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Essays on Inequality and Paid Family Leave

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ABSTRACT

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In my dissertation, I have dedicated two chapters to the field of labor economics, specifically exploring the subject of gender-based inequality in the Indian labor market and the differential impact of paid family leave policies based on socio-economic status within the labor market of the United States.

The first chapter analyzes the gender-based wage gap in India by utilizing data from the India Human Development Survey (IHDS) for two-time frames (2004-05 and 2011-12) when labor force participation was stagnant. Employing the Oaxaca-Blinder decomposition technique, the study reveals a noteworthy decline in the gender-based log wage gap (from 0.64 to 0.48) over a short period, indicating the need for further research to identify the factors contributing to the decrease. The study also employs the Juhn-Murphy-Pierce decomposition technique, revealing that education, industry changes, and occupational choice positively reduce the gender-based pay gap over time. Furthermore, no significant wage gap is discovered between married and unmarried women.

The second chapter employs difference-in-difference and difference-in-difference-in-difference techniques to examine the medium-term effects of California's Paid Family Leave (CA-PFL) program on labor outcomes for mothers. The analysis focuses on labor force participation, employment, unemployment duration, and earnings. Robust results from the analysis indicate a noteworthy 3.19% increase in labor force participation within 1-3 years after childbirth, modest improvements in employment probability, and a 3.39-week reduction in unemployment duration. However, despite the positive impact on the overall level, my research provides evidence that the policy has no significant effect on the labor force participation rate of low-income mothers and negatively affects the earnings of lower-income mothers. These findings shed light on the nuanced impacts of paid family leave policies and highlight the importance of considering socio-economic factors when assessing their effectiveness.

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Chapter One: Wage Inequality in India: Wage Decomposition by Gender and Marital Status

1 Introduction:

The present study scrutinizes the gender-based wage gap trend in the Indian economy from 2004-05 to 2011-12, a period characterized by an invariable female labor force participation rate. By applying the Oaxaca-Blinder decomposition method, this research furnishes compelling evidence that the gender-based wage gap has considerably declined from 0.64 to 0.48 within a brief span. The substantial drop in the wage gap necessitates a thorough investigation to discern the potential factors contributing to this decline. By offering an in-depth analysis of the gender-based wage gap and its determinants, this study aims to contribute to the literature on the Indian labor market and inform policy interventions that can enhance the socio-economic status of women and bolster economic growth.

I utilize the Indian Human Development Survey (IHDS) data from 2004-05 and 2011-12 to decompose the gender-based wage gap among individuals aged 15 to 65. The Oaxaca-Blinder (1993) (OB) and Juhn-Murphy-Pierce (1993) (JMP) decomposition techniques are employed to accomplish this objective. The OB approach is a static model that explains the wage gap through endowment effects, coefficient effects, and residual effects, allowing us to quantify the impact of each factor on the pay gap each year. Nevertheless, this method does not assess the evolving impact of these factors on the gender pay gap trend over time.

To bridge this gap, I employ the JMP decomposition technique. This dynamic model investigates the gender pay gap in the Indian economy for the first time (to the best of my knowledge). This research examines the impact of various factors at the static level and simultaneously evaluates their changing influence on the gender pay gap over time. Furthermore, this approach enables us to explicitly observe the impact of unobserved skills changes on the gender wage gap. The JMP method explains the wage gap trend regarding differences in endowment and residual gaps over time. We can also capture the alterations in within-group inequality and its impact on the wage gap using the JMP decomposition method.

This paper presents a notable discovery indicating a decline in the gender-based wage gap, encompassing rural and urban regions. In addition, it reveals a clear correlation between advancements in education and the reduction of wage disparity between genders. The gender-based wage gap ceases at the most advanced educational level, such as graduate and above. Interestingly, in urban areas, women experience higher returns to education with every additional year of schooling compared to men.

The analysis also explores how much marital status affects the income of married and unmarried individuals of the same sex. Using the OB decomposition technique between married and unmarried women, the study reveals that married women earn less than unmarried women, while the opposite is true for men. However, the endowment gap contributes significantly to the wage gap between married and unmarried women, and the unexplained gap is not statistically significant.

This paper makes notable contributions to the existing literature. Firstly, it seeks to investigate the trend in the remarkable gender pay gap during a period of reduced or stagnant labor force participation rates. Secondly, a dynamic method is employed to scrutinize the movement in the gender pay gap and to elucidate how alterations in various factors influence the direction. Thirdly, policymakers can utilize the results of this study to concentrate on the aspects that could further decrease the gender pay gap. Lastly, this paper examines the existence of any pay disparity based on marital status among women, and the findings suggest no significant wage gap between married and unmarried women.

This paper is organized into seven sections. In section II, I discuss my hypothesis and potential factors that may have contributed to the gender pay gap reduction. I present an overview of previous literature in section III; section IV provides a detailed explanation of the methodology used for the analysis. In section V, I give an overview of the IHDS dataset and the major variables I use. In section VI, I provide descriptive statistics of the significant variables for the different groups and discuss detailed results from the OB and the JMP decomposition techniques. Finally, section VII presents the conclusion of the paper.

2 Potential Reasons or Hypothesis:

Before delving into the intricacies of the data and methodology section, it is imperative to outline the hypotheses underlying the remarkable reduction in the gender-based wage gap observed within a condensed timeframe. The initial proposition posits a positive association between education and improving gender pay disparities. This assertion draws upon the comprehensive findings explained by Deshpande et al. (2015), which illustrate that during the 2009-10 period, an impressive 43 percent of female salaried workers possessed graduate degrees, surpassing the corresponding figure of 34 percent for their male counterparts. Furthermore, the study revealed a more pronounced decline in illiteracy rates among women vis-à-vis men. Building upon this foundation, Arulampalam et al. (2007) posit that highly qualified women exhibit a notable propensity to confront and challenge legal transgressions within the workplace. Consequently, employers may avoid discrimination between equally adept males and females, thereby fostering a climate of equitable remuneration. Thus, this evidence assumes a salient and influential role in precipitating the gradual erosion of gender-based wage differentials. Considering the conjecture, it is reasonable to surmise that higher educational achievement will yield a more pronounced reduction in the gender pay gap.

In this section, I present my second hypothesis, which explores the potential relationship between the decline in family size or fertility rate and the gender pay gap. It is commonly observed that women often interrupt their careers during childbearing years and resume work later, which may lead to lower experience levels compared to men of the same age. To tackle this problem, the Government of India has adopted policies such as The National Perspective Plan for Women's Education (1988, 2000) and the National Population Policy (2000), strongly emphasizing reducing family size and enhancing women's education. According to World Bank data, the fertility rate decreased from 4.0 to 2.4 children per woman between 1990 and 2013[1]. Furthermore, the availability of various contraceptive methods has empowered women to transcend their reproductive roles and focus on their careers at the peak of their professional lives. This enables them not only to maintain a continuous source of income but also to accumulate uninterrupted experience. As women continue to acquire knowledge and skills, employers may recognize their commitment and reliability, leading to equitable pay compared to their male counterparts.

[1] World Bank Data Source: **World Bankhttps://data.worldbank.org/indicator/SP.DYN.TFRT.IN?locations=IN&view=chart**

Consequently, if this hypothesis is substantiated, we can expect a positive correlation between experience and a reduction in the gender pay gap.

An alternative hypothesis posits that reducing the gender-based wage gap within the rural sector may be attributed to implementation of the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) in 2005. This groundbreaking legislation mandates the inclusion of a minimum of 33 percent of women among the program's beneficiaries and ensures equal remuneration for both male and female participants. The comprehensive implementation of MGNREGA exerts both direct and indirect influences on narrowing the gender pay gap. Directly, the act elevates the income levels of women engaged in the program, providing them with increased financial security. Indirectly, women involved in the agricultural domain experience additional economic benefits, as the overarching objective of MGNREGA is to improve living wellbeing in rural areas. Based on this hypothesis, one may expect a noticeable decrease in the gender pay gap, specifically within the agricultural sector and rural areas, following the implementation of MGNREGA in 2005.

A fourth hypothesis introduces the potential impact of changes in labor demand and urbanization on the gender pay gap. According to the World Bank (2015)[2], urbanization rates increased from 26% to 32% between 1990 and 2013. This accelerated urbanization can stimulate the demand for highly skilled workers, contributing to a more pronounced decline in the gender pay gap among educated workers.

Furthermore, job segregation is a prominent factor in widening gender-based wage gaps. Historically, women were more inclined to pursue low-skilled, family-friendly careers, which tend to pay less than jobs held by their male counterparts. Goldin (2014) explores the historical context in which physical labor predominated over intellectual work, resulting in distinct attribute distributions between men and women. However, the rapid technological advancements witnessed in recent decades have provided women with greater flexibility in time allocation, thus reducing the opportunity cost associated with joining the workforce. As a result, more women are opting

[2]World Bank Report Source:

https://documents1.worldbank.org/curated/en/373731468268485378/pdf/757340PUB0EPI0001300pubdate02021013.pdf

for higher-paying and time-intensive occupations, which in turn contributes to the narrowing of gender pay gaps. If these two hypotheses hold, we may anticipate a more substantial decrease in the gender pay gap within urban areas, particularly in high-skilled occupations, compared to rural areas.

The other reason for the rapid growth in the pay structure for women could be cultural progress. India is well known for its biasedness towards men, and although it is hard to believe that the cultural perspective has changed within this short period. But nuclear families have increased significantly over the past few decades. In most nuclear families, both husband and wife work to bring bread to the family table and shares household responsibilities almost equally. This support from the family reduces the opportunity cost for women to work and gives them the option to enhance their skills, further corroborating the chance of getting paid equally to men.

3 Previous Research:

The Indian labor market has been the subject of extensive research, with many scholars employing the OB decomposition technique to discern the wage gap into the explained and unexplained components. At the same time, the explained portion is attributed to endowment differences between groups, and the unexplained component results from differences in the coefficients of the endowments. Madheswaran and Atwell (2007) and Jann (2008) demonstrate that a substantial part (63%) of the gender wage gap is unexplained. In addition, Duraisamy et al. (2016) reveal that the wage gap widens for older or more experienced women. However, despite the evident gender wage gap, there is a downward trend. Bhaumik et al. (2009) utilize two rounds of the Indian National Survey (NSS) data to reveal a significant wage gap reduction between 1987 and 1999. Other studies by Kingdon et al. (2001), Goel (2009), and Khanna (2012) also employ various NSS rounds and confirm the gender pay gap's presence, with a significant portion being attributed to the coefficient gap.

Many studies have been dedicated to exploring the gender-based wage gap beyond the mean level by using different decomposition techniques to examine the gap across the wage distribution. These studies help to understand if women face a “glass ceiling” or a “sticky floor”? For example, Arulampalam *et al.* (2007) define the “glass ceiling” if the gender-based wage gap at the 90th percentile is two-percentage points more than the wage gap at all other parts of the distribution.

Similarly, they define a “sticky floor” if the wage gap at the lowest 10th percentile is a two-percentage point higher than the remaining wage distribution. Khanna (2012) employed the Machado-Mata decomposition technique and found that the wage gap is heterogenous across the wage distribution. The highest gap at the lowest quantile indicates the presence of a "sticky floor." Deshpande et al. (2018) also used the Machado-Mata technique to examine the gender-based wage gap among Regular Wage/Salaried workers in India at different income quantiles. Other studies, such as Agarwal et al. (2014) and Mehta et al. (2011), used non-parametric and JMP decomposition techniques to investigate the wage gap between males and females and the effects of trade liberalization policies on wage inequality in different industries in India.

This literature review surveys several studies investigating the gender-based wage gap in different countries. Suh (2010) analyzes the gender wage gap in the U.S. economy from 1989 to 2005. The study reveals a significant decrease in the wage gap from 74.0% to 80.4% of men's income. Meanwhile, Rotman et al. (2023) study the gender-based wage gap in the U.S. from 1980 to 2010 and found an increasing wage gap in return to education and work experience over time, favoring men. Bernard (2008) examines the gender pay gap in the U.K. between 1998 and 2006. The study indicates a decrease in the pay gap from 16.1% to 12.6%, but two-thirds of the gap remains unexplained. Akgul (2018) studies the gender wage gap in the Turkish economy from 2004 to 2017. The results suggest narrowing the raw wage gap from 17.9% to 14.7%, but the residual wage gap has widened from 18.2% to 23.1%. Finally, Ahmed et al. (2015) investigated the gender pay gap in Bangladesh from 1999 to 2005. The study shows a widening gap of about 26% at the lowest quantile and about 20% at the highest quantile. Overall, these studies provide insights into the complex nature of the gender-based wage gap and how it changes over time in different countries.

Research on the gender wage gap in other countries highlights the distinctiveness of the reduction observed in the Indian economy, underscoring the importance of a detailed examination to inform practical policy recommendations.

4 Methods:

I use the conventional Oaxaca-Blinder (1993) (OB) decomposition method to decompose the wage gap between the two groups. This decomposition method untangles the raw wage gap into ‘explained’ and ‘unexplained’ parts. The explained part (characteristics effect) is coming due to differences in endowment between the two groups. The unexplained part (coefficient effects) is coming due to the difference in endowment returns. This component captures the unobservable characteristics.

The OB decomposition method has some things that could be improved. For example, many researchers consider the coefficient effects to represent discrimination. However, the presence and degree of discrimination are debatable matters. One of the primary sources of controversy is the omitted-variable bias. The OB wage equation cannot include all relevant variables capturing skills and individual productivity. Therefore, all equivalent individuals based on the variables in the wage equation may not be genuinely equivalent. The unexplained/coefficient effects of the OB equation are the sum of the discrimination and differences in unobservable skills (which can be only seen by the employers). The JMP decomposition method provides a way to capture the effect of change in unobserved skills on the difference in the gender-based pay gap.

Juhn-Murphy-Pierce Method:

I employ Juhn-Murphy-Pierce's (1993) (JMP) decomposition technique to decompose the change in the wage pay gap. By disintegrating the residual gap, the impact of unobserved prices and endowments between the two genders can be analyzed, too (Juhn, Murphy, & Pierce, 1991, 1993; Blau & Kahn, 1996). The JMP decomposition method starts with a simple Mincerian wage equation for men:

$$Y_{mt} = X_{mt}\beta_t + u_{mt} \qquad (1)$$

Where X_{mt} is a vector containing observable factors of a male worker, β_t is a vector of regression coefficients on these factors in year *t,* and u_{mt} is the residual.

According to Juhn, Murphy, and Pierce (1993), this residual consists of two components:

$$u_{it} = \theta_{it}\sigma_t \qquad (2)$$

Where θ_{it} is a "standardized" residual (with mean zero and variance 1) and σ_t is the within-group standard deviation of wages in year t. Changes in σ_t through time reflect changes in within-group inequality. Using this, the wage gap between men and women can be written as

$$D_t = Y_{mt} - Y_{wt} = \Delta X_t \, \beta_{mt} + \sigma_{mt} \, \Delta\theta_t \tag{3}$$

Where $\Delta\theta_t$ is the difference between average standardized residual between men and women. Then convergence between men's and women's wages from year *t* to year *t'* can be written as:

$$\underbrace{D_{t'} - D_t}_{D} = \underbrace{\beta_{mt} \, (\Delta X_{t'} - \Delta X_t)}_{Q} + \underbrace{(\beta_{mt'} - \beta_{mt}) \, \Delta X_{t'}}_{P} + \underbrace{\sigma_{mt} \, (\Delta\theta_{t'} - \Delta\theta_t)}_{UQ} + \underbrace{(\sigma_{mt'} - \sigma_{mt}) \, \Delta\theta_{t'}}_{UP} \tag{4}$$

The first term (Q) on the right-hand side of equation (4) is "observed characteristic effect" or "observed endowment effect," which reflects changes in observable features (e.g., education) between men and women. This term is weighted by the men's coefficients. The second term represents the "observed remuneration effect" or "observed price effect" (P). Again, this is measured at the men's coefficients. Thus, if the returns to education for men grew, all else equal, then the gender wage gap would increase from period *t* to *t'*. The third component represents the "ranking effect" or "unobserved quantity effect" (UQ), which captures changes in the relative positions of women and men. For example, if the position of women increases in the male residual distribution, keeping the residual male wage inequality fixed, then the wage gap between men and women will decrease. A negative value of $\Delta\theta_{t'}$ implies that women, on average, earn less than the men. Finally, the last term captures the "unobserved remuneration effect" or "unobserved price effect" (UP) – the effect of changing with group inequality. The fourth term entails that a rise in wage inequality would enhance the men-women wage gap even if women maintained the same positions in the men distribution –

$$\Delta\theta_{t'} - \Delta\theta_t = 0. \tag{5}$$

The calculation of the third and the fourth term is the most tiresome in the model. According to Juhn, Murphy, and Pierce (1993), and Blau and Kahn (1997), the third term can be empirically implemented by assigning each woman in each year a percentile ranking corresponding to her position in the residual distribution of men for that year. Then, for each woman in year t*'*, the wage residual for year *t* has been computed based on her position in the men's wage distribution in year t. Therefore, the third term σ_{mt} $(\Delta\theta_{t'} - \Delta\theta_{t})$, represents the difference between the average imputed residuals and the actual average residual for women in year t. Since both calculations are based on the year *t* residual distribution, we can capture women's movements through the men's residual distribution.

The calculation of the fourth term is analogous to the calculation of the third term. According to Juhn, Murphy, and Pierce (1993) and Blau and Kahn (1997), only the men's residual distribution changes, and we compare the same year t*'* individuals. We start by assigning each woman a percentile rank based on the men's distribution in year t*'*. Then compute what residual that woman would have been in year *t* and subtract it from the actual year t*'* residual. Since the women's percentile position of women is constant in the computation, the change in this term reflects changes in residual inequality for men.

Altogether the impact of gender-specific factors is reflected in the first and the third term, the effect of different observable skills and wage ranking gaps between two genders at a given level of observable factors. The second and fourth terms reflect the wage structure, which captures the effect of changing returns to observed and unobserved characteristics.

5 Data and Variables:

5.1 Data

The India Human Development Survey Data (IHDS) is a rich source of information that covers a wide range of topics. The first wave of the survey was conducted in 2004-05 and included 41,554 households, while the second wave covered 42,152 households in 2011-12. Unlike the National Sample Survey Office (NSSO), this dataset is publicly available, easy to access, and requires minimal data cleaning. It also covers a much broader topics than the National Family Health Survey (NFHS), including income, consumption, agriculture, education, and government programs. The IHDS covers all states and union territories except the Andaman, Nicobar Islands, and Lakshadweep. The dataset captures various demographic variables such as age, gender, marital status, and social groups, and socioeconomic variables such as wages, earnings, educational attainment, employment types, and several other features.

5.2 Dependent Variables:

The primary outcome variable of interest in this study is the natural logarithm of the hourly wage. The IHDS data includes responses to various questions related to employment and income. For example, respondents were asked about the number of days they worked the previous year, the usual number of hours worked per day, and their earnings from work during that period. To calculate the hourly wage, I divide the total earnings per year by the number of days worked in a year and the number of hours worked per day.

5.3 Independent Variables:

I employ the conventional Mincer wage equation with some modification of the independent variables. To capture the human capital, I use education and potential experience. Educational information is given at the individual level and is classified under one of the seven categories, illiterate, below primary (1 – 4 years), primary (5 years), middle school (6 – 9 years), higher secondary (10 – 11 years), secondary (12 – 14 years), and graduate & above (15+ years). A notable constraint of the IHDS dataset pertains to the absence of data on actual work experience, thereby limiting the ability to directly analyze individuals' real-life professional trajectories. As a result, and to follow previous research, I am using the potential experience as a proxy for the experience. I calculate potential experience by subtracting the total years of education and six from the age. To fully capture the impact of the potential experience on the wage rate, I am adding the experience square term.

Previous studies have often treated the impact of potential experience on wages as equivalent to the impact of experience. Still, it is important to recognize that it may serve as an inaccurate proxy for experience. Potential experience refers to the cumulative number of years an individual could have potentially worked based on their age or education level. However, it fails to account for any interruptions or breaks in employment that individuals may have experienced throughout their careers, such as those resulting from various factors such as unemployment, caregiving responsibilities, educational pursuits, or health-related issues. Consequently, potential experience may overestimate an individual's actual work experience. Given these considerations, my emphasis lies in interpreting the effects of other variables while acknowledging the limitations regarding the potential experience. Importantly, this may create greater measurement error for women than for men due to men's stronger attachment to the labor force.

In addition to the independent variables used in the conventional Mincer wage equation, I include several individual-level independent variables to better capture the impact of other factors on an hourly wage. These variables include sex, marital status (categorized as married or unmarried), social groups/caste, industry, occupation, place of residence (rural or urban), and state of residence; all represented as dummy variables. These controls allow for a more comprehensive analysis of the relationship between human capital and wage rates while controlling for other factors influencing wage differentials.

6 <u>Results:</u>

6.1 Descriptive Overview:

Tables 1.1 and 1.2 exhibit the socio-economic and labor market characteristics of individuals aged 15 to 65, distinguished by the two survey waves, 2004-05 and 2011-12, as well as by their location of residence, rural and urban. The descriptive statistics reveal a persistent wage differential between males and females in rural and urban settings. Nevertheless, the gender-based wage disparity declined in rural and urban areas from 2004-05 to 2011-12.

Table 1.2 presents descriptive statistics for the log wage gap, labor force participation rate (LFP), and other relevant variables for rural and urban areas in 2004-05 and 2011-12. The results indicate that at the pooled level, the log wage gap in 2004-05 was 0.66 compared to a sharp decline of 0.46 in 2011-12. The wage gap has dropped both in rural (0.56 in 2004-05 and 0.40 in 2011-12) and urban (0.58 in 2004-05 and 0.41 in 2011-12) areas. In urban areas, the LFP rate of females is only about a quarter of that of males, and this trend is consistent for both years (15.61% for females and 66.96% for males in 2004-05 and 19.52% for females and 67.65% for males in 2011-12). In contrast, while women in rural areas also experience a gender gap in LFP rates, their rates are higher than those in urban areas but still lower than male rates.

The educational distribution of men and women varied by location and time. In rural areas, approximately 50% of women were illiterate during the first round of the survey, although this figure declined by the second round, where nearly 39% of women remained illiterate. The significant improvement in just a short time could be attributed to government policies to improve women's socioeconomic status. The situation was somewhat better in urban areas, with an average of one-quarter of women being illiterate. As we move up the education ladder, the gender disparity in education becomes less pronounced, particularly in urban areas, for both survey rounds.

As indicated in the tables, most men and women worked in the agricultural sector in rural areas during both survey rounds. This suggests that one potential explanation for the higher LFP rate among rural women is that they primarily work on their land and have less need to seek employment elsewhere. Conversely, nearly half of the employed women in urban areas work in the service sector, where wages generally exceed those in the agricultural industry. Differences may influence the wage gap between urban and rural women in education levels, the sectors, and the occupations in which they work. Additionally, the data indicates that most women work part-time in both areas and during both survey rounds.

6.2 Descriptive Overview of Raw Gender-Based Wage Gaps within Several Categories of Single Factors:

The present study examines the log hourly wages for men and women by educational subgroups, as depicted in Figures 1.1a and 1.1b. The findings reveal a significant gender-based wage gap in the lower levels of education, which gradually decreases with an increase in educational attainment. Notably, the wages for females after completing middle school education show a sharp rise for both rural and urban areas during both survey periods. However, at the highest level of education, the wage rates for both genders are quite comparable, indicating a diminishing gender disparity. This pattern aligns with Agarwal (2012), who highlights a similar trend of increased returns to education after completing middle school level education for both rural and urban areas in India.

The analysis of the log hourly wages of men and women by age groups is presented in Figures 1.2a and 1.2b for 2004-05 and 2011-12. The figures reveal that in urban areas, both males and females experience a sharp increase in wages with age, which is followed by a steep decline in their fifties. Although the wage gap decreased in rural and urban areas between 2004-05 and 2011-12, it remains a significant concern. The analysis suggests that the wage disparity between genders persists despite the improvement and requires further investigation.

Tables 1.3 and 1.4 provide insight into the gender wage gap in industries and occupations. The average female-to-male earnings ratio is higher for most industries and occupations, indicating that women earn less than men in these areas. However, there has been an improvement in the situation from 2004-05 to 2011-12, with the female-to-male earnings ratio increasing in most industries and occupations. Notably, for two industry groups (Electricity, Gas, & Water and Transport, Storage, & Communication), the female-to-male earnings ratio surpassed one in 2011-12, indicating that women earned more than men in those sectors.

6.3 Wage Gap Decomposition Results:

This section provides details of the gender-based and marital status-based wage gap decomposition. Results are organized in order of (i) male-female wage decomposition by using the OB decomposition and (ii) male-female wage decomposition by using the JMP decomposition. (iii) The OB decomposition of married-unmarried individuals of the same sex.

