THE GENDER WAGE GAP: HOW PAID FAMILY LEAVE AFFECTS WOMEN OF CHILDBEARING AGE

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By

Flannery Jane Geoghegan, B.A.

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Thesis Advisory: Stipica Mudrazija, Ph.D.

ABSTRACT

This paper investigates the effects of paid family leave on the gender wage gap for women of childbearing age. The historical background of the matter in the United States and abroad, along with prior research provide context for the importance of the family-focused policy analysis. Using a difference-in-difference-in-difference model, and in line with previous results, parental leave for women in treatment states increases their future earnings, as compared to men, only slightly. The results of the study indicate increases in wages due to paid family leave programming, while gender, race and occupation variables have negative impacts. Based on the findings, suggestions on ways to better target the gender wage disparity, either directly through a federal paid leave program and female labor force compensation or indirectly by addressing paternal leave taking patterns and improving educational outcomes are included in the study.
The research and writing of this thesis is dedicated to my family and those who helped me during my time at Georgetown University.

Many thanks,
Flannery Jane Geoghegan
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Introduction

April 10, 2018, represents Equal Pay Day in the United States; in 2017, it was April 4; in 2016, it was April 12; and in 2015, it was April 14. The dates symbolize how far into the next year the average women must work to earn what men earned in the previous year. The exact date of Equal Pay Day differs both by year and country, and for women of color the date usually occurs much later into the next year.

In 1869, a letter to the editor of the *New York Times* challenged the disconnect between the idea that men and women are equals and the practical application of this very sentiment. “Very few persons deny the justice of the principle that equal work should command equal pay without regard to the sex of the laborer. But it is one thing to acknowledge the right of a principle and quite another to practice it” (NYT 1869). The letter writer found the U.S. government guilty of this hypocrisy, noting that women employed by the Treasury Department made half as much as their male coworkers. Seeing the error in their ways, the House of Representatives overwhelmingly passed a resolution to ensure equal pay to government employees. Unfortunately, the scope was narrowed to only include new employees by the time of its passage in the Senate in 1870; enforcement of the bill was virtually non-existent.

Fast-forward to 2016, the US Census Bureau reported that of all white women working full-time they were typically paid just 80 percent of what men were paid, a gap of 20 percent (Semega et al. 2017) or about $10,500. This issue is not unique to American women, though. Data published in 2017 saw the United Kingdom (U.K.)’s gender pay gap go from 19.7 percent in 2014 to 20.8 percent the next year, the most dramatic yearly change among the largest
economies in Europe (Khan 2017). A one percent change may not seem like a lot by itself, but one percent of a missing paycheck would not go unnoticed for most people; especially when added up over a lifetime of work.

The third largest gap in Europe belongs to Germany the world’s fourth largest economy at 22 percent. The country has the widest divide among Europe’s big economies (which include the U.K., France, and Italy). Germany also concluded its gender pay equity had worsened in 2015, as had the gap in France; and despite some of the lowest unemployment rates in the past 40 years, rising gender employment parity is doing little to shrink pay discrepancies (Khan 2017).

Policy studies have been performed around the world on how the gender pay gap impacts individuals’ income and country-wide economic stability, as well as its causes. One area that researchers have returned to time and time again is the availability of employer-provided Paid Family Leave (PFL) programs. PFL is said to assist businesses with employee retention and labor force attachment, increase flexible working hours, and cut overhead cost management through creative program design and thoughtful financing structures. On a societal level, paid family leave may help shift the narrative around traditional gender roles and encourage fathers to take more time at home and an equitable approach to childrearing responsibilities.

Despite growing access to PFL programs, the gender pay gap and heteronormative standards for woman and man, both at work and at home, continue to exist. Notwithstanding significant changes in women’s labor force behavior, American culture continues to dictate that
greater expectations of responsibility for care are placed on women at the time of child birth and adoption (Selmi 2000). Lawmakers have largely ignored the uniqueness of women, and especially mothers, in the workplace.

Due to the nature of the roles of men and women in our society, the primary responsibility for family caretaking often falls on women, and such responsibility affects the working lives of women more than it affects the working lives of men. Employment standards that apply to one gender only have serious potential for encouraging employers to discriminate against employees and applicants for employment who are of that gender [The Family and Medical Leave Act of 1993 (1993)]”.

Additionally, statistical discrimination of women pervades society’s day-to-day functions. The theory is generally seen as a catch-all to describe what is otherwise left as unexplained bias, yet contributes to measurable outcomes for that group (Benhabib 2011). As it applies to the workforce, when employers have only imperfect information on individuals or groups, they resort to putting people in recognizable groupings based on apparent characteristics and average those characteristics to determine the potential productivity, efficiency, or loyalty of individuals or those within certain groups (Ehrenberg and Smith 2016). The possibility for group averaging is one reason PFL may be necessary.

The assumption that women will behave a certain way in the labor force, as compared to men, and in relation to having and raising children, is used to estimate any potential workforce disruption that could deter productivity. This practice happens regularly within the decision-making process of a human resources division. On average, women as a biologically unique group are more likely to leave the workforce to have and raise children; those born as men
cannot bear children. However, most women in the workforce now vary from the hypothesized female employment path of working for a few years after college, then departing from their jobs to have a child (or children) with the potential to remain out of the labor force for good (Selmi 2000). Women and all employees are not one-dimensional nor are they even broadly all the same. Relying on group observations can be discriminatory and is generally unlawful, yet many times that discrimination is intangible.

To counteract such biases, places of work may attempt to even the playing field by offering PFL to women and men, whether married or of childbearing age, to all those that qualify to account for inaccuracies of the unfair group assumptions. Men or single, unmarried women take leave to care for ailing parents or the adoption of a child. The assumption that women are the only group to take advantage of PFL or who may temporarily leave the workforce to bond with a child or provide care for an elderly family member is a false assumption that hurts employees and employers alike, but especially women.

On a whole, studies are finding that women are increasingly less likely to leave employment, while men are trending in the opposite direction. A Federal Reserve Bank of New York Staff Report (Albanesi & Sahn 2013) on the gender unemployment gap reasons that this demonstrates an increased labor force attachment in women.

After having children, most women return to their previous job within four to six months, and to similar hours they worked before giving birth (Selmi 2000). A study on the impact of California’s paid family leave policy found that for women who have access to the program, it
greatly improves the likelihood they will be employed a year after giving birth (Baum & Ruhm 2013). Seemingly, labor force attachment styles of women are consistent; those who on average have weak connection to the labor force before giving birth are most likely to have a similar attachment style to the market after birth, and vice versa for women with strong attachment. Retention is not a women-specific matter for businesses and policy makers to consider.

Despite the awareness of female contributions to society and the understanding that women play a crucial role in the workforce as well as in the home, the U.S. federal government has made minimal effort to curb biases and demand gender equity. Lawmakers have been unsuccessful in providing substantial support to balance the burden and opportunities associated with childbirth, rearing, and income-based work.

