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State-Provided Paid Family Leave and the Gender Wage Gap

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STATE-PROVIDED PAID FAMILY LEAVE AND THE GENDER WAGE GAP

by

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ABSTRACT

The U.S. is the only OECD country that does not offer any form of federal paid parental leave. Only three states—California, New Jersey and Rhode Island—have state paid parental leave policies; implemented in 2004, 2009 and 2014, respectively. Through descriptive statistics and a regression analysis of women and men’s wages in those three states, before and after the implementation of the policies, we assess the effects of paid leave programs on the gender wage gaps in those states. Our results show us that California’s paid family leave policy had greater effects on decreasing the gender wage gap than the policies in New Jersey and Rhode Island. In addition, our regression analysis shows us that women of childbearing age (19-45 years) saw an increase in their wages after the policy implementations, while men of childbearing age saw a decrease in their wages. This led us to the conclusion that paid family leave policies may be effective in decreasing the gender wage gap; however it is problematic that men’s wages decreased, implying that the policies may not be totally welfare optimizing. However, we came to an important conclusion that will hopefully entice more states and the federal government to implement policies to better support working parents.
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I. Introduction

Our society’s idea that motherhood is incompatible with employment is based in a historical lack of support for working parents, as well as jobs that were built for men who were able to leave the unpaid work of childrearing and housework to their wives for many years. Many jobs remain built on the assumption that working fathers in heterosexual relationships have a “woman in the wings” to deal with the care of children, even after modern society has evolved in such a way that households often include two working parents, and 40% of the time, a single working mother (American Association of University Women, 2015). Our country’s delay in reforming policies to catch up with the reality of modern society has led to a fundamental hole in support available to families, which leads to unnecessary sacrifices. Most of the time, women pay the price for these sacrifices—and the resulting inequalities such as decreased wages and a loss of human capital, are deemed a simple repercussion of her so-called “choices”, as if she had a choice in the policies and history of a lack in support for working mothers in the U.S.

One of the economic effects that come from the lack of support for working parents is a persistent gender wage gap. Currently, young women, ages 16-34, typically earn about 90% of men’s earnings, however, by age 35 women’s wages fall to a staggering 75-80% of men’s earnings (AAUW, 2015). While these statistics are combined averages of women’s wages of all races, the gender wage gap varies greatly among race; with Asian American women earning the most, at 90% of white men’s wages, and Hispanic or Latina women earning the least, at 54% of white men’s wages (AAUW, 2015). These vast differences are greatly affected by occupation and industry that women, and specifically women of color, will work in. However, around 7% of the
gender wage gap remains unexplained. If nothing changes, the gender wage gap will not close in all states until the year 2159 (Institute for Women’s Policy Research, 2015). For this reason, policies that support workingwomen are extremely necessary to speed up the process of closing the gap. In the following paper we will examine the impact of three state’s paid family leave policies on the gender wage gaps in those states.

In the U.S. there is no guaranteed paid maternity or paternity leave— making us the only OECD country without this guarantee. Without the support from federal policies, many women are forced to quit their job if they are not provided any time off from their employer. In addition, childcare in the U.S. can be so expensive that the income mothers would make at work would not be enough to afford anything besides the childcare itself—making many families decide to rely on one parent’s income, most times the father’s, and rely on a mother’s full-time “free” childcare at home. However, in the long run, exiting the workforce will be anything but free. Without paid maternity leave, women could lose ties to the workforce, and when they decide to return to work, their wages may decrease because of a perceived loss of skills to employers. Guaranteeing paid maternity leave for every woman is necessary to partly combat the gender wage gap by solidifying, incentivizing, and retaining women’s jobs.

However, if employers expect women to take maternity leave it could give them reason to discriminate against women—potentially furthering the gender wage gap rather than decreasing it. Employers may not pay women as much, or may be wary about hiring them to begin with, when they believe that they may be responsible for family commitments in the future. For this reason, it is equally as important to secure guaranteed paid paternity leave for working fathers as well, because taking time off to start a family
would no longer only be expected from women. Not only does paternity leave allow fathers the opportunity to bond with their newborns during a crucial time, but it could theoretically decrease the gender wage gap as well. Encouraging men to take leave, and reforming policies to allow fathers to more realistically do so, could change the stigmatization of women’s availability and ability in the work environment that currently penalizes their wages in a way that working fathers do not experience.

Additionally, it is important to call out the heteronormative scope of this paper. There is no doubt that both queer men and women face far greater amounts of discrimination in the workplace from their employers as well as federal and state policies that do not protect same-sex marriage or families adequately. Unfortunately, the scope of this research is limited in that it does not focus on specific ways in which same-sex couples face discrimination when starting families; as our data sources do not provide adequate information or variables to encompass how these policies would affect queer individuals and same-sex couples differently.

Presently, there are only three states with some sort of Paid Family Leave program: California, New Jersey and Rhode Island. In the following research paper we create an econometric model that will study whether the implementation of these programs in 2004, 2009 and 2014, respectively, has decreased the gender wage gaps in these states. If so, why haven’t other states or the federal government implemented similar policies? And if not, how can the policies be improved? Are not enough people taking advantage of the programs to have a substantial effect on the gender wage gap? Through an economic analysis of the programs and gender wage gaps in these three states compared to the rest of the U.S., we will evaluate these questions.
II. Previous Literature

Currently, there has been ample economic research done on the effects of unpaid maternity leave on the gender wage gap in the United States, the effects of paid paternity leave in Europe, and the effects of California’s paid parental leave program on wages and employment. However, there is currently a hole in the development of the topic. The United States implemented the Family and Medical Leave Act in 1993 that secured unpaid parental leave for “qualifying” employees (those who have worked at least 1250 hours in the prior year for an employer with at least 50 employees), and California was the first state to implement a paid parental leave program. Additionally, there are now two more states that offer similar paid parental leave programs—New Jersey and Rhode Island. Through a review of the previous literature, we can model our research using specific aspects of them all to put the effects of the paid parental leave programs in California, New Jersey and Rhode Island in conversation with one another—in a way that has previously been ignored.