6.3.1 The OB Decomposition Results:

Table 1.5 represents a summary of the results obtained from the OB decomposition analysis and the income inequality prevalent between males and females in 2004-05 and 2011-12. The combined data reveals that the predicted mean raw log wage gap between men and women declined from 0.64 to 0.48 during the period under consideration. Further, the average wage gap is partitioned into explained and unexplained components. In 2004-05, the gender-based wage gap was attributed equally to the endowment and coefficient disparities for the aggregate sample. However, in 2011-12, the mean wage gap attributable to the endowment factor registered a marked decline, while the gap owing to unexplained factors exhibited an upward trend. The widening unexplained wage gap does not necessarily imply increased discrimination against women. It is possible that male workers possess superior skills and abilities compared to their female counterparts.

Based on the descriptive statistics, it is evident that women's literacy rate in urban areas surpasses that of their rural counterparts, which, in turn, implies that the wage gap between genders is likely to be higher in the rural regions. Table 1.5, columns (3) through (6) illustrate the gender pay disparity between urban and rural areas. The unadjusted logarithmic wage gap for rural areas declined from 0.54 to 0.44 in the study period. Similarly, urban areas' average logarithmic wage gap decreased from 0.51 to 0.41. Endowment factors caused a reduction in the gender pay gap for both urban and rural areas during the study period. For the 2011-2012 survey, the gap attributable to explained factors became statistically insignificant in urban areas, indicating no gender pay gap due to labor market characteristics. This finding signifies that women have attained parity with men regarding different labor market characteristics. In the following section, the JMP decomposition analysis provides insight into how the shift in the gender pay gap is attributed to changes in various labor market characteristics over time.

Table 1.5 reveals a notable portion of the unexplained gender pay gap attributable to the constant term. The significant and positive constant term value suggests that male workers earn more than their female counterparts without considering any factors. In other words, there exists a gender wage gap that differences in human capital or job characteristics cannot explain. This gap may be due to various reasons, including women spending less time in the labor market, choosing professions that require less time and offer lower pay, or exhibiting lower productivity. Nevertheless, such factors can only be observed by employers.

Table 1.6 extensively examines the OB decomposition analysis, with variables grouped for clarity, such as education dummies categorized under "education." Education is vital in explaining the gender wage gap and exhibits a constant upward trend. Thus, the wage gap can be reduced by ensuring similar education levels between genders. Notably, the education factor's explained component of the wage gap has decreased from 0.13 to 0.08, indicating that women have made more significant gains in educational attainment than men, leading to a decline in the gender gap. Moreover, the unexplained component of education was negative (-0.04) in 2011-12, implying that women enjoy higher returns to education than men. It is worth mentioning that these results are descriptive and further investigation is needed to establish the causal impact of education on the wage gap.

The experience and experience square variables have been merged and labeled as experience. The negative coefficient of experience reveals that male workers have less potential experience than their female counterparts, on average. The experience square term's inclusion allows us to consider the non-linear relationship between potential expertise and earnings. The positive coefficients for industry (0.03 in 2004-05 and 0.02 in 2011-12) and occupation (0.09 in 2004-05 and 0.01 in 2011-12) demonstrate that men tend to select high-paying industries and occupations, indicating that the gender pay gap persists because of occupational segregation by gender. Hypothetically, if women chose industries and occupations like men, it would lower the gender pay gap by 18.75% in 2004-05 and 6.25% in 2011-12. On a positive note, the explained portion of the wage gap due to industry and occupational choice has dropped, indicating that women also started to choose high-paying industries and occupations. One possible explanation for the decreasing gender pay gap explained by industry and occupation in India could be the increasing participation of women in managerial roles. A McKinsey & Company (2015) study found that in India, women's representation in managerial positions increased from 14% in 2004-05 to 25% in 2011-12. This increase in representation could potentially reduce the gender pay gap, as women in managerial roles are expected to get higher remuneration than those in other occupations.

Tables 1.7 and 1.8 detail the OB decomposition results for rural and urban areas. In both areas, the explained coefficient for education is positive, exactly what we have seen for the pooled sample. The explained coefficient of education has dropped for both regions over time, indicating that the average education of females has gone up compared to males. Coefficients of marital status (-0.04 from Table 1.8) suggest that married women receive higher returns to their labor market characteristics than married men in urban areas. One possible explanation is that married women face more substantial incentives to work in urban areas due to the higher cost of living and greater need for dual incomes in households. As a result, married women may be more likely to invest in their human capital, such as education or job training, to increase their earning potential. Additionally, married women may face less discrimination in the urban labor market than in rural areas, where traditional gender roles may be more rigidly enforced.

In the aftermath of the OB findings, it could be concluded that the gender-based compensation disparity would have been further improved if the scholastic attainment of females were commensurate with that of males. The remunerative benefits of education consistently favor women, irrespective of geographic location. If women attain an equivalent mean educational standard as men, it will serve to rebound to their pecuniary advantage in the context of the gender-based wage gap. Contrary, it could also be possible that women who completed more education were more capable than men who did the same, reflecting discrimination on another front. Further investigation of the causal impact of education on wages is necessary to conclude with certainty. Industry and occupational segregation have also evolved, instrumental in reducing the wage gap. It is manifest from the OB findings that education, industry, and occupational segregation play a salient and indispensable role in ameliorating the predicament females face.

6.3.2 The JMP Decomposition Results:

The OB decomposition section shows that the wage gap has dropped from 2004-05 to 2011-12. The JMP decomposition method helps us examine the wage gap trend between the two survey rounds and to what extent changes in variable factors contribute to the gender pay gap trend.

Table 1.9 summarizes the Juhn-Murphy-Pierce (JMP) decomposition results of the changes in the gender pay gap in India between 2004-05 and 2011-12. Panel A shows the results for the entire sample. The table shows the difference in differential (D) (-0.15) for the pooled sample, further decomposed into two terms, the difference in the predicted gap (E) and the difference in the residual gap (U). The decomposition of the difference in the predicted gap (E) suggests that covariates (Q) account for the most significant portion of the reduction in the gender pay gap, with a value of -0.10; the significant negative value of Q implies that the two genders have become more similar. Observed prices (P) change -0.09, which indicates decreasing observable differentials between men and women. On the other hand, the decomposition of the difference in the residual gap (U) shows a positive contribution of 0.04, indicating that unexplained factors have contributed positively to the pay gap. Unobservable quantities (UQ) are positive, 0.01, which means that the relative position of women has slightly dropped in the male wage distribution. In addition, the unobserved price effect also contributes positively (0.03) toward the gender-wage gap.

In Table 1.9, Panel B and Panel C separately provide the Juhn-Murphy-Pierce (JMP) decomposition outcomes for the rural and urban areas. The findings from Panel B demonstrate that the difference in the differential between 2004-05 and 2011-12 is -0.11, implying that the gender pay gap has decreased in rural areas. The "Decomposition of Difference in Predicted Gap" (E) indicates that the changes in observable characteristics account for most of the reduction, with a value of -0.15. The "Decomposition of Difference in Residual Gap" (U) reveals that changes in unobservable features contribute only slightly to the increase in the gender pay gap, with a value of 0.04.

Panel C shows the decomposition results for the urban area. The results are like the rural area, with a difference in the differential of -0.11, indicating a decrease in the gender pay gap. The decomposition of the difference in the predicted gap (E) shows that changes in observed characteristics account for most of the decrease in the gender pay gap, with a value of -0.14. The decomposition of the difference in the residual gap (U) shows that changes in unobserved characteristics account for a slight increase in the gender pay gap, with a value of 0.03.

To examine further why the pay gap has dropped around 15% within a decade, I now check the detailed impact of each covariate in Table 1.10. Columns (1) and (2) show results for the pooled sample. The decomposition result of the covariates (Q) shows that changes in gender differences in education played a strong positive effect in reducing the wage gap. A negative value of potential experience (-0.01) shows that the combined impact of education and age positively reduces the pay gap. A negative value of the occupation (-0.03) and state (-0.03) suggests that the number of women choosing higher-wage professions has grown since 2004-05, and the marginal improvement in the women's income relative to men within different states. Other covariates have no significant effect on the gender pay gap trend.

Now considering the effect of the wage structure on the gender-based pay gap between the two survey rounds, we can see that potential experience is the only factor contributing to widening the wage gap. Nevertheless, as previously discussed, it is crucial to recognize that potential experience may not accurately reflect actual experience. Thereby we may shift our focus on interpreting other variables. For example, the industry, social groups, and marital status have no impact on reducing the wage disparity. On the contrary, education and occupational choice (together, 53.33%) have a powerful impact on reducing the wage disparity.

Columns (3) and (4) from Table 1.10 show results for the rural sample. A negative value for the covariate component (Q) for education (-0.01) suggests that changes in the education levels of men and women have contributed to a decrease in the gender pay gap. A negative value of the occupation (-0.04) suggests that changes in the distribution of men and women across occupations have contributed to a decrease in the gender pay gap. Put differently, the number of women choosing higher-wage occupations has grown since 2004-05. Finally, a negative value of states (-0.02) also shows the marginal improvement in the women's income relative to men within different states. Social groups/caste, marital status, and industry do not significantly affect the gender pay gap trend. Based on the results from the rural sample, we can say that the improvement in the rural sector might be because of the existence of MGNREGA and women's educational attainment.

Now consider the effect of the wage structure on the gender-based pay gap between the two survey rounds, we can see that experience and industry are the only factors contributing to widening the wage gap. In other words, we can say that though women are quickly catching up with men in terms of education, the number of men working in higher-paying industries is still high. Social groups and marital status have no impact on reducing the wage disparity. On the contrary, education and occupational choice (together, 81.81%) have a powerful effect on reducing the wage disparity.

Columns (5) and (6) from Table 1.10 show results for the urban sample. A negative value for the covariate component (Q) for education (-0.04) suggests that changes in the education levels of men and women have a substantial impact on reducing the gender pay gap. A negative value of potential experience (-0.01) shows that the combined effect of education and age positively reduces the pay gap. A negative value of the occupation (-0.03) suggests that changes in the distribution of men and women across occupations have contributed to a decrease in the gender pay gap. Put differently, the number of women choosing higher-wage occupations has grown since 2004-05. Finally, a negative value of states (-0.02) also shows the marginal improvement in the women's income relative to men within different states. Social groups/caste, marital status, and industry do not significantly affect the gender pay gap trend.

In conclusion, the JMP decomposition analysis provides an encouraging outlook for women's labor market returns. The findings are consistent with the results of the OB decomposition analysis, indicating that educational improvements have a positive effect on reducing the gender pay gap. Furthermore, the occupational choices of women have played a crucial role in this reduction. As seen in Table 1.1 and Table 1.2, the proportion of women in the service sector, production, and transportation industries has increased. Correspondingly, Table 1.4 reveals that the earnings ratio (W_f/W_m) has also increased for these sectors. Therefore, it can be inferred that the positive impact of occupation stems from the shift in supply and demand of workers across industries that offer more equitable pay for both genders.

6.3.3 Marital Penalty:

This section investigates potential disparities in treatment between married and unmarried cohorts of the same gender. In the context of India, women primarily leave their paternal homes upon marriage and transition to cohabiting with their in-laws. Even today, the burden of household responsibilities remains unevenly distributed between married men and women. On the demand side of the labor market, employers may exhibit a preference for unmarried women, as they generally shoulder fewer domestic obligations, thereby enabling them to dedicate greater attention to their work. To examine this proposition, I conduct an analysis employing the Oaxaca-Blinder decomposition technique, which dissects the wage gap between married and unmarried workers of the same gender. Specifically, I focus solely on wage earners aged between 15 and 65 years. To initiate this section, I present summary statistics pertaining to the married and unmarried cohorts.

6.3.3.1 Descriptive Statistics of the Married & Unmarried Female Workers:

Table 1.11 presents an overview of the demographic and labor market characteristics of married and unmarried females aged 15 to 65 residing in rural and urban areas. From the summary statistics, several noteworthy patterns emerge. Interestingly, married women tend to earn slightly lower incomes than their unmarried counterparts during the two rounds of the survey. For instance, in 2004-05 average logarithmic wage for married women were 2.27 compared to 2.36 for the unmarried cohort. In 2011-12 wage rate has gone up for both the cohorts, however, the married women (2.61 logarithmic wage) still earn relatively lower wage rate than their unmarried counterparts (2.69 logarithmic wage). On the other hand, in 2004-05, the labor force participation (LFP) rate for married women stood at approximately 37% (which increased to around 39% in 2011-12), while the unmarried group exhibited a much lower participation rate of only about 16% (which increased to about 18% in 2011-12).

Moreover, educational attainment demonstrates consistent disparities between these two cohorts. 2004-05, around 50% of married women were found to be illiterate, and this proportion decreased to approximately 42% in 2011-12. Regarding industry and occupation distribution, both groups exhibit a striking similarity, with a significant majority of women engaged in the agricultural sector. However, even in terms of employment type, we observe a similarity between the cohorts, as a substantial proportion of women from both married and unmarried groups work as part-time employees.

6.3.3.2 Descriptive Statistics of the Married & Unmarried Male Workers:

Table 1.12 presents the demographic and labor market characteristics of married and unmarried males aged 15 to 65. The data reveals a consistent earnings advantage for married males over their unmarried counterparts. The labor force participation (LFP) rate among men is generally higher compared to women, and within the male population, married individuals exhibit a higher LFP rate than unmarried men.

It is worth noting that the average age of the unmarried cohort is below twenty, suggesting that a significant portion of this group may still attend school and voluntarily choose not to participate in the labor market. This age-related factor could contribute to the lower LFP rate observed among unmarried men.

The analysis reveals significant disparities in educational attainment between married and unmarried individuals. In 2004-05, approximately 25.69% of married men were found to be illiterate, which decreased to around 21.61% in 2011-12. Notably, the literacy rate among unmarried cohorts was higher for both periods.

The distribution of workers across different industries and occupations demonstrates the remarkable similarity between the married and unmarried cohorts. This consistency persists across both periods, suggesting a stable occupational preference among individuals from both groups.

In terms of employment type, a noteworthy pattern emerges. Most married men exhibit a higher inclination towards full-time work. This distinction may be attributed, in part, to the fact that the average age of unmarried men was below twenty. It is plausible that a considerable proportion of this group was still pursuing education and therefore chose part-time work to accommodate their studies.

Based on the descriptive statistics presented, without controlling for any other factors, it is evident that the married males tend to earn higher incomes than their unmarried counterparts. However, the educational distribution appears to be more favorable for the unmarried group.

From the descriptive statistics portion, the results point toward the marriage-based penalty for women. In the next section, I have employed the Oaxaca-Blinder (OB) decomposition method to examine the possible existence of a marriage-based penalty, is employed. This method allows for the decomposition of wage differences between married and unmarried individuals of the same sex, thereby providing insights into the specific factors contributing to any observed wage disparities.

6.3.3.3 The OB Decomposition of Married-Unmarried Female Workers:

Table 1.13 summarizes the Oaxaca-Blinder (OB) decomposition results for the wage gap between married and unmarried females. The findings indicate that unmarried women earned slightly higher incomes than their married counterparts in both periods.

The decomposition analysis reveals that the explained portion of the wage gap accounts for more than 70% of the total gap for both rounds. This suggests that observable characteristics and factors, such as education, experience, and other endowments, explain most of the wage differential between the two groups. Furthermore, the unexplained portion of the wage gap is found to be statistically insignificant, indicating that there is no significant differential treatment in terms of returns to endowments between married and unmarried women.

Turning to the detailed results of the OB decomposition (Table 1.14), it is observed that the education gap between the married and unmarried cohorts has a positive and significant effect on the wage gap. Specifically, the education endowment for the unmarried cohort is higher, as evidenced by the positive coefficients of 0.15 in 2004-05 and 0.22 in 2011-12. This finding aligns with the conclusions drawn from the descriptive statistics.

The analysis also merges the experience and experience square variables, labeling them "experience." The wage structure analysis reveals that, in 2011-12, only state, and occupational choice had a significant impact on the wage gap, while other variables are either statistically insignificant or do not contribute significantly to the wage gap between the married and unmarried groups.

6.3.3.4 The OB Decomposition of Married-Unmarried Male Workers:

From Table 1.13, it is evident that married men earned higher incomes compared to their unmarried counterparts in both rounds. The endowment gap, which captures the differences in characteristics and attributes between the two groups, explains approximately 80% of the wage gap between married and unmarried men.

Analyzing the detailed results in Table 1.15, it is observed that the endowment effect of education is positive for both rounds. This indicates that the unmarried group tends to have higher education levels than the married group. While the overall unexplained gap is insignificant, the coefficients for the area and occupational choices are found to be significant. The positive coefficients for occupation (0.29 in 2004-05 and 0.11 in 2011-12) suggest that unmarried men have an advantage over the married group regarding occupational choice.

In summary, the OB decomposition results indicate that a substantial fraction of the remuneration differences between married and unmarried men can be attributed to the endowment gap. This suggests that differences in characteristics, such as education, are crucial in explaining the wage differential. However, no significant evidence of discrimination or disadvantage for the married group is found.

7 Conclusion:

This study investigated the gender-based wage gap within the Indian economy and aimed to examine the existence of marriage-based penalties for women. While the gender-based wage gap has decreased over time, a substantial portion still needs to be accounted for. Prior research (Lama & Majumder, 2018; Balakarushna et al., 2019) has suggested that the expansion of this unexplained component stems from labor market discrimination, but the scope of this paper does not allow for definitive claims regarding discrimination. Instead, my focus is highlighting factors contributing to narrowing the gender-based wage gap.

I have demonstrated a positive association between education, change in occupational choice, and wage gap reduction. Both the OB and JMP decomposition analyses support these associations. Although this paper does not predict a causal analysis, these findings could be attributed to various initiatives commenced by the Indian government to improve women's educational attainment.

From the OB decomposition between married and unmarried women, I have seen that the wage of unmarried women is slightly more than the married group, and the reverse is true for men. A considerable fraction of the wage difference between married-unmarried women comes from the explained portion, while cannot say if married women face any workplace, further exploration of other socio-cultural variables may add some insights into this matter.

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Chapter 1 Tables & Figures of the Paper:

Table 1: Summary Statistics of Selected Dependent and Independent Variables - Male and Female (2004-05)

	All		Rural		Urban	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables						
Log Hourly Wage	2.89	2.23	2.68	2.12	3.32	2.74
	(0.007)	(0.008)	(0.008)	(0.008)	(0.013)	(0.024)
Work participation	71.820	32.280	74.500	41.360	66.958	15.605
Independent Variables						
Educational Level:						
Illiterate	19.793	41.118	24.591	49.961	11.080	24.879
Below Primary	8.467	7.180	10.135	7.997	5.439	5.681
Primary	7.489	7.369	8.226	7.560	6.220	7.019
Middle-School	30.008	22.210	30.793	20.471	28.583	25.403
Secondary	15.430	10.492	13.646	7.820	18.669	15.399
Higher-Secondary	9.336	5.971	7.369	3.645	12.907	10.274
Graduate and above	8.985	4.949	4.755	1.777	16.667	10.774
Experience (years)	17.735	8.895	18.829	11.556	15.750	4.015
Marital Status:						
Married	64.796	77.335	66.094	79.108	62.441	74.081
Unmarried	35.204	22.665	33.906	20.892	37.559	25.919
Social Groups:						
General	22.890	23.100	19.050	19.470	29.870	29.770
Other Backward Caste	33.870	33.900	35.940	36.080	30.110	29.890
Dalit (Schedule Caste)	19.740	19.480	21.680	21.300	16.210	16.130
Adivasi (Schedule Tribe)	7.900	7.990	10.420	10.440	3.310	3.480
Muslim	12.200	12.170	9.880	9.830	16.430	16.450
Others (Christian, Sikh, Jain)	3.400	3.370	3.030	2.880	4.070	4.270
Industry						
Agriculture, Hunting, Forestry, and Fishing	33.53	63.11	49.13	76.94	6.27	14.02
Mining and Quarrying	1.38	0.37	1.15	0.26	1.76	0.76
Manufacturing	11.16	10.09	7.12	7.16	18.23	20.47
Electricity, Gas, and Water	2.09	0.24	1.31	0.14	3.45	0.58
Construction	14.69	6.04	15.63	5.72	13.04	7.17
Wholesale, Retail, Trade and Restaurants	5.17	1.55	2.76	0.71	9.39	4.54
Transport, Storage, and Communication	10.11	1.02	7.17	0.55	15.25	2.7
Financing, Insurance, Real Estate, and Business Services	2.7	0.94	0.91	0.18	5.82	3.64
Community, Social, and Personal Services	19.17	16.64	14.82	8.33	26.78	46.13
Occupation:						
Professional, technical, and related workers	6.530	6.490	4.500	2.490	10.160	20.540
Administrative, executive, and managerial workers	1.790	0.350	0.520	0.100	4.050	1.220
Clerical and related workers	7.560	2.630	4.020	0.880	13.890	8.790
Sales workers	3.920	0.950	1.910	0.300	7.530	3.230

Service workers	5.770	7.110	4.010	3.730	8.920	18.970
Farmers, fishermen, hunters, loggers, and related workers	31.200	61.280	45.490	74.960	5.650	13.240
Production and related workers, transport equipment operators and laborers	43.230	21.200	39.550	17.550	49.800	34.020
Types of Employment:						
Part-time	35.550	26.320	44.650	35.410	19.010	9.620
Full-time	36.280	5.960	29.850	5.950	47.940	5.990
Average hours worked per day	5.260	3.037	4.712	2.791	6.408	4.337

Notes: Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Chapter 1 Tables & Figures of the Paper:

Table 1.1: Summary Statistics of Selected Dependent and Independent Variables - Male and Female (2004-05)

	All		Rural		Urban	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables						
Log Hourly Wage	2.89	2.23	2.68	2.12	3.32	2.74
	(0.007)	(0.008)	(0.008)	(0.008)	(0.013)	(0.024)
Work participation	71.820	32.280	74.500	41.360	66.958	15.605
Independent Variables						
Educational Level:						
Illiterate	19.793	41.118	24.591	49.961	11.080	24.879
Below Primary	8.467	7.180	10.135	7.997	5.439	5.681
Primary	7.489	7.369	8.226	7.560	6.220	7.019
Middle-School	30.008	22.210	30.793	20.471	28.583	25.403
Secondary	15.430	10.492	13.646	7.820	18.669	15.399
Higher-Secondary	9.336	5.971	7.369	3.645	12.907	10.274
Graduate and above	8.985	4.949	4.755	1.777	16.667	10.774
Experience (years)	17.735	8.895	18.829	11.556	15.750	4.015
Marital Status:						
Married	64.796	77.335	66.094	79.108	62.441	74.081
Unmarried	35.204	22.665	33.906	20.892	37.559	25.919
Social Groups:						
General	22.890	23.100	19.050	19.470	29.870	29.770
Other Backward Caste	33.870	33.900	35.940	36.080	30.110	29.890
Dalit (Schedule Caste)	19.740	19.480	21.680	21.300	16.210	16.130
Adivasi (Schedule Tribe)	7.900	7.990	10.420	10.440	3.310	3.480
Muslim	12.200	12.170	9.880	9.830	16.430	16.450
Others (Christian, Sikh, Jain)	3.400	3.370	3.030	2.880	4.070	4.270
Industry						
Agriculture, Hunting, Forestry, and Fishing	33.53	63.11	49.13	76.94	6.27	14.02
Mining and Quarrying	1.38	0.37	1.15	0.26	1.76	0.76
Manufacturing	11.16	10.09	7.12	7.16	18.23	20.47
Electricity, Gas, and Water	2.09	0.24	1.31	0.14	3.45	0.58
Construction	14.69	6.04	15.63	5.72	13.04	7.17
Wholesale, Retail, Trade and Restaurants	5.17	1.55	2.76	0.71	9.39	4.54
Transport, Storage, and Communication	10.11	1.02	7.17	0.55	15.25	2.7
Financing, Insurance, Real Estate, and Business Services	2.7	0.94	0.91	0.18	5.82	3.64
Community, Social, and Personal Services	19.17	16.64	14.82	8.33	26.78	46.13
Occupation:						
Professional, technical, and related workers	6.530	6.490	4.500	2.490	10.160	20.540
Administrative, executive, and managerial workers	1.790	0.350	0.520	0.100	4.050	1.220
Clerical and related workers	7.560	2.630	4.020	0.880	13.890	8.790
Sales workers	3.920	0.950	1.910	0.300	7.530	3.230