The aim of this study is twofold. First, and most broadly, is the focus on the relationship between state and national family leave programs and the gender wage gap. A treatment group of states with paid family leave policies (California, New Jersey and Rhode Island) is compared to control states, or all other states who operate under the unpaid Family and Medical Leave Act (FMLA) program. Secondly, the observations are made between wages and females of childbearing age in treatment states and wages for females of childbearing age in control states. Furthermore, factors such as race, level of education, marital status, having young children, urban location, and occupation are included to determine if a gender impact is observed and if it significant.
The remainder of the paper is as follows: additional background information on the Family and Medical Leave Act of 1993, as well as the origination of state-level paid family leave programs in the United States; reviews of literature on the FMLA and maternity leave space, both domestic and internationally; laying out the conceptual framework for the paper’s hypothesis; addressing the data used and econometric modeling process; a look at the results of the model; and proposals for policy making and future implications of PFL research.

**Background**

Paid family leave in the United States does not exist on the federal level to this day. It leaves the U.S. as the only Organization for Economic Cooperation and Development (OECD) country and industrialized nation without federal law guaranteeing job-protected *paid* family leave programming. Papua New Guinea is the only remaining country in the world without a statutory national paid leave program.

One way the United States decided to acknowledge the plight of working families and equity towards working women was in the form of the Family and Medical Leave Act of 1993. The bill was the first signed into law by the Clinton administration after two vetoes from President George H. W. Bush.

The FMLA offers job-protected family or medical leave for up to 12 weeks. This is required for employers with 50 or more workers, within a 75-mile radius of the worksite. To qualify, employees must have worked at least 1250 hours in the previous year. Leave under the FMLA can be used to bond with a newborn or newly adopted child, recuperate from a serious health issue, or to take care of a sick family member. The law does not require payment to staff...
while they use the program, but it does require employers who provide health insurance coverage before the time of the leave request to continue doing so during the leave period (FMLA 2016).

Women continue to unduly bear the burdens of caregiving and childrearing, as well as the negative financial effects of work-family clashes and decision making. Failure to establish programs like paid family leave and those that specifically tend to the needs of those doing a “second shift” holds back half of the workforce and perpetuates women’s economic inequality (Klerman, et. al. 2012). University of California – Berkeley sociologist Arlie Hochschild wanted to see how family’s in the late 1980s were adjusting to the influx of women in the workforce. She found that of the 50 couples she studied, women came home from a full day of paid work to another demanding segment of unpaid housework and childcare. Ms. Hochschild concluded that women were working, whether paid or unpaid, an additional 30 days more than their husbands each year because of the “second shift” (Schulte 2014).

Some states – California, New Jersey, Rhode Island, New York, Washington, and the District of Columbia – have taken it upon themselves to provide additional female-centric economic cover and take the FMLA a step further by implementing or enacting their own versions of paid family leave systems (eight other states provide varied unpaid Family Medical Leave provisions). Implementation for California in 2004; New Jersey in 2009; and Rhode Island in 2014, was done through the legislative process. New York, Washington, and the District of Columbia will see their programs become fully effective in 2018, 2019, and 2020, respectively. See Table 1 for details on implemented programs.

1 Tables are found in the Appendix
Much of the rationale for states to implement paid leave programs, in addition to providing more family-friendly policies, is that women make up nearly half of the American population, and thus half of its human capital. Mothers with access to PFL have an increased likelihood of remaining attached to the labor force, their company and pre-child work habits, as well as economic investment in their country (Baum & Ruhm 2013). One particular Swedish study revealed that allowing males to participate in the program contributed to better outcomes for women’s pay after they returned to work (Johansson 2010).

Even though American states have tried, either on a state-wide or company level, to improve its family leave policies it lags behind many of its European counterparts in terms of the quantity of eligible leave time. In Sweden, parents are given 480 days paid leave per child (Killian 2011). Belgium offers 15 weeks of paid leave through Social Security; for the first 30 days, 82 percent of the salary is covered and 75 percent thereafter. Germany provides 14 weeks of leave at 100 percent salary. The program is paid for by Social Security until it meets a ceiling, then the employer pays the difference afterwards. Iceland offers two months. The U.K. offers up to 50 weeks of leave shared between spouses (the first two after childbirth are mandatory), 37 weeks of which is paid. France offers 16-26 weeks at 100 percent salary, while Italy provides five months with 80 percent pay from Social Security (ILO 2014).

Attempts to expand and more robustly fund the United States’ national FLMA was taken on by the Obama Administration. Multiple attempts were made to mandate at least a week of
paid sick leave for those working on government contracts and paid parental leave for federal employees. Both were blocked along political party lines.

The economic impacts of America’s dawdling family leave policies have not gone unnoticed. Past Cabinet officials have projected that if working-aged women in the United States mirrored labor market participation rates of those in Canada or Germany, two countries with paid family leave and widespread family-focused policies, an additional five million women would be in the U.S. workforce. This would translate into more than $500 billion of additional economic activity per year (Shierholz 2014). America has the potential to increase its human and economic utility if PFL programming is successful. The effectiveness of the programs would have to be determined either on the local or national level, however, a baseline should be to provide the opportunities for women and families to take necessary leave while earning an income and remaining attached to the labor force.

**Literature Review**

There is extensive research into the impacts of various family and labor-focused policies in the United States and around the world. This paper contributes to the political and social economic conversation to examine how businesses and governments can best utilize their constituencies’ talents to provide further equity and economic growth at home and nationally. The relationship between work and family is an important one to study because it is ever-present; it underwrites social and national identities and helps ensure stability.

Currently, the literature on paid family leave, especially papers looking at labor force participation, work place retention, and wages of women provide evidence for primarily positive
impacts; however, some results are inconclusive. Despite skeptics who claim PFL programs are costly and place unfair burden on employers – either through financial or hiring obstacles unique to organizations impacted by the change or continuation of providing paid leave programs – evidence from California, New Jersey, and Rhode Island, as well as other developed countries, suggest otherwise. Data shows that paid family leave policies rarely cause interruptions significant enough to reduce productivity, profitability, or change workforce culture of a particular business. A California survey found that over 90 percent of the 253 employers surveyed confirm these findings (Applebaum and Milkman 2011). In this section, I will look at ways in which leave programs influence low wage workers; the various level of health and economic efficiency based on the length of parental leave; and the availability, usage, and impact of paternity leave.

