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# The Impact of State-Provided Paid Family Leave on Wages: Examining the Role of Gender

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# THE IMPACT OF STATE-PROVIDED PAID FAMILY LEAVE ON WAGES: EXAMINING THE ROLE OF GENDER

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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-provided paid leave policies; implemented in 2004, 2009 and 2014, respectively. Through descriptive statistics and difference-in-difference-in-difference regression analyses of the wages of women and men of childbearing age (19-45 years) in those three states, we assess whether the paid leave programs have effected wages, and whether these effects vary depending on gender. Our results show that wages of women of childbearing age saw negligible net effects post-policy in policy states, although statistically insignificant. On the other hand, the wages of men of childbearing age saw improvements post-policy implementation in policy states, compared to wages in non-policy states. Although the policies do not necessarily widen the gender wage gap, they do not work to help close it, due to flaws in the policies. To be more effective in reducing gender wage gaps, these policies need to increase the amount of paid support, and implement job protection rights in order to decrease the opportunity costs of men taking leave. If more men are able to take paid leave, then potentially parts of the gender wage gap that are due to employers viewing women as less attached to the workforce can decrease. Through this research we came to important conclusions that highlight the ways in which support of working parents in the US is lacking, and offered recommendations to create more equitable and effective policies.

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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 sexist policies and the history of inadequate 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 (which is an important issue that needs addressing in its own capacity). 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 facilitate expediting the process of closing the gap. In the following paper we will examine the impact of the paid family leave policies on the wages of women and men 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 them—potentially furthering the gender wage gap rather than decreasing it. Employers may not pay women as much, pass over them for promotion opportunities, or 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 help decrease portions of 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 sufficient 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 we create econometric models that will study whether the implementation of these programs in 2004, 2009 and 2014, respectively, have had an effect on the wages of childbearing aged individuals, and whether or not these effects differed based on gender. From the wage effects, we can potentially come to conclusions about whether or not the policies have affected the gender wage gap in the way that we have hypothesized. 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? Through an economic analysis of the programs and wages of women and men in these three states compared to the rest of the U.S., we will evaluate these questions.

## II. Previous Literature

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). Eleven years later, California was the first state to implement a paid parental leave program in 2004. Additionally, New Jersey was the second state to implement their paid leave program in 2009, and Rhode Island in 2014. 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. 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 goes on to dissect the thought-process and climate of the Supreme Court before the FMLA was implemented:

> 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. (Caplan-Cotenoff, 1987)

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's access to 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 due to the job security rights. 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 aiming 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 wages already differ by state, and that wages may have grown over time regardless of the policy implementation. 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. Selmi goes on to explain how dismantling expected gender roles will help in decreasing the gap:

> To close the gender gap further 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. In addition, it can potentially help us understand why women may in fact see negative wage effects as a result of paid leave.

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, the effects of unpaid parental leave in the U.S. on women's employment and wages, 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 (FMLA) was implemented in 1993, parents were forced to rely on unpaid federal maternity and 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 have paid 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 not as good as 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, and introducing paid leave would decrease these opportunity costs for men. Theoretically, the greater number of men that take time off for paternity leave, the less likely it would be that employers would subconsciously, or consciously, discriminate against women by giving them lower salaries, passing them up for promotions, or refraining from hiring them because they expect them to take time off to start families. 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 implementations of the paid parental leave programs, women of childbearing age in policy states will see higher wages than women of childbearing age in non-policy states. Additionally, we hypothesize that if all other factors remain constant, including men's wages, the gender wage gap in states with a paid leave policy would narrow by a greater amount than the gender wage gaps in states without a paid leave policy. It is important to note that the term "wage gap" cannot be used synonymously with "discrimination", because discrimination of this kind can only make up a fraction of our total gender wage gap. Our hypothesis is that when women are viewed as just as committed to the workforce as men are, due to an increase in men taking paid paternity leave, women's wages will no longer be subject to discrimination of this kind and will increase to become closer to men's wages—narrowing this portion of the gender wage gap.

However, it is also likely that we may not see this result 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 are in, or the level of education that 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 the 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. Another reason that women's wages may decline post-policy implementation is that instead of incentivizing more men to take leave, the policies may merely incentivize more women to take leave than before because they may be better off receiving 55% of their wages rather than 0% from the unpaid FMLA. If even more women begin taking leave, there will be the opposite effect on employer's perceptions of women's labor force attachment; potentially resulting in the opposite outcome.

**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 4,003,761 observations over the span of 15 years.

Throughout the following regressions, we use different combinations of 118 dependent variables and one independent variable; outlined as follows. We created 16 dummy variables for each year from 2000-2015; 3 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; 5 dummy variables for race (White, Black, Hispanic, Asian/Pacific Islander, Native American/Aleut/Eskimo); 51 dummy variables for each state including Washington D.C.; 11 dummy variables for occupation (Management, Professional, Service, Sales, Administrative, Farming and Agriculture, Construction, Repairs, Production, Transportation, and Armed Forces); as well as 14 dummy variables for industry (Agriculture, Mining, Construction, Manufacturing, Retail, Transportation, Information, Finance, Business, Education/Health Services, Leisure, Public Administration, Armed Forces, and Other). In addition, we used the dummy variable "ch05" from the dataset to distinguish whether or not an individual has children between the ages of 0 and 5, as parents to children in this age range would be most affected by the policies, before their children are in school. Additionally, we created an "$age^2$" variable, as well as two interaction terms. The first interaction term named "Post-policy in treatment states" 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 "Post-policy in treatment states of childbearing age" 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. In our final regressions we then replaced the "Post-policy in treatment states" and "Post-policy in treatment states of childbearing age" interaction terms with 11 lead and lag variables to determine the wages of childbearing age individuals each year leading up to policy implementation over a span of 5 years, the year of policy implementation, and the effect of the policy each year after the implementation over the span of 5 years. And finally, our dependent variable used in all regression analyses is "real wages" in 2014 dollars.

We first completed initial descriptive statistics on men and women's real wages in different states before and after the implementation of the policies. By focusing on real wages, we deduce the effects of the policies on gender wage gaps by subtracting men's real wages from women's real wages. We then look at the differences in changes in the gender wage gaps between policy and non-policy states before and after the years of policy implementations to see if states with policies saw larger decreases in their gender wage gaps as a result of the policies. Following, we completed a series of simple regressions without complete control variables, a series of difference-in-difference-in-difference regressions, as well as a series of difference-in-difference-in-difference regressions including lead and lag variables. The regression analysis aims to determine whether the wage effect from the policies differed in regards to gender.