Service workers	5.770	7.110	4.010	3.730	8.920	18.970
Farmers, fishermen, hunters, loggers, and related workers	31.200	61.280	45.490	74.960	5.650	13.240
Production and related workers, transport equipment operators and laborers	43.230	21.200	39.550	17.550	49.800	34.020
Types of Employment:						
Part-time	35.550	26.320	44.650	35.410	19.010	9.620
Full-time	36.280	5.960	29.850	5.950	47.940	5.990
Average hours worked per day	5.260	3.037	4.712	2.791	6.408	4.337

Table 1.2: Summary Statistics of Selected Dependent and Independent Variables - Male and Female (2011-12)						
	All		Rural		Urban	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables						
Log Hourly Wage	3.12	2.66	2.99	2.59	3.38	2.97
	(0.007)	(0.009)	(0.008)	(0.009)	(0.013)	(0.023)
Work participation	72.526	33.650	75.519	42.15	67.653	19.517
Independent Variables						
Educational Level:						
Illiterate	16.123	34.307	19.851	39.147	8.514	21.223
Below Primary	7.408	6.582	8.352	7.082	5.347	5.572
Primary	7.258	7.768	8.004	8.202	5.568	6.892
Middle-School	30.860	24.347	32.134	23.983	27.223	25.081
Secondary	16.431	11.878	15.340	10.136	17.791	15.392
Higher-Secondary	12.043	8.674	10.260	6.742	14.873	12.570
Graduate and above	9.725	6.338	5.900	2.946	16.455	13.181
Experience (years)	18.557	10.000	19.515	12.391	16.695	5.177
Marital Status:						
Married	65.289	77.550	66.744	78.902	62.463	74.822
Unmarried	34.711	22.450	33.256	21.098	37.537	25.178
Social Groups:						
General	21.850	21.930	18.870	19.130	27.650	27.590
Other Backward Caste	33.440	33.410	34.990	34.990	30.420	30.230
Dalit (Schedule Caste)	20.890	20.770	22.320	22.150	18.110	17.970
Adivasi (Schedule Tribe)	8.380	8.420	10.950	10.800	3.390	3.620
Muslim	12.620	12.720	10.280	10.430	17.180	17.330
Others (Christian, Sikh, Jain)	2.820	2.750	2.590	2.490	3.260	3.270
Industry						
Agriculture, Hunting, Forestry, and Fishing	22.72	46.82	32.16	56.8	3.54	10.68
Mining and Quarrying	1.1	0.29	0.96	0.15	1.38	0.81
Manufacturing	15.08	9.62	11.02	7.44	23.32	17.51
Electricity, Gas, and Water	2.13	0.28	1.45	0.14	3.5	0.78
Construction	26.27	20.7	32.66	24.01	13.28	8.74
Wholesale, Retail, Trade and Restaurants	5.18	1.53	2.82	0.7	9.97	4.54
Transport, Storage, and Communication	10	1.28	7.31	0.58	15.48	3.85
Financing, Insurance, Real Estate, and Business Services	2.49	0.94	1.03	0.25	5.46	3.44
Community, Social, and Personal Services	15.04	18.53	10.59	9.93	24.07	49.65
Occupation:						
Professional, technical, and related workers	5.920	8.670	4.200	4.760	9.420	22.820
Administrative, executive, and managerial workers	1.500	0.360	0.550	0.130	3.450	1.190
Clerical and related workers	7.320	3.830	4.050	1.920	13.970	10.760
Sales workers	4.850	0.930	2.380	0.380	9.870	2.900
Service workers	4.990	7.880	3.380	3.620	8.260	23.350
Farmers, fishermen, hunters, loggers, and related workers	22.600	46.830	32.060	56.810	3.310	10.610

Production and related workers, transport equipment operators and laborers	52.830	31.510	53.380	32.380	51.710	28.360
Types of Employment:						
Part-time	35.950	27.770	44.770	36.050	18.790	11.070
Full-time	37.580	6.880	30.750	6.110	50.860	8.450
Average hours worked per day	5.116	2.840	4.492	2.513	6.523	4.481

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.3: Sex Earnings Ratio by Industry

National Industry Classification (NIC)	*Hourly Wage (W_f/W_m)*	
	2004-05	2011-12
	(1)	(2)
Agriculture, Hunting, Forestry, and Fishing	0.65	0.69
Mining and Quarrying	0.58	0.57
Manufacturing	0.40	0.57
Electricity, Gas, and Water	0.81	1.14
Construction	0.64	0.79
Wholesale, Retail, Trade and Restaurants	0.78	0.91
Transport, Storage, and Communication	0.88	1.13
Financing, Insurance, Real Estate, and Business Services	0.81	0.85
Community, Social, and Personal Services	0.77	0.68

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.4: Sex Earnings Ratio by Occupation

National Occupational Classification	*Hourly Wage (W_f/W_m)*	
	(1)	(2)
	2004-05	2011-12
Professional, technical, and related workers	0.80	0.69
Administrative, executive, and managerial workers	0.88	0.85
Clerical and related workers	0.87	0.83
Sales workers	1.05	0.92
Service workers	0.50	0.51
Farmers, fishermen, hunters, loggers, and related workers	0.67	0.70
Production and related workers, transport equipment operators and laborers	0.54	0.68

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.5: Summary of the OB Decomposition Results Between Male-Female Wage Gap

	Full Set		Rural		Urban	
	(1)	(2)	(3)	(4)	(5)	(6)
	2004-05	2011-12	2004-05	2011-12	2004-05	2011-12
Panel A:						
Male Mean Wage	2.92***	3.10***	2.67***	2.95***	3.35***	3.41***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Female Mean Wage	2.28***	2.62***	2.12***	2.51***	2.84***	3.00***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Panel B:						
Raw Gap	0.64***	0.48***	0.54***	0.44***	0.51***	0.41***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Explained	0.32***	0.12***	0.25***	0.09***	0.13***	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Unexplained	0.32***	0.36***	0.29***	0.35***	0.38***	0.42***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Constant	0.26*	0.43**	0.32	0.18	0.56**	0.81**
	(0.18)	(0.21)	(0.23)	(0.27)	(0.28)	(0.35)
Panel C:						
Explained (%)	50.00	25.00	46.30	20.45	25.49	2.44
Unexplained (%)	50.00	75.00	53.70	79.55	74.51	102.44
Observations	44,224	50,389	29,828	35,288	14,396	15,101

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.6: Detail Results of the OB Decomposition Between Male-Female (Pooled Sample), Aggregated by Variable Types

	2004-05		2011-12	
	(1)	(2)	(3)	(4)
	Explained	Unexplained	Explained	Unexplained
Education (Base: Illiterate)	0.13***	0.01	0.08***	-0.04***
	(0.00)	(0.01)	(0.00)	(0.01)
Experience (Experience, and Experience Square)	-0.02***	0.18***	-0.03***	0.01
	(0.00)	(0.03)	(0.00)	(0.04)
Social Groups/ Caste (Base: General Caste)	0.01***	-0.01	0.01***	-0.02
	(0.00)	(0.02)	(0.00)	(0.02)
Marital Status (Base: Married)	0.00	-0.01***	0.00	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
State-ID	0.05***	-0.21*	0.01***	-0.08
	(0.00)	(0.11)	(0.00)	(0.15)
Industry (Base: Agriculture, Hunting, Forestry, and Fishing)	0.03**	0.01	0.02*	0.11
	(0.01)	(0.05)	(0.01)	(0.07)
Occupation (Base: Professional, technical, and related workers)	0.09***	0.07	0.01*	-0.04
	(0.01)	(0.08)	(0.01)	(0.08)
Area (Base: Rural)	0.04***	0.02***	0.02***	0.00
	(0.00)	(0.00)	(0.00)	(0.01)

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.7: Detail Results of the OB Decomposition Between Male-Female in the Rural Area, Aggregated by Variable Types

	2004-05		2011-12	
	(1)	(2)	(3)	(4)
	Explained	Unexplained	Explained	Unexplained
Education (Base: Illiterate)	0.09***	0.01	0.05***	0.00
	(0.00)	(0.01)	(0.00)	(0.01)
Experience (Experience, and Experience Square)	-0.02***	0.20***	-0.02***	0.06
	(0.00)	(0.04)	(0.00)	(0.04)
Social Groups/ Caste (Base: General Caste)	0.01***	0.03	0.01***	-0.01
	(0.00)	(0.02)	(0.00)	(0.02)
Marital Status (Base: Married)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
State-ID	0.07***	-0.30**	0.02***	0.08
	(0.00)	(0.14)	(0.00)	(0.21)
Industry (Base: Agriculture, Hunting, Forestry, and Fishing)	0.01	0.02	0.03*	0.13**
	(0.01)	(0.03)	(0.01)	(0.06)
Occupation (Base: Professional, technical, and related workers)	0.10***	0.01	0.00	-0.10
	(0.01)	(0.13)	(0.01)	(0.11)

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.8: Detail Results of the OB Decomposition Between Male-Female in the Urban Area, Aggregated by Variable Types

	2004-05		2011-12	
	(1)	(2)	(3)	(4)
	Explained	Unexplained	Explained	Unexplained
Education (Base: Illiterate)	0.11***	-0.04	0.05***	-0.12***
	(0.01)	(0.03)	(0.01)	(0.04)
Experience (Experience, and Experience Square)	-0.01*	-0.00	-0.02***	-0.13*
	(0.00)	(0.07)	(0.00)	(0.07)
Social Groups/ Caste (Base: General Caste)	0.00	-0.01	-0.00***	-0.01
	(0.00)	(0.03)	(0.00)	(0.03)
Marital Status (Base: Married)	0.01	-0.04***	0.00	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
State-ID	0.01***	-0.16	-0.00	-0.28
	(0.00)	(0.18)	(0.00)	(0.18)
Industry (Base: Agriculture, Hunting, Forestry, and Fishing)	0.02***	-0.01	-0.00	0.14
	(0.00)	(0.15)	(0.01)	(0.24)
Occupation (Base: Professional, technical, and related workers)	-0.01	0.08	-0.04***	0.04
	(0.01)	(0.06)	(0.01)	(0.06)

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.9: Summary of the JMP Decomposition Results of Changes in the Gender Pay Gap, 2004-05 & 2011-12

	(1)	(2)	(3)
Panel A: Full Sample			
Difference in Differential (D):	D	E	U
	-0.15	-0.19	0.04
Decomposition of Difference in Predicted Gap (E):	E	Q	P
	-0.19	-0.10	-0.09
Decomposition of Difference in Residual Gap (U):	U	UQ	UP
	0.04	0.01	0.03
Panel B: Rural Area			
Difference in Differential (D):	D	E	U
	-0.11	-0.15	0.04
Decomposition of Difference in Predicted Gap (E):	E	Q	P
	-0.15	-0.07	-0.08
Decomposition of Difference in Residual Gap (U):	U	UQ	UP
	0.04	0.02	0.02
Panel C: Urban Area			
Difference in Differential (D):	D	E	U
	-0.11	-0.14	0.03
Decomposition of Difference in Predicted Gap (E):	E	Q	P
	-0.14	-0.09	-0.05
Decomposition of Difference in Residual Gap (U):	U	UQ	UP
	0.03	-0.01	0.04

Author's own calculation by using the ado packages JMPierce and JMPierce2 provided by Ben Jann in STATA.

Table 1.10: Details of the JMP Decomposition Results of Changes in the Gender Pay Gap, 2004-05 & 2011-12

	Pooled Sample		**Rural Area**		**Urban Area**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Covariates (Q)	Observed Prices (P)	Covariates (Q)	Observed Prices (P)	Covariates (Q)	Observed Prices (P)
Education (Base: Illiterate)	-0.02	-0.04	-0.01	-0.03	-0.04	-0.02
Experience (Experience, and Experience Square)	-0.01	0.01	-0.01	0.01	-0.01	0.00
Social Groups/ Caste (Base: General Caste)	0.00	0.00	0.00	0.00	0.00	0.00
Marital Status	0.00	0.00	0.00	0.00	0.00	0.00
State-ID	-0.02	-0.01	-0.03	-0.02	0.00	-0.01
Industry (Base: Agriculture, Hunting, Forestry, and Fishing)	0.00	0.00	0.00	0.02	0.00	-0.02
Occupation (Base: Professional, technical, and related workers)	-0.04	-0.04	-0.03	-0.06	-0.03	-0.01
Area	-0.01	-0.01	-	-	-	-

Author's own calculation by using the ado packages JMPierce and JMPierce2 provided by Ben Jann in STATA.

Table 1.11: Summary statistics of Selected dependent and independent variables – Married-Unmarried Female Workers				
	2004-05		2011-12	
	Married	Unmarried	Married	Unmarried
Dependent Variables:				
Log Hourly Wage	2.27 (0.01)	2.36 (0.03)	2.61 (0.01)	2.69 (0.03)
Work participation	37.04	15.86	39.49	17.67
Independent Variables:				
Educational Level:				
Illiterate	50.11	11.44	42.44	5.94
Below Primary	7.55	6.14	7.34	3.94
Primary	7.75	6.29	8.68	4.6
Middle-School	17.56	38.93	20.45	38.14
Secondary	8.58	17.42	9.67	19.68
Higher-Secondary	4.12	12.52	5.99	18.14
Graduate and above	4.32	7.26	5.43	9.55
Experience	11.081	1.276	12.443	1.42
Social Groups:				
General	23.11	23.06	22.13	21.22
Other Backward Caste	34.57	31.6	34.17	30.77
Dalit (Schedule Caste)	19.75	18.55	20.66	21.15
Adivasi (Schedule Tribe)	7.81	8.57	8.36	8.65
Muslim	11.45	14.65	11.95	15.39
Others (Christian, Sikh, Jain)	3.32	3.55	2.73	2.8
Industry:				
Agriculture, Hunting, Forestry, and Fishing	64.83	50.59	47.97	38.17
Mining and Quarrying	0.36	0.46	0.32	0.11
Manufacturing	8.97	18.19	8.76	16.04
Electricity, Gas, and Water	0.23	0.26	0.22	0.75
Construction	6.36	3.73	22.13	10.02
Wholesale, Retail, Trade and Restaurants	1.35	3.01	1.28	3.46
Transport, Storage, and Communication	0.96	1.51	1.00	3.41
Financing, Insurance, Real Estate, and Business Services	0.71	2.62	0.65	3.14
Community, Social, and Personal Services	16.23	19.63	17.68	24.89
Occupation:				
Professional, technical, and related workers	5.73	12.11	7.6	16.71
Administrative, executive, and managerial workers	0.31	0.58	0.28	0.96
Clerical and related workers	2.32	4.96	3.27	8.06
Sales workers	0.71	2.7	0.61	3.31
Service workers	7.5	4.19	8.21	5.45
Farmers, fishermen, hunters, loggers, and related workers	62.86	49.65	47.97	38.23
Production and related workers, transport equipment operators and laborers	20.57	25.82	32.07	27.28
Types of Employment:				
Part-time	30.15	13.09	31.85	13.43
Full-time	6.89	2.76	7.64	4.24
Average hours worked per day	3.129	2.425	2.937	2.264

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.12: Summary statistics of Selected dependent and independent variables – Married-Unmarried Male Workers

	2004-05		2011-12	
	Married	Unmarried	Married	Unmarried
Log Hourly Wage	2.97	2.68	3.14	2.96
	(0.01)	(0.01)	(0.01)	(0.01)
Work participation	88.19	41.43	88.29	45.56
Independent Variables:				
Educational Level:				
Illiterate	25.69	9.12	21.61	5.8
Below Primary	9.81	6.1	9	4.43
Primary	8.33	6.03	8.52	4.9
Middle-School	24.8	40.1	27.16	38
Secondary	14.35	17.66	14.63	19.91
Higher-Secondary	7.39	13.08	9.04	17.78
Graduate and above	9.63	7.92	10.04	9.17
Experience	25.07	3.95	25.98	4.46
Social Groups:				
General	22.93	22.82	22	21.58
Other Backward Caste	34.43	32.82	34.01	32.35
Dalit (Schedule Caste)	20.04	19.19	20.78	21.09
Adivasi (Schedule Tribe)	8.03	7.65	8.67	7.83
Muslim	11.22	14.03	11.74	14.29
Others (Christian, Sikh, Jain)	3.35	3.48	2.8	2.86
Industry:				
Agriculture, Hunting, Forestry, and Fishing	33.84	32.22	23.94	18.43
Mining and Quarrying	1.46	1.02	1.17	0.85
Manufacturing	10.67	13.27	14.2	18.18
Electricity, Gas, and Water	2.17	1.72	2.16	2
Construction	14.6	15.06	26.54	25.31
Wholesale, Retail, Trade and Restaurants	4.35	8.63	4.29	8.31
Transport, Storage, and Communication	10.27	9.46	10.03	9.9
Financing, Insurance, Real Estate, and Business Services	2.73	2.55	2.39	2.83
Community, Social, and Personal Services	19.90	16.06	15.28	14.19
Occupation:				
Professional, technical, and related workers	6.86	5.13	5.91	5.95
Administrative, executive, and managerial workers	1.99	0.93	1.64	1.03
Clerical and related workers	8.01	5.65	7.62	6.24
Sales workers	3.32	6.5	3.82	8.48
Service workers	5.95	5.02	5.1	4.57
Farmers, fishermen, hunters, loggers, and related workers	31.47	30.05	23.77	18.46
Production and related workers, transport equipment operators and laborers	42.41	46.73	52.14	55.27
Types of Employment:				
Part-time	40.50	25.01	40.74	25.17
Full-time	47.52	15.97	47.37	19.97
Average hours worked per day	5.35	4.88	5.24	4.99

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.13: Summary of the OB Decomposition Results of the Wage Gap between Married-Unmarried Individuals of Same Sex

	Women		Men	
	2004-05	2011-12	2004-05	2011-12
Unmarried-Groups Mean Wage	2.36***	2.68***	2.68***	2.96***
	(0.02)	(0.02)	(0.01)	(0.01)
Married-Groups Mean Wage	2.27***	2.61***	2.97***	3.14***
	(0.01)	(0.01)	(0.01)	(0.00)
Raw Gap	0.09***	0.07***	-0.29***	-0.19***
	(0.02)	(0.02)	(0.01)	(0.01)
Explained	0.07***	0.05*	-0.28***	-0.15***
	(0.02)	(0.02)	(0.01)	(0.01)
Unexplained	0.02	0.03	-0.02	-0.03***
	(0.02)	(0.03)	(0.01)	(0.01)
Panel C:				
Explained (%)	77.78	71.43	96.56	78.95
Unexplained (%)	22.22	28.57	3.44	21.05
Observations	12,311	15,056	31,913	35,334

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.14: Detail Result of OB Decomposition Between Married-Unmarried Women (Pooled Sample), Aggregated by Variable Types

	2004-05		2011-12	
	(1)	(2)	(3)	(4)
	Explained	Unexplained	Explained	Unexplained
Education (Base: Illiterate)	0.15***	0.07*	0.22***	0.07
	(0.01)	(0.04)	(0.02)	(0.06)
Experience	-0.20***	0.18***	-0.24***	0.05
	(0.02)	(0.06)	(0.02)	(0.05)
Social Groups/Case (Base: General Caste)	-0.00	-0.14***	-0.00*	0.01
	(0.00)	(0.05)	(0.00)	(0.05)
Area (Base: Rural)	0.02***	-0.00	0.03***	0.01
	(0.00)	(0.02)	(0.00)	(0.02)
State-ID	0.03***	0.19	0.02***	0.47***
	(0.01)	(0.21)	(0.01)	(0.18)
Industry (Base: Agriculture, Hunting, Forestry, and Fishing)	-0.01	0.26***	-0.04**	0.13
	(0.02)	(0.09)	(0.02)	(0.15)
Occupation (Base: Professional, technical, and related workers)	0.08***	0.60***	0.05***	0.28**
	(0.02)	(0.14)	(0.02)	(0.13)

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Table 1.15: Detail Result of OB Decomposition Between Married-Unmarried Men (Pooled Sample), Aggregated by Variable Types

	2004-05		2011-12	
	(1)	(2)	(3)	(4)
	Explained	Unexplained	Explained	Unexplained
Education (Base: Illiterate)	0.03***	-0.01	0.04***	-0.01
	(0.00)	(0.02)	(0.00)	(0.02)
Experience	-0.27***	-0.03	-0.20***	-0.01
	(0.01)	(0.03)	(0.01)	(0.03)
Social Groups/Case (Base: General Caste)	-0.00*	0.02	0.00	-0.01
	(0.00)	(0.02)	(0.00)	(0.02)
Area (Base: Rural)	-0.00	-0.06***	0.01***	-0.05***
	(0.00)	(0.01)	(0.00)	(0.01)
State-ID	0.00	-0.01	0.01***	0.23
	(0.00)	(0.16)	(0.00)	(0.24)
Industry (Base: Agriculture, Hunting, Forestry, and Fishing)	-0.01***	-0.05	-0.01*	0.14*
	(0.00)	(0.06)	(0.00)	(0.08)
Occupation (Base: Professional, technical, and related workers)	-0.03***	0.29***	-0.01***	0.10**
	(0.00)	(0.06)	(0.00)	(0.05)

*Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1,*

Author's own calculation by using the IHDS dataset for the years 2004-05 & 2011-12

Figure 1.1: Log Hourly Wages for Males and Females by Education Level (2004-05)

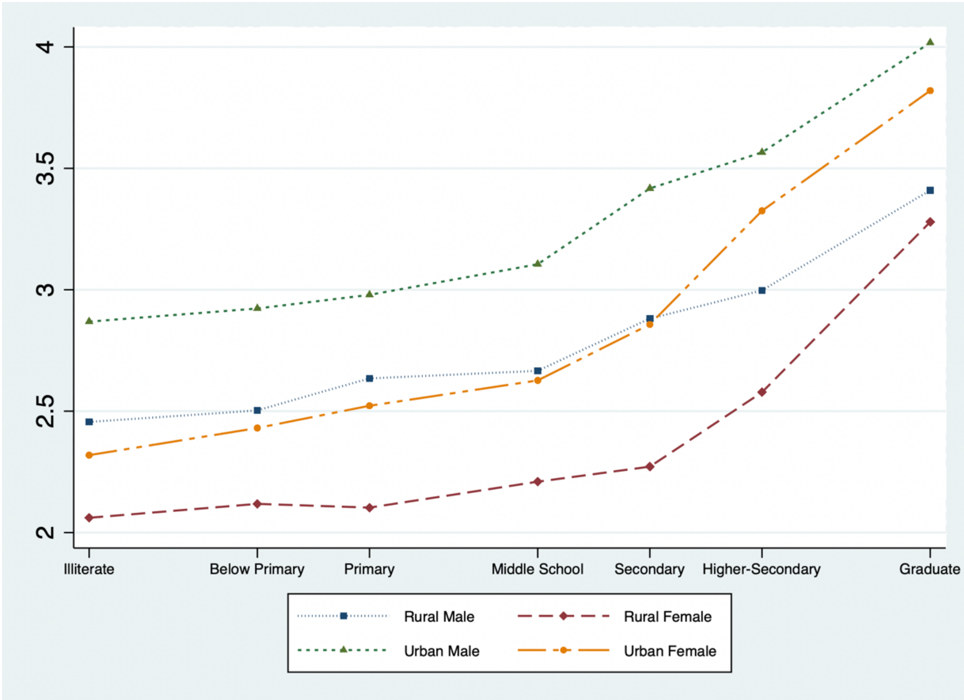


Figure 1.2: Log Hourly Wages for Males and Females by Education Level (2011-12)

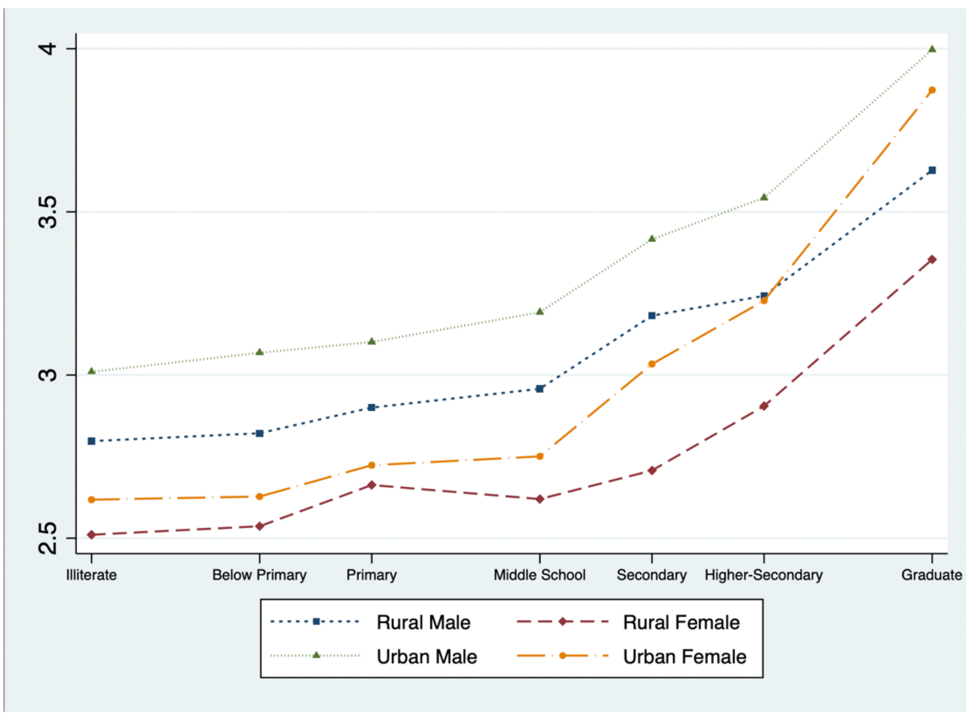


Figure 1.3: Log Hourly Wages for Males and Females by Age Group (2004-05)