**Impact of Paid Leave on Low Wage Workers**

Since FMLA was passed in 1993, a majority of Americans have called for a paid upgrade to the program. Polls have indicated that 88 percent of Democratic and 71 percent of Republican voters support requiring employers to offer some sort of paid compensation for those out of the office with a new child or a sick family member (Isaacs 2017). Despite the emphasis on expanding the old, non-paid program, only about 12 percent of private sector workers currently have access to paid parental and family leave through their employers, and about 40 percent can access paid medical leave through short-term disability benefits (Perez 2015). This leaves a significant gap of non-covered workers who could receive paid benefits.
While unpaid leave is much more common in the United States, even that does not collectively cover all workers. Individuals who work for companies with less than 50 employees or who have been at a job for less than 12 months may not be eligible for unpaid leave, leaving nearly four in ten workers ineligible for unpaid benefits (Klerman 2012). The bulk of those who fall into an ineligible category are low wage, hourly workers – a population that makes up nearly 59 percent of the American workforce (Miller 2018). Typically, those jobs are near minimum wage and offer few to no benefits, the least of which is job protection. Hourly employees are also generally much less likely to be able to afford unpaid leave or newborn child care to assist in their return to the workforce. According to Lynda Laughlin who studies maternity leave and employment patterns of first-time mothers, between 2006-2008, 37.2 percent of part-time working women quit their jobs due to pregnancy. Minority low wage female workers are also almost twice as likely to have unmet leave needs as compared to white workers (Perez 2015).

Gaps in access and benefits continue to exacerbate workplace and socioeconomic inequality, despite real GDP growth from $9.5 trillion in 1993 at the time of FMLA’s passage to $17 trillion in 2017 (Amadeo 2018). In effect, the broad lack of access to PFL programs contributes to the erosion of the middle class and expands income disparities across the country.

Most economically-minded employers strive to retain their highly skilled, highly paid employees over those who are low skilled, do not cost the company much in wages, and could easily be replaced. In a 2009-2010 study of the California PFL program, 93.5 percent of respondents with high-quality jobs – employees who are exempt from overtime pay or are in managerial or professional positions – had access to employer-provided PFL, compared to 62.1 percent of those with low-quality jobs (Applebaum 2011). Paid family leave could level the
playing field if all those who are eligible – in California it is nearly all private sector and nonprofit workers – understood their eligibility status and utilized the program. However, those that may need it most – low-wage workers, immigrants, and minorities – are the least likely to know if they qualify for the benefit.

Only about half of those in the 2009-2010 California survey were aware of PFL, in general. For those who could possibly take the most advantage of the program, they knew the least about the program, except when it came to gender; women were more aware of PFL than men due to care responsibilities. Respondents under 35, an age within the childbearing range, were less aware of PFL than older workers; Latinos and immigration populations (where there is a lot of overlap) were less aware of the program than other racial groups or those born in the United States. Those surveyed with fewer years of education, and those with annual household incomes less than $30,000 or $15 per hour were half as likely to know about the opportunity for paid leave (Applebaum).

During the most recent presidential election cycle, both parties’ major candidates put forth family leave policies, creating national headlines and continuing the conversation on the benefits of the programming. However, to date, no new laws have been implemented, but a greater number of private sector organizations have taken it upon themselves to provide PFL coverage for both salaried and hourly workers.

Beginning May 1, 2018, the 20 largest employers in the United States will all offer PFL to some of their employees (Miller 2018). The latest to join these ranks, Lowe’s, will provide
mothers with 10 weeks of paid leave and all other parents, either salaried or full-time hourly employees, will have two weeks of paid leave. Similar to the high poll numbers, these major companies – who employee millions – offering such benefits could be a positive sign of grassroots demand and industry competition to retain their best workers, regardless of gender or biological circumstances.

Length of Leave

To maximize the efficiency of paid family leave programs for employers, leave-takers, and local economies, the length of eligible leave should be considered. Lengths of PFL vary greatly around the world, from a few days to a few years. Lengths of leave can have broader impacts than just time away from the office; some of the earliest policies in Europe date back to the late 1800s and only provided leave for women, further entrenching traditional gender roles and increasing women’s caregiving burden (Schulte, et al 2017). Presently, OECD countries average nearly 18 weeks of leave allowance for new and adoptive mothers. Further unique opportunities for mothers to take leave appear in countries like Bulgaria and the U.K. where almost a year of time with a new child is available. Fathers also average eight weeks, with Japan and South Korea providing the most substantial leave of up to one year (Schulte, et al 2017).

Generous leave policies are seemingly ideal – they allow for women to prepare for and recover from giving birth and bonding time for both parents – what many might believe to be the definition of health and happiness around the arrival of a child. However, a Pew Research Center (Livingston 2013) study found that some countries with generous leave policies have the largest
wage gaps among men and women ages 30 to 34. Of the 16 OECD countries studied, New Zealand and Belgium have some of the narrowest pay gaps while providing more limited paid time off. Countries with higher gaps include the Czech Republic and Austria, both of which offer new parents about 10 months of paid parental leave. Much of these findings can be attributed to the fact that women still take the majority of available leave compared to men, who work more weeks at full salary during the same time that women are taking a cut or are not paid at all.

Figure 1 shows some OECD countries’ wages gaps in association to allowable time off.

Figure 1. Weeks of Paid Leave and the Wage Gap in OECD Countries
Similarly, additional *New America* analyses, using hundreds of national and international studies, is able to recommend the optimal length of leave in a number of important metrics surrounding birth, child health, and gender equality. They found the best possible outcome for infant health is one year of paid time off, divided between both parents. To give women the best chance to properly recover from the physical efforts of the gestation period and birth is six months paid time off. *New America* also recommends offering equal amounts of paid time off for both parents and nine months to a year of paid family leave as the best option for the business economy (Schulte, et al 2017).

More focused research in the U.S. has shown the impacts of PFL in California, New Jersey, and Rhode Island. California and New Jersey allow for six weeks of paid leave, while Rhode Island offers four. Since implementation of these programs, research has shown the wage gaps in each state has become smaller. In California, the average hourly wage in 2000, for a full-time white male worker was $20.83, while the same demographic of women at the time only earned $17.03; a gap of about 18 cents for every dollar paid to men (Reed & Cheng 2003). More recently, in 2017, the National Partnership for Women and Families found that California’s wage gap was 14 cents, with women making around 86 cents per every dollar made by a man.

In New Jersey, the American Association of University Women reported that women made 78 cents per ever dollar men made in 2008. The National Partnership found it be 82 cents in 2017. For Rhode Island, the National Partnership also found that women made 80 cents for every dollar men did in 2012 and 86 cents in 2017 (National Partnership 2012 & 2017). The studies do not prove causality between PFL and the wage gap, but the results are of interest to
the debate on the most efficient length of leave since the three states do not offer the same amount time off nor are they similar across all factors within their leave programs.

Short-term labor force disruptions, such as medical or family leave, are unlikely to result in a loss of employees’ skills and have a smaller impact on an employer’s bottom line than the permanent loss of an employee. (Selmi 2000). Likewise, Baum and Ruhm (2013) found that the availability of paid leave might persuade some mothers to work in the nine to twelve-month period following delivery and take short paid leave after it, rather than quitting the job held during pregnancy, thus creating job continuity rather than permanent exits.