### C. Research Methods: Descriptive Statistics & The Gender Wage Gap

We examine the changes in the gender wage gaps in the three treatment states with paid parental leave policies compared to the non-policy states by summarizing real wages for females and males in states with policies and states without policies, before and after the years of implementation. We subtracted male mean wages from female mean wages in order to visualize the difference between their average real wages, and additionally took the ratio of their mean real wages to determine how many cents to the dollar women make compared to men. When creating control groups to compare to each treatment state, we excluded states that had already implemented their policies at the time of that specific state's policy implementation to more accurately identify a non-policy group for comparison. This means that California's control group of "Non-Policy States" includes every other state, because California was the only state with a paid family leave policy at the time of their policy implementation in 2004. 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. 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 changed 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.

In Table 1 we see that women in California pre-policy made $4.28 less than men on average, equivalent to making $0.83 for every $1 that men make. After the policy was implemented, we saw the real wage gap in California between men and women narrow by about $0.27 on average, or an increase of $0.01 for women per every $1 that men make. While this seems to be some steady, yet small, progress in decreasing the gender wage gap post-policy, when compared to the changes made in the same period in non-policy states, California's women's wages actually increased by less than women's wages in non-policy states by about $0.27 on average. This is what we call the difference-in-difference calculations of our summary statistics, which aim 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 a potential reason for changes in the gap. This difference in gender wage gaps between California versus control states indicates that California's gender wage gap did not improve more than other states after the implementation of their paid leave policy, meaning the policy was perhaps ineffective in this regard.

Similarly, after New Jersey's policy was implemented in 2009, the gap between men and women's real wages narrowed by $0.49, equal to an increase of $0.02 for women per every $1 that men make. While this is small but steady progress in decreasing the gender wage gap, we see that non-policy states saw a larger increase to women's real wages by about $0.06 on average during the same time period. 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 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 2014 policy implementation narrowed by $0.72 on average, the equivalent to a $0.03 increase to women's wages per every $1 of men's wages. The changes in the gender wage gap in states without a paid family leave program (all states besides Rhode Island, New Jersey, and California) changed by the same amount—a $0.03 increase in women's wages per every $1 in men's wages. Because the change in pre-policy and post-policy gender wage gaps in Rhode Island and non-policy states were the same, it seems that the changes in wages were likely not a result of the policy itself, and rather a result of many other factors that effected all states.

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 & The Effect on Wages**

To begin forming our econometric models, we created the variable log (real wages) for our dependent y-variable to create a log-linear model. We performed this 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 real wages for every *unit* change of each x-variable. 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 policy implementation, state and year. They are defined as follows:

(1) $\log RW_{ist} = \alpha + \beta_1 PLP_{st} + \mu_s + \lambda_t + \varepsilon_{ist}$

(2) $\log RW_{ist} = \alpha + \beta_1 PLP_{st} + \mu_s + \lambda_t + \varepsilon_{ist}$ *if FEMALE==1*

(3) $\log RW_{ist} = \alpha + \beta_1 PLP_{st} + \mu_s + \lambda_t + \varepsilon_{ist}$ *if FEMALE==0*

where $\beta_1 PLP_{st}$ is a dummy variable representing all treatment states after their policy implementation year in order to see the policies' effects on real wages compared to non-policy states. $\mu_s$ is a vector for the California, Rhode Island and New Jersey dummy variables, $\lambda_t$ is a vector for 2000-2015 year dummy variables, and $\varepsilon_{ist}$ represents the error term. In Equation 1 we can see the variables' effects on real wages of both men and women combined, 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: 0.0031 for Equation 1, 0.0048 for Equation 2, and 0.0026 for Equation 3. These R-squared values represent the percentage change of the variation in real wages that can be explained by the independent variables (post-policy implementation, state, and year). In this case, only 0.31%, 0.48% and 0.26% of the percentage change 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, industry, and race—as these initial results may be biased because they fail to account for individual human capital characteristics.

In the difference-in-difference-in-difference 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 extensive control variables discussed in detail below. In addition, they use clustered errors with the state variable. The regressions are modeled as follows:

(4) $\log RW_{ist} = \alpha + \beta_1 PLP_{st} + \beta_2 (PLPxCB)_{ist} + X_{ist}\gamma + \mu_s + \lambda_t + \varepsilon_{ist}$

(5) $\log RW_{ist} = \alpha + \beta_1 PLP_{st} + \beta_2 (PLPxCB)_{ist} + X_{ist}\gamma + \mu_s + \lambda_t + \varepsilon_{ist}$ *if FEMALE==1*

(6) $\log RW_{ist} = \alpha + \beta_1 PLP_{st} + \beta_2 (PLPxCB)_{ist} + X_{ist}\gamma + \mu_s + \lambda_t + \varepsilon_{ist}$ *if FEMALE==0*

where $\beta_1 PLP_{st}$ is the same dummy variable used in Equations 1-3, representing all treatment states after their policy implementation year, and $\beta_2 (PLPxCB)_{ist}$ is an interaction term combining the post-policy dummy variable with the childbearing age variable representing individuals ages 19-45. This interaction term is meant to provide even better insight into the effectiveness of the paid leave policies, as it focuses on the wage effects after the policy only on people who the policies were aimed to target in their utilization—specifically people ages 19-45. $X_{ist}\gamma$ is a vector of individual workers' characteristics. These include: race, highest level of education attained, age, age$^2$, whether they are married or not, whether they have children between the ages of 0-5 years, occupation, and industry. $\mu_s$ is a vector of all 50 state dummy variables (excluding DC due to multicollinearty), $\lambda_t$ is a vector for years 2000-2015 dummy variables, and

$\varepsilon_{ist}$ represents the error term. In Equation 4 we can see the variables' effects on real wages of both men and women, Equation 5 on real wages of women, and Equation 6 on real wages of men; the results of which are discussed below, and can be found in Table 3.