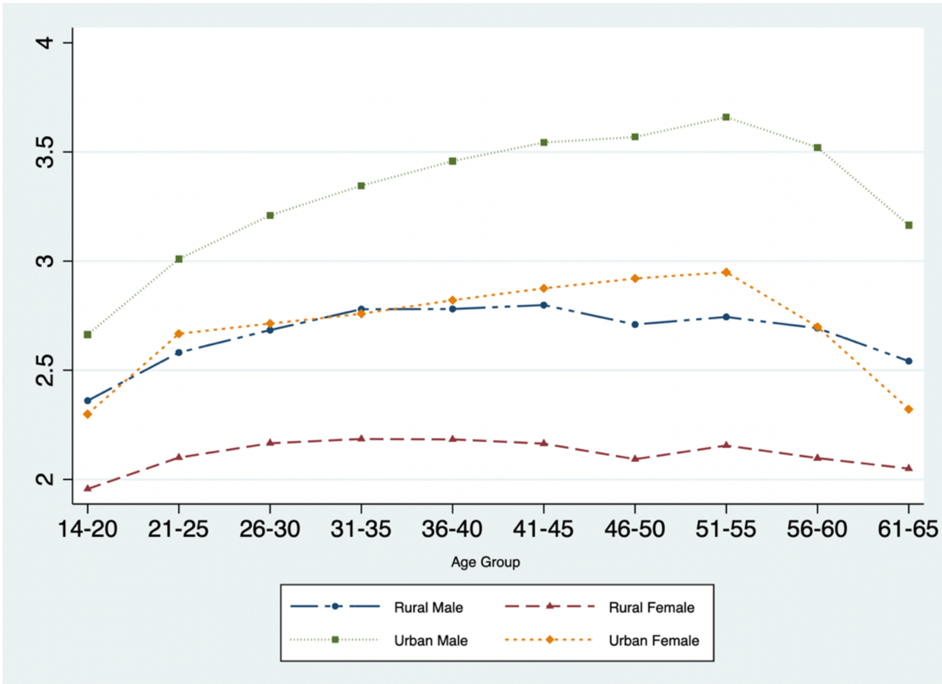
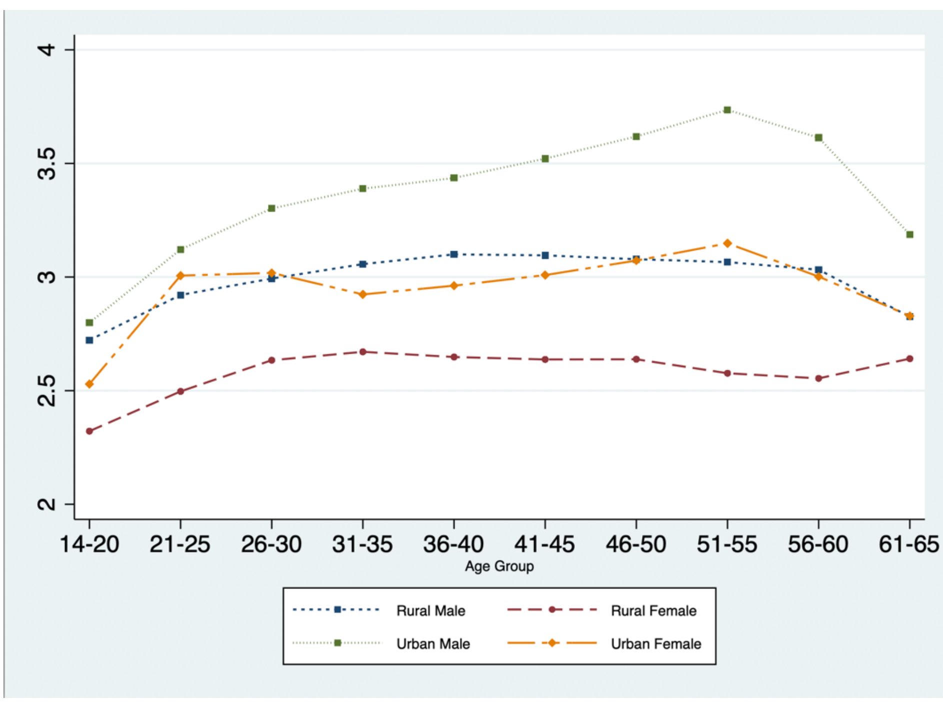


Figure 1.4: Log Hourly Wages for Males and Females by Age Group (2011-12)



Chapter Two: The Effect of California's Paid Family Leave on Mothers' Labor Market Outcomes - Labor Force Participation, Employment, Unemployment Duration, And Earnings

1 Introduction:

The paper is a comprehensive examination to understand the implications of California's paid family leave initiative on the labor market behaviors of mothers over the medium term. Commencing in 2004, California emerged as the first state to enact a paid family leave program, known as CA-PFL, catering to mothers' imperative need to foster a nurturing connection with their newborn or adopted child. By meticulously investigating the intricate implications of CA-PFL, this research endeavors to illuminate its influence on various pivotal labor market outcomes (encompassing labor force participation decisions, employment status, earnings, and duration of unemployment) on mothers with the youngest child of one to three years. Additionally, a profound emphasis is placed on discerning the differential impact of this policy across diverse population subgroups. By thoroughly examining the effects of the policy among various sub-groups, I found that the policy could is not effective among mothers of the lower socio-economic status, and most of the benefits are accrued by the people belonging to the above 500% of the poverty line.

Using the Current Population Survey (CPS) data spanning the years 1994 to 2020, this study employs the double-difference (DD) and triple-difference (DDD) methodological approaches. The objective is to examine a comparative study of labor market outcomes experienced by mothers with the youngest child aged 1 to 3 years (designated as the treatment group) and mothers with the youngest child aged 10 to 15 years (serving as the control group), both within and outside of California, before and after the implementation of the policy under investigation. Multiple control groups were employed to ensure the robustness of the findings, and their inclusion is comprehensively discussed in the results section.

I also examine the heterogeneous impact of the policy based on mothers' different income levels, education levels, and marital statuses. Examining the effects of paid leave on the labor market outcomes of disadvantaged or lower-income mothers holds significant importance within labor economics. The potential impact of paid parental leave on the labor force participation of disadvantaged mothers, in contrast to their more privileged counterparts with bachelor's degrees, has garnered considerable attention (Byker, 2016).

Key findings of this paper suggest that CA-PFL is associated positively with young mothers' labor market behaviors. The law is causing a 3.19 % increase in mothers' (of younger children) labor force participation, a 0.77% increase in employment probability, and a 2.6-week reduction in unemployment duration. The impact of the law on earnings is positive. However, the result is not statistically significant. I also find the heterogeneous impact of the law on young mothers based on different demographic subgroups. One alarming finding is no significant association of the policy with low-income mothers' labor force participation rate compared to their high-income peers. My analysis also reveals that the impact of the policy is negative and significant on lower-income mothers' earnings. Lower-income or socioeconomically disadvantaged mothers stand to derive the most significant benefit from the policy, as they often lack access to alternative policy advantages. These findings unveil the tendency for the policy's overall positive impact to obscure the adverse consequences experienced by these marginalized mothers, thereby prompting inquiries into the policy's effectiveness and advocating for subsequent policy amendments to assist mothers from disadvantaged groups.

The paper is organized into distinct sections to facilitate a comprehensive analysis. Section II delves into the background by examining the state laws about paid leave and thoroughly reviewing existing literature on paid leave programs within the United States and other developed countries. This section establishes a contextual foundation for the subsequent analysis. Moving forward, Section III outlines the data sources utilized and the methods employed in this study. A detailed description of the data collection process and the analytical techniques ensures transparency and replicability. The subsequent section, Section IV, presents the findings from the analysis. The results are meticulously presented, allowing for a comprehensive understanding of the impact of paid leave on the desired labor market outcomes. Finally, Section V provides an in-depth discussion of the results, highlighting their implications, significance, and potential avenues for future research.

2 Background:

2.1 State Laws:

Individuals trying to get leave to nurture parent-child bonding or redress acute health concerns possess the alternative to avail themselves of their private employer's benefits, contingent upon availability, or they may opt to employ the unpaid leave provisions explicated within the ambit of the Family and Medical Leave Act (FMLA). Enacted by President Bill Clinton in 1993, The FMLA grants workers the privilege to engage in up to 12 weeks of unpaid yet job-protected leave. This leave can be utilized for the explicit purpose of fostering a bond with a recently born, adopted, or newly placed child, as well as attending to the grave illnesses afflicting immediate family members, encompassing progeny, spouses, and progenitors, or tending to their severe health emergencies. To satisfy the eligibility criteria for FMLA benefits, employees must have concluded a minimum tenure of 12 months with their extant employer, rendered services amounting to no less than 1250 hours for the employer within the antecedent 12-month interval, been engaged in gainful occupation within a radial distance of 75 miles from the employer, and the employer must exhibit a personnel count consisting of no fewer than 50 employees within this prescribed territorial expanse (U.S. Department of Labor, 2012).

In addition to the coverage provided by the Family and Medical Leave Act (FMLA), numerous other states and the District of Columbia have implemented extended unpaid family leave provisions. Table 2.1 comprehensively outlines the paid leave benefits offered by different states. These benefits predominantly manifest in two distinct forms. The first form materializes through implementing the Temporary Disability Insurance (TDI) program. Five states, namely Rhode Island (1942), California (1946), New Jersey (1948), New York (1949), and Hawaii (1969) commenced the provision of paid leave benefits after the birth of a child under their respective TDI programs. Notably, the TDI programs do not guarantee job protection and classify mothers taking leave following pregnancy as temporarily disabled. These programs enable mothers to avail themselves of up to six weeks of paid yet job-unprotected leave (Ruhm, 2011). The second form of leave is explicitly recognized as paid parental leave (PPL). Five states—California, New Jersey, Rhode Island, New York, Washington, and the District of Columbia—have enacted legislation to establish PPL.

The inception of the CA-PFL program took place in 2004 as an extension of California's State Disability Insurance Program (CA-SDI), followed by New Jersey in 2008. Notably, the CA-PFL program adopts a gender-neutral approach, allowing mothers and fathers to take a maximum of six weeks (eight weeks from July 1, 2020) of paid leave. Unlike the FMLA, CA-PFL exhibits more leniency by not imposing stringent prerequisites such as a minimum threshold of working hours in the previous year, earning levels, or firm size. Moreover, self-employed individuals who contribute to the State Disability Insurance (SDI) program can avail themselves of the paid leave benefit to foster parent-child bonding or attend to seriously ill relatives.

This leave can be utilized to establish a profound connection with their newborn/adopted child or tend to the immediate care needs of their family members. Initially, the program provided a weekly wage replacement of 55% or a maximum weekly benefit amounting to $728. Remarkably, a study conducted by the Connecticut General Assembly in 2020 revealed that approximately 87% to 90% of claims made under the CA-PFL program were explicitly intended for bonding with a new child. This empirical evidence underscores the fundamental role played by the CA-PFL program in facilitating and promoting crucial familial connections during the early stages of a child's life. Employees who possess the privilege of availing themselves of job-protected family leave within the Family and Medical Leave Act (FMLA) framework are also eligible to partake in the California Paid Family Leave (CA-PFL) program, thereby capitalizing on both programs concurrently. Specifically, employees covered by the FMLA can derive considerable advantages from a job-protected paid leave benefit. Furthermore, female employees can request a six-week paid leave through the State Disability Insurance (SDI) program, provided they obtain a medical prescription. Subsequently, they can claim an additional six weeks of paid leave through the CA-PFL program.

2.2 Existing Research:

Research on the impact of PFL has been studied by plenty of researchers and on plenty of outcome variables. Most of this research has focused on other developed countries. However, a growing number of studies are recently focusing on analyzing the impact of California’s PFL program. In this section, I summarize some previous work on the CA-PFL.

Klerman and Leibowitz (1994) proposed theoretical insights into the complex consequences resulting from the implementation of PFL programs. The impact of PFL on employment outcomes presents a nuanced ambiguity, necessitating careful examination. After childbirth, women face a trichotomous decision framework, where they choose to continue working, take a leave of absence, or leave their pre-birth employment to care for their newborn. This complexity intensifies when women are granted parental leave allowances, which are expected to increase the likelihood of taking leave. However, it is crucial to determine whether increased leave utilization stems from those who would have remained employed or voluntarily resigned from their pre-birth employment. Understanding the composition of the increased leave-taking is essential to assess the impact on overall employment levels. Thus, comprehensive forecasts are needed to elucidate the intricate relationship between PFL and women's employment dynamics.

A significant body of research has explored the effects of paid family leave on labor market outcomes for women in developed countries. Ruhm (1998) investigated data from nine European nations between 1969 and 1993 and demonstrated that access to paid leave increases the employment-to-population ratio. However, extended leave benefits contribute to a decline in women's earnings. Other studies, such as Gupta et al. (2018) and Schonberg and Ludsteck (2014), have examined the impact of paid family leave outside the United States and consistently found a positive relationship with women's employment outcomes.

Many researchers have focused on investigating the impact of PFL within the Unit, particularly in California, which has a pioneering program. Empirical analyses of California's PFL have yielded mixed findings. Rossin-Slater et al. (2013); and Baum & Ruhm (2016) found positive associations between the policy and women's employment and earnings. Rossin-Slater et al. (2013) examined the medium-term consequences of the policy using data from the March Current Population Survey (CPS) from 1999 to 2010. Their findings indicated that, given a certain level of employment, mothers' work hours increased by 10% to 17% after the policy's implementation. However, statistical significance still needs to be established for the upward trajectory in wage income. Utilizing the National Longitudinal Survey of Youth 1997 (NLSY-97) data, Baum et al. (2016) found a positive impact of California's PFL on working hours and weeks, suggesting improved job continuity for new mothers. In contrast, Das and Polachek (2015) discovered a positive relationship between California's PFL and labor force participation and the unemployment rate of young women, indicating increased labor supply and reduced employer demand. Contrary to the positive effects, Bailey (2019) used Internal Revenue Service (IRS) tax data to assess the short-term and long-term impact of the program and found that new mothers who utilized PFL experienced decreases in earnings and employment.

Only a few studies, such as those conducted by Hamad et al. (2019) and McKay et al. (2016), have examined the effects of CA-PFL on various health outcomes among low-income mothers. Kang et al. (2021) analyzed the impact of CA-PFL on labor force participation, specifically among low-income mothers, considering women between the ages of 20 and 40 with income levels below 150% of the federal poverty level.

This paper has several contributions to the existing literature. First, this paper examines young mothers' labor force participation decisions and the impacts on employment probability, earnings, and unemployment duration. Few articles (Das and Polachek, 2015; Stock et al., 2021) examine the policy's impact on young women's labor market behavior but not specifically on mothers who are more likely to get impacted by the policy. Rossin-Slater (2013) examines the medium-term impact of the policy on mothers' employment outcomes, but they did not capture the policy's impact on labor force participation behavior.

Another significant contribution of this paper to the existing literature is to capture the heterogeneous impact of the program based on income level. More attention should be given to investigating the heterogeneous effects of the program based on income level. Workers in lower-income strata typically do not benefit from the Family and Medical Leave Act (FMLA) coverage. Consequently, they face a constant risk of job loss if they choose to utilize paid leave. This analysis allows me to capture if there exists any differential impact of CA-PFL on mothers with access to job-protected paid leave benefits from mothers with access to no-job-protected paid leave benefits.

3 Data and Methodology:

3.1 Data:

This study utilizes the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC) Integrated Public Use Microdata Series (IPUMS) data spanning the years 1994 to 2020. The CPS data source offers a wealth of information about various labor market behaviors and earnings, making it suitable for analysis with a large and nationally representative sample. The treatment group for this study comprises women aged between 24 and 50 whose youngest child falls within the age range of 1 to 3 years. Additionally, the inclusion criterion of at least 24 years of age is applied to minimize the likelihood of changes in significant subjects or shifts across education groups, as individuals in this age bracket are typically more settled in their educational pursuits.

This study diverges from conventional approaches by adopting a broader dataset that includes individuals regardless of their employment status, in contrast to restricting the analysis to solely employed individuals from the previous year. The rationale behind this deviation is rooted in the recognition that the availability of the California Paid Family Leave (CA-PFL) program may motivate new entrants to the labor market or induce existing workers to exit temporarily to leverage the benefits of the leave program. Consequently, limiting the analysis to employed individuals alone could introduce estimation biases (Das et al., 2015). By considering all individuals, irrespective of employment status, this study allows for a comprehensive examination of the impact of the policy on the labor supply decisions of young mothers at an extensive margin.

The primary focus of this study is to assess the effect of the CA-PFL program on the likelihood of labor force participation and various labor market outcomes among mothers in California with the youngest child aged one to three years. Underlying the investigation is the hypothesis that CA-PFL facilitates the synchronization of work and family life for mothers, thus increasing the probability of labor force participation. If the hypothesis holds, it will support an additional conjecture that the presence of a PFL program mitigates the likelihood of mothers exiting the labor force altogether. It is important to note that the impact of CA-PFL on employment probability is theoretically ambiguous, as an increase in labor force participation may adversely affect employment probability. Similarly, the influence on earnings and unemployment duration is also an empirical question with no theoretical direction and warrants further investigation.

The Current Population Survey (CPS) datasets offer a valuable classification of individual income status into distinct categories, including those below the poverty line, individuals at 100-124 percent of the low-income level, those at 125-149 percent of the low-income level, and individuals at 150 percent and above the low-income level. However, not all individuals who fall into the 150 percent and above category can be classified as affluent; rather, even those marginally above the poverty line still belong to the lower-income group. Thus, to comprehensively understand the impact of the policy on low-income mothers, it is essential to explore its effects across various income thresholds, including those in marginal groups.

The CPS dataset provides information about the total family income (OFFTOTVAL) by the official poverty guidelines of the federal. The dataset also consists of the cutoff variable (CUTOFF), the official poverty threshold used by the Census Bureau to evaluate poverty status. For instance, for a family of 2 individuals, both of whom are under 65, with no children, the poverty threshold 1989 was 7,495 dollars. If a sampled family of this composition reported income below 7,495 dollars that year, they would be coded as "below poverty" in the POVERTY variable[3]. On the other hand, if a sample family of the same composition reported an income of 10,000 dollars, then they would be considered at 125-149 percent of the low-income level (Actually, (10,000/7495) *100 = 133.42 percent of the low-income level).

By utilizing these two variables, I have reclassified the income status of mothers into four subcategories based on the percentage of the low-income level. These subcategories are as follows: 150-299 percent of the low-income level, 300-499 percent of the low-income level, 500-749 percent above the poverty line, 750-999 percent of the low-income level, and 1000 percent above the low-income level. This categorization allows for a comprehensive examination of the impact of the policy on mothers.

3.2 Empirical Analysis:

To assess the impact of the policy, this study employs a double difference approach (Equation 1). This approach compares the labor market outcomes before and after the policy implementation for two groups: California mothers with the youngest child aged 1 to 3 years (treatment group) and California mothers with the youngest child aged between 10 to 15 years (control group), who experienced similar changes unrelated to the policy. By isolating the effect of the policy, we can identify the causal impact on the treatment group.

[3] IPUMS CPS: descr: CUTOFF. https://cps.ipums.org/cps-action/variables/CUTOFF

Furthermore, another double-difference approach (Equation 2) is utilized to compare the changes in labor market outcomes before and after the policy for mothers with the youngest child aged 1 to 3 years in California (treatment state) and their counterparts in other states (control state), apart from New Jersey, Rhode Island, and New York, which have similar policies to CA-PFL. This methodology allows us to examine the specific impact of the CA-PFL policy by differentiating it from any general trends or regional factors that may affect the control state.

By employing these rigorous analytical approaches, we can effectively evaluate the causal impact of the policy on labor market outcomes for California mothers in the treatment group and distinguish it from other factors that may influence labor market changes.

$$Y_{ist} = \alpha_0 + \gamma_1 \text{Treat}_i + \gamma_2 \text{Post}_t + \gamma_3 \text{ Treat}_i * \text{Post}_t + \beta \boldsymbol{X}_{ist} + \text{T}_t + e_{it} \quad \ldots (1)$$

$$Y_{ist} = \alpha_0 + \gamma_1 \text{CA}_s + \gamma_2 \text{Post}_t + \gamma_3 \text{ CA}_s * \text{Post}_t + \beta \boldsymbol{X}_{ist} + \eta \boldsymbol{U}_{st} + \boldsymbol{S}_s + \text{T}_t + e_{ist} \quad \ldots (2)$$

The variable Y_{ist} alternatively denotes labor force participation, employment (if in the labor force), unemployment duration, and earnings for individual *i*, in state *s*, and at time *t*. For the labor force participation analysis, $Y_{ist} = 1$ if the i^{th} individual is in state s and surveyed at time t, is in the labor force, and zero otherwise. Similarly, for the employment analysis, the dependent variable is 1 if the individual *i* is in state s and surveyed at time t is employed (given in the labor force) and zero otherwise. For the unemployment duration analysis, Y_{ist} represents the weeks unemployed during the survey period *(t)* for the individual *i* residing in state *S*. Lastly, I drop self-employed, armed force, and unpaid family workers from the sample for the earning analysis. Y_{ist} denotes the last year's log wage earnings of the workers.

The variable Treat_i is 1 for mothers with a youngest child three years or below and zero for those in the control group (mothers with the youngest child 10 to 15 years). Post_t is 1 for all the observations after implementing the law in 2004 and zero otherwise. CA_s is 1 for all California mothers in all years and zero for the mothers in the control states (all other states).

The variable $\boldsymbol{X}_{ist}$ incorporates a comprehensive set of individual-level variables: mothers' age categories (20-25, 26-30, 31-35, 36-40, 41-45, 46-50), education (Less than High-School Graduate, High School Graduates, some years in college, bachelor's degree and above). The variable also encompasses race, considering three categories: white, black, and others. Marital status also differentiates between married, separated, divorced, widowed, and never married/single. Moreover, relevant factors like household income, the number of total family members, and the number of children in the household are included to analyze the sample comprehensively. The earning equation incorporates additional control variables to examine the relationship between earnings and these variables. These include the employee's industry, occupation, and farm size to capture the influence of job characteristics on earnings.

By including these control variables, the empirical analysis ensures that the estimated effects of the CA-PFL policy on labor market outcomes are not confounded by other factors that may affect the results. This comprehensive approach allows for a robust examination of the impact of the policy on labor market outcomes while effectively controlling for various relevant factors.

Variable $\boldsymbol{U}_{st}$ includes state-specific factors that can influence the labor supply decision: labor force/ unemployment rate of the state S at year t, log-population rate. $\boldsymbol{S}_s$ and T_t indicate state and time-fixed effects, respectively. γ_3 from equation 1 shows the effect of CA-PFL on mothers of younger children compared to mothers of older children (in California). γ_3 from equation 2 shows the effect of CA-PFL on California mothers of younger children compared to mothers of younger children in other states. The population weights both equations 1 and 2. Since equation 2 includes control states, and CA-PFL is California-specific, I cluster the standard errors at the state levels.

To ensure the validity of the difference-in-differences (DD) estimations obtained from Equation 1 and Equation 2, it is crucial to address potential biases arising from differences in labor market outcomes between the treated and control groups, as well as between the treatment and control states, prior to the implementation of the California Paid Family Leave (CA-PFL) policy. However, testing this assumption directly poses inherent challenges. To mitigate this concern, I employ several alternative control groups and states to assess the robustness of my results.

The critical identification assumption in equation 1 relies on a common trend in labor market outcomes between mothers with younger and older children. This assumption would be violated if changes in pre- and post-policy labor market outcomes were driven by factors unrelated to CA-PFL. To address this issue, I compare California mothers with children below or equal to three years of age to their counterparts residing outside of California, who are not eligible for the PFL program and therefore serve as a control group. By examining the differences in outcomes between these two groups, I can assess the impact of CA-PFL while accounting for changes that are not specific to California.