**Partner Leave**

During the 1990s, a portion of OECD countries began including men in their leave policies. It included job protection and “use it or lose it” provisions to incentivize male partners to take time to care for new children and work to promote gender equality at home and in the workplace (Schulte et al 2017). Having both parents take leave for the birth or adoption of a child may have long-term effects on financial earnings, as well as household and childrearing responsibilities.

According to Baum and Ruhm (2013), PFL appears to have increased the leave-taking of fathers. The strongest effects occur directly after the birth, which is consistent with their findings of the causal nature of California-PFL, since many women utilize Temporary Disability Insurance (TDI) leave after delivery, which fathers are not eligible for. In another study,
Nepomnyaschy and Waldfogel (2007) found that the men who were most involved in their child’s life near its first birthday – play, feeding, and general participation – had taken longer leave immediately following the birth of the child.

However, women continue to bear the burden of longer term infant care, despite efforts to share in the sacrifice with their male counterparts. This may be in part due to the rigidity of the male perspective regarding labor force norms. Women have undergone a seismic shift in their labor market behavior since the 1960s, with more women entering the market, attaining higher degrees, and rising in rank (Gelb 1996). Men have not experienced this same shift and many lack motivation to adopt new family-minded policies that depart from their instinctual labor market behavior, such as FMLA. Notwithstanding frequent claims by men that they would like more time to be involved with their families, few men take more than two weeks of paternity leave or shoulder equal responsibility for parenting (Galinsky 1996). This trend makes evident that current efforts to advertise the importance of families as a value to companies, and society, are not yet taking hold (Selmi 2000). Without new methods to force adoption of family-minded policies, women will continue to take more than their equal share of leave around the birth or adoption of their child.

A Swedish study did find that the longer men were on leave, the more positive impact it had on maternal earnings after women returned to the labor force. Researchers found parental leave to have no impact on fathers’ earnings, yet for each additional month that the father stays on leave increases the mother’s earnings by 6.7 percent (Johansson 2010). The effect was larger than the women’s own leave on her future earnings, emphasizing the that the lack of paternal
involvement may contribute to the gender wage gap. The study also inferred that since the status quo of many parental leave programs focus on maternal leave, by shifting some mothers to take shorter spans of leave (and having fathers home longer) could signal a stronger commitment to the work force (Johansson 2010) and balance out the utilization of leave between mother and father.

**Conceptual Framework**

While most existing academic literature has yet to examine the relationship between individual level access to PFL programs and the gender wage gap in the United States, it has evaluated the impact of both the FMLA and state level programs, on wage and employment, before and after implementation (a difference-in-difference model). Consequently, my conceptual model (Figure 2) lays out some of the components of today’s gender wage gap in America.
Figure 2. Conceptual Framework

The model, a difference-in-difference-in-difference (DDD) paradigm, suggests that primary factors determining wages are: gender, state-based policies and in this case if a state has PFL; and if they are of childbearing age. Secondary factors include level of education achieved, occupation, race, and if they have children between the ages of zero and five. Marital status and location, like a central city, are also factors that may determine wage, but can be unrelated to the previously mentioned independent variables, while still being directly connected to potential earnings.

Based on the conceptual framework, the study hypothesizes that women in treatment states who are of childbearing age should earn more than those who are female, and of
childbearing age in a non-treatment state. Less specifically, on average women in treatment states should earn more than women in non-treatment states.

An individual’s unique characteristics, such as age, marital status (married versus never married) or demographic location (urban versus rural), might make them more predisposed to having access to PFL and utilizing it. At the same time, these individual-specific characteristics may be correlated to a workplace with larger disparities in wages and benefits.

The results of the model should highlight the difference in states that provide paid leave and those that operate under the federal, unpaid FMLA. Women and men who have access to a paid leave program should be more financially stable around the time of welcoming a new child and thus set them up for future financial success, notwithstanding other financial and personal factors that may contribute to economic up or downturn over time.

**Data and Methods**

The data set used for this analysis is from the Center for Economic Policy Research’s (CEPR) Uniform Extracts of the Current Population Survey (CPS) Outgoing Rotation Group (ORG), also known as the “Earnings Files” or “Quarter Sample” of the CPS. The CPS is a monthly household survey conducted by the Bureau of Labor Statistics to measure labor force participation and employment. The ORG is a unique element to this data set because each household surveyed initially participates for four months, then is left out of the survey for eight months, and then is interviewed again for four months, totally a 16-month period. New households enter the survey each month, so one in four households are in an outgoing rotation each month. This allows the CPS to collect data that is easily comparable month-to-month and
year-to-year. The data set will represent answers based on survey questions from years 2002-2016.

The data set contains detailed information about individuals’ earnings, education, employment status, citizenship, and demographic characteristics that may or may not influence the hypothesized question that women of childbearing age experience more narrow gender wage gaps in states with PFL policies.

The data set is narrowed (see Figure 3), from more than 16 million observations to about 4 million observations. First, by focusing on individuals of typical working age, 18-64, about 3.5 million observations are cut. Second, variables unrelated to my question, like similar race variables, the veteran population, and those who are self-employed are dropped and the sample is cut to about 10.5 million observations. Dummy and interaction terms are created to best fit the conceptual framework, but do not substantially add or take away from the final pared down sample size. Finally, transforming the model from a multivariate linear model to a log-linear model by observing the dependent variable “real wages” as the log of real wages drastically cuts down the sample to just over four million observations. Without the log transformation the sample contains about 7.5 million observations.
The refined sample will largely focus on the age range of 18-45, those who are likely to be in the workforce and of childbearing age (age_CBA). Of the individuals within that segment, dummy variables for numeric categorical variables are created. Those include the treatment state vector of California, New Jersey, and Rhode Island (TREATSTATES); interactions between
treatment states and those of childbearing age (TREATSTATES_CBA); an interaction between treatment states and women (TREATSTATES_FEMALE); and for women of childbearing age (CBA_FEMALE). The dummy variable TS_CBA_F is created through the interaction of all three key independent variables. Other independent variables like race (wbhao); a college education (educ_Coll); having children between the ages of zero and five (CH05); marital status (marstat_marr); and central city location are used. Control variables include occupation, years, and states.

By creating summary statistics, examining the impact of paid family leave policies on the women in treatment states against women in FMLA-only states should highlight wage disparities due to policy.

Econometric Model

The effect of PFL on women’s wages is found by comparing their wages before and after PFL is implemented in treatment states. The comparison to non-treatment states is the double difference, and the further comparison to women of childbearing age is the triple difference.

To begin forming the econometric models, a log variable is produced for the dependent y-variable, real wages, to create a log-linear model:

\[ \log Y = \beta_0 + \beta_1 X + \beta_2 X + \ldots + \beta_k X \]

This way, when observing variations for every unit change for each x-variable, the dependent variable real wages (rw) is understood as a percentage change. Independent variables
are kept in their original unit scale. It could then be presumed that a percentage change in real wages will have a greater impact in interpreting regression results than a change in wages by dollar values alone.