In the final three models we include lead and lag variables to measure the yearly changes in wages five years leading up to the policies, year of policy implementation, and each year following the policy implementation for five years. In doing so, we are effectively completing a robustness check on the original difference-in-difference-in-difference regressions to account for the fact that there may be patterns in wage change in individual years that are cannot be seen by merely looking at the "average" post-policy effect. These models use clustered errors with the state variable as well. The regressions are modeled as follows:

(7) $$\text{logRW}_{ist} = \alpha + \sum_{j=1}^{5} \beta_{+j}(\text{PLPxCB})_{i,s,t+j} + \sum_{j=0}^{5} \beta_{-j}(\text{PLPxCB})_{i,s,t+j} + \text{X}_{ist}\gamma + \mu_s + \lambda_t + \varepsilon_{ist}$$

(8) $$\text{logRW}_{ist} = \alpha + \sum_{j=1}^{5} \beta_{+j}(\text{PLPxCB})_{i,s,t+j} + \sum_{j=0}^{5} \beta_{-j}(\text{PLPxCB})_{i,s,t+j} + \text{X}_{ist}\gamma + \mu_s + \lambda_t + \varepsilon_{ist}$$

*if FEMALE==1*

(9) $$\text{logRW}_{ist} = \alpha + \sum_{j=1}^{5} \beta_{+j}(\text{PLPxCB})_{i,s,t+j} + \sum_{j=0}^{5} \beta\ \text{j}(\text{PLPxCB})_{i,s,t+j} + \text{X}_{ist}\gamma + \mu_s + \lambda_t + \varepsilon_{ist}$$

*if FEMALE==0*

where $\beta_{+j}$ captures the lead effects up to five years before a paid family leave policy is implemented and $\beta_{-j}$ captures the lag effects, which include the year of policy implementation and up to five years after the laws become effective. Note that the lead and lag effects have been created with the interaction term that combines both policy states and individuals of childbearing age. $\text{X}_{ist}\gamma$ is the same vector of individual worker's characteristics as seen in Equations 4-6. These still include: race, highest level of education attained, age, age$^2$, whether they are married or not, whether they have children between the ages of 0-5 years, occupation and industry. $\mu_s$ is the same vector of all 50 state dummy variables (excluding DC due to multicollinearty), $\lambda_t$ is the same vector for years 2000-2015 dummy variables, and $\varepsilon_{ist}$ represents the error term. In Equation 7 we can see the variables' effects on real wages of both men and women, Equation 8 on real wages of women, and Equation 9 on real wages of men; the results of which are discussed below, and can be found in Table 4, as well as Graphs 1-3.

**E. Results**

*1. Equations 1-3 (Table 2)*

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 in comparison to the wages of women and men in non-policy states. In these three equations, the "Post-policy in treatment states" coefficient represents the percentage difference in wages between states with policies compared to states without policies, during the post-policy implementation time period. If the coefficient is positive for women, this will mean that women's wages are higher 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 were less than men's in non-policy states, post-policy implementation. In the first equation results, we find that the average real wages of both genders are 0.48% greater than wages in non-policy states, after policy implementation took place. However, this result is statistically insignificant.

In Equation 2, we find that women's real wages in states with policies after their policies were implemented were about 0.58% *lower* than women's wages in non-policy states, significant at the 90% level. This means that the real wages of women in California, New Jersey, and Rhode Island post-policy implementation may be worse off as a result of the policy. Although this percentage difference is quite small, the results may show that women's wages were negatively affected by the policy changes.

In Equation 3, the results show that men's real wages in policy states post-policy implementation were approximately 0.73% *higher* than the wages of men in non-policy states during the same time period, at the 95% confidence level. 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 may be positively affected.

The results of the first three simple regressions show that women's wages would be negatively affected as a result of the policies, while men's wages would be positively affected. However, the amounts in which their wages differed from women and men in non-policy states are very small—below 1%. Because all three of the R-squared values are quite small (0.0031, 0.0048, and 0.0026), 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 and more accurate picture of women and men's wages after these policies were implemented.

*2. Equations 4-6 (Table 3)*

The results of these more complete difference-in-difference-in-difference models include much more extensive controls for individual characteristics and human capital characteristics that the first three equations do not include. In addition, these equations include an additional interaction term that allows us to see the effects of the family leave policies more accurately than the "Post-policy in treatment states" variable in the simpler regressions. The interaction term combines this "Post-policy in treatment states" which represents the wages of men and women after policy implementation in the treatment states, with the "childbearing age" variable to only include men and women ages 19-45, the standardly used age range for "childbearing age"; creating the interaction term "Post-policy in treatment states of childbearing age." This variable will show us the effectiveness of the policy even more clearly, as this is the age group that the policy aims to target. We include all observations of childbearing age whether or not they have children, because employers may expect this age group to have families in the short-term future, which may affect wages regardless of whether or not they already have children. Equation 4 represents the real wages of both genders, Equation 5 represents the real wages of women, and Equation 6 illustrates real wages of men.

In our results for Equation 5, the coefficient for "Post-policy in treatment states" (the variable we focused on in equations 1-3), displays that with all of the control variables included, women's wages were actually 2.6% *higher* after policy implementation compared to women in states without similar policies. This is quite different from the results that we found in Equation 2 that showed that women's wages in states with policies would be 0.58% *less* than those of women in non-policy states. It is most likely due to controlling for education, race, industry and occupation that allowed such a difference in results. In addition, the R-squared value for Equation 5 is 0.3672; meaning 36.72% of the dependent y-variable (wages) can be explained by the various x-variables. This is a huge improvement from the 0.48% that could be explained by the limited variables in Equation 2, the simple regression equation for women. It is quite clear that by adding more extensive control variables, our model has much more explanatory value. While this result seems to show that the paid leave policies may have had a positive effect on women's wages, we find something quite different when looking specifically at the wage effect on women of childbearing age only. The coefficient for "Post-policy in treatment states of childbearing age" reveals that women aged 19-45 saw 1.45% *lower* real wages after the policy implementation compared to women of childbearing age in non-policy states, statistically significant at the 99% level. Although women's wages overall increased in states with paid leave policies, women of the age group directly targeted by the policies saw the opposite effect.