Similarly, the critical identification assumption in equation 2 requires no changes in labor market outcomes between California and non-California mothers with children below or equal to three years of age, unrelated to CA-PFL. By comparing the outcomes of these two groups, I can examine the impact of CA-PFL specifically for California while controlling for any external factors that may affect labor market outcomes.

By utilizing the alternative control groups and states, I aim to address potential biases and strengthen the robustness of the DD estimations. These comparisons allow me to isolate the effects of CA-PFL on labor market outcomes, providing more reliable and credible findings. In addition to the double difference (DD) approach outlined in Equation 1 and Equation 2, I employ a Difference-in-Differences-in-Differences (DDD) model to enhance the robustness of the analysis. The DDD model allows for a comprehensive comparison by combining the treatment and control groups from both Equation 1 and Equation 2.

The DDD estimation involves comparing the labor market outcomes of California mothers with younger children to those of California mothers with older children and their counterparts outside California before and after implementing the CA-PFL policy. This approach assumes that in the absence of CA-PFL, the changes in outcome variables between mothers of younger and older children in California would follow a similar pattern to that observed in other states.

$$Y_{ist} = \alpha_0 + \gamma_1 \text{Treat}_i + \gamma_2 \text{Treat}_i * \text{Post}_t + \gamma_3 \text{CA}_s * \text{Treat}_i + \gamma_4 \text{CA}_s * \text{Treat}_i * \text{Post}_t + \beta \boldsymbol{X}_{ist} + \boldsymbol{S}_s + \text{T}_t + \theta_{st} + e_{ist} \quad \dots (3)$$

Y_{ist}, $\boldsymbol{X}_{ist}$, $\boldsymbol{S}_s$, and T_t are the same as in equations 1 and 2. The DDD estimation also controls for state-by-year fixed effects (θ_{st}). The parameter of interest is γ_4, which represents the effect of CA-PFL on California mothers of younger across time compared to California mothers of older children while controlling for similar changes in outcomes in states that did not pass PFL law. In equation 3, I use population weights and cluster the standard errors at the state levels.

I use the linear probability model for labor force participation and employment analysis since the marginal effects of the interaction terms are hard to interpret (Ai and Norton, 2003). However, results are very similar when I use a Probit model[4].

4 Empirical Results:

4.1 Descriptive Statistics:

Table A1.A through Table A4.B presents comprehensive descriptive statistics of the dependent and independent variables weighted by the population. These tables provide a comprehensive overview of the mean results for both the treatment group, comprising mothers with the youngest child aged 1 to 3 years, and the control group, comprising mothers with the youngest child aged 10 to 15 years, in California and other states. The descriptive statistics cover the periods before and after the implementation of the policy, allowing for a detailed examination of the changes over time. These tables serve as a valuable resource for understanding the characteristics and trends within each group and across different geographical locations.

The analysis includes key dependent variables: labor force participation, employment status, unemployment duration, and log earnings. Table A1.A and Table A1.B provides an overview of the labor force participation rate (LFPR) trends for California mothers with children aged 1 to 3 years, both during the pre-policy and post-policy periods. The LFPR during the post-policy period increased to 59.3% compared to 55.5% in the pre-policy period. Notably, the LFPR also experienced growth for mothers with young children in other states. However, the growth rate observed among California mothers with young children surpasses that of all other comparison groups.

Turning to employment probability, Table A2.A and Table A2.B reveals an upward trend in employment probability for California mothers with younger children, increasing from 90.8% in the pre-policy period to 91.5% in the post-policy period (out of the labor force participation). In contrast, employment probability declined for mothers with older children in California and other

4 For the brevity of the paper, I do not include the results from the Probit models, however, they are available on request.

states. These findings highlight the distinct impact of the policy on employment outcomes for mothers in California compared to their counterparts in other states.

Examining unemployment duration, Table A3.A and Table A3.B demonstrates an overall increase during the post-policy period across all groups. However, the growth rate in unemployment duration for California mothers with younger children stands at 6.64 weeks, which is comparatively lower than that observed for all other groups. This indicates a relatively more favorable labor market experience for California mothers with young children following the policy implementation.

Table A4.A and Table A4.B presents a concerning result regarding log earnings. The logarithmic mean wage for California mothers with younger children is 9.967, lower than the pre-treatment mean wage of 9.770. In contrast, the mean wage during the post-policy period increased for all other groups. This decline in wage rate for California mothers may be attributed to the increased LFPR observed among them during the post-policy period.

In summary, the analysis reveals distinct patterns in labor market outcomes for California mothers with young children compared to other groups. The increase in LFPR and employment probability, coupled with relatively nominal growth in unemployment duration, suggests a positive impact of the policy on labor market participation. However, the decline in log earnings for California mothers warrants further investigation and consideration of potential underlying factors influencing wage dynamics.

Figure 2.1 through Figure 2.4 represents the trend in the dependent variables over time, separately for the treatment and control groups in the treatment and control states from 1994 to 2020. Figure 1 captures the LFPR among California mothers compared to mothers from other states throughout the study duration. Notably, the LFPR of California mothers consistently appears lower than that of mothers in other states, which aligns with the findings reported by Das and Polachek (2015). Furthermore, the LFPR among mothers in other states exhibits a relatively stable pattern compared to the fluctuations observed among California mothers. Specifically, Figure 2.1 reveals that the LFPR of California mothers with younger children experiences a more significant increase than their counterparts in other states. Moreover, during the subsequent recession, the LFPR among

California mothers with younger and older children demonstrates a noticeable decline. Notably, the decline in LFPR is particularly pronounced among mothers with older children.

Figure 2.2 illustrates the employment rate among California mothers compared to mothers residing in other states. An intriguing pattern emerges following the implementation of the policy, the employment rate of California mothers with younger children experiences a decline. This decline may be attributed, in part, to the simultaneous increase in the labor force participation rate observed within the same group. Notably, a similar trend is observed among California mothers with older children, whereby the recession period leads to a higher decline in employment rate compared to their counterparts in other states.

Figure 2.3 displays the unemployment duration of mothers with younger and older children in California and other states. Following the recession, there was a noticeable increase in unemployment duration for both the treatment and control groups. Importantly, this increase is more pronounced for California mothers than in other states. Notably, among California mothers with younger children, the recession period is characterized by the most substantial growth in unemployment duration.

However, it is encouraging to observe that after the recession, California mothers with younger children experience a sharp decline in unemployment duration, indicating a positive trend. The magnitude of the decline in unemployment duration is the highest among this group compared to other states.

Figure 2.4 illustrates the earning trend for mothers in California compared to mothers in other states. California mothers consistently exhibit higher earning rates than their counterparts in other states throughout the study period. This finding aligns with the notion that California offers relatively better earning opportunities for mothers. However, the earning trend in other states has been relatively stable over time. In contrast, the earning trend among California mothers exhibits more variability, suggesting potential factors at play within the state's economic landscape that may contribute to fluctuations in earnings.

4.2 DD and DDD Estimation Results:

4.2.1 Labor force participation:

PFL can increase women's labor force participation rate by reducing the opportunity cost of continuing with the current job. The policy can enhance the retention of young mothers with their employers by allowing them to utilize the paid leave; otherwise, they would have quit their jobs. However, PFL can also boost costs to the employers, including temporary replacement costs of the leave-taking workers, training costs of the temporary workers, increasing work hours of other workers to cover up the leaver-takers' work responsibilities, and various administrative costs to comply with the policy. If this is the case, PFL can reduce demand for young women and reduce employment opportunities for them.

PFL can impact young mothers in other indirect ways as well. Some young mothers might get discouraged from participating in the labor force if they can anticipate a shift in demand from them toward men and older women. This demand/supply phenomenon can shift the labor-force participation rate of young mothers in any direction. Theoretically, the impact of CA-PFL needs to be clarified.

Table 2.2 presents the estimated impact of the California Paid Family Leave (CA-PFL) policy on mothers' labor force participation within 1 to 3 years after their child's birth. The availability of paid family leave can incentivize mothers to engage in the labor force and secure employment during the year preceding the birth, as they can take advantage of the benefits offered by the policy.

To examine whether CA-PFL encourages California mothers to participate in the labor force, I compare the outcomes of mothers in California to their counterparts in other states (equation 2). I use population weights and cluster the standard errors at the state levels. The results in Table 2.2 (column 1) show the effects of CA-PFL on mothers of younger children in California relative to their peers in other states. The difference-in-differences (DD) coefficients indicate that CA-PFL leads to a modest increase of 0.2 percentage points in young mothers' labor force participation rate. This represents a 0.36% increase in the labor force participation rate from the pre-treatment mean of 56 percent.

In column 2, I estimate the effect of CA-PFL specifically for California mothers of younger children compared to California mothers of older children (equation 1). Suppose CA-PFL has a discernible impact on mothers' mid-term labor force participation decisions (1 to 3 years after childbirth) and influences them differently than older mothers. In that case, we expect to observe a significant coefficient associated with the policy. The DD estimate in column 2 reveals a substantial increase of 3.6 percentage points (equivalent to a 6.39% increase) in the labor force participation rate for young mothers compared to their counterparts with older children.

These findings provide empirical evidence that CA-PFL positively affects mothers' labor force participation in California, particularly for those with younger children. The results support the notion that the policy catalyzes increased participation in the labor market among mothers, highlighting its potential as a mechanism for promoting women's employment and economic empowerment.

Columns 3 to 6 of the estimation results in Table 4 present the findings of the Difference-in-Differences-in-Differences (DDD) analysis. As displayed in column 3, the DDD specification incorporates individual-level controls and includes various fixed effects, such as time-fixed effects, state-fixed effects, and state-year fixed effects. The estimation results indicate that the California Paid Family Leave (CA-PFL) policy leads to a 0.18 percentage point increase in labor force participation, corresponding to a 3.19% rise from the pre-treatment level of 56 percent.

To examine the robustness of the results, alternative specifications are explored in columns 4 to 6. Column 4 demonstrates that the estimated effect remains robust even when state-year fixed effects are excluded from the model. This indicates that the observed impact of CA-PFL on labor force participation is not driven solely by the specific combination of states and years included in the analysis.

In column 5, time-varying state-specific variables, such as the labor force participation rate, unemployment rate, and log of population, are included in the model. This specification enables an examination of whether the estimation results are attributable to CA-PFL or other labor market shocks. The robust findings in column 5 indicate that the estimated effect is driven explicitly by the CA-PFL policy's impact on mothers of younger children rather than overall changes in the labor force participation rate.

Furthermore, column 6 presents the robust results obtained after including state-year fixed effects and time-varying state variables. By incorporating these controls, the estimation remains robust, providing further support for the impact of CA-PFL on mothers with younger children.

In summary, the DDD estimation results from columns 3 to 6 confirm that the CA-PFL policy significantly and robustly affects labor force participation for mothers of younger children. The preferred specification and the various robustness checks provide strong evidence that implementing CA-PFL specifically drives the estimated impact and is not influenced by other factors or labor market shocks.

4.2.2 Employment:

Table 2.3 presents the estimated effect of the California Paid Family Leave (CA-PFL) policy on the employment probability of young mothers in California compared to their counterparts in other states. The impact of the policy on mothers' employment probability is theoretically uncertain as various factors come into play.

One argument suggests that since the paid leave period is limited to six weeks, some mothers may choose to quit their jobs rather than continue with their current employers. These mothers may intend to return to the labor market after taking the desired leave. If this argument holds, it could increase mothers' labor supply with young children. Conversely, employers might perceive women of child-bearing age as more likely to quit their jobs in the future, leading to reduced demand for young women. The combination of these two effects could result in a lower employment probability for young mothers in California compared to control states and men and older women.

On the other hand, after implementing the policy, new mothers are more likely to maintain their employment and return to work after utilizing paid leave. If employers expect women to continue working even after childbirth, they may be less skeptical about hiring young women, resulting in a minimal impact on employment demand. Consequently, the employment probability for young women in California may experience a surge compared to other states.

The findings from column 1 of Table 2.3 reveal a positive impact of the CA-PFL policy on the employment of California mothers with children aged 1 to 3 years. The policy leads to a 0.5 percentage point increase in employment probability, representing a 0.55% rise from the pre-policy mean employment rate of approximately 91% (out of the total labor force participation rate). However, in column 2, the estimated effect of the policy on California mothers with younger children compared to those with older children is not statistically significant.

The DDD specification, as presented in column 3 of Table 2.3, confirms that the California Paid Family Leave (CA-PFL) policy positively impacts the employment probability of mothers with young children in California. The estimated effect shows that CA-PFL increases the employment probability by 0.5 percentage points, equivalent to a 0.77% increase from the pre-treatment mean. This effect is observed when comparing California mothers with younger children to California mothers with older children and mothers in other states.

Columns 4 to 6 show that the result is robust with the inclusion of time-varying state variables, exclusion of state-year fixed effects, and the inclusion of both time-varying state variables and state-year fixed effects, respectively.

In conclusion, the results suggest that the CA-PFL policy positively impacts the employment probability of young mothers in California, particularly those with children aged 1 to 3 years. These findings support the effectiveness of the policy in promoting employment among this demographic.

4.2.3 Unemployment Duration:

Table 2.4 provides insightful estimations regarding the impact of the California Paid Family Leave (CA-PFL) policy on unemployment duration. Considering the positive employment outcomes observed for mothers with younger children following the policy implementation, it is reasonable to anticipate a decrease in unemployment duration among California mothers.

In column 1, the estimation results indicate a significant reduction in unemployment duration for mothers with children aged 1 to 3 years due to the CA-PFL policy. Specifically, the policy is associated with a decrease of 2.4 weeks in unemployment duration relative to their counterparts in other states. Column 2 examines the unemployment duration for California mothers with children aged 1 to 3 years compared to California mothers with older children. The analysis reveals a substantial decline of 4.6 weeks in unemployment following the policy implementation for the former group of mothers.

In column 3 of Table 2.4, the DDD estimation result reveals a significant reduction in unemployment duration due to the implementation of the California Paid Family Leave (CA-PFL) policy. Specifically, the policy is associated with decreasing unemployment by 3.4 weeks for mothers with young children in California.

Moving to column 4, the inclusion of time-varying variables has a marginal impact on the estimated effect of the CA-PFL policy. The reduction in unemployment duration is slightly attenuated to 2.6 weeks when accounting for these variables. However, in column 5, the estimation result is statistically insignificant, suggesting that additional time-varying state variables do not significantly influence the impact of the CA-PFL policy on unemployment duration. On the other hand, the robustness of the result is confirmed in column 6, where the preferred specification is maintained, and the estimated effect of the CA-PFL policy on unemployment duration remains consistent.

The observed reduction in unemployment duration among mothers with young children in California aligns with the findings from the employment analysis, where an increase in employment probability was observed. This suggests that the improved employment outcomes may be a potential mechanism contributing to the decline in unemployment duration.

4.2.4 Earnings:

Table 2.5 provides valuable insights into the effects of the California Paid Family Leave (CA-PFL) policy on the earnings of mothers in California with children aged 1 to 3 years relative to their counterparts in other states. It is imperative to scrutinize how CA-PFL influences the wage income of mothers. Considering the initial findings, it is not unreasonable to posit that an expansion in labor supply could engender a decline in wage income.

Consistent with expectations, column 1 unveils a discernible adverse impact of CA-PFL on the log earnings of mothers with young children in California. The implementation of the policy correlates with a reduction in log earnings by 1.7 percentage points, compared to the pre-treatment level of 9.49.

Column 2 presents a notable departure from this trend, indicating that CA-PFL augments the income of the treated group of mothers with younger children in California relative to those with older children. The estimated effect reveals a 4.9 percentage point increase in income.

Columns 3 through 6 encapsulate the estimation results derived from the Difference-in-Differences-in-Differences (DDD) analysis, shedding light on the association between CA-PFL and income growth among California mothers with younger children. However, it is worth noting that the precision of these estimates is limited, and the observed results could be more statistically significant.

4.3 Heterogenous Effect of PFL by Subgroups:

4.3.1 Heterogenous Effect of PFL Based on Poverty-Level of Mothers:

This section explores the heterogeneous impact of the California Paid Family Leave (CA-PFL) policy on various labor market outcomes for California mothers with the youngest child aged 1 to 3 years. Previous research by Rossin-Slater (2013) has demonstrated that the availability of PFL has increased the utilization of leave among all mothers in California, regardless of their educational attainment, marital status, or racial background. Therefore, it is exciting to investigate whether CA-PFL effectively improves labor market outcomes for disadvantaged mothers.

Table 2.6 analyzes the heterogeneous effects of Paid Family Leave (PFL) on different labor market outcomes based on the poverty level of mothers, and I estimate the result using Equation 3. The table examines the impact of PFL on labor force participation, employment, unemployment duration, and earnings for mothers across various income brackets. Heterogenous impact based on poverty level sheds light on the impact of the policy on low-income mothers.

From Panel A, negative and statistically insignificant coefficients from columns 1 through 3 indicate that the policy's overall positive impact on labor force participation is camouflaging the actual impact on low-income mothers. For mothers in the income brackets below 125-149% of the low income, the coefficients are negative but statistically insignificant, indicating no impact of the policy on mothers in this group. For group, 150%-299% of the low-income, the direction of the coefficient is positive but still insignificant. The insignificant effect of CA-PFL on low-income mothers could be due to the lower monetary coverage by the policy. The lower monetary benefit of the policy could be the reason for the insignificant impact on the lower-income group. The policy typically provides 55% of the worker's average wage during the leave period. However, low-income workers often have lower wages, so the replacement rate may need to be increased to cover their basic living expenses. It is essential to mention, on the other hand, Low-income mothers may be more vulnerable to losing their jobs or facing negative consequences when taking time off, as they may be employed in less secure or flexible positions. The fear of job loss or adverse career effects can deter them from participating in the labor force and utilizing the leave benefits.

The coefficients are statistically significant and positive for mothers in the income brackets of 300-499%, 500-749%, and 750-999% of the low-income, suggesting significant increases in labor force participation. The most considerable effect is observed for mothers in the highest income bracket of 1000% and above the low income, with a statistically significant and positive coefficient indicating a substantial increase in labor force participation.

Regarding employment (Panel B), The overall impact of the policy is positive for mothers below the poverty level and 125-149% above the poverty line. The positive coefficient indicates that mothers from these cohorts participating in the labor force are more likely to get a job.

From panel C, we can see that the coefficients are not statistically significant for any subgroups. The policy does not significantly impact California mothers based on their poverty status. Regarding earnings (Panel D), the impact of the policy varies for different income brackets. For mothers in the income bracket of 100-124%, 150-299%, and 300-499% of the low-income, the coefficients are statistically significant and negative, indicating a significant decrease in earnings. For mothers in the income bracket of 750-999% of the low-income, the coefficient is statistically significant and positive, indicating a significant increase in earnings. The coefficient is not statistically significant for mothers in the highest income bracket of 1000% and above the low income, suggesting no significant impact on earnings.

4.3.2 Heterogenous Effect of PFL Based on Education-Level of Mothers:

Table 2.7 presents the heterogeneous effects of Paid Family Leave (PFL) on different labor market outcomes based on mothers' educational attainment. The table examines the impact of PFL on labor force participation, employment, unemployment duration, and earnings for mothers with varying levels of education.

For high-school graduates, the estimated result suggests that the CA-PFL increases labor force participation by 0.03 percentage points (5.26% from the pre-policy mean) (see Panel A of Table H1). However, the coefficient is not statistically significant for some years in college, suggesting no significant impact on labor force participation. Conversely, the coefficient is statistically significant and positive for mothers with a bachelor's degree and above (0.05 percentage point), demonstrating a significant increase in labor force participation.

From Table 2.7 regarding employment (Panel B), as already discussed, the effect of CA-PFL on mothers is ambiguous. The table shows that the effect of CA-PFL is statistically significant and positive (0.03 percentage points or 3.33% from the pre-treatment mean) for high-school graduates, indicating a positive effect of PFL on employment rates. For those with a bachelor's degree and above, the coefficient is statistically significant and negative, indicating decreased employment rates after implementing PFL. Women with bachelor's degrees and above are more likely to have access to FMLA, which is job-protected, along with their access to CA-PFL. Consequently, this group is more likely to use their leave benefit than others. So, it is possible that employers are skeptical about hiring them, and as a result, there is a declining employment probability for mothers with bachelor's degrees and above.

Regarding unemployment duration, the results suggest that CA-PFL does not significantly affect high-school graduates or individuals with a bachelor's degree or higher. However, for mothers with some years in college, the coefficient estimate for CA-PFL is negative and significant at the 1% level, indicating a reduction in unemployment duration.

Analyzing earnings, the results vary across education levels. For high-school graduates and individuals with some years in college, the impact of CA-PFL on earnings is not statistically significant. However, for those with a bachelor's degree or higher, CA-PFL positively and significantly affects earnings (10.0%).

4.3.3 Heterogenous Effect of PFL Based on Marital Status of Mothers:

Table 2.8 presents the heterogeneous effects of Paid Family Leave (PFL) on different labor market outcomes based on mothers' marital status. The table examines the impact of PFL on labor force participation, employment, unemployment duration, and earnings for mothers based on their marital status. CPS datasets classify an individual's marital status into married, separated, divorced, widowed, and single/never married. I am referring to mothers with separated, divorced, or widowed marital status as previously married mothers. It is possible that mothers without spouses or single mothers are staying with their current unwed partners, and their response toward the policy might differ from mothers who are staying alone.

Panel A from Table 2.8 represents the impact of the policy on LFPR based on marital status. For married mothers, the effect of the policy is statistically significant and positive for labor force participation, indicating a significant increase in participation rates after the implementation of PFL. However, for previously married mothers, the coefficient is statistically significant and negative (-0.03 percentage points), suggesting a significant decrease in labor force participation. Similarly, for single/never married mothers, the coefficient is statistically significant and negative (-0.09 percentage points), implying a significant decrease in labor force participation. One possible explanation for the result could be that introduction of a paid family leave program may incentivize young single mothers to take time off to care for their newborn or adopted child. However, this temporary interruption in their career can decrease labor force participation as they prioritize their childcare responsibilities.

Concerning employment, as evidenced by Panel B of Table 2.8, the influence of the policy on married mothers needs to attain statistical significance, signifying a lack of substantial impact on employment rates. Conversely, the coefficient exhibits statistical significance and positivity for previously married mothers at 0.07 percentage points, thus indicating a significant surge in employment rates attributable to the Paid Family Leave (PFL) program. The positive coefficient associated with employment reveals that previously married mothers actively engaged in the labor force are more prone to securing employment opportunities. However, the coefficient lacks statistical significance for single/never married mothers, implying an absence of significant influence on employment outcomes within this group.

The analysis conducted in Panel C of Table 2.8 delves into the ramifications of Paid Family Leave (PFL) on the duration of unemployment, providing valuable insights into the labor market dynamics. The findings showcase divergent effects across distinct subgroups of mothers. Specifically, in the case of married and single mothers, the effect of the PFL policy on unemployment duration exhibits a negative trend (-3.88 weeks, and -3.63, respectively). These results suggest that the implementation of PFL significantly influences the duration of unemployment among married mothers.

Conversely, for separated mothers, the coefficient associated with the PFL policy displays a positive trend but fails to reach statistical significance. This implies that introducing PFL does not engender a statistically significant impact on unemployment duration for this subgroup.

In examining the impact of the policy on earnings, we find notable variations across different marital statuses. The coefficient associated with the policy does not exhibit statistical significance for married mothers, suggesting no significant effect on earnings. Conversely, for previously married mothers, the coefficient demonstrates the statistical significance and a positive trend, indicating a substantial increase in earnings following the implementation of the Paid Family Leave (PFL) program. This finding highlights the positive influence of PFL on the earnings of previously married mothers, highlighting its role in fostering improved economic outcomes for this subgroup.

In contrast, for single/never married mothers, the coefficient reveals the statistical significance and a negative trajectory, implying a noteworthy decrease in earnings after introducing PFL. This result points to a significant adverse impact on the earnings of single/never married mothers, highlighting the potential challenges and disparities they face in the labor market post-PFL implementation.

