# The Family and Medical Leave Act of 1993: Impact on Female Employment and Income

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Abstract

The enactment of the Family and Medical Family Leave of 1993 (FMLA), along with variations in state policies prior to its passing and differences in eligibility requirements, all allow for the study of the FMLA as a "natural experiment" with "as-if" random effects on labor market outcomes. In this essay, I argue why such a claim holds given the strength of similar legislation in some states relative to others prior to 1993, as well as political preferences that reflect each state's propensity to support maternity leave benefits prior to 1993. Using the Survey of Income and Program Participation (SIPP) between 1990 and 2013, I estimate the effects of the FMLA on female employment and wages of a nationally representative sample, as well as in select industries, and by occupation types. Using Difference-in-Difference (DD) and Difference-in-Difference-in-Difference (DDD) estimation models, I find that the enactment of the FMLA in 1993 disrupted a trend of growing employment rates and income levels. Moreover, I find that the FMLA had a small, negative and statistically significant effect on female employment, wages and earnings. I also find that the FMLA had a disproportionate impact on different industries and occupations.

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## 1. Introduction:

The purpose of this essay is to evaluate the effects of women-friendly policies in the workplace on female employment and wages. I define women-friendly policies as mandates that require employers to provide benefits to women in order to aid them with balancing work and family requirements. Such benefits generally include job-protected unpaid or paid leave for medical and family reasons. For working women, a need may arise to take leave from work in the case of (i) medical reasons such as disability from a pregnancy, childbirth, illness or (ii) family reasons such as an adoption of a child or illness of a family member. Some benefits are more generous than others, and include paid leave or a flexible use of the policy to care for an ageing parent.

Compared with other highly industrialized countries, the United States has one of the least generous leave policies for women of childbearing age. Until 1993, there was no federal law that required employers to provide job-protected maternity leave. Only eleven states had some laws in place to accommodate women who intended to give birth or spend some time at home after a child is born or adopted[1]. The Family and Medical Leave Act (FMLA) of 1993 was the first federal policy to require some employers to provide maternity leave to eligible women[2]. Since then, some states have gone beyond the federal Law to provide additional benefits for women in the workplace, such as a paid parental leave policy in California, the only one of its kind in the US. Variations in state policies before and after the FMLA, in addition to variations in eligibility requirements under the FMLA, as well as documented coverage and usage of the law in hindsight, all provide us with an opportunity to study

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[1] See Table A2 in Appendix A for a full description of the mandates in each of the 11 states, and how they compare to the federal law.

[2] More details on the specific eligibility requirements are presented in Section 5.1.1

differences in labor market outcomes as if the FMLA were a "natural experiment" that led to "as-if" random effects.

Many in the literature have previously utilized the FMLA as a testing mechanism for the effect of maternity leave on female employment and wages. This paper contributes to the extensive literature in three main ways. First, unlike most papers, this essay provides a more elaborate argument on why the FMLA can be considered a "natural experiment," whose effects are exogenous to some states' labor market production structures. This is formalized by the use of a unique instrumental variable, which takes into account each state's acceptance of the federal legislature given each state's political preferences. Second, this essay provides multiple data sources that span a longer time period (1990-2013) than most papers. Finally, this essay isolates the effects of the FMLA on employment and wages in select industries and types of occupations.