Before the FMLA guaranteed 12 weeks of unpaid parental leave to “qualifying” employees in 1993, the United States was lacking any sort of support for pregnant, working, women. Caplan-Cotenoff (1987) uses Supreme Court cases Geduldig v. Aiello (1974), General Electric Co. v. Gilbert (1976) and Nashville Gas Co. v. Satty (1977) to illustrate the way in which pregnancy was excluded from disability insurance legislation at the time, placing a substantial burden on women that was not imposed on men—including women being fired when becoming pregnant, and not being provided with job security after giving birth. Caplan-Cotenoff (1987) continues to dissect the thought-process of the Supreme Court before the FMLA.
“The members of the Supreme Court are children of their times […] these cases define the scope of human experience in male terms […] as men are unable to become pregnant and women’s entry into the workforce was limited, exclusion of pregnancy was perfectly acceptable […] These statements may manifest a belief that because women are more suited for domestic work than for careers outside the home, employee benefit packages need not cover a uniquely female condition” (p. 77-78).

Although this excerpt is taken from a law journal rather than an economics paper, it allows us to view the historical context and need for legislation to attempt to eradicate the blatant sexual discrimination of the time—leading to the FMLA and subsequent state policies that we will be using for review and economic analysis.

Waldfogel (1999) wrote one of the most-cited pieces of past literature related to this topic, studying the following four questions: “Did coverage increase as a result of the FMLA? Did utilization increase as a result of the FMLA? Did the FMLA have an effect on women’s employment? Did the FMLA have an effect on women’s wages?” She was the first to research the FMLA’s effects on women’s wages—research before this point focused solely on the FMLA’s effects on motherhood employment and attachment to the workforce. Waldfogel explains that only 11 states had laws to protect the right to employer-provided maternity leave prior to the FMLA’s implementation; making the these 11 states the control group, where the FMLA potentially had no effect on women being provided with unpaid maternity leave. Rather than using time-series analysis, the study uses difference-in-difference analysis to compare the changes in states for which there was no law change (the control group) to states where there was a change after the
implementation of the FMLA. Waldfogel acknowledges that this methodology could produce some biased estimates if there were differences in the states that were not caused by the implementation of the FMLA. To address this potential bias, she uses a difference-in-difference-in-difference method, identifying more than one “treatment” group (those affected by the law) and more than one “control” group (those not affected by the law). In Waldfogel’s analysis of employment and wages, she uses two treatment groups: women ages 19-45 (childbearing age) with children, and women ages 19-45 with children under 1 year old; excluding self-employed women and part-time workers, as the FMLA only benefits employees who have worked 1250 hours during the prior year, for an employer with at least 50 employees. The three control groups she uses are as follow: women ages 19-45 without children, men ages 19-45, as well as women ages 46-60; the FMLA was meant to mainly benefit mothers of newborns, however, the change may have affected the employment and wages of women if they are of childbearing age (19-45), even if they are childless, because of employer’s assumptions about their potentially imminent pregnancies. Waldfogel’s first hypothesis is that wages of women of childbearing age will decrease, as employers will pass along the costs of the FMLA to those who will potentially utilize the leave. The second hypothesis is that wages of women using the FMLA will increase, as they will retain their jobs. The results of her tests conclude that the FMLA had essentially zero net wage effects in the short run as the two hypotheses effectively cancel one another out. Waldfogel’s work will be a useful model for our own research, because we are both looking at wages before and after the implementation of a given parental leave program—the difference being that the programs observed in the
scope of our research will be state-implemented paid parental leave programs, rather than an unpaid federal program.

Baum (2003) uses similar difference-in-difference-in-difference estimators to Waldfogel’s, while explaining how she aims to expand and improve upon the past research. Baum explains that one potential reason that Waldfogel’s study found that maternity leave legislation had statistically insignificant effects on wages is that Waldfogel’s treatment and control groups “do not accurately identify those covered by the legislation”; many mothers who are assumed to have government-mandated maternity leave are not actually covered because their employer does not meet the minimum of 50 employees—something that Waldfogel does not take into account in her treatment and control groups. Baum attempts to improve upon the work of others by identifying whether or not women work for employers that are covered by the FMLA and controlling for sample selection bias—as maternity leave legislation may prompt low-wage women to enter the workforce to benefit from it. In addition, Baum uses state-specific dummy variables and year-specific dummy variables to control for the fact that different states have higher wages, and that wages may have grown over time regardless of maternity leave legislation. Regardless of her improvements to the past research, Baum ultimately comes to the same conclusion that Waldfogel did—the FMLA had little effect on women’s wages. While it is a positive that maternity leave legislation did not decrease women’s wages as Waldfogel hypothesized, it also did not increase women’s wages and help decrease the perpetual gender wage gap either. One explanation that Baum offers is that the FMLA is not generous enough in its support for working mothers, because it is unpaid.
Selmi (2000) focused on paid family leave—specifically paternity leave. The research suggested that incentivizing fathers to take paid paternity leave would help decrease the gender pay gap. “To close the gender gap further” Selmi explains, “we need to take steps to disrupt both the reality and the expectations of how women’s relation to their children affects their labor market behavior and rewards. Second, creating a workplace where it is expected that workers will have, and take care of, children is essential to furthering our societal interest in the family…If men begin to act more like women, employers may come to expect their employees to undertake the responsibilities of child rearing and to accommodate that responsibility more than they have so far been willing to do […] family leave benefits would then become part of the standard package of employee benefits […] which today are seen as an integral part of doing business despite their cost” (Selmi, 2000). Essentially, it was predicted that to decrease the gender wage gap, employers must expect both men and women to take time off to have children, dismantling stereotypes and discrimination in wage and hiring practices that can exist when employers expect only the women they hire to leave their job at some point during their child-bearing years. This expectation allows employers to perceive women as having a lower commitment to the work force, and whether consciously or not, may effect the way that they treat them in terms of hiring, starting salary, and promotions if they are uncertain that they may leave to start a family. By making it the norm for men to take paternity leave, employers will be unable to have these perceptions of only women, hopefully creating greater gender equality. In addition to incentivizing fathers to take leave, Selmi suggests that legislation should mandate leaves be paid rather than unpaid, similar to Baum’s suggestion in 2003. It is financially unrealistic to expect people to be
able to afford weeks off from work without being paid—especially after having a child, and for this reason, many people who would like to take parental leave cannot realistically do so. Selmi’s conclusions were helpful in modeling the economic theory surrounding our hypothesis.