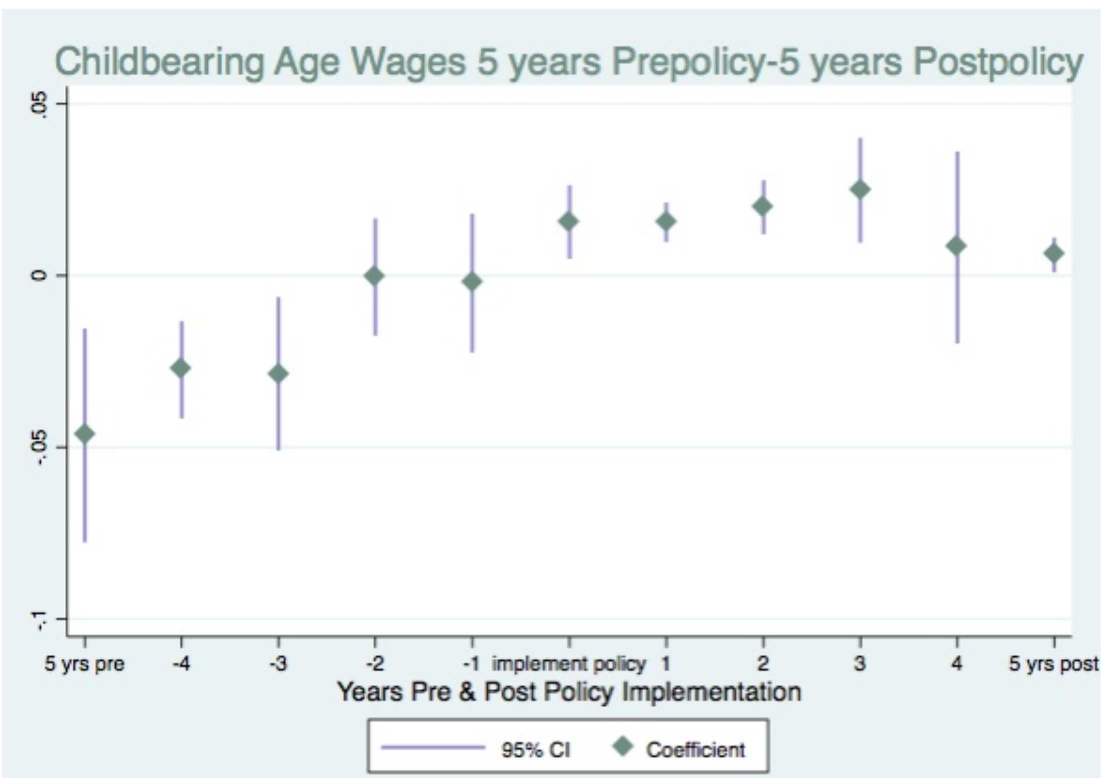
In Equation 6, the coefficient for "Post-policy in treatment states" displays that with all of the control variables included, men's wages are 4.24% *higher* in policy states than in non-policy states after policy implementation. Similar to the women's results, these results differ from what we saw in the simpler regression analysis. In Equation 3, the simpler regression for males, we found that wages of men in policy states were only 0.73% higher than the wages of men in non-policy states. Again, it is most likely due to controlling for education, race, industry and occupation that allowed such a difference in results, and the R-squared value increased from only 0.26% of the dependent y-variable (wages) being explained by the various x-variables in Equation 3, to 36.27% being explained by the x-variables in Equation 6. However, similar to the women's results, the story is quite different when looking at the effects on wages post-policy on men of childbearing age only. In this case, men of childbearing age saw 0.28% *lower* wages than men in non-policy states; however this result is insignificant.

The overall results of these equations show that the wages of all women were 2.6% higher in states with the paid family leave policies, while the wages of all men in those states were 4.2% higher. On the other hand, the wages of women of childbearing age were 1.4% lower than in states without paid leave policies, while men of childbearing age saw 0.28% lower wages than men of childbearing age in non-policy states. This seems to show that the policies were not welfare improving for either men or women in the age group that the paid leave policies were meant to target. However, the results for men were insignificant, leaving this inference inconclusive.

*3. Equations 7-9 (Table 4)*

In the last three models we introduced 11 new variables that aim to capture changes in real wages each year pre-policy implementation for 5 years, the year of policy implementation, and each year post-policy implementation for 5 years. By creating these lead and lag variables, we effectively completed a robustness check on the original difference-in-difference-in-difference regressions to account for the fact that there could have been movement in the trend of wages that was convoluted with the policy implementation. Essentially, this is a way of finding out, for example, whether the policy had a positive effect on wages directly after implementation that suddenly declined that we would not be able to see with the previous variables that merely showed the average wage effect post-policy.

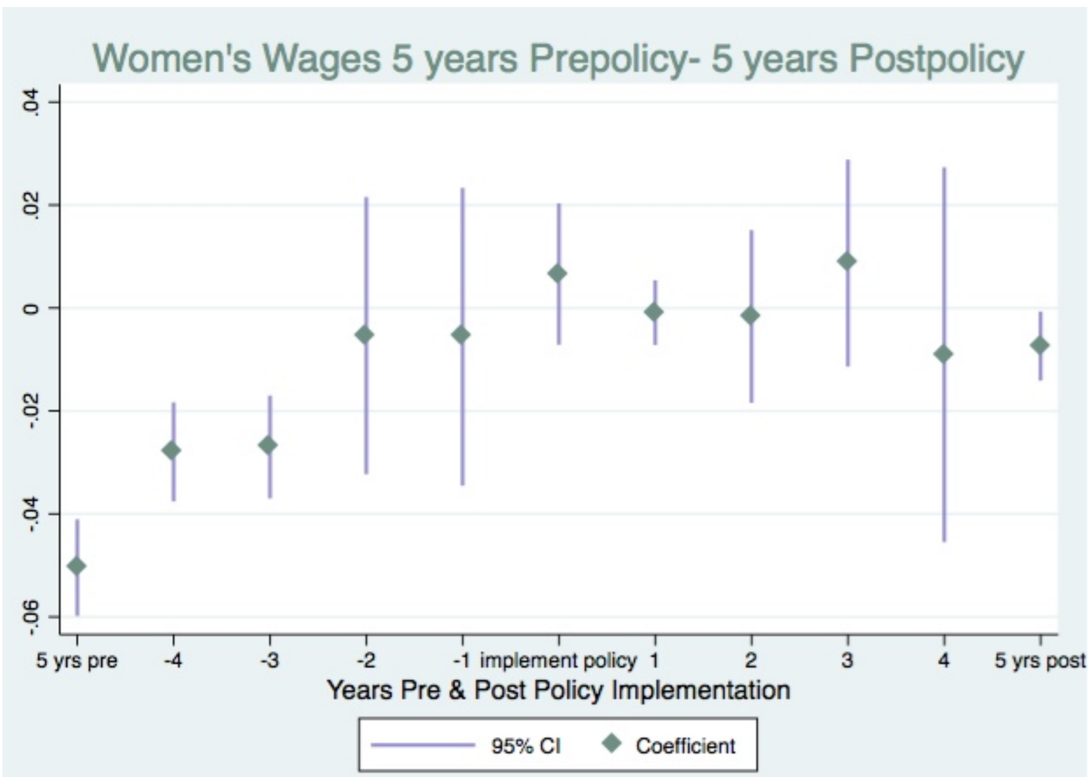
In Graph 1, we can visually see the results of Equation 7 that are also reflected in Table 4 for wage effects on both genders before and after policy implementation. We find that pre-policy implementation wages of childbearing aged individuals in policy states were *smaller* than the wages of childbearing aged people in non-policy states. From five years pre-policy implementation up until implementation, this difference became smaller and smaller (with 4.6% smaller wages 5 year pre-policy, to a miniscule 0.2% smaller wages a year before implementation). After implementation, wages hover around 1.5%-2% *higher* in policy states, until this drops to a negligible amount of a less than 1% difference in wages 4 and 5 years post-policy. Overall, it appears that the policies may