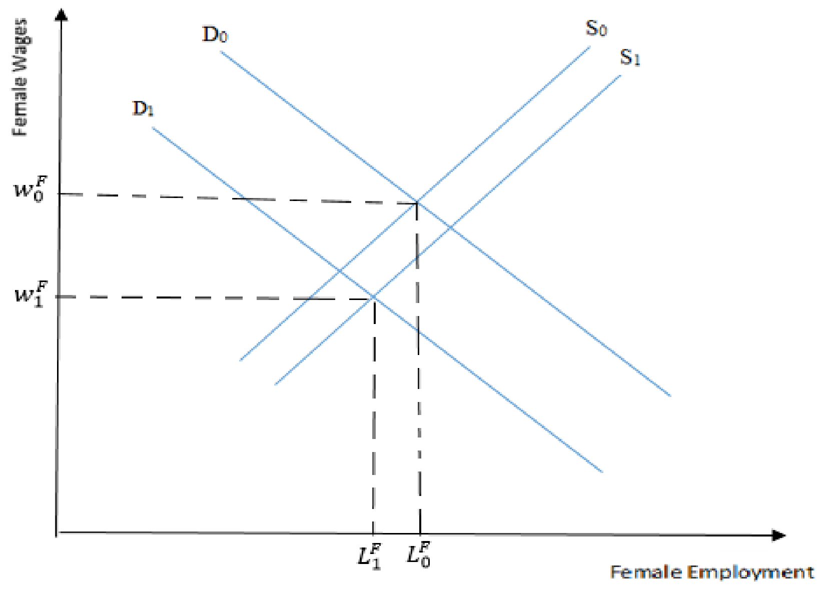
The essay is organized as follows. In section 2, I review the existing theory concerning the effects of mandated benefits on labor markets. In section 3, I review the empirical literature on the effect of such benefits in and outside the United States, covering previous papers that have identified the enactment of the FMLA as a "natural experiment". In section 4, I present the research design of this paper, including an overview of the FMLA and its coverage, and an extensive argument for why its enactment could be considered as a "natural experiment." In section 5, I describe data sources, data constructions and imputations, as well as descriptive statistics of select demographic groups. I present two econometrics models in section 6. I present empirical results in section 7, and conclude in section 8. Appendix A contains information on the history of maternity leave legislation in the US and eligibility requirements for the FMLA. Appendix B contains further details on data sources, constructions and imputations. Appendix C contains full table results for all specifications.

**2. Theory:**

Before discussing the effects of mandated benefits, such as parental leave, on labor market outcomes, it is worth discussing why the need for a mandated benefit arises in the market place. In a competitive labor market, if employees value such a benefit, they will negotiate with their employers over the terms of their compensation package until they reach a mutually desirable outcome. Summers (1989) outlines a few arguments for why this negotiation does not occur between employers and employees. Firstly, the “merit good” argument specifies that individuals tend to underestimate the probability that certain events might occur, such as a serious medical condition or a child’s illness that would require a sustained leave. Secondly, there may be positive externalities associated with such benefits that neither employers nor employees can grasp, such as the externality of a healthy employee on the health of her community. Thirdly, in the event of adverse selection, if employees have disproportionate information about whether they will need a certain benefit, they will flock to employers who voluntarily provide such benefits, which increases the cost of hiring them. These arguments suggest that it may be optimal for the government to intervene in the provision of these benefits.

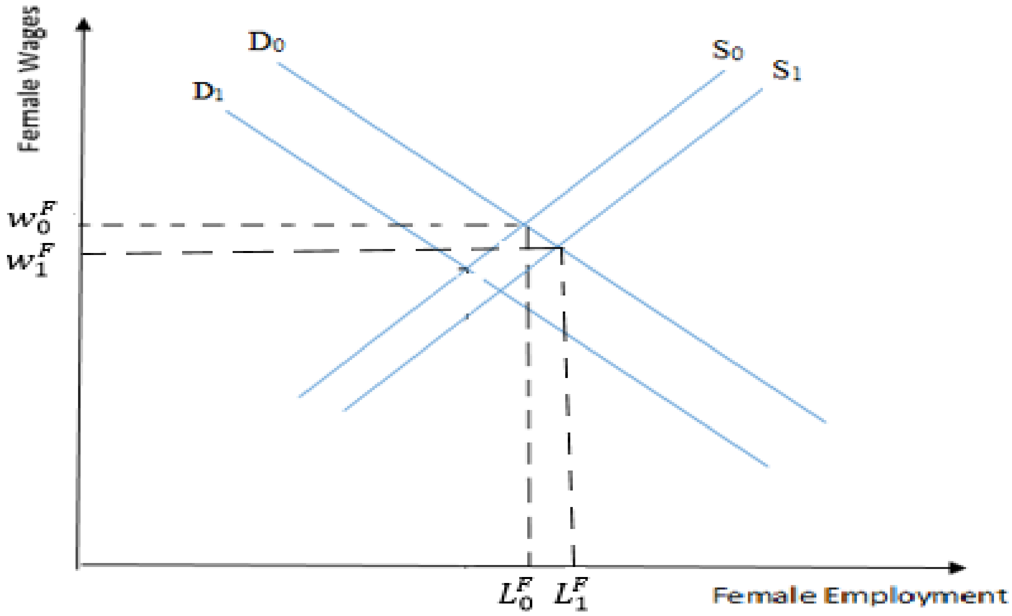
Assuming free and competitive labor markets, a mandated benefit acts as a public program financed by benefit taxes to the employer (Summers, 1989). As such, a mandated leave raises labor costs and shifts the labor demand curve to the left because maternity benefits act as a tax on the employment of women, given that they are paid for by the firms. Therefore, the demand for the labor of female workers shifts to the left by the expected value of the benefit for any quantity of labor (Rhum, 2007 and Zveglich et al., 2003). While they introduce an additional cost to employers, mandated benefits become neutral if employers can reduce the deadweight loss from their enactment by passing the increased cost to their employees through decreased wages (Summers, 1989). Receiving the leave benefits induces women employees to accept a lower wage for a given quantity of labor supplied (Summers, 1989), thus shifting their supply curve simultaneously to the right. The new equilibrium wage is thus lower, while the effect on employment is ambiguous. Figure 1 represents the case of a maternity leave policy, and depicts the effect of a mandated benefit on market forces, illustrating the case when female employment increases as female labor supply increases, but is met with a larger fall in female labor demand.