Cools, Fiva, and Johannessen (2011) studied the effects of paid paternity leave in Norway. In Norway, parents are entitled to 38 weeks of 100% paid leave, with an additional 4 weeks of leave reserved only for fathers. If fathers do not take these 4 weeks, then the couple loses those weeks all together—in a “use or lose it” policy fashion. Cools, Fiva, and Johannessen study the effects of two different policy changes; the first of which occurred in 1992 when the parental leave policy extended by 3 weeks from 32 weeks to 35 weeks. The second policy change occurred one year later in 1993. The parental leave policy increased from the 35 weeks to 38 weeks, plus the additional 4 weeks that only fathers could use. In their methodology, Cools, Fiva, and Johannessen focused only on families that are eligible for the coverage based on employment status (similar to Baum’s method), and used a difference-in-difference methodology by comparing the difference between the 1992 pre-reform and post-reform groups to the corresponding 1993 pre-reform and post-reform groups. To analyze changes in wages, they constructed dummy variables to identify whether parents work part time (at least 20 hours) or full time (at least 30 hours). Summary statistics were created from the samples and illustrate mean earnings of all fathers with children ages 2-5 and 6-9, mean earnings of fathers working full-time with children ages 2-5 and 6-9, and mean earnings of fathers working part-time with children ages 2-5 and 6-9, as well as the same data for mothers. Using these statistics, they could see that contrary to popular belief, such as Selmi’s predictions, paid
paternity leave in Norway had statistically significant negative effects on women’s labor market outcomes. Cools, Fiva and Johannessen suggest that the 4 weeks of paternity leave may not be enough time to produce the hypothesized effects on women’s wages in the long run. Additionally, perhaps because females took longer leaves after the implementation of the policies, they saw negative effects on their human capital, and their attachment to the workforce or job security. Although this research was conducted in Europe, it is a useful model for conducting our own research on the before-and-after effects of a paid parental leave program on mothers’ and fathers’ wages, and how to effectively compare them.

Other studies such as Appelbaum and Milkman (2004) have researched the effectiveness of California’s paid family leave program. Appelbaum and Milkman used the Golden Bear Omnibus Survey and the Survey of California Establishments to study public attitudes and awareness towards the paid family leave program, and the extent to which California employers provide family leave beyond what the state program implemented. Using the survey’s data, they produced F-statistic tests based on Chi-square statistics, two-sample t-tests to test the significance of differences in weighted means, and a series of weighted logistic regression analyses. Appelbaum and Milkman concluded that only about 1 in 5 Californians are even aware of the new paid parental leave program. Workers with the most family-friendly employers are the ones that are the most aware of the program, even though they likely already receive family leave benefits from their employer, and are likely higher-income workers. Consequently, low-income workers who are usually not offered leave from their employer have the greatest need for a state-implemented paid family leave program, but are usually unaware of it, and thus,
the program is not as effective as possible. Although Appelbaum and Milkman do not specifically study the program’s effect on women’s wages and the gender pay gap, it is important to use their conclusions about the limitations of the policy, and lack of policy awareness, to better understand our own results.

The works cited in the paragraphs above by Caplan-Cotenoff (1987), Waldfogel (1999), Baum (2003), Selmi (2000), Cools, Fiva, and Johannessen (2011) and Appelbaum and Milkman (2004) are some of the most-cited literature previously written on the topic of maternity and paternity leave. This selection of literature focuses on all aspects of family leave including: the need for legislation to eradicate gender inequality, unpaid parental leave in the U.S., paid parental and paternity leave in Norway, and the paid parental leave program in California. From this broad selection we can essentially combine all of their past methods to create the following study on the effects of the paid parental leave programs in California, New Jersey and Rhode Island on wages and the gender wage gap—filling a void in the previous literature that has not yet been touched upon by economists.
III. Data, Model & Results

A. Economic Theory

After the Federal Medical Leave Act was implemented in 1993, parents were forced to rely on unpaid federal maternity or paternity leave if their employer did not offer an independent plan. In 2004, California was the first state to implement a paid parental leave program. The specifics of the program in California entitle employees up to 55% of their wages for 6 weeks, after they pay into the State Disability Insurance (SDI) fund. New Jersey followed in 2009, as did Rhode Island in 2014, with similar programs. California’s state paid leave program improved upon the FMLA because any employee is eligible if they have paid into the State Disability Insurance, regardless of how many employees their employer has, or how many hours they worked in the previous year. However, the state program is also worse off than the FMLA, in that the program does not provide guaranteed job security after taking leave, creating a difficult and risky decision for people to make before applying for it.

Economic theory leads us to determine that increasing the ability for employees to take paid leave would increase the number of men taking leave overall. Because men are usually the one making a higher income (or else there would not be a gender wage gap), taking time off for unpaid leave would have a much higher opportunity cost for them, as compared to women. Theoretically, the greater number of men that take time off for parental leave, the less likely it would be that employers would subconsciously, or consciously, discriminate against women by giving them lower salaries because they expect them to take time off to start families in the future. When women are seen as less
committed to the workforce compared to men, employers will either demand their labor
less, or will offer them lower wages than they would offer men.