Many analyses that look at the causal impacts of PFL use a difference-in-difference estimation model to observe the effects of a policy on the outcome of a treatment group compared to the changes in the outcome for the control group. This is done by removing the impacts of time and place on a sample before and after policy implementation to isolate the results of the policy alone. However, by adding a third difference – time, place, and another variable – the additional difference may reduce bias, as it is accounting for another factor that may contribute to the policy impacts of the treatment group in the estimate of the effect of the overall policy (Berck & Villas 2015). In the instance of this study, by eliminating factors other than the paid family leave policy impact on women of childbearing age - year of implementation/how long the policy has been in effect and treatment versus non-treatment states – would potentially allow this study to reduce the bias in the estimate of the effects of paid family leave policies on women.

To build the DDD model, observing how PFL impacts women of childbearing age in states that have PFL policies, is the first step. The key independent variables are in Equation 1.

(1) reg logrw TREATSTATES age_CBA female
Within the TREATSTATES variable are the states of California from years 2005-2016; New Jersey from 2010-2016; and Rhode Island in 2015 and 2016. These are the three states that have PFL at a state-wide level and the years after the law was implemented to 2016. It also provides a baseline for the impacts of treatment states, childbearing age, and females, separate from one another. Using the constant variable, the opposite – men of non-childbearing age in non-treatment states – is also observable.

In Equation 2, additional interaction terms are added to Equation 1.

\[(2) \text{ reg logrw TREATSTATES age}_\text{CBA} \text{ female TREATSTATES}_\text{CBA} \text{ TREATSTATES}_\text{ FEMALE} \text{ CBA}_\text{FEMALE} \]

To create a triple interaction, each of my three key independent variables must interact with each other. Adding interaction variables to form Equation 2 provides observations for those of childbearing age in treatment states, women in treatment states, and women of childbearing age. Again, observing the constant variable in the regression output, the opposite characteristics may be reviewed (individuals from non-treatment states, of non-childbearing age who are male, as well as interaction of non-treatment states and those of non-childbearing age; non-treatment states and males; and males who are not of childbearing age).

Finally, including a triple interaction of my key independent variables – treatment states, childbearing age, and females – plus controls, accounts for the final model (Equation 3).

\[(3) \text{ reg logrw TREATSTATES age}_\text{CBA} \text{ female TREATSTATES}_\text{CBA} \]
Above, the model shows the study’s three key independent variables separately, interacted in twosomes, and a triple interaction. Not only does a DDD control for some additional bias from omitted variables, it also allows researchers to observe the impacts of PFL on wages before and after implementation in treatment states for women of childbearing age. To complete the equation including additional descriptive variables like race, education, if an individual has young children, marital status, location, occupation, state, year and final weight are necessary.

The DDD is important because it allows researchers to focus in on exactly who the policy is meant to impact – women who are most likely to use the policy while they are out of the office having children – rather than the broad impact on wages before and after policy implementation in the state.

**Results**

The results of the main empirical specification, regressing the log of real wages on a series of dummy variables generated by a DDD model are shown in the tables in the Appendix.
Descriptive Statistics

The results below aim to assess whether the hypothesis – women of childbearing age earn higher wages after PFL implementation than their female counterparts in non-PFL states – holds true. The finding from the CPS data can be observed in Tables 2, 3, 4, and 5 in the Appendix. The first four variables of Table 2 – treatment states, non-treatment states (NTS), childbearing age and female – make up the key characteristics of the treatment and control groups of the study. The mean for Treatment States (0.12) is smaller than the mean of non-treatment states (0.88) because it is based on a population count; more specific population numbers are listed in Table 3. NTS is individuals from all states excluding California, New Jersey, or Rhode Island. Both variables are binaries, meaning an individual in the study, when asked if they are from California or another treatment states as well as Wisconsin or a different non-treatment state can answer either ‘yes’ or ‘no’. The closer the variable mean is to one, the greater the likelihood that respondents answered ‘yes’ for that particular category as compared to the answers of the entire population.

Childbearing age is also a binary variable. Almost a third of the sample population were of childbearing age. The standard deviation (0.47) is near the mean (0.32), indicating the data is more reliable because of its average proximity to the mean or expected value. The Female variable has a mean of 0.55, indicating that slightly more of the sample population is female than male. The Race variable has a mean of 1.53, demonstrating that most survey participant are white; however, the standard deviation is 0.98 which shows balance in representation since a larger standard deviation can reflect a greater amount of variance within the population. Most of
those surveyed do not have a College Education (0.13) nor children between the ages of zero and five (0.09). These are important indicators for the hypothesis, PFL is aimed at assisting those who have young children or will have them. A college education may increase the likelihood of working at a place with PFL benefits, regardless of state of residence, however, that is unproven.

The Married variable has a mean of 0.52; about half of the women in the survey are married. This may lend itself to the conversation surrounding dual incomes or further studies on how even though women are married, they are penalized in far greater ways than their partners when it comes to PFL utilization and salaries around the time of the new child. Lastly, the Central City variable has a mean of 0.23, not nearly a third of respondents live in a central city.

Table 4 further breaks down the female population and its characteristics. The Female variable is interacted with the previously mentioned key indicator variables and observed from either a non-treatment state or treatment state perspective. Fewer women have college degrees in non-treatment states (0.08) than treatment states. Within both sample groups, children between zero and five are sparsely indicated, yet more women with young children reside in NTS. Perhaps this is related to the fact that the average female is married at higher numbers in NTS (0.24) than in treatment states (0.01). More women in non-treatment states live in central cities than those in treatment states with a narrow difference of about 0.08.

The second half of Table 4 observes the same characteristics of females, yet focuses on those who are also of childbearing age. Far more women of childbearing age reside in NTS (0.21) than treatment states (0.03). This should not be surprising since the NTS population, when
only observing females, is almost quadruple the amount as the treatment population (Table 3). NTS females of childbearing age show more variation within the age range (0.41) than that of treatment states (0.17). Females of childbearing age in all other categories – college education, children between zero and five, married, and living in a central city – are more prevalent in NTS, and with greater variance than those in treatment states.

Many of the statistical differences can be based on population sizes. Overall, the male and female NTS population is greater than 14 million while the TS population is just under 2 million, with California alone accounting for over eight percent of the sample’s total population. The same applies for females and females of childbearing age. NTS females make up 45.92 percent of the total population sample while about seven percent of the TS population is female.

**Inferential Statistics**

By analyzing the changes of real wages by gender, independently of one another, data can explain the differences between the average earnings of men as compared to women. If female wages increase after policy implementation while male wages remain constant or decrease, then generally, the wage gap has become narrower than before policy implementation.