*Graph 1: Pre and Post-Policy Wages of Both Genders of Childbearing Age*

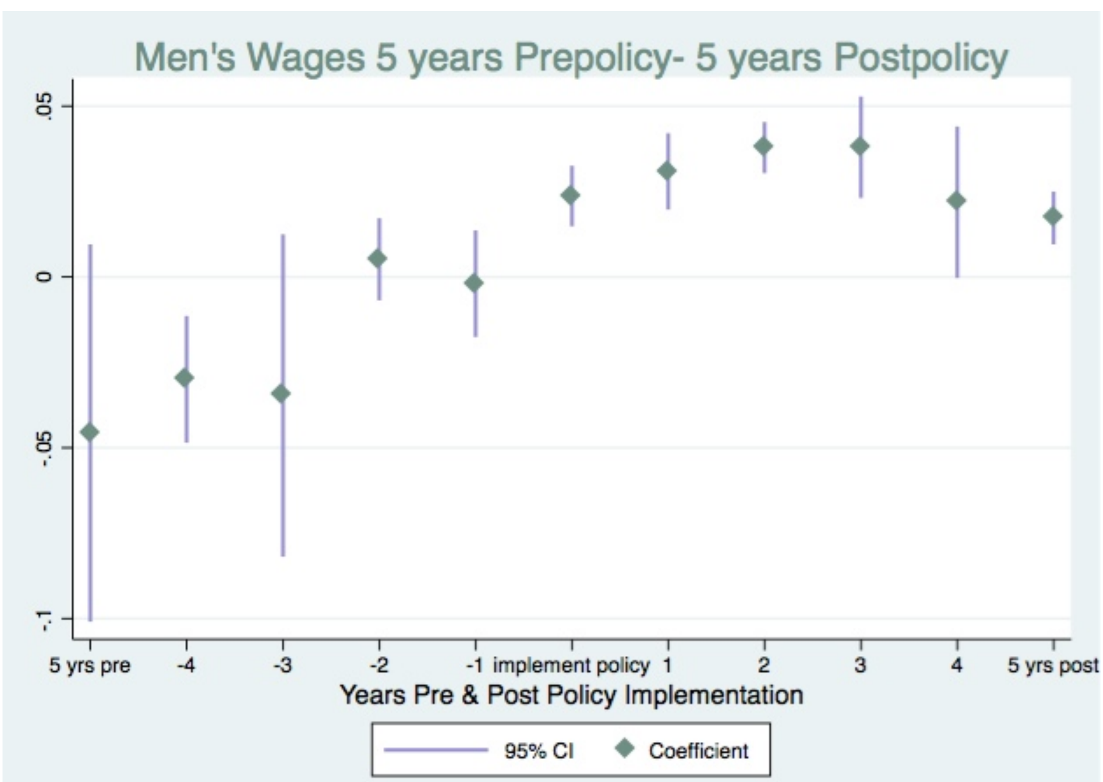
not have much of an effect on wages in the long run. By creating graphs like this we are able to visualize the necessity of creating lead and lag variables to better understand the pattern of wages instead of only utilizing the average post-policy effect that combined the wage effects of all years in the previous regressions.

In Equation 8, we struggle to come to concrete conclusions about the yearly policy effects on the wages of women of childbearing age, as many of the yearly results are statistically insignificant. What we can gather overall is that wages of women of childbearing age in states that would later implement policies were initially *smaller* than those of women of childbearing age in states in non-policy states. Each year leading up to policy implementation, this wage differential decreased. Five years pre-policy, childbearing aged women's wages in policy states were 5.04% *smaller* than wages of childbearing aged women in non-policy states (significant at the 99% level), while the year right before policy implementation, women in policy states only had 0.56% smaller wages (this is an insignificant result). The year of policy implementation, women in policy states saw 0.66% *greater* wages than women not in policy states. While this result would indicate that the policies had some sort of small, yet positive, effect on wages, this result is insignificant, and could merely represent the slow and steady wage increases that were already happening separate from the policy itself. The results for years post-policy are also insignificant and very small in magnitude, but generally show that women's wages in policy states return to being *lower* than the wages of women in non-policy states in the long run. In Graph 2, we can visually see the trend of childbearing aged women's wages spanning the 5 years pre-policy implementation, to the 5 years after policy implementation. Although it is quite clear that the differential between women's wages in policy states and non-policy states declined since 5 years pre-policy, it is inconclusive whether or not the policy itself had any net effect on wages, as after policy implementation, women's wages in policy states remain around zero or below zero. Our overall conclusions regarding the wages of women of childbearing age after the implementation of paid leave policies is that they were negligibly affected with insignificant changes that were smaller than -1%; we can generally say that on the whole, the wages of women of childbearing age were not effected by these policies one way or another.




*Graph 2: Pre and Post-policy Wages of Women of Childbearing Age*

In Equation 9, looking at the yearly effects of policy implementation on men of childbearing age, we find that more years have significant results than results of the women's regressions. Each year leading up to policy implementation, wages of men of childbearing age in policy states were *smaller* than those of childbearing aged men in non-policy states; from 4.6% *smaller* five years pre-policy (significant at the 90% level), to only 0.12% *smaller* one year pre-policy implementation (an insignificant result). This indicates that wages in treatment states were increasing prior to policy implementation. Starting from policy implementation year and each subsequent year, men of childbearing age appear to enjoy fairly large *positive* wage differentials in comparison to men of childbearing age in non-policy states—the largest being a positive 3.8% difference 2 and 3 years post-policy implementation; significant at the 99% level. This trend is visually clear in Graph 3 below. Although men's wages appear to have been gradually increasing over time, there is a suddenly steeper and more constant positive wage differential right after the policy implementation. It appears that the policy may have had a positive effect on men's wages, contradictory to our original hypothesis.




*Graph 3: Pre and Post-policy Wages of Men of Childbearing Age*

## IV. Conclusion

In this paper we have explored the effects of paid family leave policies on real wages of men and women, aiming to discover whether or not these types of paid leave policies have differing wage effects dependent on gender. We began by creating descriptive statistics to take a look at gender wage gaps before and after policy implementation; comparing the changes to the gender wage gaps in states with paid leave policies to changes in the gender wage gaps in states without paid leave policies. Using CPS data, we then created log-linear difference-in-difference-in-difference regression models to see the difference in wages of women and men in policy states compared to women and men in non-policy states. Additionally, we created interaction terms combining post-policy wage effects and childbearing age (19-45 years) to view wage effects specifically on people of the cohort who should be most affected by the use of these policies. Lastly, we created lead and lag variables to view yearly wage differentials in order to see patterns of the policies' effects on wages, rather than relying on solely the average effect that the policies had in all years.