Our hypothesis then, is that after the implementation of the paid parental leave
programs, the gender wage gaps in states with a paid leave policy would decrease by a
greater amount than the gender wage gaps in states without a paid leave policy—leaving
all other variables constant. However, although the term “discrimination” cannot be used
synonymously with “wage gap”, (because discrimination of this kind can only make up a
fraction of our total gender wage gap) this fraction of the wage gap is what we
hypothesize can be improved by the implementation of paid family leave programs, and
is the focus of this research.

However, it is also likely that we may not see this economic theory affect our
results as expected for a variety of reasons. Receiving 55% of wages is not the same as
100%, and the incentive to leave the workforce for six weeks to care for a new child may
still not outweigh the potential opportunity cost of 45% of lost wages. In addition, the
type of occupation that the parents have, or the level of education they have received,
may influence whether or not they are aware of the state programs to begin with, or if
their employer offers a better option for parental leave that they can take advantage of.
Both of these scenarios would lead to no increase in paternal participation in the state
programs.

In addition, there are theoretical reasons to expect women’s outcomes to actually
worsen as a result of paid leave programs. One of these reasons is that these state-
implemented paid leave programs do not provide guaranteed job security, as the unpaid
FMLA does. Women who wish to utilize these programs risk losing their jobs as a consequence, potentially worsening women’s outcomes as an effect of the program.

**B. Data**

The data set compiled for this analysis is from the CEPR (Center for Economic and Policy Research) Uniform Extracts of the CPS ORG (Outgoing Rotation Group), also known as the “Earnings Files” or “Quarter Sample” of the CPS (Current Population Survey). This data set contains detailed information about individual’s earnings, education, labor-market status, and demographic characteristics. Additionally, the data is collected monthly from about 56,000 households. Individuals in a household are interviewed for four consecutive months, and again the following year for the same four months. This method of data collection allows the CPS to obtain reliable month-to-month and year-to-year comparisons. To keep the dataset smaller, we have only kept observations from individuals ages 18-64 (typical “working” age), and dropped a number of unrelated variables, while adding our own dummy variables and interaction terms. After trimming the data in this manner, the following research contains 4,610,756 observations and 100 variables over the span of 15 years.

The 100 variables that are used in our analysis are outlined as follows. We created fifteen dummy variables for each year from 2000-2014; three dummy variables for the highest level of education received (High school/Associate’s degree, Bachelor’s degree, and Masters degree or higher); one for “childbearing age” (ages 19-45); one for age (18-64); one for married; five dummy variables for race (White, Black, Hispanic, Asian/Pacific Islander, American Indian/Aleut/Eskimo); 51 dummy variables for each
state including Washington D.C.; nine dummy variables for occupation
(Professional/Executive, Professional Technicians, Sales and Administrative, Public and
Private Services, Farming and Agriculture, Construction and Repairs, Textiles, Machine
Operators, and Transportation Operators); as well as nine dummy variables for industry
(Professional/Executive, Administrative, Personal Service, Public Service, Trade,
Finance, Farming and Agriculture, Construction and Repairs, and Manufacturing). In
addition, we used the variable “ch05” from the dataset to distinguish how many children
between the ages of 0 and 5 someone has; as parents to children in this age range would
be most affected by the policies. In addition, we created an “age” variable, as well as two
interaction terms. The first interaction term named “post” represents the time period after
the implementation of the policy in each of the states that have a policy. For example,
post=1 in California in 2005 and afterwards, post=1 in New Jersey in 2010 and
afterwards, and post=1 in Rhode Island in 2014. Because this variable illustrates the
intersection of treatment state and time period post-policy implementation, this is the
variable that will reveal whether or not the policy itself influenced changes in the gender
wage gap that were not due to changes over time. The second interaction term
“childbearing_post” represents people of childbearing age, in states with policies, post-
policy implementation. This variable represents the group of people that the policy was
aimed to effect, and can shed light onto whether or not these policies were effective in
decreasing the gender wage gap. And finally, our dependent variable used in our
regression analyses is “real wages” in 2014 dollars.

We will first complete initial descriptive statistics on men and women’s real
wages in different states before and after the implementation of the policies. Following,
we will complete a form of regression analysis to determine whether the policies themselves had a significant effect on the real wages of men and women. By focusing on real wages, we can deduce the effects of the policy on gender wage gaps by subtracting women’s real wages from men’s real wages.

C. Research Methods: Descriptive Statistics

We examine the changes in the gender wage gaps in the three states with paid parental leave policies versus the states without similar policies by using the data compiled from the CPS from years 2000-2014. To create the summary statistics in Table 1 we summarized real wages for females and males in each state, recording their mean real wages before and after the year their policy was implemented. In addition, when calculating the mean wages of the control group (states without paid parental leave), we summarized the real wages in all states while purposefully excluding the three states with policies (the treatment group) after the years they were implemented, so that we could effectively compare states with and without a paid leave policy. This means that California’s pre-policy control group “Other” includes every other state; because California was the only state with a paid family leave policy at the time of their policy implementation. However, New Jersey’s “Other” group excludes California; and Rhode Island’s “Other” group excludes both California and New Jersey. By calculating gender wage gaps in this fashion, we can more accurately compare states with paid leave policies to the selected states without paid leave policies.

After recording the mean real wages of men and women in each treatment and control group, we then calculated the gender wage gaps by subtracting women’s mean
real wages from men’s mean real wages. We completed this for each state before the year of their policy implementation, and after their policy implementation, to see whether or not the gender wage gap in the states with a paid family leave policy decreased by a greater amount than the states in the control groups during the same time period. If so, the faster rate in decrease of the gender wage gap in the treatment group could be due to the policy change, rather than just a consistent change over time that would influence the gender wage gap of every state, regardless of these policies.