In the equation, the TREATSTATES, age_CBA and Female coefficients explain how the paid family leave policies affected real wages of individuals in California, New Jersey and Rhode Island; those of childbearing age across the sample population, as well as females. Each coefficient, by itself relates to either a positive or negative relationship with wages. In the
regression, being in a treatment state has a positive percentage change, by 16.8 percent, for every one-unit increase in wages. Having a college education (19.9), small children (3.7), being married (18.1) and in a central city (1.6) all positively impact wages, gender left unspecified, while Race has a negative impact on wages (-4.1 percent).

Regressing Female on the log of real wages, by itself, has a large negative impact of 23.9 percent for every one-unit change in wages; this is statistically significant. Regardless of which state a female works or resides in they earn less than men.

When variables are interacted, like living in a treatment state and being of childbearing age, a negative association with wages is present. For every one-unit change in TREATSTATES_CBA wages decrease by 2.2 percent. However, being female in a treatment state increases ones’ wages by 3.3 percent. The interaction is also statistically significant.

Using the DDD interaction – treatment states, childbearing age, and female – for every one-unit change in the interaction, those within it experience a 0.59 percent wage increase; it is statistically significant with a p-value of 0.1. This tells us there is a positive relationship between women of childbearing age who live in a treatment states and their wages.

The equations also allow observations on certain occupations, years and states. While the reference category is ‘business and financial’ occupations, all other fields have a negative association with wage, as compared to the reference category. Each coefficient is statistically significant. Rhode Island, a treatment state, has a negative wage association (-8 percent) with a
one-unit change, while New Jersey is positive (2.1 percent). Years 2009, 2010, and 2016 have a positive relationship with wage, while all other years have a negative association.

Following these observations, one can conclude that the gender wage gap effectively decreases post-policy implementation for women of childbearing age in treatment states, even if only by a small margin. That being said, the regression also provides substantial information on states with only FMLA (three states compared to 47, plus the District of Columbia). An African American woman in South Dakota (-6.0) will be much worse off than an African American woman in Iowa (-0.1) even if they have the same level of education and are both married.

States’ policies may be dictated by its historical context, grassroots politics, and demographic makeup. Potentially painting a much different picture from one state to the next. The wealth of a state also impacts wages. Oklahoma has not given its public-school teachers a raise in a decade (Goldstein 2018). Most of those teachers are also female. Additional control variables can always be used in the regression to paint a fuller picture of women and men’s wages after policy implemented and in states around the country.

Interestingly, being of childbearing age has a negative impact – decrease of 14.5 percent for every one-unit change in wages – for all individuals. This may be a time when people are still in school, working their lowest paying job or the least attached to the workforce. Another interesting coefficient is marital status. Those that are married may be in a dual income household, which could explain the 18 percent leap for a one-unit change. This could also relate to the idea that men who take PFL increase their spouse’s future earnings once they have
returned to work. The alternative might be true as well, single income households primarily are those that have the highest income levels; women are doing unpaid housework. There is no causal relationship for either, however.

**Discussion and Policy Implications**

This analysis set out to find if paid family leave programs had a causal relationship with increased wages for women of childbearing age after state-level policy implementation. The results show confirmation of the original hypothesis that women in treatment states who are of childbearing age earn more than those who are female and do not reside in treatment states. The difference is just over a half of one percent. The secondary hypothesis is also confirmed. On average, women in treatment states earn more than women in non-treatment states (0.17)².

Women of Childbearing Age and Treatment States, when interacted together, have a positive association with wages. However, individually, Female and Childbearing Age are two of the most negative indicator variable outside of Race and Occupation. Previous literature states that the individuals who may need PFL programming the most, but either do not have access to it or are not aware of their eligibility for it, are predominantly female and of a minority race. Race and sex, for the most part, are variables that an individual does not have a choice in nor will change over the course of their lifetime. Policy makers should make more of an effort to address these dichotomous variables that have such a large impact on wages and contribution to American society and the labor force.

² Regression output can be found in Table 5
The TS_CBA_F variable is positively associated with improved wages, yet a woman in the District of Columbia (D.C.) will also have a positive association with wages and a District-wide PFL program has yet to be implemented. Paid family leave will take effect in 2020, yet the positive association between females and wages may only apply to Caucasian women in certain neighborhoods within the District. Alternatively, a woman of childbearing age in a treatment state, but who lives in a rural part of the state may fair differently (more negatively) than a white woman in a central city within the same state. The same goes for communities who shares or straddle a treatment/non-treatment state border. This study did not address in-state or regional geographical discrepancies.

The study is also limited because of collinearity with the ‘California’ state observation. Its impact is felt in the TREATSTATES interaction terms, but is unobservable in isolation. The study does not address women who had children before policy implementation in a treatment state and then another afterwards within the same treatment state to see if there were changes in wage. If there were additional time to work through these variables, the study may have narrowed the focus to address the results of non-white women, as well as those of a lower socio-economic background.

The results also suggest future research could focus on various sectors within the childbearing age segment of available data, looking more closely at men and women in certain occupational fields, as well as compensation packages outside of family leave availability. The political makeup of a state or rural versus urban communities may be impacted differently for those of childbearing age.
These limitations notwithstanding, the data and results collected in this study add to the literature on gender equality and how it may be achieved through paid family leave programming and suggest changes to length of leave, how to may be doled out, and cost saving ideas.

**Policy Implications**

Having a PFL policy does more for earnings than the absence of the policy. Also, when the Female and Treatment State variables are interacted, and the Female and Childbearing Age variables are interacted, separate of a triple interaction, each pairing earn more, and earn more than when the three key variables are interacted together. This indicates that there may be several ways to address the wage gap.

Outgoing House Speaker Paul Ryan made an off the cuff remark in 2018, that America needs to produce more children. The current $1,000 Child Tax Credit does not do enough to incentivize childbearing when the return is seen once a year and is not enough to offset the annual costs of childcare or diapers, which may be critical factors in how and when individuals and especially women return to the labor force. The purchasing power of the return is not significant enough to spur action.

Tax credits are not known to indirectly produce children, but marriage may. From the results of the data, those who are married earn more. This does not directly address women’s earnings, but bolsters the conversation around how paid leave is used and can incentivize certain
lengths of leave and usage by a certain parent for the potential cultural shifts in the workplace and home over time. Like America’s European counterparts, the U.K., Denmark and Norway have paid family leave policies that allow for spouses to share leave privileges and/or curtail extremely lengthy leave for one parent that benefits salaries, the return on investment for employers and maintains a narrower wage gap than the United States (see Figure 1).

As much as it is wrong to group women into one labor force category, the same goes for men. Many of them would like to take more time off to help their partners and children in the immediate phase(s) after welcoming a new baby. The literature suggests that if policies are in place that force men – use it or lose it – to take that time, their children and spouse may be better off in the long run in terms of health and financial well-being. These successes do not detract from men’s salaries or general happiness. As in Sweden, for every additional month at home it increases the mothers wage by 6.7 percent upon return to the workforce. More work needs to be done to normalize paternal leave taking that is longer than two weeks.