4.3.4 Event Study Analysis or Dynamic Effect of CA-PFL:

In addition to conducting rigorous Difference-in-Differences (DD) and Difference-in-Differences-in-Differences (DDD) estimations, I have expanded my analytical framework to include an event study design, comprehensively exploring the policy's heterogeneous impact over time. Notably, the seminal works of Milkman and Appelbaum (2004 and 2011) shed light on the program's public awareness through a meticulous series of surveys, wherein it was found that a mere 56.1 percent of women were cognizant of its availability during the 2009-2010 survey period. By embracing the event-study analysis approach, I have captured the policy's dynamic treatment effect on diverse labor market outcomes, accounting for the evolving nature of its implementation. To operationalize this event-study model effectively, I have employed the following equation as the cornerstone of my analysis:

$$Y_{st} = \alpha + \sum_{j=2}^{J} \beta_j (\text{lag j})_{st} + \sum_{k=0}^{k} \gamma_k (\text{lead k})_{st} + \Gamma \boldsymbol{X}_{st} + \boldsymbol{S}_s + T_t + e_{st} \qquad \ldots (4)$$

S_s and T_t are state and time-fixed effects, respectively. $\boldsymbol{X}_{st}$ are time-varying controls, and e_{st} is an unobserved error term. Lags and leads are binary variables and indicate the number of years California is away from implementing CA-PFL. J and K lags and leads are included, respectively. β_j captures the impact of CA-PFL j years prior to the implementation of paid family leave program. Correspondingly, $\gamma_k$captures the impact of CA-PFL k years after the program's implementation. Figure 5 through Figure 8 represents the corresponding event study plots for labor force participation, employment, unemployment duration, and earnings separately. I used mothers of 1 to 3 years old in other states as the control groups, with the coefficients normalized to zero in 2003 (first lag, j=1).

Figure 2.5 presents the event study analysis focusing on the LFPR. The findings reveal a notable surge in LFPR during the post-policy period for mothers with children aged 1 to 3 years compared to the control groups. This observed increase in LFPR over time suggests that new mothers are becoming more aware of the availability of the policy and actively choosing to participate in the labor force. The upward trend in LFPR reflects the potential positive impact of the policy in motivating and enabling mothers to join or remain in the workforce.

Figure 2.6 displays the event study plots for employment, showcasing the trend in employment probability for mothers with younger children in California. Although these diagrams exhibit some noise, a careful examination provides insights into the employment dynamics. Figure 7 demonstrates that immediately after introducing the policy, there was a noticeable increase in employment among California mothers with young children, surpassing the employment levels in other states. Subsequently, during the recession period in 2008, there was a decline in employment probability. However, the figures indicate a consistent improvement in employment during the subsequent recovery period.

Within Figure 2.7, the event study plots for unemployment duration are presented. While this visual representation exhibits some noise level, an evident decline in unemployment duration is observed a decade after the policy's implementation. As previously discussed, this decline can be attributed to employers' growing trust in young women of childbearing age, thus bolstering their employment prospects. This increased employment probability may explain this group's reduction in unemployment duration.

Furthermore, Figure 2.8 showcases the findings regarding earnings. Initially, no notable changes in earnings are observed for California mothers compared to their counterparts in other states following the policy's introduction. However, a decade later, a decline in earning rates becomes apparent. As previously discussed, this decline in earnings can be attributed to the increase in labor supply among young women in response to the availability of the policy.

4.4 Robustness Check:

To assess the robustness of my findings, I conducted various sensitivity tests using alternative control groups and states. These tests examined whether the results remained consistent and reliable across different specifications. Overall, the outcomes of these sensitivity tests provide further evidence supporting the robustness of my primary findings.

4.4.1 Alternate Control States:

I conducted additional analyses using alternate control states to examine the robustness of my DD and DDD specifications. Drawing on the work of Rossin-Slater et al. (2013) and Byker (2016), I selected Texas, Florida, and three neighboring states of California (Arizona, Nevada, and Oregon) as my alternate control states. These states were chosen based on their similarity in size and demographic characteristics to California. However, I did not include New York as a control state due to the presence of a Temporary Disability Insurance (TDI) program that closely resembles the CA-PFL, as including New York could introduce bias into the estimation results. By incorporating these alternate control states, I sought to ensure the robustness and generalizability of my findings.

In addition to implementing DD and DDD estimations, I employed the synthetic control method (SCM) to evaluate the treatment effects using synthetic control states. Initially developed by Abadie and Gardeazabal (2003), the SCM assigns positive weights to control states, ensuring that the weights sum up to one. By constructing synthetic control states, we establish counterfactual scenarios for the treatment states, thereby preserving the necessary parallel trend assumption crucial for the DD and DDD models. To select appropriate control states, I considered each dependent variable individually, recognizing that paid leave benefits in control states can influence the labor market behavior of mothers. It is important to note that assigning positive weights to control states with such benefits could attenuate the estimated treatment effects for California. To eliminate any potential contamination in the estimation results, I excluded New York, Hawaii, New Jersey, and Rhode Island from the analysis as they have implemented TDI or PFL programs like CA-PFL.

Table A5 presents the weights assigned to different control states generated using the SCM method. Figures 2.9 through 2.12 depict the LFPR, employment rates, unemployment duration, and log earnings in California and Synthetic California from 1994 to 2020. Despite some fluctuations observed in the graphs, it is evident that California diverges from synthetic California for all variables following the implementation of the policy. Notably, Graph 2.12 demonstrates a pronounced decline in earnings for mothers with young children immediately after the policy, thus reinforcing the robustness of my baseline analysis.

Tables 2.9 and Table 2.11 through Table 2.14 present the results of the DD and DDD estimations utilizing alternate states and the synthetic control states. The DDD estimation yields essential insights, revealing that the LFPR for California mothers with children aged 1 to 3 years increases by 4.5 to 3.4 percentage points. Although the estimation result for employment is not statistically significant, it aligns with the direction observed in the baseline analysis. Moreover, the estimation result for the unemployment rate exhibits a reduction in unemployment duration ranging from 1.09 weeks to 6.21 weeks. Notably, the earnings estimation result showcases a 4.0% to 3.3% increase in earnings for California mothers within 1 to 3 years after childbirth.

Based on these findings, the robustness of my baseline estimation results is upheld when utilizing alternate comparison states for all dependent variables. The consistency observed across various specifications provides further confidence in the validity and reliability of the estimated treatment effects.

4.4.2 Alternate Control Groups:

To ensure the robustness of my main findings, I conducted additional analyses by varying the minimum and maximum age of the youngest child in the comparison group. In the baseline analysis, I assumed that mothers with children aged 10 to 15 would exhibit similar labor market behavior to mothers with younger children without the treatment. To test this assumption, I explored the labor market behavior of mothers with children aged 7 to 17 and 9 to 11 as alternative control groups. By comparing the DD and DDD estimation results using these alternate groups, I aimed to verify the consistency of my main findings.

Tables 2.10 through 2.14 present these alternate control groups' DD and DDD estimation results. Although the results for LFPR demonstrate a similar direction of effect (ranging from 0.1 to 0.6 percentage points), they do not reach statistical significance. However, the employment results reveal an increase in employment probability of 0.6 to 1.0 percentage points for California mothers with younger children. Furthermore, the results for unemployment duration exhibit a consistent trend with the main findings, indicating a decline ranging from 2.05 weeks to 3.39 weeks. While the earnings estimation yields negative coefficients (-0.015 to -0.016), they are not statistically significant, aligning with the main results.

Based on these findings, the robustness of my baseline estimation result is upheld when utilizing alternate comparison groups for all dependent variables. The consistent direction of effects across various specifications provides further confidence in the reliability and validity of the estimated treatment effects.

4.4.3 Placebo Regression:

Following the approach outlined by Rossin-Slater (2013), I conducted a placebo test to examine the effects of the paid family leave (PFL) program on states that have temporary disability insurance (TDI) programs, namely New York, Hawaii, and Rhode Island. It is important to note that Rhode Island implemented its PFL program in 2014, so the analysis for this state focuses on the period from 1994 to 2014. These TDI states offer some form of paid leave, typically requiring a doctor's prescription, following the birth of a child. By conducting this placebo test, I aimed to assess whether the observed changes in labor market behavior for California mothers with children aged 1 to 3 years are indeed driven by the introduction of the PFL program or if they can be attributed to other unobserved factors associated with paid leave programs.

Table 2.15 presents the results of the placebo estimation, and it is noteworthy that all coefficients are statistically insignificant. This finding strengthens the robustness of my main results, indicating that the changes in medium-term labor market behaviors observed among California mothers with young children can be attributed to implementing the CA-PFL program. The lack of significant effects in the placebo states with TDI programs suggests that the observed impacts in California are not merely a result of unobserved correlates of paid leave programs but are the direct consequence of the CA-PFL policy.

These findings support the causal link between the CA-PFL program and the changes in California's labor market outcomes for mothers of young children. The absence of significant effects in the placebo states strengthens the validity of my main estimation results, underscoring the unique impact of the CA-PFL program on maternal labor market behavior.

4.4.4 Parallel Trend:

To assess the validity of the parallel-trend assumption, crucial for interpreting the difference-in-difference (DD) estimation as a causal impact of the CA-PFL program, I conducted additional analyses by incorporating variables for pretreatment differences between the treatment and comparison groups. Specifically, I extended Equation (3) by including the variables PPL*Treat*5–6 years pre, PPL*Treat*3–4 years pre, and PPL*Treat*1–2 years pre. This adjustment allowed me to control for any preexisting disparities in labor market outcomes before implementing the CA-PFL program.

For this analysis, I utilized data from 1999 to 2020. The objective was to examine whether the coefficients for these lag periods are statistically significant, as their significance would suggest the presence of systematic pre-treatment differences between the groups. Rejecting the null hypothesis of parallel trends would imply that the treatment and comparison groups needed to follow similar paths before introducing the CA-PFL program.

Table 2.16 presents the results of this analysis, indicating that the coefficients for the lag periods, PPL*Treat*5–6 years pre, PPL*Treat*3–4 years pre, and PPL*Treat*1–2 years pre, are statistically insignificant. These findings suggest no systematic pretreatment differences between the treatment and comparison groups in labor force participation, employment, unemployment duration, and earnings. Therefore, we can infer that the baseline results and those obtained from other models are unlikely to be driven by preexisting disparities across these groups.

These results support the validity of the parallel-trend assumption, bolstering the interpretation of the difference-in-difference estimation as a causal impact of the CA-PFL program on labor market outcomes. By demonstrating the absence of significant pretreatment differences, this analysis strengthens the confidence in the estimated effects of the CA-PFL policy on maternal employment and other labor market indicators.

5 Discussion:

The implementation of California's Paid Family Leave (CA-PFL) program has marked a significant milestone as the first paid family leave program in the United States. This program enables individuals to take paid time off from work to establish a bond with a newborn or newly adopted child. The potential for such policies to be adopted in other states is evident, with the Department of Labor (2015) reporting that eighteen states are considering implementing paid family leave programs.

Through my study, it has become apparent that CA-PFL has had a more pronounced impact on the labor market behaviors of mothers in California compared to other states. Specifically, California mothers' LFPR has notably increased by 1.8 percentage points after 1 to 3 years following childbirth, surpassing the outcomes observed in the control groups and other states. Further analysis reveals that CA-PFL is positively associated with the employment probability of California mothers, resulting in a 0.7 percentage point increase and a reduction in unemployment duration by 3.39 weeks. However, despite these positive findings, no statistically significant impact of the policy on California mothers' earnings has been identified in this study.

One of the significant contributions of this paper is its endeavor to capture the heterogeneous impact of the policy on low-income mothers. Lower-income or disadvantaged mothers are expected to benefit most from such policies. However, my findings reveal that the overall positive impact of the policy masks the negative impact experienced by disadvantaged mothers.

Specifically, the law has shown no impact on the labor force participation decisions of lower-income mothers, and it has been found to negatively affect the earnings of single mothers with younger children compared to their higher-income counterparts. These findings raise significant concerns and underscore the need for further policy revisions to provide targeted support to mothers from less advantageous segments of society.

According to the CPS dataset, the analysis does not encompass the effects of privately provided paid leave. Consequently, it would be intriguing to explore the influence of the California Paid Family Leave (CA-PFL) program in conjunction with the availability of private-sector paid leave. In future studies, examining this interplay could provide valuable insights into the impact of different paid leave policies on various outcomes.

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Chapter 2 All the Tables of the Paper:

Table 2.1: State Parental Leave Benefits in Addition to FMLA

States	Temporary Disability Insurance	Paid Family Leave
California	1996	2004
Hawaii	1969	-
New Jersey	1948[a]	2009
New York	1950[b]	2018
Rhode Island	1942	2014
Washington	-	2007[c]

Note: a TDI began covering pregnant women or women recovering from pregnancy in 1970, b TDI began covering pregnant women or women recovering from pregnancy in 1977, and c Washington has yet to implement it due to budgetary restrictions.

Table 2.2: Effect of CA-PFL on Mothers' Labor Force Participation Decision

Dependent Variable: Labor Force Participation	(1)	(2)	(3)	(4)	(5)	(6)
	DD State	DD 10-15	DDD	DDD	DDD	DDD
CA*post	0.002					
	(0.006)					
post*treat		0.036***				
		(0.011)				
CA*post*treat			0.018***	0.019***	0.019***	0.018***
			(0.006)	(0.006)	(0.006)	(0.006)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	Yes	No	No	No	Yes	Yes
State-Year FE	No	No	Yes	No	No	Yes
Observations	129,675	29,176	281,023	281,023	281,023	281,023
R-squared	0.075	0.086	0.085	0.076	0.080	0.085
Pre-Treatment Mean	0.5638	0.5638	0.5638	0.5638	0.5638	0.5638
Percentage Change	0.36%	6.39%	3.19%	3.37%	3.37%	3.19%

Notes: *** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses, and clustered at the state level. March CPS data is used from 1994-2020. For columns 1 to 6, mothers with young children between 1 to 3 years in California are considered as the treatment group. For columns 1 and 2, mothers with young children between 1 to 3 years in other states and mothers of younger children between 10-15 are used as a control group. Column 3 excludes state-specific linear trends. Column 4 excludes state-specific linear trends, and state-year fixed effects, while column 5 excludes only state-year fixed effects. Column 6 includes control variables, state, time fixed effects, state-specific linear trends, and state-year fixed effects as well.

Table 2.3: Effect of CA-PFL on Mothers' Employment						
Dependent Variable: Employment	(1)	(2)	(3)	(4)	(5)	(6)
	DD State	DD 10-15	DDD	DDD	DDD	DDD
CA*post	0.005**					
	(0.002)					
post*treat		0.002				
		(0.008)				
CA*post*treat			0.007**	0.007***	0.008***	0.007***
			(0.003)	(0.003)	(0.003)	(0.003)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	Yes	No	No	No	Yes	Yes
State-Year FE	No	No	Yes	No	No	Yes
Observations	85,377	19,284	206,950	206,950	206,950	206,950
R-squared	0.055	0.048	0.046	0.036	0.040	0.044
Pre-Treatment Mean	0.9061	0.9061	0.9061	0.9061	0.9061	0.9061
Percentage Change	0.55%	0.22%	0.77%	0.77%	0.88%	0.77%

Notes: *** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses, and clustered at the state level. March CPS data is used from 1994-2020. For columns 1 to 6, mothers with young children between 1 to 3 years in California are considered as the treatment group. For columns 1 and 2, mothers with young children between 1 to 3 years in other states and mothers of younger children between 10-15 are used as a control group. Column 3 excludes state-specific linear trends. Column 4 excludes state-specific linear trends, and state-year fixed effects, while column 5 excludes only state-year fixed effects. Column 6 includes control variables, state, time fixed effects, state-specific linear trends, and state-year fixed effects as well.

Table 2.4: Effect of CA-PFL on Mothers' Unemployment Duration

Dependent Variable: Unemployment Duration	(1)	(2)	(3)	(4)	(5)	(6)
	DD State	DD 10-15	DDD	DDD	DDD	DDD
CA*post	-2.400*					
	(1.310)					
post*treat		-4.568*				
		(2.384)				
CA*post*treat			-3.390**	-2.614*	-2.589	-3.390**
			(1.659)	(1.501)	(1.568)	(1.649)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	Yes	No	No	No	Yes	Yes
State-Year FE	No	No	Yes	No	No	Yes
Observations	4,699	1,421	9,934	9,934	9,934	9,934
R-squared	0.129	0.123	0.061	0.224	0.088	0.224
Pre-Treatment Mean	18.26	18.26	18.26	18.26	18.26	18.26

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors in parentheses, and clustered at the state level. March CPS data is used from 1994-2020. For columns 1 to 6, mothers with young children between 1 to 3 years in California are considered as the treatment group. For columns 1 and 2, mothers with young children between 1 to 3 years in other states and mothers of younger children between 10-15 are used as a control group. Column 3 excludes state-specific linear trends. Column 4 excludes state-specific linear trends, and state-year fixed effects, while column 5 excludes only state-year fixed effects. Column 6 includes control variables, state, time fixed effects, state-specific linear trends, and state-year fixed effects as well.

Table 2.5: Effect of CA-PFL on mothers' Earnings

Dependent Variable: Earnings	(1)	(2)	(3)	(4)	(5)	(6)
	DD State	DD 10-15	DDD	DDD	DDD	DDD
CA*post	-0.017*					
	(0.009)					
post*treat		0.049*				
		(0.025)				
CA*post*treat			0.016	0.018	0.019	0.016
			(0.013)	(0.014)	(0.014)	(0.013)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	Yes	No	No	No	Yes	Yes
State-Year FE	No	No	Yes	No	No	Yes
Observations	87,736	19,393	210,178	210,178	210,178	210,178
R-squared	0.472	0.463	0.453	0.383	0.384	0.459
Pre-Treatment Mean	9.49	9.49	9.49	9.49	9.49	9.49

Notes: *** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses, and clustered at the state level. March CPS data is used from 1994-2020. For columns 1 to 6, mothers with young children between 1 to 3 years in California are considered as the treatment group. For columns 1 and 2, mothers with young children between 1 to 3 years in other states and mothers of younger children between 10-15 are used as a control group. Column 3 excludes state-specific linear trends. Column 4 excludes state-specific linear trends, and state-year fixed effects, while column 5 excludes only state-year fixed effects. Column 6 includes control variables, state, time fixed effects, state-specific linear trends, and state-year fixed effects as well.

Table 2.6: Heterogenous Effect of PFL on mothers' Different Labor Market Outcome: Based on Poverty Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below Poverty	100-124% of the low-income	125-149% of the low-income	150-299% of the low-income	300-499% of the low-income	500-749% of the low-income	750-999% of the low income	1000% and above the low-income
Panel A: Dependent Variable: Labor Force Participation								
CA*post*treat	-0.04	-0.01	-0.02	0.01	0.02**	0.02*	0.11***	0.13***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	38,850	12,902	13,534	78,495	74,190	38,462	12,808	11,690
R-squared	0.10	0.24	0.24	0.12	0.08	0.08	0.13	0.17
Pre-Treatment Mean	0.34	0.40	0.51	0.60	0.69	0.74	0.73	0.60
Percentage Change	-11.76%	-2.50%	-3.92%	1.67%	2.70%	2.70%	15.01%	21.67%
Panel B: Dependent Variable: Employment								
CA*post*treat	0.04**	-0.02	0.07***	0.00	-0.01***	-0.01***	-0.02*	0.00
	(0.02)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Observations	18,932	7,967	8,883	57,804	60,976	32,476	10,878	8,960
R-squared	0.11	0.15	0.14	0.04	0.03	0.04	0.11	0.11
Pre-Treatment Mean	0.70	0.83	0.86	0.93	0.97	0.96	0.98	0.98
Percentage Change	5.71%	-2.41%	8.14%	0.00%	-1.03%	-1.04%	-2.04%	0.00%
Panel C: Dependent Variable: Unemployment Duration								
CA*post*treat	2.40	-10.07	21.60	-5.03	3.35	-8.94	6.02	0.00
	(3.21)	(13.70)	(15.25)	(2.77)	(6.20)	(11.64)	(11.62)	(0.00)
Observations	3,603	769	615	2,666	1,404	555	197	125
R-squared	0.35	0.60	0.72	0.41	0.53	0.78	0.96	0.95
Pre-Treatment Mean	21.83	16.36	11.69	17.44	18.40	12.5	6.63	6.33
Panel D: Dependent Variable: Earnings								
CA*post*treat	-0.06	-0.11*	0.03	-0.05***	-0.03*	0.05	0.22***	0.01
	(0.05)	(0.06)	(0.05)	(0.02)	(0.02)	(0.03)	(0.08)	(0.09)
Observations	16,863	7,709	8,616	56,010	59,439	31,902	10,648	8,734
R-squared	0.47	0.45	0.46	0.36	0.34	0.37	0.44	0.48
Pre-Treatment Mean	8.31	8.95	9.22	9.44	9.90	10.23	10.50	10.72
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.7: Heterogenous Effect of PFL on mothers' Different Labor Market Outcome: Based on Education

	(1)	(2)	(3)
	High-School Graduate	Some Years in College	Bachelor's Degree and Above
Dependent Variable: Labor Force Participation			
CA*post*treat	0.03***	-0.01	0.05***
	(0.01)	(0.01)	(0.01)
Observations	108,636	85,737	86,650
R-squared	0.07	0.07	0.07
Pre-Treatment Mean	0.57	0.66	0.67
Percentage Change	5.26%	-1.52%	7.46%
Dependent Variable: Employment			
CA*post*treat	0.03***	0.00	-0.01**
	(0.01)	(0.00)	(0.00)
Observations	72,139	65,770	69,041
R-squared	0.06	0.04	0.02
Pre-Treatment Mean	0.90	0.93	0.97
Percentage Change	3.33%	0.00%	-1.03%
Dependent Variable: Unemployment Duration			
CA*post*treat	4.70	-3.58***	-0.29
	(3.62)	(4.33)	(6.42)
Observations	5,515	2,973	1,446
R-squared	0.27	0.40	0.55
Pre-Treatment Mean	19.68	17.74	17.25
Dependent Variable: Earnings			
CA*post*treat	-0.02	-0.02	0.10***
	(0.02)	(0.01)	(0.02)
Observations	67,896	63,622	66,756
R-squared	0.46	0.47	0.43
Pre-Treatment Mean	9.53	9.76	10.17
Individual Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
State-Year Controls	No	No	No
State-Year FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses, and clustered at the state level. March CPS data is used from 1994-2020. For columns 1 to 8, mothers with young children between 1 to 3 years in California are considered as the treatment group.

Table 2.8: Heterogenous Effect of PFL on mothers' Different Labor Market Outcome: Based on Marital Status

	(1)	(2)	(3)
	Married	Previously Married	Single/Never Married
Dependent Variable: Labor Force Participation			
CA*post*treat	0.05***	-0.03**	-0.09***
	(0.01)	(0.01)	(0.01)
Observations	209,872	40,596	30,555
R-squared	0.09	0.09	0.12
Pre-Treatment Mean	0.54	0.63	0.62
Percentage Change	16.67%	-17.46%	-14.52%
Dependent Variable: Employment			
CA*post*treat	0.00	0.07***	0.02
	(0.00)	(0.01)	(0.01)
Observations	150,848	33,240	22,862
R-squared	0.03	0.07	0.11
Pre-Treatment Mean	0.93	0.80	0.82
Percentage Change	0.00%	17.5%	2.44
Dependent Variable: Unemployment Duration			
CA*post*treat	-3.88*	5.71	-3.63**
	(2.06)	(4.30)	(5.32)
Observations	5,151	2,242	2,541
R-squared	0.29	0.46	0.39
Pre-Treatment Mean	18.59	16.20	17.72
Dependent Variable: Earnings			
CA*post*treat	0.01	0.29***	-0.08**
	(0.01)	(0.03)	(0.04)
Observations	145,386	31,226	22,365
R-squared	0.44	0.69	0.72
Pre-Treatment Mean	9.66	9.41	9.36
Individual Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
State-Year Controls	No	No	No
State-Year FE	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses, and clustered at the state level. March CPS data is used from 1994-2020. For columns 1 to 8, mothers with young children between 1 to 3 years in California are considered as the treatment group.