For example, in Table 1 we can see that California’s gender wage gap decreased by $0.1542 post-policy implementation in 2004, while the states without a similar policy actually increased their gender wage gap by $0.336 after 2004. In the Difference in Difference column of Table 1, we calculated the difference between these amounts to visualize whether or not the gender wage gap in California changed by more or less than the gender wage gap in other states—illustrating whether or not the policy was effective in helping the gender wage gap. Our result for California is a positive $0.492. This difference in gender wage gaps between California versus control states indicates that California’s gender wage gap did indeed improve more than other states after the implementation of their paid leave policy, meaning the policy was effective—agreeing with our hypothesis.

After New Jersey’s policy was implemented in 2009, their gender wage gap decreased by $0.4861, while the gender wage gap in states without a family leave policy (all states except California) decreased by $1.1156 after 2009. This means that the gender wage gap in New Jersey actually changed by a smaller amount during the same time period than the gender wage gap in states without a paid leave policy. This difference is
equal to -$0.6295, and could indicate that the paid family leave policy was in fact not
effective in helping the gender wage gap in New Jersey, contrary to our hypothesis.

Lastly, in Rhode Island the gender wage gap after the policy implementation in
2014 was $0.3024, while the gender wage gap in states without a paid family leave
program (all states besides Rhode Island, New Jersey, and California) had changed by
$1.2205. Similar to New Jersey’s results, the -$0.9181 difference in these differences of
pre- and post-policy gender wage gaps could reveal that the policy did not have the
hypothesized effect on the wage gap in Rhode Island.

Based on the results of these summary statistics in Table 1, we see that the
decrease in the gender wage gaps in New Jersey and Rhode Island were actually smaller
than the decrease in the gender wage gaps in states without paid leave policies—contrary
to our original hypothesis that a paid parental leave policy would cause the gender wage
gaps to decrease more greatly in states with the policies. However, the paid family leave
policy in California did support our original hypothesis, meaning that by implementing a
paid family leave policy, this fraction of their state’s gender wage gap was effectively
decreased.

There could be several reasons that California’s policy effectively decreased the
gender wage gap post-policy, while New Jersey and Rhode Island’s gender wage gaps
decreased less than the states without policies. Rhode Island’s policy results seem
ineffective for a more clear reason; we do not have very much data post-policy
implementation, as their policy was only implemented in January of 2014. While we have
12 months of data post-policy, we do not have access to 2015 data quite yet, and this
small dataset would have likely affected our results.
As for New Jersey, it is important to think about the year in which the policy was implemented. New Jersey’s paid family leave policy was implemented in the midst of the financial crisis, in which many people, especially women, were losing their jobs. Rubery and Rafferty (2013) have researched “the extent to which women might act as a flexible reserve over the business cycle” dependent on three factors: “the pattern of gender segregation and its relationship to employment change; women’s commitment to labor market participation; and state policy and support for women’s employment”, using the context of the 2008/2009 recession. Rubery and Rafferty concluded that while women are now resisting taking on the role of flexible labor supply by increasing their permanent attachment to the work force, women within certain sectors continue to bear a larger share of job-loss amidst recessions. Because New Jersey’s policy was implemented in 2009, women’s wages were likely decreasing for recession-related reasons, and families did not need to utilize, or did not have the resources to utilize, the paid family leave policies.

There could be additional factors that are unique to each state and/or year in which the state implemented its policy, which is justification for the approach used in the following section to create a separate variable for each state and each year—attempting to control for their potential differences.

D. Research Methods: Econometric Models

To begin forming our econometric models, we created the variable log (real wages) for our dependent y-variable to create a log-linear model:

\[
\log Y = \beta 0 + \beta 1X + \beta 2X + ... \beta kX
\]
We must perform a log transformation on the dependent variable, real wages \((rw)\), while keeping the independent variables in their original unit scale because we are interested in the percentage change in the \(y\)-variable for every unit change of each \(x\)-variable. In the case of our dummy variables, the “unit” change will be whether the characteristic of the dummy variable is present or not. A percentage change in real wages will have much greater meaning in interpreting our regression results than a change in wages by just one dollar.

The first three of our empirical models are the simplest models, controlling only for state, year, post-policy implementation, and sex. They are defined as follows:

(1) \[
\text{LOGRW}_i = \beta_0 + \beta_1 \text{CA} + \beta_2 \text{NJ} + \beta_3 \text{RI} + \beta_4 \text{POST} + \beta_5 \text{YEAR2001} + \\
\beta_6 \text{YEAR2002} + \beta_7 \text{YEAR2003} + \beta_8 \text{YEAR2004} + \beta_9 \text{YEAR2005} + \beta_{10} \text{YEAR2006} + \\
\beta_{11} \text{YEAR2007} + \beta_{12} \text{YEAR2008} + \beta_{13} \text{YEAR2009} + \beta_{14} \text{YEAR2010} + \beta_{15} \text{YEAR2011} + \\
\beta_{16} \text{YEAR2012} + \beta_{17} \text{YEAR2013} + \beta_{18} \text{YEAR2014} + \epsilon_1
\]