Women are going to college and all other levels of postsecondary education in higher numbers than men (Carnevale et al 2018). From the data results, those with a college degree earn almost an additional 20 percent more than those who have not graduated. Employers who want to invest in their employees should consider providing an educational stipend for those pursuing part-time undergraduate or graduate degrees in a related field. This would allow women to stay in the workforce while advancing their skills at a low cost to themselves and their employer.
Larger cities, many of them with the United States’ and the world’s best universities, in states like Washington, Florida, Illinois, and New York attract some of the top female students. The cost of living is also usually higher, but so might be the pay in certain sectors. The study data indicates that those in cities do better than those in rural areas when it comes to pay.

In Washington, D.C., and the large cities located in states mentioned previously, there is a positive association with wages. Many of the city’s best and brightest also begin their tenure with unpaid internships. This can make long-term commitment to a city more difficult, even when earning potential is high. As such, it can be more challenging for women who begin their careers with no or low pay and who temporarily exit the workforce when they are still making comparable money to men. Programs to make city living affordable for women – on-site childcare, work from home flexibility, and paid family leave – allow individuals to afford their contribution to society in any numbers of ways they choose to. As history explains, life’s circumstances are not always a choice. Having safety nets and mechanisms to account for accidents or purposeful decisions, without fear of penalization, are paramount to a thriving society and economy.

Furthermore, females are significantly more impacted by changes in wages than men. The coefficient for Female suggests almost a 24 percent dip for every one-unit change in real wages. The wage gap has remained stagnant even has degrees and labor force participation increase. Perhaps the value of work done by women is not regarded as highly. Equal pay for equal work may never be realized until the idea that women’s work is of equal value is a nation
value. Again, ideas on what ‘national values’ are largely depends on cultural values, many of which are acted out in the workplace and in the home.

To make PFL policies more accessible, the way states fund leave is important. Employees should contribute via payroll text, while employers of a certain size should be required to match a portion of the percentage an employee contributes. That way, even women who do not have children or men who never utilize personal disability are still able to use the program if a parent or sibling becomes ill. The employer requirement lends itself to changing workplace and home cultural norms and traditional gender roles if all persons can access PFL, also potentially addressing any low programmatic take-up rates.

Additionally, since many people who currently have access to PFL, whether in their states or from their place of work, are salaried, providing 100 percent of pay during the first month or the entire period of leave should not be a stretch. If that money has already been allocated, then it can continue to be given out. Money from the payroll tax can be awarded for additional time for either parent or implementing additional paternal leave, hiring a temporary employee, an initial pilot program.

Overall, these results lend support to the importance of promoting policies that encourage women’s involvement, retention, and promotion in the workforce. Their contributions and potential are innumerable. The analysis of paid family leave programming also underscores the importance of men understanding their role in creating equity for their spouses, colleagues and children, and for future generations to come.
### Table 1. State Paid Family Leave Insurance Laws, July 2017

<table>
<thead>
<tr>
<th>Date Implemented</th>
<th>California</th>
<th>New Jersey</th>
<th>Rhode Island</th>
</tr>
</thead>
</table>
| Reasons for Paid Leave | 1. Bonding with new child (birth, adoption, foster)  
2. Care for family member with serious health condition  
3. Care for own disability (includes pregnancy) | 1. Care for new child (birth, adoption, foster)  
2. Care for family member with serious health condition  
3. Care for own disability (includes pregnancy) | 1. Bonding with new child (birth, adoption, foster)  
2. Care for family member with serious health condition  
3. Care for own disability (partially unemployed workers may be able to claim benefits) |
| Definition of Family Member | Child, parent, spouse, domestic partner, grandparent, grandchild, sibling and parent-in-law | Child, parent, spouse, domestic partner, civil union partner | Child, parent, grandparent, spouse, domestic partner |
| Max. Length of Paid Leave | 6 weeks for family leave. 52 weeks for own | 6 weeks for family leave. 26 weeks for own disability | 4 weeks for family leave. 30 weeks for own disability |
| Employee Eligibility Requirements | Earnings of $300 in a 12-month period | Earnings of at least $8,300 in a 12-month period or at least $165 a week for 20 weeks | Earnings of $10,800 in a 12-month period or $3,600 in a 12-month period and at least $1,800 in one quarter and total earnings of at least 150 percent higher than highest quarter earnings |
| Method to Fund Insurance System | Own disability and family care are funded by the employee only (currently at 1% of worker’s first $114,967 in wages). | State’s TDI program is financed by employee and employer payroll contributions. As of January 1, 2018, each worker contributes 0.19% of the taxable wage base per year. Employers’ contribution rate is between 0.10 - 0.75%. | Own disability and family care are funded by the employee only. The current withholding rate is 1.1% of worker’s first $69,300 in wages. |
| Weekly Wage Replacement Rate | 55 percent, increasing to 60 and 70 percent in 2018 | 67 percent | 55 percent |
| Job Protection While on Leave | No, not more than under FMLA and the California Family Rights Act | No. Workers may be covered by FMLA and NJ Family Leave Act | Yes, for family care, but leave for own disability is no more protected than under FMLA or RI PFMLA |

Source: National Partnership for Women & Families
Table 2. Key Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable Name</th>
<th>Sample Size</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Stand. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment State</td>
<td>TREATSTATES</td>
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<td>0.12</td>
<td>0</td>
<td>1</td>
<td>0.33</td>
</tr>
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<td>Non-Treatment States</td>
<td>NTS</td>
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<td>0.88</td>
<td>0</td>
<td>1</td>
<td>0.33</td>
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<td>Childbearing Age</td>
<td>age_CBA</td>
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<td>0.32</td>
<td>0</td>
<td>1</td>
<td>0.47</td>
</tr>
<tr>
<td>Female</td>
<td>female</td>
<td>16,279,229</td>
<td>0.55</td>
<td>0</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>Race</td>
<td>wbhao</td>
<td>16,279,229</td>
<td>1.53</td>
<td>1</td>
<td>5</td>
<td>0.98</td>
</tr>
<tr>
<td>College Education</td>
<td>educ_Coll</td>
<td>16,279,229</td>
<td>0.13</td>
<td>0</td>
<td>1</td>
<td>0.34</td>
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<tr>
<td>Have Children</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between 0-5</td>
<td>CH05</td>
<td>16,279,229</td>
<td>0.09</td>
<td>0</td>
<td>1</td>
<td>0.28</td>
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<tr>
<td>Married</td>
<td>marstat_marr</td>
<td>16,279,229</td>
<td>0.52</td>
<td>0</td>
<td>1</td>
<td>0.5</td>
</tr>
<tr>
<td>Live in Central City</td>
<td>centcity</td>
<td>16,279,229</td>
<td>0.23</td>
<td>0</td>
<td>1</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Note: summations done without log