When completing our full regression analyses, with lead and lag variables and complete control variables included, we saw an interesting outcome. Women of childbearing age in treatment states saw negative effects on their wages almost every year post-policy; however, they were very negligible in size, and statistically insignificant. On the other hand, men of childbearing age in policy states appear to have seen fairly significant positive effects on their wages as a result of the paid leave policies. Our hypothesis was that with an increase in access to paid leave, more men would be able to take leave, which would in turn help decrease the portion of the gender wage gap that is due to employer's beliefs that only women will be less attached to the workforce. This would happen by the wages of childbearing aged women increasing by some amount equal to this discriminatory portion of the gender wage gap, keeping men's wages constant. However, we can come to the conclusion that these policies did not help close the gender wage gap within childbearing aged men and women, as women's wages in policy states did not increase compared to the wages of women in non-policy states, and men's wages did not hold constant. Our results do not show the hypothesized effect on wages or gender wage gaps, however, they are still important findings nonetheless.

Although the policies did not necessarily widen the wage gap, they may be complicit in maintaining it due to flaws and limitations of the policies themselves. While the paid leave programs pay approximately 55% of wages, this is still nowhere near 100%. If men were the spouses with higher incomes, it still would not make sense for them to be the one who takes this leave when they have higher 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's research (2004) found that many employees do not apply for benefits for fear of negative employment consequences, because the paid family leave program in California does not come with job protection rights like the unpaid FMLA does. Because of this policy limitation, it would make sense why men would still not take the paid family leave, even though it provides a partial payment of wages. If men have higher wages, it would not make sense for them to be the one who risks losing their job to take the leave. These results are similar to those of Baum (2003), who found that the implementation of the FMLA had little effect on women's wages because it was not generous enough in its support because it was unpaid. It seems that the state paid leave programs are still not generous enough to have a substantial effect.

These two major flaws in the policies may have created oppositional forces on wages that are at the core of why women saw basically zero net change to their wages post-policy implementation. Although the policies were not great enough incentive to get men to take leave, they perhaps incentivized more women than before to take maternity leave, due to being offered 55% of wages instead of 0% from the FMLA. Perhaps because childbearing aged women as a whole are now more willing to exit the labor market, there could be the chance that employers are now demanding their labor less, as they are seen as less reliable and less attached to the work force; and because the program does not offer job security rights, women who already have jobs could potentially be let go. The opposing forces of women's labor supply decreasing (which would increase market wages) is potentially matched by women's labor demand decreasing as well (which would decrease market wages). The push and pull of positive and negative wage effects from the shifts of supply and demand of women in the labor market may have effectively cancelled one another out, leading to the negligible effects close to zero that we observe in the results. This conclusion is similar to conclusions made by Waldfogel (1999) about the effects of the FMLA. She found that the FMLA had essentially zero net wage effects in the short run as her two hypotheses—that women's wages may decrease as employers pass on the costs of the FMLA to those who will potentially utilize it (women of childbearing age), and that women's wages may potentially increase, as women will retain their jobs because the FMLA had job protection rights—effectively cancelled one another out.

The positive effects we saw on men's wages post-policy are perhaps explainable by also thinking about general labor market economics as well. If more women were willing to exit the labor market due to paid leave policies, the supply of the entire labor force would decrease, shifting in. With no change in the demand for childbearing aged men, decreasing the labor supply would result in an increase in their wages. However, as more women are willing to exit the labor market, there is the potential that men may be seen as even more committed to the workforce in comparison than they were before, and firms may increase their demand for male workers. If so, the demand curve for male workers may shift out, creating an even larger and intensified wage increase for them when happening in conjunction with the wage increases from a decrease in the labor supply.

Although it may seem like this result is contradictory to our original hypothesis, in economic theory it is not. We hypothesized that *paid* leave in general would incentivize more men to take leave, therefore potentially eradicating the idea on behalf of employers that women are less attached to the workforce than men are. This would have resulted in men's wages seeing no change and women's wages increasing, to decrease the gender wage gap overall. We may have in fact still proven the validity of this theory, it just happened to the opposite gender due to the limitations of the policy. Because the paid leave programs do not have high enough wages to incentivize men to take it, and incentivized women instead, women's wages ended up staying about the same whilst men's wages increased. Perhaps if the paid leave programs had paid 100% of wages rather than 55%, there would have been enough incentive for men to take leave and our original hypothesis would have been proven instead.

It is important to point out that the women of childbearing age may have seen differing effects on wages dependent on whether or not they actually utilized the paid leave. Women who actually took the paid leave may have been left better off than they would have been with unpaid maternity leave, yet this does not mean that all women of childbearing age are left better off on the whole. The cohort of women of this age group may have seen wage decreases due to a potential decrease in demand for women workers by employers, while women who took the paid leave perhaps did see benefits to their wages. On the contrary, there could have been the opposite effect. Women of childbearing age who did not take the leave perhaps saw wage increases due to a decrease in the labor supply as other women took leave (similar to the wage effect on men), while the women who did take the leave were perhaps the ones worse off because of the lack of job protection rights. Due to limitations in our dataset we are unable to identify specifically which women in our “childbearing women in treatment states” cohort took the leave, and so we looked at the changes in their wages as an entire group. If data of this sort were made available, this would be an interesting possibility for continued research on this topic.

Other limitations in our research create additional avenues for future work. To begin with, Rhode Island’s available data is limited since their policy was only implemented in January 2014, allowing us only two full years 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, and framed our research around whether paid leave policies have a direct effect on wage gaps, rather than on gendered wage outcomes. 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. Furthermore, 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. And finally, Appelbaum and Milkman (2004) provide evidence in their research that public awareness of the program in California remains limited. Individuals who are employed in jobs that do not provide substantial family leave may be the same individuals that do not have the resources to seek and obtain knowledge about the state-provided programs as well—limiting the program's access to the demographic group who need it and would utilize it most. As this was written in 2004, updated research on this topic would be helpful in determining whether or not public knowledge and access has increased since then; if not, this is additionally a call to action for policymakers to continue in attempts to increase the awareness of these programs.

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, securing job protection rights, and increasing 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. Without changing the way our country supports parents through more effective policy changes, we will continue to see a stigma be placed on workingwomen. Having a family should not be something that only women are penalized for—children could not be made without men either.