(2) \[
\text{LOGRW}_i = \beta_0 + \beta_1 \text{CA} + \beta_2 \text{NJ} + \beta_3 \text{RI} + \beta_4 \text{POST} + \beta_5 \text{YEAR2001} + \\
\beta_6 \text{YEAR2002} + \beta_7 \text{YEAR2003} + \beta_8 \text{YEAR2004} + \beta_9 \text{YEAR2005} + \beta_{10} \text{YEAR2006} + \\
\beta_{11} \text{YEAR2007} + \beta_{12} \text{YEAR2008} + \beta_{13} \text{YEAR2009} + \beta_{14} \text{YEAR2010} + \beta_{15} \text{YEAR2011} + \\
\beta_{16} \text{YEAR2012} + \beta_{17} \text{YEAR2013} + \beta_{18} \text{YEAR2014} + \epsilon_1 \text{ if FEMALE==1}
\]

and,

(3) \[
\text{LOGRW}_i = \beta_0 + \beta_1 \text{CA} + \beta_2 \text{NJ} + \beta_3 \text{RI} + \beta_4 \text{POST} + \beta_5 \text{YEAR2001} + \\
\beta_6 \text{YEAR2002} + \beta_7 \text{YEAR2003} + \beta_8 \text{YEAR2004} + \beta_9 \text{YEAR2005} + \beta_{10} \text{YEAR2006} + \\
\beta_{11} \text{YEAR2007} + \beta_{12} \text{YEAR2008} + \beta_{13} \text{YEAR2009} + \beta_{14} \text{YEAR2010} + \beta_{15} \text{YEAR2011} + \\
\beta_{16} \text{YEAR2012} + \beta_{17} \text{YEAR2013} + \beta_{18} \text{YEAR2014} + \epsilon_1 \text{ if FEMALE==0}
\]

where \(\text{LOGRW}\) is the log of real wages, CA is a dummy variable representing California, NJ is a dummy variable representing New Jersey, RI represents Rhode Island, YEAR2001-YEAR2014 are dummy variables for each year from 2001-2014, respectively. POST is a dummy variable for the time period after policy implementation in each state (after 2005 if in California, after 2009 if in New Jersey, and after 2014 if in
Rhode Island). In equation 1 we can see the variables’ effects on real wages of both men and women, equation 2 on real wages of women, and equation 3 on real wages of men, the results of which are discussed below, and can be found in Table 2.

The R-squared values of equations 1-3 are rather low: 0.0033 for Equation 1, 0.0042 for Equation 2, and 0.0075 for Equation 3. These R-squared values represent the percentage change of the variation in real wages that we can explain by the independent variables (state, year, and post-policy implementation). In this case, only 0.33%, 0.42% and 0.75% of the percentage of real wages can be explained by the x-variables. While the R-squared values are not the only means for reliable regression analysis in determining goodness of fit, with such low values it may be reason to believe that additional control variables are needed for our model such as level of education, occupation, and race—as these initial results may be biased because they fail to account for individual human capital characteristics.

In the regression models below we have included extensive control variables to better estimate our model, while keeping the same log-linear function with log (real wages) as our dependent y-variable. These three equations include all of the variables in our dataset, except for four variables that were omitted due to multicollinearity; discussed in detail below. The 96 variables used encompass: highest level of education obtained, age, age^2, childbearing age, marital status, race, number of children ages 0-5, state (every state—not just the three treatment states used in the first 3 equations), occupation, industry, year, post-policy implementation in states with policies, and childbearing age post-policy implementation. In addition, these three models use robust standard errors. The regressions are modeled as follows:
\[(4) \quad \text{LOGRWi} = \beta_0 + \beta_1 \text{EDUC} \_\text{BACH} + \beta_2 \text{EDUC} \_\text{HIGHER} + \beta_3 \text{CHILDBEARING} \_\text{AGE} + \beta_4 \text{AGE} + \beta_5 \text{AGE}^2 + \beta_6 \text{MARRIED} + \beta_7 \text{WHITE} + \beta_8 \text{BLACK} + \beta_9 \text{HISPANIC} + \beta_{10} \text{ASIAN} + \beta_{11} \text{NATIVEAMERICAN} + \beta_{12} \text{OCC} + \beta_{13} \text{CA} + \beta_{14} \text{NJ} + \beta_{15} \text{RI} + [... ] + \beta_{62} \text{HI} + \beta_{63} \text{PROFEXEC} \_\text{OCC} + \beta_{64} \text{PROFTECH} \_\text{OCC} + \beta_{65} \text{SALESADMIN} \_\text{OCC} + \beta_{66} \text{SERVICES} \_\text{OCC} + \beta_{67} \text{FARMING} \_\text{OCC} + \beta_{68} \text{CONSTRUCTION} \_\text{OCC} + \beta_{69} \text{TEXTILE} \_\text{OCC} + \beta_{70} \text{MACHINE} \_\text{OCC} + \beta_{71} \text{TRANSPORT} \_\text{OCC} + \beta_{72} \text{FARMING} \_\text{IND} [... ] + \beta_{80} \text{ADMIN} \_\text{IND} + \beta_{81} \text{YEAR} \_\text{2001} + \beta_{82} \text{YEAR} \_\text{2002} + \beta_{83} \text{YEAR} \_\text{2003} + \beta_{84} \text{YEAR} \_\text{2004} + \beta_{85} \text{YEAR} \_\text{2005} + \beta_{86} \text{YEAR} \_\text{2006} + \beta_{87} \text{YEAR} \_\text{2007} + \beta_{88} \text{YEAR} \_\text{2008} + \beta_{89} \text{YEAR} \_\text{2009} + \beta_{90} \text{YEAR} \_\text{2010} + \beta_{91} \text{YEAR} \_\text{2011} + \beta_{92} \text{YEAR} \_\text{2012} + \beta_{93} \text{YEAR} \_\text{2013} + \beta_{94} \text{YEAR} \_\text{2014} + \beta_{95} \text{POST} + \beta_{96} \text{CHILDBEARING} \_\text{POST} + \varepsilon_1\]

\[(5) \quad \text{Same as EQUATION 4} \quad \text{if } FEMALE == 1\]

\[(6) \quad \text{Same as EQUATION 4} \quad \text{if } FEMALE == 0\]

When creating dummy variables, we are often times faced with the issue of multicollinearity. In the full regression models we had to drop one of our year variables, one of our race variables, one of our states, and one of our education variables—as these variables are all highly correlated within one another. We decided to drop the year 2000 because it is the earliest year in our dataset, as well as the “mixed” race variable because out of the other race variables, it had the smallest number of observations; and so hopefully, the smallest impact on our results. In addition, we dropped the DC “state” variable, as Washington D.C. is in fact not a state, and perhaps would not have a state-implemented paid leave policy of this kind. And finally, we dropped the variable denoting that the highest level of education received was a high school or associates degree, as the Bachelor’s degree and Master’s degree estimates that we kept can be read as “the effect of this level of education relative to the baseline of a high school degree”.