Table 3. Key Descriptive Statistics – Female Population Sizes in Non-Treatment States, California, New Jersey, and Rhode Island

<table>
<thead>
<tr>
<th></th>
<th>NTS Sample Size</th>
<th>California Sample Size</th>
<th>New Jersey Sample Size</th>
<th>Rhode Island Sample Size</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Females &amp; Males</td>
<td>14,320,333</td>
<td>1,343,447</td>
<td>347,568</td>
<td>267,881</td>
<td>87.97</td>
</tr>
<tr>
<td>Females</td>
<td>7,475,269</td>
<td>696,739</td>
<td>183,524</td>
<td>141,939</td>
<td>45.92</td>
</tr>
<tr>
<td>Females of CBA</td>
<td>3,377,379</td>
<td>345,256</td>
<td>81,515</td>
<td>61,622</td>
<td>20.75</td>
</tr>
</tbody>
</table>

Note: tabulations done without log
Table 4. Mean Differences Between Non-Treatment States vs. Treatment States

<table>
<thead>
<tr>
<th></th>
<th>Non-Treatment States</th>
<th>Treatment States</th>
<th>Difference in Means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Mean</td>
</tr>
<tr>
<td>Females</td>
<td>0.46 (0.00)*</td>
<td>0.5</td>
<td>0.06 (0.00)*</td>
</tr>
<tr>
<td>Females with a College Education</td>
<td>5.03e-06 (0.00)*</td>
<td>0.00</td>
<td>1 (0.00)*</td>
</tr>
<tr>
<td>Females with Children Between 0-5</td>
<td>0.06 (0.00)*</td>
<td>0.23</td>
<td>0.01 (0.00)*</td>
</tr>
<tr>
<td>Females Married</td>
<td>0.24 (0.00)*</td>
<td>0.43</td>
<td>0.03 (0.00)*</td>
</tr>
<tr>
<td>Females Living in a Central City</td>
<td>0.1 (0.00)*</td>
<td>0.30</td>
<td>0.02 (0.00)*</td>
</tr>
<tr>
<td>Females of CBA</td>
<td>0.21 (0.00)*</td>
<td>0.41</td>
<td>0.03 (0.00)*</td>
</tr>
<tr>
<td>Females of CBA w/ College Education</td>
<td>0.04 (0.00)*</td>
<td>0.2</td>
<td>0.01 (0.00)*</td>
</tr>
<tr>
<td>Females of CBA w/ Children Between 0-5</td>
<td>0.06 (0.00)*</td>
<td>0.23</td>
<td>0.01 (0.00)*</td>
</tr>
<tr>
<td>Females Married</td>
<td>0.1 (0.00)*</td>
<td>0.3</td>
<td>0.01 (0.00)*</td>
</tr>
<tr>
<td>Females of CBA Living in Central City</td>
<td>0.05 (0.00)*</td>
<td>0.22</td>
<td>0.01 (0.00)*</td>
</tr>
</tbody>
</table>

Note: Robust standard errors are in parenthesis. *<0.01 **<0.05 ***<0.10
Table 5. Regression Output for DDD Model – Regional Groupings

| Logrw                                | Coef. | Std. Err. | P>|t| | [95% Conf.] | Interval |
|--------------------------------------|-------|-----------|-----|-------------|----------|
| Treatment States                     | 0.17  | 0.00      | 0.00| 0.16        | 0.17     |
| Childbearing Age                     | -0.15 | 0.00      | 0.00| -0.15       | -0.14    |
| Female                               | -0.24 | 0.00      | 0.00| -0.24       | -0.24    |
| Childbearing Age in Treatment States | -0.02 | 0.00      | 0.00| -0.03       | -0.02    |
| Females in Treatment States          | 0.03  | 0.00      | 0.00| 0.03        | 0.04     |
| Females of Childbearing Age          | 0.04  | 0.00      | 0.00| 0.04        | 0.05     |
| Females of Childbearing Age in       | 0.01  | 0.00      | 0.09| 0.00        | 0.01     |
| Treatment States                     |       |           |     |             |          |
| Race                                 | -0.04 | 0.00      | 0.00| -0.04       | -0.04    |
| College Education                    | 0.20  | 0.00      | 0.00| 0.20        | 0.20     |
| Have Children Between 0-5            | 0.04  | 0.00      | 0.00| 0.04        | 0.04     |
| Married                              | 0.18  | 0.00      | 0.00| 0.18        | 0.18     |
| Live in Central City                 | 0.02  | 0.00      | 0.00| 0.01        | 0.02     |
| Massachusetts                        | 0.17  | 0.00      | 0.00| 0.17        | 0.18     |
| Rhode Island                         | -0.08 | 0.00      | 0.00| -0.08       | -0.08    |
| Connecticut                          | 0.19  | 0.00      | 0.00| 0.19        | 0.20     |
| New York                             | 0.14  | 0.00      | 0.00| 0.14        | 0.15     |
| New Jersey                           | 0.02  | 0.00      | 0.00| 0.02        | 0.03     |
| Maryland                             | 0.18  | 0.00      | 0.00| 0.17        | 0.18     |
| District of Columbia                 | 0.30  | 0.00      | 0.00| 0.29        | 0.30     |
| Iowa                                 | -0.01 | 0.00      | 0.00| -0.01       | -0.01    |
| North Dakota                         | -0.01 | 0.00      | 0.00| -0.02       | -0.01    |
| South Dakota                         | -0.06 | 0.00      | 0.00| -0.06       | -0.05    |
| Florida                              | 0.05  | 0.00      | 0.00| 0.05        | 0.06     |
| Mississippi                          | -0.05 | 0.00      | 0.00| -0.05       | -0.04    |
| Oklahoma                             | -0.03 | 0.00      | 0.00| -0.03       | -0.02    |
| Utah                                 | -0.01 | 0.00      | 0.04| -0.01       | 0.00     |
| Washington                           | 0.16  | 0.00      | 0.00| 0.15        | 0.16     |
| Oregon                               | 0.07  | 0.00      | 0.00| 0.07        | 0.08     |
Bibliography

Albanesi, Stefania, and Aysegul Sahn “The Gender Unemployment Gap.” Federal Reserve Bank of New York Staff Reports, Apr. 2013
https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr613.pdf


Berck, Peter, and Sofia B. Villas-Boas. “A Note on the Triple Differences in Econometric Models.” Applied Economics Letters, 3 August 2015,
https://www.tandfonline.com/doi/abs/10.1080/13504851.2015.1068912#aHR0cHM6Ly93d3cuZGZvbmxpbmVuY29tL2RvaS9wZGYvMTAuMTA4MC8xMzUwNDg1MS4yMDE1LjEwNjg5MTIjbmVlZEFjY2Vzcz10cnVlQEBAMA==