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**VI. Tables:**

*Table 1: Descriptive Statistics results*

Gender Wage Gaps between mean real wages in Policy and Non-Policy states
(Female Real Wages-Male Real Wages)

| | Pre-Policy Wage Gap | Post-Policy Wage Gap | Change in Wage Gap (Pre-Post) | Difference in Difference (Change in Policy state- Change in Non-Policy states) |
|---|---|---|---|---|
| California: | -$4.28 ($0.83 women/ $1 men) | -$4.01 ($0.84 women/ $1 men) | $0.27 ($0.01 women/ $1 men) | -$0.27 (-$0.01 women/ $1 men) |
| Non-Policy states: | -$5.21 ($0.78 women/ $1 men) | -$4.67 ($0.80 women/ $1 men) | $0.54 ($0.02 women/ $1 men) | |
| New Jersey: | -$6.66 ($0.77 women/ $1 men) | -$6.17 ($0.79 women/ $1 men) | $0.49 ($0.02 women/ $1 men) | -$0.06 (-$0.01 women/ $1 men) |
| Non-Policy states: | -$4.99 ($0.79 women/ $1 men) | -$4.44 ($0.82 women/ $1 men) | $0.55 ($0.03 women/ $1 men) | |
| Rhode Island: | -$4.41 ($0.82 women/ $1 men) | -$3.69 ($0.85 women/ $1 men) | $0.72 ($0.03 women/ $1 men) | $0.13 $0 women/$1 men) |
| Non-Policy states: | -$4.88 ($0.80 women/ $1 men) | -$4.29 ($0.83 women/ $1 men) | $0.59 ($0.03 women/ $1 men) | |

*Table 2: Simple Model Results*

| | **Equation 1:** Both genders | **Equation 2:** Females | **Equation 3:** Males |
|---|---|---|---|
| **Independent variables:** | | | |
| Post-policy in treatment states | 0.004802 | -0.0058017* | 0.0072746** |
| CA | 0.0699462*** | 0.1024505*** | 0.0316509*** |
| NJ | 0.1712212*** | 0.1647654*** | 0.1757517*** |
| RI | 0.0527835*** | 0.0713125*** | 0.0417478*** |
| 2000 | Omitted | Omitted | Omitted |
| 2001 | 0.02018*** | 0.0247494*** | 0.016285*** |
| 2002 | 0.0351682*** | 0.0446397*** | 0.0279893*** |
| 2003 | 0.0369208*** | 0.049968*** | 0.0276137*** |
| 2004 | 0.0338589*** | 0.0471993*** | 0.0230897*** |
| 2005 | 0.0270201*** | 0.0460198*** | 0.0105823*** |
| 2006 | 0.0295982*** | 0.0474979*** | 0.0135077*** |
| 2007 | 0.0374572*** | 0.0537617*** | 0.024088*** |
| 2008 | 0.0373655*** | 0.0557226*** | 0.0225261*** |
| 2009 | 0.0574922*** | 0.0772161*** | 0.0434911*** |
| 2010 | 0.0501766*** | 0.0770821*** | 0.028834*** |
| 2011 | 0.0318982*** | 0.0623722*** | 0.0058161* |
| 2012 | 0.0309349*** | 0.0566633*** | 0.0082251*** |
| 2013 | 0.0366342*** | 0.0658842*** | 0.0100811*** |
| 2014 | 0.0293296*** | 0.061288*** | -0.0002503 |
| 2015 | Omitted | Omitted | Omitted |
| Constant | 2.854648*** | 2.73234*** | 2.972152*** |
| N-observations | 2,441,310 | 1,206,511 | 1,234,799 |
| R-squared | 0.0031 | 0.0048 | 0.0026 |
| *** if p-value <=0.01, ** if p-value <=0.05, *if p-value <=0.10 | | | |

*Table 3: Difference-in-Difference-in-Difference Model Results*

| | **Equation 4:** Both genders | **Equation 5:** Females | **Equation 6:** Males |
|---|---|---|---|
| **Independent variables:** | | | |
| Post-policy in treatment states | 0.0310974*** | 0.0261862*** | 0.0423625*** |
| Post-policy in treatment states of childbearing age | -0.0061977*** | -0.0144857*** | -0.0027925 |
| | | | |
| High School or Associates Degree | 0.2408541*** | 0.2200201*** | 0.256044*** |
| Bachelor's Degree | 0.5421242*** | 0.5043322*** | 0.5429488*** |
| Masters Degree or higher | 0.7128659*** | 0.677926*** | 0.6903971*** |
| Childbearing age | 0.0188208*** | 0.0140153*** | 0.0209004*** |
| Age | 0.0463151*** | 0.0389272*** | 0.0555105*** |
| Age^2 | -0.0004511*** | -0.0003858*** | -0.0005518*** |
| Married | 0.0872597*** | 0.0285187*** | 0.0665407*** |
| White | 0.0251119*** | 0.0169438*** | 0.0300472*** |
| Black | -0.0772406*** | -0.0311912*** | -0.1405597*** |
| Hispanic | -0.0766098*** | -0.0445075*** | -0.0986535*** |
| Asian | -0.0388227*** | -0.013308** | -0.0555858*** |
| Native American | -0.0355309*** | -0.0193242** | -0.0510479*** |
| Children (0-5 yrs.) | 0.0534795*** | 0.0346032*** | 0.030073*** |
| CA | -0.0810053*** | -0.0988864*** | -0.075598*** |
| NJ | -0.0455559*** | -0.0829834*** | -0.0133725*** |
| RI | -0.1312024*** | -0.1495165*** | -0.1102951*** |
| DC | Dropped | Dropped | Dropped |
| -47 additional states- | | | |
| | | | |
| Occupations: | | | |
| Management | 0.4796296*** | 0.2524431** | 0.3920667*** |
| Professional | 0.3798392*** | 0.1492168** | 0.3094027*** |
| Sales | 0.1995098*** | -0.0789902** | 0.1728168*** |
| Services | 0.0268612** | -0.2231966** | -0.0500887** |
| Administrative | 0.1184452*** | -0.0281255*** | 0.0060574 |
| Construction | 0.3281339*** | 0.0716642*** | 0.1687511*** |
| Repairs | 0.3702773*** | 0.1152294** | 0.1853372*** |
| Production | 0.12914*** | -0.1867246** | 0.047561* |
| Transportation | 0.1155645*** | -0.163615** | -0.0300863 |
| Farming | Omitted | -0.2672663* | -0.0904704*** |
| Armed Forces | Dropped | Dropped | Dropped |
| | | | |
| Industry: | | | |