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E. Results

\textit{a. Equations 1-3}

The first equation is meant to estimate whether the policies had significant effects on real wages as a whole—regardless of gender—while the second equation looks at effects on women’s wages, and the third equation looks at effects on men’s wages. By separating the changes of real wages for women and men, we can then estimate what the changes in the gender wage gap would be—if women’s wages increased while men’s have no change, or decreased, then we theoretically know that the overall gender wage gap decreased. In these three equations, the POST coefficient is the part of the regression that will tell us how the paid family leave policies affected real wages of men and women. If the coefficient is positive for women, this will mean that women’s wages increase when they are in one of the treatment states (California, New Jersey, or Rhode Island), after the year the policy was implemented in that state. Similarly, if the coefficient were negative for men, this would mean that their wages decreased post policy implementation in one of the treatment states. Following, we could come to the conclusion that the gender wage gap effectively decreased post-policy implementation. However, these are not the results that we see in our regression analysis.

The POST coefficient for Equation 2 is -0.0087, with a p-value of <=0.01, meaning it is significant. This means that the real wages of women in California post-policy implementation in 2005, or in New Jersey post-policy implementation in 2010, or in Rhode Island post-policy implementation in 2014, would decrease by 0.87%. Although this percentage change is small, the results show that women’s wages were negatively affected by the state’s policy changes—contradictory to our hypothesis.
In addition, the POST coefficient for Equation 3 is equal to 0.0035. This result estimates a seemingly positive relationship between the policies and real wages of men; if you are a man in one of the treatment states after their policies were implemented, your wages would increase by 0.35%. However, with a p-value of 0.331, this outcome is not significant.

The results of the first three simple regressions show that women’s wages would decrease as a result of the policies, while men’s wages would increase. This means that the gender wage gap actually increased—contrary to our hypothesis. However, because the results for POST in Equation 3 are not significant, and all three of the R-squared values are rather small (0.0033, 0.0042, and 0.0075), it is reasonable to believe that these results are not showing the entire picture. Additional control variables are needed in the regression to paint a full picture of women and men’s wages after these policies were implemented.

b. Equations 4-6

The results of these three more complete equations include controls for education, age, marital status, race, number of children ages 0-5, occupation and industry that the first three equations do not include. In addition, these equations include an additional interaction term that allow us to see the effects of the family leave policies even better than the POST coefficient does. The interaction term CHILDBEARING_POST not only represents the wages of men and women after policy implementation in the treatment state (like POST does), but it only includes men and women ages 19-45, the standardly used age range for “childbearing age”. This variable will show us the effectiveness of the policy even more clearly, because we are interested in how the policies affect wages of
people of childbearing age with children, as well as people of childbearing age who do not have children, who employers may expect to have families in the short-term future. Equation 5 represents the changes of women’s wages, and Equation 6 illustrates changes of men’s wages. Like the previous set of equations, we will be able to tell whether there were changes to the gender wage gap based on the changes of wages of men and women.

The CHILDBEARING_POST coefficient in the results of Equation 5 is 0.056, with a p-value equal to 0, meaning that it is very significant. This coefficient reveals that the real wages of women of childbearing age increased by 5.6% after the implementation of the policies in the treatment states. This is a huge difference from the 0.87% decrease in women’s wages that our results in the simpler model indicated. In addition, the R-squared value for Equation 5 is 0.1763; meaning 17.63% of the dependent variable (wages) can be explained by the x-variables. This too is a huge improvement from the 0.42% that could be explained by the limited variables in the simple regression equation for women.

In Equation 6, the coefficient for CHILDBEARING_POST is -0.0334, with a p-value equal to 0, making this coefficient very significant as well. This coefficient illustrates that the real wages of men of childbearing age in treatment states after the policies were implemented, would decrease by 3.34%. This result is a big improvement from the coefficient of POST in Equation 3, which did not have a significant p-value. In addition, the R-squared value for this equation is 0.2366; making 23.66% of the dependent variable explainable by the independent variables—an improvement from 0.75% explained in the simple regression, Equation 2.
The overall results of these equations show that the wages of women of childbearing age increased by 5.6% in states with the paid family leave policies, while the wages of men of childbearing age in those states decreased by 3.34%. Because women’s wages increased while men’s wages decreased, we can conclude that the paid family leave policies did in fact decrease the gender wage gaps in states with these policies—potentially proving our hypothesis to be correct.
IV. Conclusion

In this paper, we have explored the effects of paid family leave policies on real wages of men and women. This research aimed to discover whether or not these types of paid leave policies have had a direct effect on gender wage gaps.

Using CPS data, we created summary statistics and log-linear regression models to see the difference in gender wage gaps between states that have paid leave policies, and states that don’t. Additionally, we compared changes in real wages of women and men of childbearing age (19-45 years) to women and men not of childbearing age—as individuals of this cohort were meant to be the most affected by the paid leave policies.

Our initial summary statistics showed that the paid family leave policies had a positive effect in California, but we did not observe a large effect of the policy on gender wage gaps in New Jersey or Rhode Island. However, we discussed possible reasons for this disparity—the 2008/9 financial crises when New Jersey’s policy was implemented, as well as the small dataset available for Rhode Island post-policy implementation in 2014.