Table 2.9: Effect of PFL on Mothers with Alternate Control States

Dependent Variable:	Labor Force Participation		Employment		Unemployment Duration		Earnings	
	DD Alternate State	DD-SC State	DD Alternate State	DD-SC State	DD Alternate State	DD-SC State	DD Alternate State	DD-SC State
post*treat	0.023**	0.027***	0.006	-0.005*	-3.939	-5.222***	-0.002***	-0.018*
	(0.011)	(0.000)	(0.005)	(0.009)	(3.288)	(0.068)	(0.001)	(0.005)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No	No	No	No	No
State-Year FE	No	No	No	No	No	No	No	No
Observations	35,117	32,421	20,999	14,612	1,476	1,435	20,999	24,585
R-squared	0.074	0.473	0.052	0.078	0.162	0.151	0.052	0.475

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.10: Effect of PFL on Mothers with Alternate Control Groups

Dependent Variable:	Labor Force Participation		Employment		Unemployment Duration		Earnings	
	DD Youngest Child 7-17	DD Youngest Child 9-11	DD Youngest Child 7-17	DD Youngest Child 9-11	DD Youngest Child 7-17	DD Youngest Child 9-11	DD Youngest Child 7-17	DD Youngest Child 9-11
post*treat	0.026***	0.025*	0.003	0.008	-2.913	-5.871*	0.003	0.016
	(0.009)	(0.013)	(0.007)	(0.009)	(2.026)	(3.505)	(0.007)	(0.032)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No	No	No	No	No
State-Year FE	No	No	No	No	No	No	No	No
Observations	42,350	22,952	28,629	14,458	2,035	1,113	28,629	14,568
R-squared	0.079	0.080	0.043	0.055	0.121	0.152	0.043	0.470

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.11: DDD Estimation Result on Labor Force Participation with Alternate Control Groups and Alternate Control States

Dependent Variable: Labor Force Participation	(1)	(2)	(3)	(4)
	DDD-OS	DDD-SCM	DDD-7-17	DDD-9-11
CA*post*treat	0.045***	0.034***	0.006	0.001
	(0.008)	(0.005)	(0.006)	(0.006)
Individual Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Observations	73,853	66,300	411,427	213,858
R-squared	0.090	0.095	0.078	0.085
Pre-Treatment Mean	0.5638	0.5638	0.5638	0.5638
Percentage Change	7.98%	6.03%	1.06%	0.18%

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.12: DDD Estimation Result on Employment with Alternate Control Groups and Alternate Control States

Dependent Variable: Employment	(1)	(2)	(3)	(4)
	DDD-OS	DDD-SCM	DDD-7-17	DDD-9-11
CA*post*treat	0.007	-0.003	0.006**	0.010***
	(0.006)	(0.015)	(0.003)	(0.003)
Individual Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Observations	50,522	34,125	309,205	151,588
R-squared	0.039	0.054	0.040	0.052
Pre-Treatment Mean	0.9061	0.9061	0.9061	0.9061
Percentage Change	0.77%	0.33%	0.66%	1.10%

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.13: DDD Estimation Result on Unemployment Duration with Alternate Control Groups and Alternate Control States

Dependent Variable: Unemployment Duration	(1)	(2)	(3)	(4)
	DDD-OS	DDD-SCM	DDD-7-17	DDD-9-11
CA*post*treat	-1.094	-6.207*	-3.390**	-2.047
	(4.286)	(2.432)	(1.649)	(2.030)
Individual Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Observations	3,039	2,886	9,934	6,684
R-squared	0.178	0.166	0.224	0.264
Pre-Treatment Mean	18.26	18.26	18.26	18.26

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.14: DDD Estimation Result on Earnings with Alternate Control Groups and Alternate Control States

Dependent Variable: Earnings	(1)	(2)	(3)	(4)
	DDD-OS	DDD-SCM	DDD-7-17	DDD-9-11
CA*post*treat	0.040**	0.033	-0.015	-0.016
	(0.013)	(0.021)	(0.012)	(0.013)
Individual Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Observations	51,029	57,992	313,594	154,624
R-squared	0.450	0.465	0.445	0.459
Pre-Treatment Mean	9.49	9.49	9.49	9.49

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.15: DDD Estimation Result with New York, Rhode Island, and Hawaii as Treated State (Falsification Analysis)

Dependent Variables:	LFPR	Employment	Unemployment	Earnings
expansion*post*treat	0.016	0.010	7.168	0.008
	(0.007)	(0.004)	(1.671)	(0.017)
Individual Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Observations	169,171	120,946	6,193	123,558
R-squared	0.083	0.051	0.262	0.455

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses

Table 2.16: Tests for Parallel Trends				
Dependent Variables:	LFPR	Employment	Unemployment	Earnings
expansion*treat*5-6 years pre	-0.022	0.000	-0.083	-0.022
	(0.015)	(0.008)	(1.998)	(0.027)
expansion*treat*3-4 years pre	-0.002	0.007	-0.166	-0.022
	(0.008)	(0.005)	(2.095)	(0.024)
expansion*treat*1-2 years pre	0.013	0.042***	-5.901*	0.003
	(0.008)	(0.006)	(3.211)	(0.025)
expansion*treat*post	0.016*	0.017***	-4.202**	0.009
	(0.009)	(0.004)	(1.927)	(0.021)
Individual Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
State-Year Controls	No	No	No	No
State-Year FE	Yes	Yes	Yes	Yes
Observations	281,023	206,950	9,934	210,178
R-squared	0.085	0.046	0.224	0.453

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses

All the Figures of the Paper:

Figure 2.1: Labor Force Participation Rate of Mothers with Youngest (1 to 3 Years) and Oldest Children (10 to 15 Years)

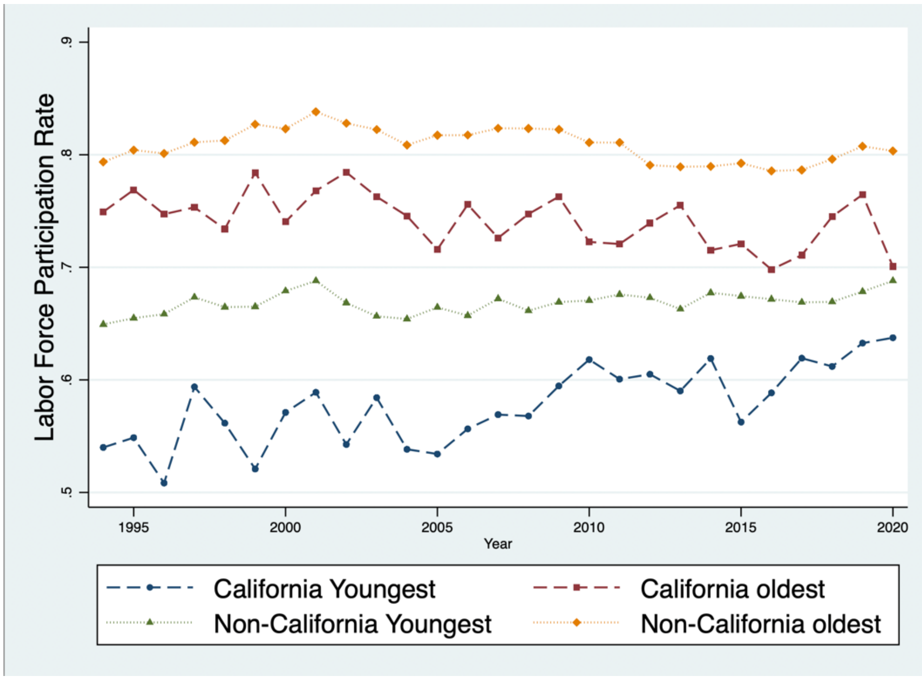


Figure 2.2: Employment Rate of Mothers with Youngest (1 to 3 Years) and Oldest Children (10 to 15 Years)

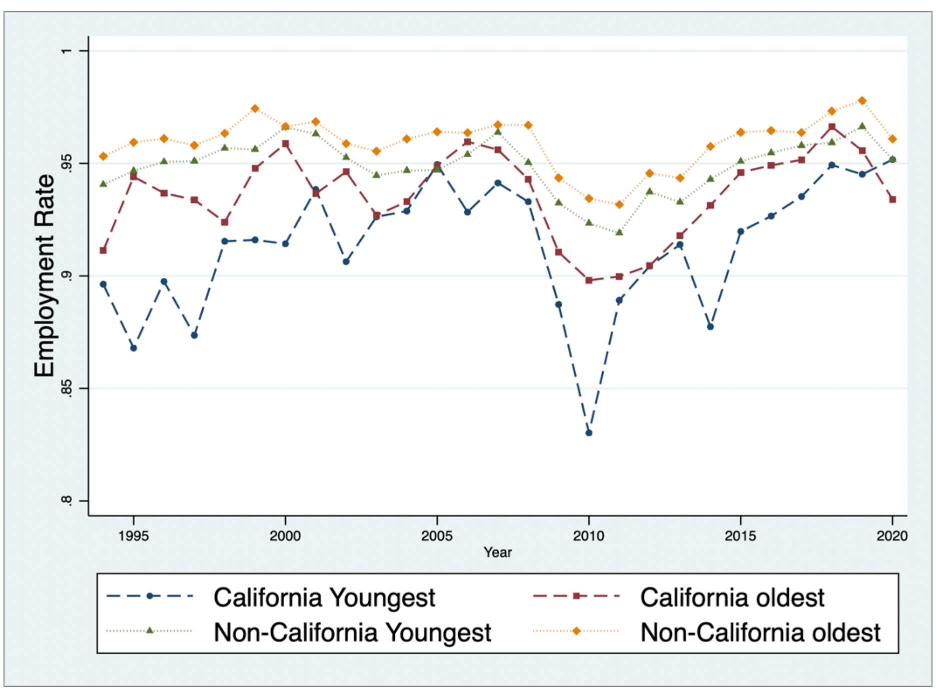


Figure 2.3: Unemployment Duration (Weeks) of Mothers with Youngest (1 to 3 Years) and Oldest Children (10 to 15 Years)

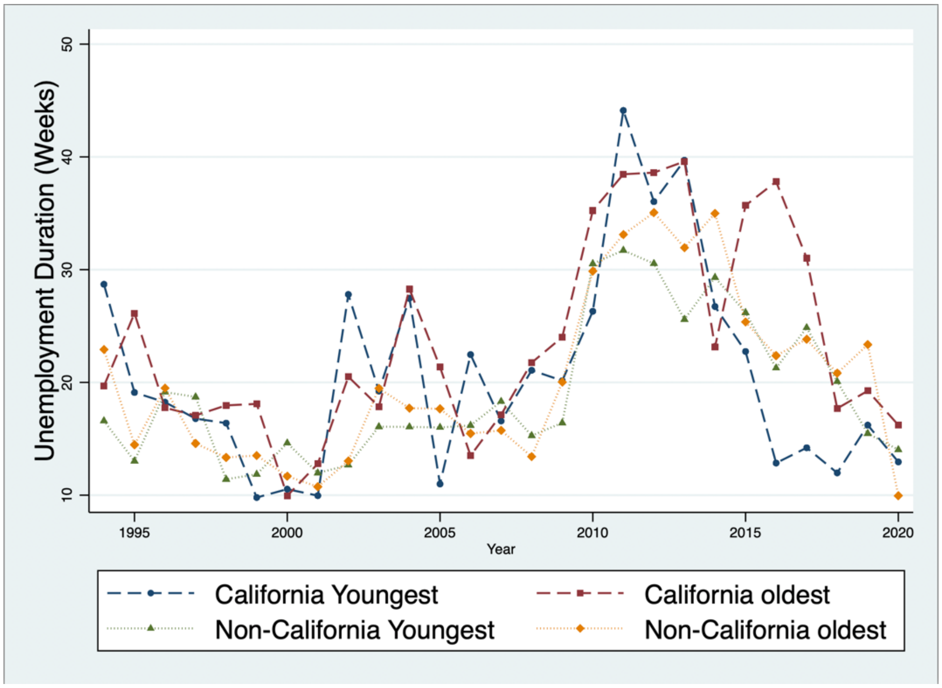


Figure 2.4: Log Earnings of Mothers with Youngest (1 to 3 Years) and Oldest Children (10 to 15 Years)

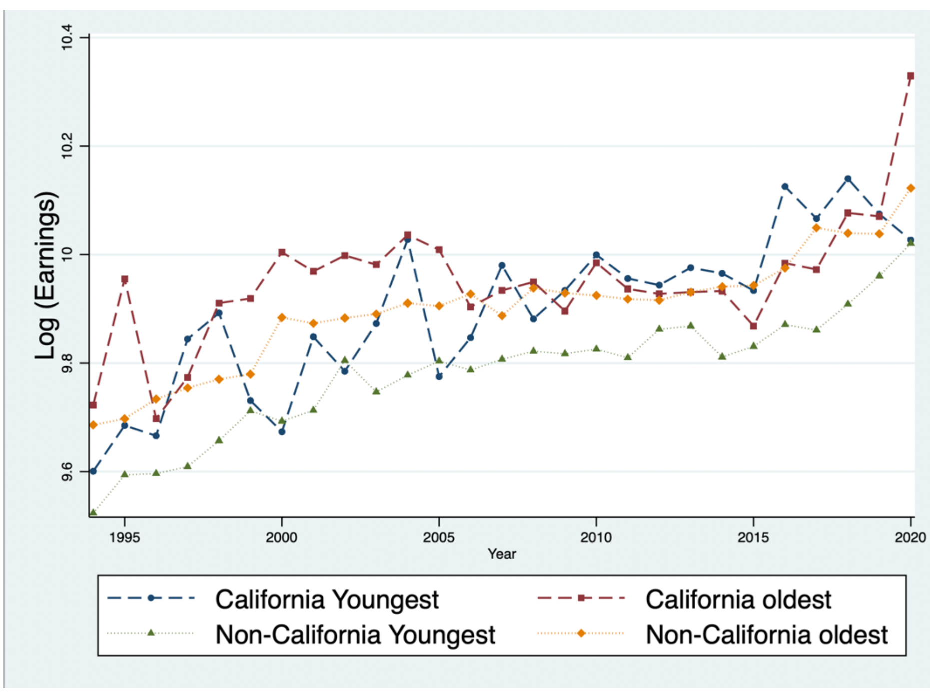


Figure 2.5: Event Study Graph for Labor Force Participation Rate, Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Other States

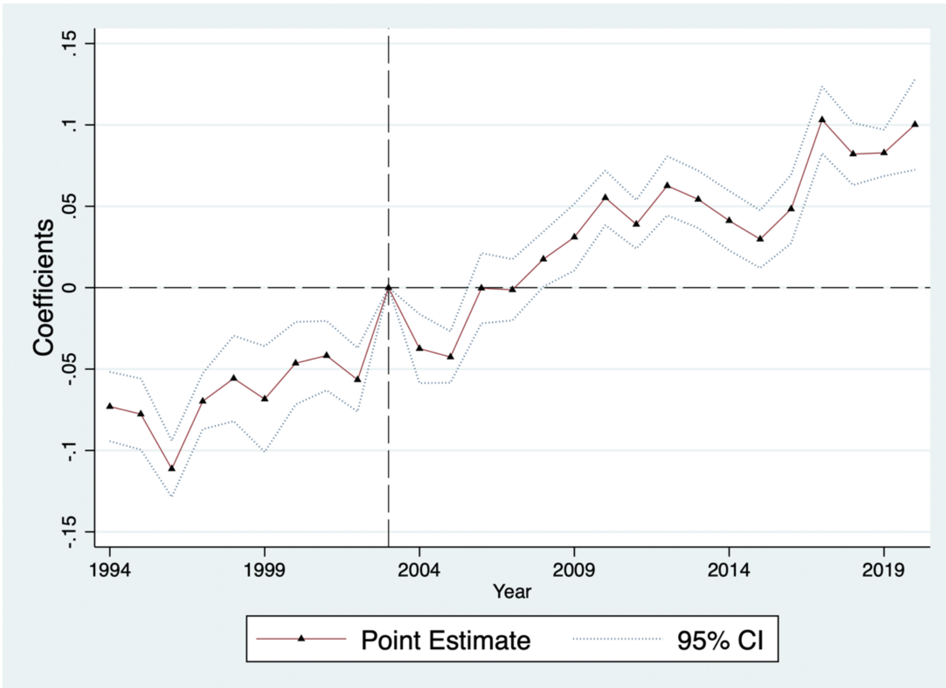


Figure 2.6:Event Study Graph for Employment Rate, Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Other States

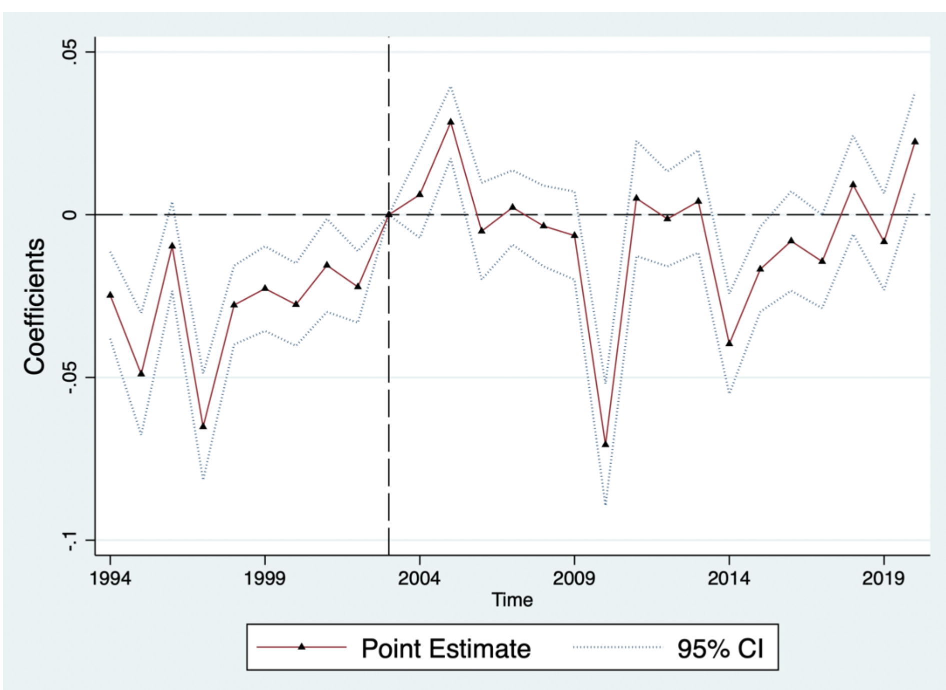


Figure 2.7: Event Study Graph for Unemployment Duration (Weeks), Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Other States

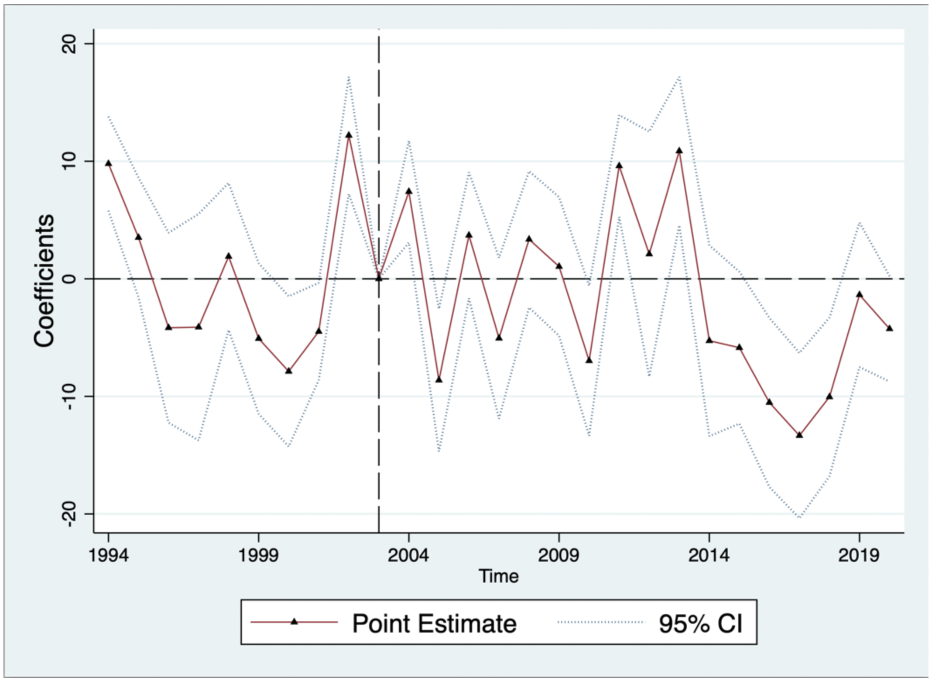


Figure 2.8: Event Study for Earnings, Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Other States

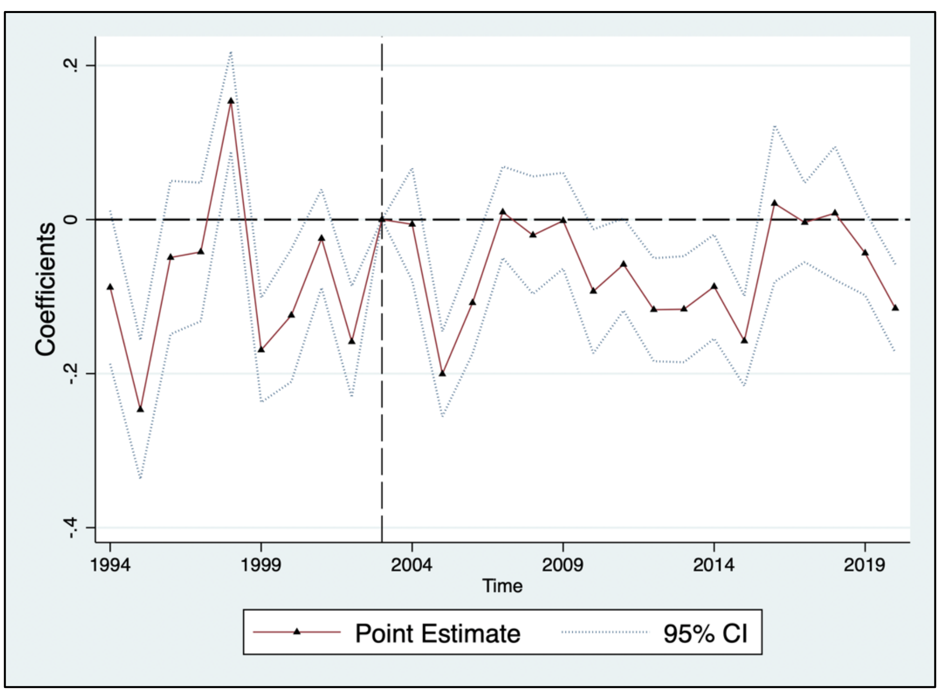


Figure 2.9: Labor Force Participation Rate, Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Synthetic California

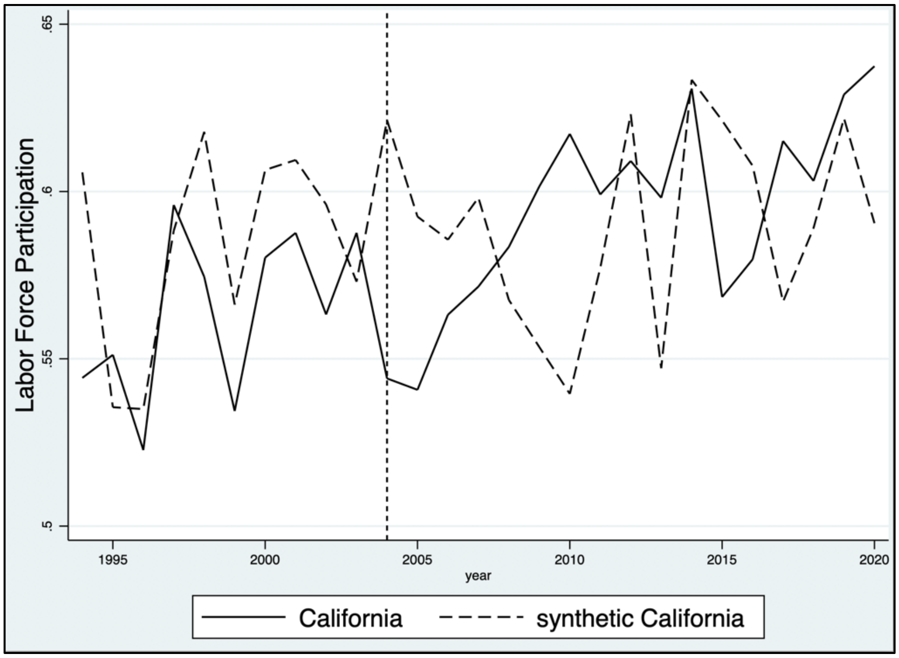


Figure 2.10: Employment Rate, Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Synthetic California