| | | | |
|---|---|---|---|
| Farming and Agriculture | -0.3385111*** | -0.0584822 | -0.3391354*** |
| Construction | -0.1705002*** | 0.0597099 | -0.1478758*** |
| Manufacturing | -0.1527711*** | 0.1132089 | -0.1357976*** |
| Retail | -0.322693*** | -0.0676483 | -0.2518822*** |
| Transportation | -0.1097998*** | 0.1389827 | -0.0857685*** |
| Information | -0.1921079*** | 0.0662423 | -0.1352612*** |
| Finance | -0.1980079*** | 0.0892364 | -0.1203268*** |
| Business | -0.1966774*** | 0.0651373 | -0.1434161*** |
| Education/Health Service | -0.356925*** | 0.0078582 | -0.3050812*** |
| Leisure | -0.4844831*** | -0.2012651 | -0.3799595*** |
| Public Administration | -0.144329*** | 0.11318 | -0.0993108*** |
| Other | -0.4045761*** | -0.0839886 | -0.3450888*** |
| Mining | Omitted | 0.222764 | omitted |
| Armed Forces | Dropped | Dropped | Dropped |
| | | | |
| 2000 | Omitted | Omitted | Omitted |
| 2001 | 0.0161033*** | 0.0222556*** | 0.0101574*** |
| 2002 | 0.0255971*** | 0.0362642*** | 0.0164716*** |
| 2003 | 0.0380653 | 0.0143055 | 0.0336858*** |
| 2004 | 0.036723 | 0.0103585 | 0.0340604*** |
| 2005 | 0.0253091 | 0.0034079 | 0.0192905*** |
| 2006 | 0.0258476 | 0.0019362 | 0.0224864*** |
| 2007 | 0.0259575 | 0.0013067 | 0.0245655*** |
| 2008 | 0.0240222 | -0.0007651 | 0.0224792*** |
| 2009 | 0.0404606 | 0.0169858 | 0.0372114*** |
| 2010 | 0.0342347 | 0.017633 | 0.0217791*** |
| 2011 | 0.0122221 | -0.0038362 | -0.0010997 |
| 2012 | 0.0080151 | -0.0165237 | 0.0030764 |
| 2013 | 0.0103977 | -0.0096414 | Omitted |
| 2014 | 0.0039415 | -0.012003 | -0.0097518*** |
| 2015 | Omitted | Omitted | Omitted |
| | | | |
| Constant | 1.591321*** | 1.746967*** | 1.524752*** |
| N-observations | 1,624,205 | 836,912 | 787,293 |
| R-squared | 0.3638 | 0.3672 | 0.3627 |

*** if p-value <=0.01, ** if p-value <=0.05, *if p-value <=0.10

*Table 4: Model Results with Leads and Lags*

| | **Equation 7:** Both genders | **Equation 8:** Females | **Equation 9:** Males |
|---|---|---|---|
| **Independent variables:** | | | |
| 5 years Pre-policy x Childbearing | -0.0465311*** | -0.0504387*** | -0.0456687* |
| 4 years Pre-policy x Childbearing | -0.027439*** | -0.0279521*** | -0.0299784*** |
| 3 years Pre-policy x Childbearing | -0.0285995** | -0.0269979*** | -0.0347021 |
| 2 years Pre-policy x Childbearing | -0.0004106 | -0.0053729 | 0.0051727 |
| 1 year Pre-policy x Childbearing | -0.0021801 | -0.0055997 | -0.0019687 |
| Policy Implementation year x Childbearing | 0.0156089*** | 0.0065891 | 0.0236751*** |
| 1 year Post-policy x Childbearing | 0.0154972*** | -0.0009 | 0.0308973*** |
| 2 years Post-policy x Childbearing | 0.019931*** | -0.0016427 | 0.0378692*** |
| 3 years Post-policy x Childbearing | 0.0248775*** | 0.0087175 | 0.0379615*** |
| 4 years Post-policy x Childbearing | 0.0081774 | -0.0090743 | 0.0218581** |
| 5 years Post-policy x Childbearing | 0.0060089** | -0.0073951** | 0.0172691*** |
| High School or Associates Degree | 0.2407623*** | 0.2198896*** | 0.2560064*** |
| Bachelor's Degree | 0.541969*** | 0.504162*** | 0.5428232*** |
| Masters Degree or higher | 0.7126781*** | 0.6777112*** | 0.6902357*** |
| Childbearing Age | 0.0186617*** | 0.0141059*** | 0.0203735*** |
| Age | 0.0463076*** | 0.038915*** | 0.0555065*** |
| Age^2 | -0.0004509*** | -0.0003856*** | -0.0005517*** |
| Married | 0.0872218*** | 0.0284891*** | 0.0665403*** |
| White | 0.0252119*** | 0.0171119*** | 0.0300687*** |
| Black | -0.0772217*** | -0.0310891*** | -0.1406318*** |
| Hispanic | -0.0770272*** | -0.0449411*** | -0.0990372*** |
| Asian | -.0386886*** | -0.0133448*** | -0.0552186*** |
| Native American | -0.0355487*** | -0.0192803*** | -0.0511511*** |
| Children (0-5 yrs.) | 0.0535129*** | 0.0346388*** | 0.0300956*** |
| CA | -0.0613868*** | -0.0815594*** | -0.0501898*** |
| NJ | -0.0360963*** | -0.0733863*** | -0.0020974 |
| RI | -0.1264023*** | -0.1443638*** | -0.1051721*** |
| | | | |
| 2000 | Omitted | Omitted | Omitted |
| 2001 | 0.0151062*** | 0.0210898*** | 0.0093523*** |
| 2002 | 0.0246341*** | 0.0350273*** | 0.0158852*** |
| 2003 | 0.0355886 | 0.0129573 | 0.0298923*** |
| 2004 | 0.0343116 | 0.0090089 | 0.0305732*** |
| 2005 | 0.0245631 | 0.0032992 | 0.0181174*** |
| 2006 | 0.0248386 | 0.0018567 | 0.0207154*** |
| 2007 | 0.024772 | 0.0012497 | 0.022554*** |
| 2008 | 0.0223092 | -0.0015117 | 0.0200577*** |
| 2009 | 0.0399624 | 0.0175177 | 0.0360371*** |

| | | | |
|---|---|---|---|
| 2010 | 0.034068 | 0.0181355 | 0.0213077*** |
| 2011 | 0.012329 | -0.0035756 | -0.000842 |
| 2012 | 0.0078647 | -0.0164497 | 0.0029894 |
| 2013 | 0.0102174 | -0.0096737 | Omitted |
| 2014 | 0.0042542 | -0.0116373 | -.0091479** |
| 2015 | Omitted | Omitted | Omitted |
| | | | |
| Constant | 1.59218*** | 1.748133*** | 1.525087*** |
| N-observations | 1,624,205 | 836,912 | 787,293 |
| R-squared | 0.3638 | 0.3672 | 0.3627 |
| *** if p-value <=0.01, ** if p-value <=0.05, *if p-value <=0.10 | | | |