data are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>HSgrad</strong></td>
<td>This continuous variable measures the percentage of the county population aged 25 and older whose highest level of education is a high school degree. These data are gathered from the ACS.</td>
</tr>
<tr>
<td><strong>Married</strong></td>
<td>This continuous variable measures the percentage of county households that contain a married couple. These estimates are obtained from the ACS.</td>
</tr>
<tr>
<td><strong>Obese</strong></td>
<td>This continuous variable measures the percentage of the county population that is obese. The Centers for Disease Control (CDC) defines obesity in adults as Body Mass Index greater to or equal to 30 (CDC 2013). For years 2010 and 2011, these estimates are obtained from the County Health Rankings and Roadmaps data set. For 2007, the data is gathered from the CDC. See footnote ## for an explanation of how the two data sets were compiled.</td>
</tr>
</tbody>
</table>
Table 2. Descriptive Statistics for Dependent, Key Independent and Control Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of Population receiving SSDI in the County</td>
<td>5.10</td>
<td>0.39</td>
<td>16.73</td>
<td>2.04</td>
</tr>
<tr>
<td>Percentage of the County that is Disabled</td>
<td>12.90</td>
<td>3.00</td>
<td>39.60</td>
<td>4.36</td>
</tr>
</tbody>
</table>

**Economic Characteristics**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>County Unemployment Rate</td>
<td>7.44</td>
<td>1.77</td>
<td>29.17</td>
<td>2.85</td>
</tr>
<tr>
<td>Percentage of County that is Employed in Construction Sector</td>
<td>7.62</td>
<td>0</td>
<td>26.50</td>
<td>2.60</td>
</tr>
<tr>
<td>Percentage of County that is Employed in Manufacturing Sector</td>
<td>13.09</td>
<td>0</td>
<td>52.30</td>
<td>6.92</td>
</tr>
<tr>
<td>Percentage of County that earns less than $25,000 in Income Per Year</td>
<td>26.35</td>
<td>4.90</td>
<td>53.80</td>
<td>7.65</td>
</tr>
<tr>
<td>Poverty Rate</td>
<td>13.7</td>
<td>0.40</td>
<td>48.40</td>
<td>5.62</td>
</tr>
</tbody>
</table>

**Demographic Characteristics**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of County Population that is Male</td>
<td>49.52</td>
<td>43.8</td>
<td>67</td>
<td>1.55</td>
</tr>
<tr>
<td>Percentage of County Population that is Black, non-Hispanic</td>
<td>9.23</td>
<td>0</td>
<td>81.6</td>
<td>12.6</td>
</tr>
<tr>
<td>Percentage of County Population that is Hispanic</td>
<td>8.58</td>
<td>0</td>
<td>95.6</td>
<td>12.22</td>
</tr>
<tr>
<td>Percentage of County Population that is Elderly</td>
<td>14.02</td>
<td>4.6</td>
<td>43.9</td>
<td>3.58</td>
</tr>
<tr>
<td>Percentage of County Population that is Between Ages of 55 and 64</td>
<td>11.83</td>
<td>4</td>
<td>21.4</td>
<td>1.97</td>
</tr>
<tr>
<td>Percentage of County Population without a High School Degree</td>
<td>15.17</td>
<td>2.4</td>
<td>48.5</td>
<td>6.31</td>
</tr>
<tr>
<td>Percentage of County Population with a High School Degree, but not more</td>
<td>33.52</td>
<td>9.2</td>
<td>56.8</td>
<td>7.21</td>
</tr>
<tr>
<td>Percentage of County Households with Married Couple</td>
<td>52.01</td>
<td>23.7</td>
<td>95.3</td>
<td>6.73</td>
</tr>
<tr>
<td>Percentage of County Population that is Obese</td>
<td>28</td>
<td>11.7</td>
<td>42.7</td>
<td>3.58</td>
</tr>
</tbody>
</table>

N = 4732
Table 3. Estimated Coefficients for Models Predicting Number of SSDI Recipients

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<tr>
<td>County and Year Fixed Effects</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
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<tr>
<td><strong>Key Independent Variable</strong></td>
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<td></td>
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<tr>
<td>Disability</td>
<td>0.352***</td>
<td>0.325***</td>
<td>0.183***</td>
<td>-0.018***</td>
<td>-0.017***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.003)</td>
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<tr>
<td>Economic Variables</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High Unemployment</td>
<td>-0.010</td>
<td>0.933***</td>
<td>-0.387***</td>
<td>-0.615***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.210)</td>
<td>(0.265)</td>
<td>(0.050)</td>
<td>(0.089)</td>
<td></td>
</tr>
<tr>
<td>Disability* High Unemployment</td>
<td>0.090***</td>
<td>0.062***</td>
<td>0.046***</td>
<td>0.035***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.012)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
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<tr>
<td>Unemployment Rate</td>
<td>0.225***</td>
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<td></td>
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<tr>
<td></td>
<td>(0.009)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty Rate</td>
<td>-0.044***</td>
<td>-0.008***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Construction</td>
<td>-0.031***</td>
<td></td>
<td>0.012***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
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<tr>
<td>Manufacture</td>
<td>-0.015***</td>
<td>-0.020***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income &lt; $25K</td>
<td>0.081***</td>
<td>0.010***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
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<tr>
<td>Demographic Variables</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>-0.049***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>-0.003*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.031***</td>
<td>-0.064***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elderly</td>
<td>0.026***</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age 55-64</td>
<td>0.206***</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>
</tr>
<tr>
<td>No High School Diploma</td>
<td>0.065***</td>
<td></td>
<td>-0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High School Diploma</td>
<td>0.005</td>
<td></td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.569***</td>
<td>0.689***</td>
<td>-1.698***</td>
<td>4.756***</td>
<td>0.688</td>
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<tr>
<td></td>
<td>(0.062)</td>
<td>(0.063)</td>
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<td>R-squared</td>
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<td>0.624</td>
<td>0.806</td>
<td>0.833</td>
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<td>F-Statistic and p-value of Joint Hypothesis</td>
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<td>Disability and</td>
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<td>High Unemployment*Disability</td>
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<td>65.30***</td>
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</table>
Robust standard errors are given in parentheses under coefficients and p-values are given in parentheses under F-Statistics

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


U.S. Census Bureau, “American Community Survey: Design & Methodology”. Issued April 2009.  