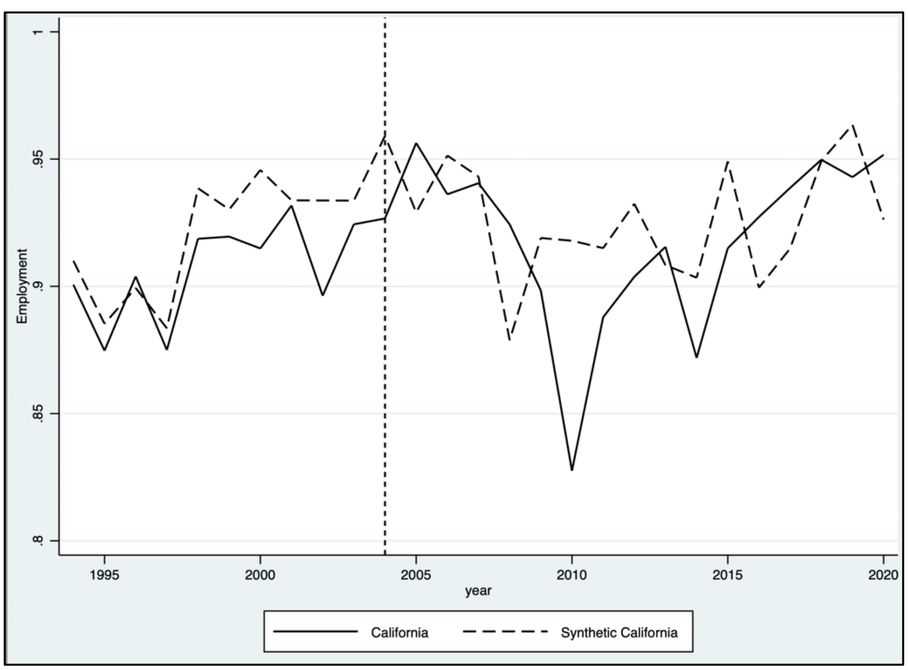


Figure 2.11: Unemployment Duration (Weeks), Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Synthetic California

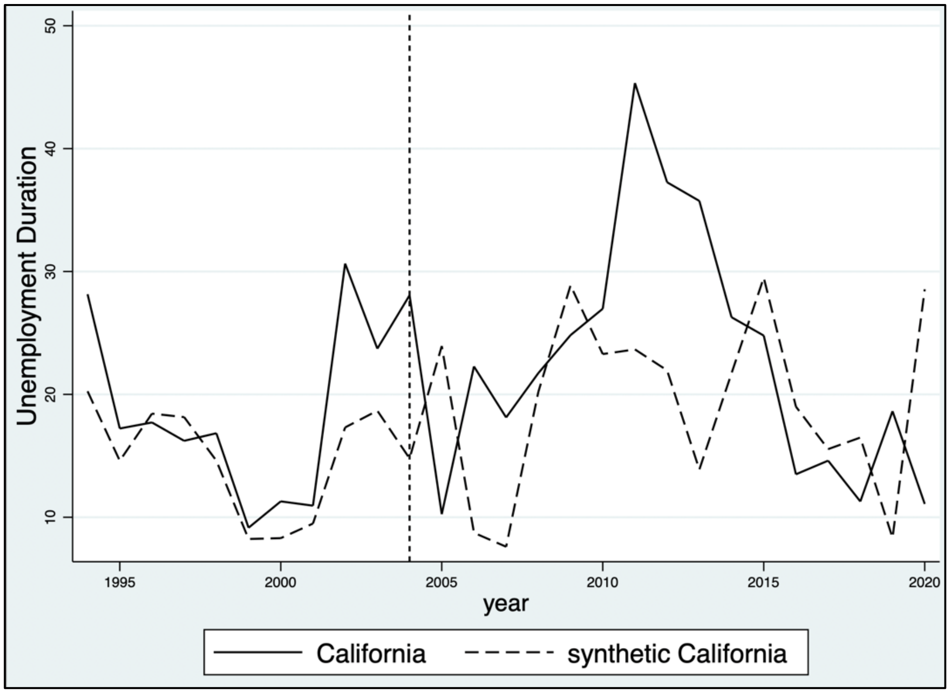
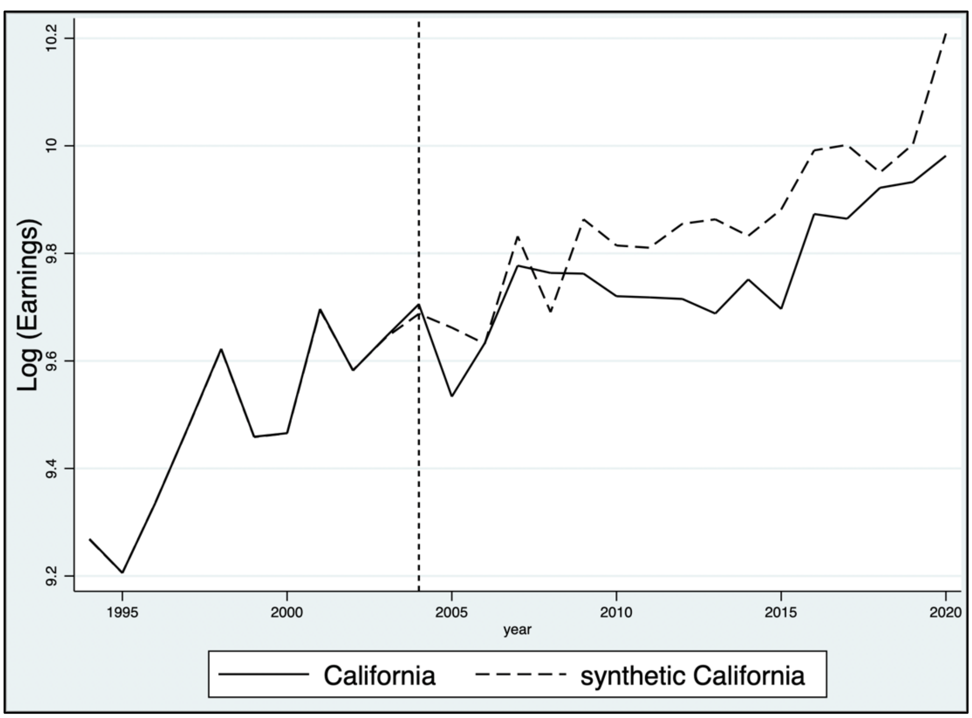


Figure 2.12: Log Earnings, Mothers of 1 to 3 Years Old Children in California vs. Mothers of 1 to 3 Years Old Children in Synthetic California



CHAPTER TWO APPENDIX:

Table A1.A: Summary Statistics for Mothers' Labor Force Participation in California

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
	Mean	S.E.	Mean	S.E.	Mean	S.D.	Mean	S.D.
Dependent Variables:								
Labor force participation	0.555	0.007	0.593	0.005	0.759	0.006	0.732	0.004
Independent Variables:								
Education:								
less than HS education	0.303	0.001	0.190	0.000	0.248	0.004	0.213	0.002
HS graduate	0.226	0.000	0.223	0.000	0.245	0.003	0.233	0.001
Some college education	0.255	0.001	0.261	0.000	0.308	0.003	0.279	0.001
Bachelor's degree and above	0.257	0.000	0.261	0.001	0.199	0.003	0.275	0.003
Age:								
24-30	0.403	0.001	0.340	0.000	0.023	0.000	0.024	0.000
31-35	0.311	0.000	0.306	0.000	0.113	0.002	0.101	0.000
36-40	0.206	0.001	0.244	0.002	0.276	0.002	0.229	0.002
41-45	0.068	0.002	0.089	0.000	0.355	0.002	0.339	0.002
46-50	0.010	0.000	0.020	0.000	0.233	0.003	0.307	0.003
Race:								
White	0.831	0.001	0.786	0.001	0.798	0.003	0.782	0.001
Black	0.041	0.000	0.049	0.000	0.063	0.001	0.050	0.000
Others	0.128	0.000	0.165	0.003	0.139	0.002	0.167	0.002
Marital Status:								
Married	0.798	0.003	0.778	0.002	0.716	0.002	0.723	0.002
Separated	0.042	0.002	0.032	0.000	0.054	0.001	0.045	0.000
Divorced	0.036	0.000	0.034	0.000	0.133	0.002	0.115	0.002
Widowed	0.004	0.000	0.003	0.001	0.023	0.001	0.014	0.003
Never Married/ Single	0.121	0.001	0.153	0.002	0.074	0.002	0.102	0.001
Number of own children in the HH	2.321	0.016	2.226	0.012	2.076	0.013	2.106	0.009
Family size	4.564	0.022	4.537	0.017	4.104	0.019	4.198	0.014
Household income	53208.780	777.197	86436.420	1077.82	62579.460	872.043	90308.860	1020.650
Observations	5500		8879		5100		9697	

Notes: Author's own calculation by using March CPS data from 1994-2020

Table A2.B: Summary Statistics for Mothers' Labor Force Participation in Other Control States (Except California, New Jersey, Rhode Island)

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
	Mean	S.E.	Mean	S.E.	Mean	S.D.	Mean	S.D.
<u>*Dependent Variables:*</u>								
Labor force participation	0.665	0.002	0.670	0.002	0.817	0.002	0.805	0.001
<u>*Independent Variables:*</u>								
<u>Education:</u>								
less than HS education	0.109	0.000	0.096	0.004	0.104	0.005	0.088	0.000
HS graduate	0.289	0.001	0.225	0.000	0.364	0.000	0.273	0.001
Some college education	0.308	0.000	0.295	0.000	0.308	0.005	0.321	0.005
Bachelor's degree and above	0.293	0.001	0.384	0.000	0.223	0.008	0.318	0.002
<u>Age:</u>								
24-30	0.427	0.000	0.391	0.000	0.024	0.001	0.022	0.000
31-35	0.323	0.002	0.322	0.004	0.134	0.001	0.114	0.002
36-40	0.185	0.004	0.203	0.004	0.296	0.001	0.244	0.002
41-45	0.056	0.004	0.070	0.001	0.345	0.004	0.341	0.003
46-50	0.007	0.001	0.013	0.000	0.200	0.001	0.279	0.004
Race:								
White	0.849	0.003	0.821	0.003	0.846	0.003	0.836	0.003
Black	0.102	0.002	0.104	0.002	0.112	0.000	0.114	0.002
Others	0.050	0.005	0.074	0.002	0.042	0.002	0.060	0.003
<u>Marital Status:</u>								
Married	0.806	0.003	0.766	0.006	0.733	0.010	0.707	0.000
Separated	0.030	0.001	0.026	0.001	0.037	0.001	0.035	0.000
Divorced	0.055	0.002	0.050	0.001	0.152	0.002	0.146	0.002
Widowed	0.004	0.000	0.004	0.000	0.016	0.000	0.015	0.000
Never Married/ Single	0.105	0.004	0.154	0.007	0.063	0.003	0.097	0.005
Number of own children in the HH	2.195	0.006	2.207	0.004	1.972	0.004	1.991	0.003
Family size	4.203	0.006	4.241	0.005	3.853	0.005	3.891	0.004
Household income	56299.810	275.019	106575.200	11094.090	62693.270	254.000	100542.600	8575.419
Observations	42057		73240		52418		84134	

Notes: Author's own calculation by using March CPS data from 1994-2020

Table A3.A : Summary Statistics of Employed Mothers in California

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Dependent Variables:								
Employment Rate	0.908	0.005	0.915	0.004	0.936	0.004	0.935	0.003
Independent Variables:								
Education:								
less than HS education	0.210	0.001	0.132	0.004	0.196	0.002	0.177	0.003
HS graduate	0.233	0.005	0.199	0.001	0.249	0.004	0.220	0.003
Some college education	0.298	0.004	0.279	0.003	0.337	0.003	0.302	0.001
Bachelor's degree and above	0.258	0.001	0.389	0.001	0.219	0.004	0.300	0.005
Age:								
24-30	0.386	0.001	0.324	0.001	0.020	0.001	0.025	0.001
31-35	0.314	0.004	0.304	0.004	0.115	0.002	0.100	0.001
36-40	0.210	0.001	0.258	0.003	0.283	0.003	0.230	0.003
41-45	0.081	0.001	0.094	0.003	0.360	0.003	0.342	0.003
46-50	0.010	0.001	0.020	0.001	0.222	0.004	0.303	0.004
Race:								
White	0.804	0.001	0.759	0.003	0.793	0.004	0.774	0.002
Black	0.056	0.003	0.057	0.002	0.068	0.001	0.054	0.001
Others	0.140	0.001	0.185	0.001	0.139	0.003	0.171	0.003
Marital Status:								
Married	0.771	0.003	0.745	0.004	0.703	0.003	0.689	0.004
Separated	0.049	0.003	0.035	0.001	0.054	0.001	0.050	0.001
Divorced	0.042	0.001	0.042	0.000	0.149	0.003	0.138	0.003
Widowed	0.004	0.005	0.004	0.003	0.020	0.002	0.014	0.004
Never Married/ Single	0.134	0.002	0.172	0.005	0.073	0.002	0.109	0.002
Number of own children in the HH	2.167	0.020	2.099	0.015	2.031	0.015	2.057	0.011
Family size	4.378	0.027	4.384	0.021	4.044	0.022	4.101	0.015
Household income	59892.21	1001.18	101239.70	1522.86	66109.12	958.93	95106.27	1161.84
Observations	3050		5262		3872		7100	

Notes: Author’s own calculation by using March CPS data from 1994-2020

Table A4.B: Summary Statistics of Employed Mothers in Other Control States Other States (Except California, New Jersey, and Rhode Island)

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
<u>Dependent Variables:</u>								
Employment Rate	0.952	0.001	0.946	0.001	0.961	0.001	0.957	0.007
<u>Independent Variables:</u>								
<u>Education:</u>								
less than HS education	0.075	0.000	0.063	0.000	0.081	0.003	0.066	0.002
HS graduate	0.283	0.001	0.206	0.001	0.360	0.000	0.263	0.001
Some college education	0.324	0.000	0.302	0.001	0.322	0.005	0.329	0.001
Bachelor's degree and above	0.317	0.001	0.429	0.002	0.236	0.007	0.342	0.002
<u>Age:</u>								
24-30	0.429	0.001	0.382	0.001	0.024	0.001	0.022	0.000
31-35	0.326	0.003	0.327	0.002	0.132	0.009	0.112	0.005
36-40	0.184	0.001	0.208	0.002	0.302	0.001	0.244	0.003
41-45	0.053	0.005	0.070	0.003	0.347	0.001	0.346	0.001
46-50	0.008	0.001	0.013	0.000	0.194	0.001	0.276	0.000
<u>Race:</u>								
White	0.842	0.001	0.816	0.003	0.849	0.004	0.827	0.004
Black	0.113	0.003	0.118	0.002	0.111	0.001	0.116	0.002
Others	0.044	0.005	0.066	0.000	0.040	0.003	0.056	0.010
<u>Marital Status:</u>								
Married	0.788	0.001	0.742	0.001	0.725	0.005	0.699	0.001
Separated	0.032	0.000	0.030	0.000	0.036	0.001	0.035	0.001
Divorced	0.063	0.002	0.056	0.002	0.163	0.003	0.157	0.003
Widowed	0.004	0.000	0.004	0.000	0.015	0.000	0.013	0.000
Never Married/ Single	0.113	0.001	0.168	0.000	0.061	0.005	0.096	0.005
Number of own children in the HH	2.070	0.006	2.082	0.005	1.951	0.004	1.967	0.003
Family size	4.062	0.007	4.090	0.006	3.812	0.005	3.848	0.004
Household income	58934.59	318.85	119338.90	14401.90	64151.35	264.63	107136.60	10647.16
Observations	27964		49102		42851		67751	

Notes: Author’s own calculation by using March CPS data from 1994-2020

Table A5.A: Summary Statistics of Unemployed Mothers in California

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Dependent Variables:								
Unemployment Duration	18.808	1.459	25.456	1.397	19.697	1.552	29.028	1.346
Independent Variables:								
Education:								
less than HS education	0.442	0.005	0.329	0.004	0.389	0.006	0.354	0.004
HS graduate	0.253	0.005	0.219	0.004	0.287	0.005	0.284	0.005
Some college education	0.221	0.004	0.287	0.003	0.234	0.005	0.234	0.004
Bachelor's degree and above	0.083	0.004	0.165	0.003	0.090	0.005	0.129	0.003
Age:								
24-30	0.467	0.005	0.427	0.003	0.029	0.002	0.037	0.002
31-35	0.301	0.004	0.282	0.003	0.148	0.004	0.133	0.003
36-40	0.185	0.005	0.181	0.003	0.344	0.004	0.247	0.004
41-45	0.047	0.002	0.083	0.002	0.316	0.005	0.301	0.003
46-50	0.001	0.000	0.027	0.002	0.164	0.005	0.282	0.004
Race:								
White	0.812	0.006	0.770	0.003	0.807	0.007	0.817	0.002
Black	0.091	0.003	0.117	0.003	0.086	0.004	0.052	0.002
Others	0.098	0.005	0.113	0.003	0.106	0.005	0.131	0.002
Marital Status:								
Married	0.583	0.006	0.612	0.004	0.574	0.006	0.614	0.005
Separated	0.109	0.002	0.045	0.002	0.066	0.004	0.072	0.002
Divorced	0.040	0.002	0.061	0.002	0.176	0.004	0.146	0.004
Widowed	0.014	0.002	0.005	0.001	0.029	0.002	0.029	0.001
Never Married/ Single	0.254	0.005	0.278	0.004	0.156	0.006	0.140	0.003
Number of own children in the HH	2.696	0.089	2.427	0.061	2.102	0.062	2.120	0.048
Family size	4.743	0.105	4.713	0.084	4.193	0.012	4.260	0.070
Household income	28258.91	1811.62	53082.14	3185.91	38365.26	3064.07	54593.22	2790.56
Observations	276		443		244		458	

Notes: Author's own calculation by using March CPS data from 1994-2020

Table A6.B: Summary Statistics of Unemployed Mothers in Other Control States (Except California, New Jersey, Rhode Island)								
	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Dependent Variables:								
Unemployment Duration	14.871	0.497	22.966	0.525	16.195	0.506	24.501	0.503
Independent Variables:								
Education:								
less than HS education	0.212	0.001	0.172	0.001	0.199	0.001	0.162	0.001
HS graduate	0.381	0.002	0.336	0.002	0.424	0.001	0.345	0.001
Some college education	0.274	0.001	0.318	0.002	0.276	0.005	0.332	0.005
Bachelor's degree and above	0.133	0.002	0.174	0.004	0.100	0.000	0.162	0.000
Age:								
24-30	0.562	0.001	0.561	0.003	0.051	0.004	0.038	0.002
31-35	0.242	0.005	0.243	0.001	0.217	0.001	0.180	0.001
36-40	0.141	0.001	0.134	0.006	0.322	0.001	0.274	0.005
41-45	0.048	0.001	0.047	0.002	0.169	0.001	0.292	0.003
46-50	0.006	0.001	0.016	0.002	0.141	0.001	0.216	0.002
Race:								
White	0.662	0.001	0.660	0.001	0.722	0.001	0.728	0.001
Black	0.256	0.001	0.262	0.001	0.222	0.001	0.217	0.001
Others	0.082	0.008	0.078	0.004	0.056	0.003	0.055	0.003
Marital Status:								
Married	0.559	0.002	0.468	0.001	0.523	0.001	0.503	0.005
Separated	0.059	0.001	0.060	0.004	0.073	0.001	0.067	0.002
Divorced	0.101	0.004	0.092	0.004	0.210	0.001	0.197	0.005
Widowed	0.005	0.001	0.003	0.002	0.027	0.003	0.024	0.002
Never Married/ Single	0.275	0.001	0.378	0.000	0.166	0.001	0.209	0.001
Number of own children in the HH	2.311	0.033	2.264	0.023	1.908	0.023	1.981	0.017
Family size	4.256	0.041	4.216	0.029	3.689	0.031	3.785	0.022
Household income	32786.87	1023.68	154792.20	113198	37771.89	1119.87	50751.68	1147.22
Observations	1330		2650		1635		2898	

Notes: Author’s own calculation by using March CPS data from 1994-2020

Table A7.A: Summary Statistics of Earnings of Mothers in California

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
Dependent Variables:	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Log Earnings	9.770	0.021	9.967	0.016	9.880	0.017	9.957	0.012
Independent Variables:								
Education:								
less than HS education	0.187	0.001	0.109	0.004	0.187	0.000	0.167	0.000
HS graduate	0.233	0.001	0.202	0.000	0.252	0.000	0.219	0.000
Some college education	0.306	0.005	0.283	0.004	0.336	0.000	0.310	0.000
Bachelor's degree and above	0.273	0.001	0.406	0.001	0.225	0.000	0.304	0.001
Age:								
24-30	0.383	0.003	0.321	0.003	0.021	0.000	0.026	0.000
31-35	0.318	0.005	0.311	0.004	0.119	0.000	0.101	0.000
36-40	0.207	0.005	0.259	0.004	0.284	0.000	0.234	0.000
41-45	0.081	0.004	0.090	0.002	0.358	0.000	0.343	0.000
46-50	0.011	0.001	0.019	0.004	0.218	0.001	0.296	0.000
Race:								
White	0.795	0.001	0.748	0.001	0.796	0.004	0.771	0.000
Black	0.055	0.002	0.054	0.004	0.070	0.002	0.056	0.001
Others	0.151	0.001	0.197	0.001	0.134	0.003	0.173	0.004
Marital Status:								
Married	0.786	0.004	0.756	0.004	0.702	0.004	0.689	0.004
Separated	0.039	0.004	0.032	0.002	0.055	0.000	0.049	0.000
Divorced	0.045	0.002	0.040	0.001	0.152	0.000	0.135	0.003
Widowed	0.003	0.006	0.004	0.005	0.020	0.000	0.013	0.000
Never Married/ Single	0.127	0.000	0.168	0.000	0.071	0.003	0.114	0.002
Number of own children in the HH	2.096	0.021	2.053	0.016	2.019	0.016	2.049	0.011
Family size	4.319	0.029	4.348	0.022	4.033	0.024	4.096	0.017
Household income	62757.41	1100.93	106367.80	1694.88	66611.62	960.92	96283.01	1218.82
Observations	2416		4276		3220		5872	

Notes: Author’s own calculation by using March CPS data from 1994-2020

Table A8.B: Summary Statistics of Earnings of Mothers in Other Control States (Except California, New Jersey, Rhode Island)

	Mothers with the youngest child 1 to 3 years				Mothers with the youngest child 10 to 15 years			
	Pre		Post		Pre		Post	
Dependent Variables:	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Log Earnings	9.674	0.007	9.865	0.005	9.815	0.005	9.958	0.004
Independent Variables:								
Education:								
less than HS education	0.068	0.000	0.054	0.001	0.077	0.003	0.062	0.000
HS graduate	0.282	0.001	0.199	0.001	0.357	0.001	0.259	0.001
Some college education	0.323	0.007	0.298	0.006	0.327	0.006	0.328	0.008
Bachelor's degree and above	0.327	0.002	0.448	0.002	0.242	0.007	0.351	0.002
Age:								
24-30	0.435	0.001	0.379	0.002	0.024	0.001	0.022	0.001
31-35	0.327	0.000	0.332	0.000	0.132	0.001	0.112	0.000
36-40	0.180	0.000	0.208	0.001	0.302	0.001	0.246	0.000
41-45	0.050	0.001	0.069	0.000	0.348	0.000	0.347	0.000
46-50	0.008	0.002	0.013	0.001	0.194	0.002	0.274	0.005
Race:								
White	0.843	0.006	0.818	0.004	0.849	0.001	0.826	0.011
Black	0.114	0.000	0.115	0.001	0.112	0.000	0.117	0.000
Others	0.042	0.006	0.066	0.003	0.039	0.001	0.055	0.000
Marital Status:								
Married	0.786	0.001	0.749	0.001	0.722	0.000	0.699	0.000
Separated	0.033	0.002	0.029	0.001	0.036	0.001	0.034	0.002
Divorced	0.064	0.003	0.056	0.002	0.168	0.000	0.158	0.002
Widowed	0.004	0.000	0.004	0.000	0.014	0.000	0.013	0.001
Never Married/ Single	0.113	0.000	0.163	0.000	0.060	0.001	0.095	0.001
Number of own children in the HH	2.012	0.007	2.035	0.005	1.944	0.004	1.956	0.003
Family size	4.002	0.008	4.0449	0.006	3.805	0.005	3.836	0.004
Household income	60176.40	340.70	121163.90	15435.32	64725.50	273.02	110438.60	12276.24
Observations	23439		41487		37344		58755	

Notes: Author’s own calculation by using March CPS data from 1994-2020

Table A9: Synthetic Control States and Weights for Selected States

Labor Force Participation		Employment		Unemployment Duration (Weeks)		Earnings	
States	*Weights*	*States*	*Weights*	*States*	*Weights*	*States*	*Weights*
Arizona	0.549	Alaska	0.346	Alaska	0.547	Alaska	0.113
Idaho	0.046	District of Columbia	0.184	Florida	0.231	Arizona	0.027
New Mexico	0.287	Maryland	0.155	Illinois	0.087	Connecticut	0.075
Texas	0.039	Missouri	0.158	Ohio	0.088	District of Columbia	0.270
Utah	0.079	West Virginia	0.157	Oklahoma	0.046	Indiana	0.154
						Maine	0.046
						Michigan	0.027
						Minnesota	0.023
						Nevada	0.046
						New Hampshire	0.219

Notes: Author's own calculation by using March CPS data from 1994-2020. To select appropriate control states, I considered each dependent variable individually.