Nonetheless, when completing our full regression analysis, with complete control variables included, we saw a different outcome. Women of childbearing age would see their wages increase by 5.6%, while men of childbearing age would see their wages decrease by 3.34%. Our hypothesis was that with an increase in access to paid leave, more men would be able to take paternity leave, which would in turn help decrease the portion of the gender wage gap that is due to employer’s heteronormative and sexist belief that women will be less attached to the workforce because family would be their responsibility and not their spouse’s.
The lack of a more substantial effect on gender wage gaps may be due to flaws in the policies. While the paid leave programs pay approximately 55% of wages, this is still nowhere near 100%. If men were the spouses with higher income, it still would not make sense for them to take leave with such high opportunity costs in their lost wages. To be truly effective, our paid leave policies would need to offer closer to 100% of wages to outweigh the opportunity costs, similar to programs in many other OECD countries.

Additionally, Appelbaum and Milkman (2011) provide evidence in their research that public awareness of the program in California remains limited. In addition, their research found that many employees do not apply for benefits—even if they have knowledge of the program—for fear of negative employment consequences, since the paid family leave program in California does not come with job protection rights like the unpaid FMLA does. In addition, individuals who are employed in jobs that do not provide substantial family leave may be individuals that do not have the resources to seek and obtain knowledge about the state-provided programs in the first place—limiting the program’s access to the demographic group who need it and would utilize it most.

Limitations in my research create avenues for continued future research on this topic. To begin with, Rhode Island’s available data is limited since their policy was only implemented in January 2014, allowing us only one full year of observations post-policy. Future research could easily have more solid evidence and results if there were a greater amount of data to view Rhode Island’s policy effects. In addition, we could have created variables for the gender wage gaps to set as the dependent variables, rather than conduct two regressions for changes in men and women’s wages to deduce the change in gender wage gaps from. Additionally, a necessary topic of further research is the various effects
that family leave policies have on same-sex couples; for example, the ways in which their wages may be effected by an employer’s impression of whether they believe their employee will be the main caretaker of the newborn. And finally, it is important to remember that these paid family leave policies may have been effective and valuable for working parents in ways other than decreasing the gender wage gap. Further research on the effects of these policies on other aspects of employment, work-life balance, and employee happiness and retention would be important topics of further research in this field.

Our findings allow us to see the importance in continuing to amend policies that can support working parents in order to help decrease the portion of the gender wage gap that is due to women being expected to take maternity leave, and be less committed to the workforce than men are. While the paid family leave policies in California, New Jersey and Rhode Island were a step in the right direction, without more paid support and increased education about the programs, other states will not be inclined to enact similar policies without seeing that they are truly effective for the three states that have them now. In addition, it is problematic that these programs reduced the gender wage gap by both increasing women’s wages as well as decreasing men’s wages. While this allows the gender wage gap to narrow more quickly, it is not welfare-optimizing overall, which is a cause for concern. Without changing the way our country supports parents through more effective policy changes, we will continue to see a stigma be placed on working women. Having a family should not be something that only women are penalized for—children could not be made without men either.
V. References:


VI. Tables:

Table 1: Descriptive Statistics

Gender Wage Gaps (Male Real Wages-Female Real Wages)

<table>
<thead>
<tr>
<th></th>
<th>Pre-Policy Wage Gap</th>
<th>Post-Policy Wage Gap</th>
<th>Difference (Pre-Post)</th>
<th>Difference in the Differences (Treatment-Control)</th>
</tr>
</thead>
<tbody>
<tr>
<td>California:</td>
<td>$4.3396</td>
<td>$4.1854</td>
<td>$0.1542</td>
<td>$0.492</td>
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<tr>
<td>Other:</td>
<td>$5.1638</td>
<td>$5.4998</td>
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<td></td>
</tr>
<tr>
<td>New Jersey:</td>
<td>$6.6834</td>
<td>$6.1974</td>
<td>$0.4861</td>
<td>-$0.6295</td>
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<tr>
<td>Other:</td>
<td>$5.66481</td>
<td>$4.5492</td>
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<tr>
<td>Other:</td>
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<td>$4.2005</td>
<td>$1.2205</td>
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Table 2: Simple model outcomes

<table>
<thead>
<tr>
<th>Independent variables:</th>
<th>Equation 1: both genders</th>
<th>Equation 2: females</th>
<th>Equation 3: males</th>
</tr>
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<tbody>
<tr>
<td>Constant</td>
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<td>2.7282***</td>
<td>2.9867***</td>
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<td>ca</td>
<td>0.0724***</td>
<td>0.1057***</td>
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</tr>
<tr>
<td>nj</td>
<td>0.1718***</td>
<td>0.1679***</td>
<td>0.174***</td>
</tr>
<tr>
<td>ri</td>
<td>0.0505***</td>
<td>0.0707***</td>
<td>0.0374***</td>
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<td>POST</td>
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<td>year2003</td>
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<td>year2004</td>
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<tr>
<td>year2005</td>
<td>0.0284***</td>
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</tr>
<tr>
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<td>0.0346***</td>
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<tr>
<td>R-squared</td>
<td>0.0033</td>
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<td>0.0075</td>
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*** if p-value <=0.01, ** if p-value <=0.05, *if p-value <=0.10
Table 3: Complete model outcomes

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<tr>
<th>Independent variables:</th>
<th>Equation 4: both genders</th>
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<th>Equation 6: males</th>
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<td>Childbearing age</td>
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<tr>
<td>Age</td>
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<td>0.0282***</td>
<td>0.0891***</td>
</tr>
<tr>
<td>Age2</td>
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*** if p-value <= 0.01, ** if p-value <= 0.05, * if p-value <= 0.10