**Figure 1. Labor Market Pre- and Post- the Mandated Benefit (Scenario 1)**



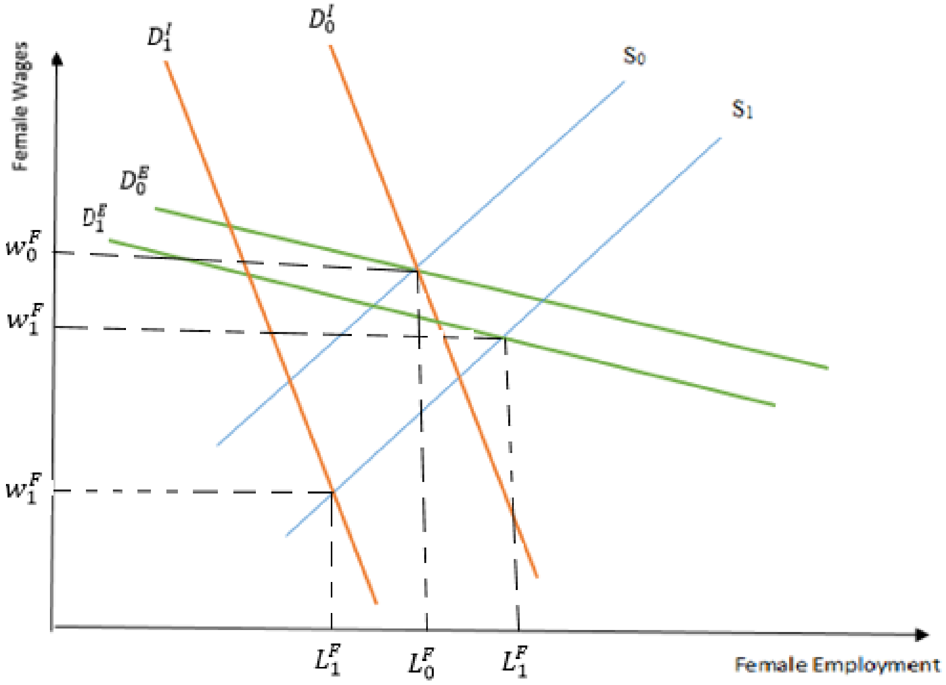

Rhum (1997) argues that there may be additional dynamic effects of the benefit, such as an increase in labor productivity if the leave permits mothers to return to their former occupations, as opposed to looking for a new job and starting at the bottom of the career ladder. This increased labor productivity either shifts the demand curve to the right or reduces the extent of the inward shift due to the mandated benefit, effectively increasing employment and decreasing the wage reduction or actually leading to a rise in earnings. Figure 2 below depicts this scenario.

**Figure 2. Labor Market Pre- and Post- the Mandated Benefit (Scenario 2)**




In free and competitive markets, another factor that may impact the extent of changes in female employment and wages as a result of maternity leave, is the elasticity of labor demand with respect to wages. The demand for female labor is (in)elastic when changes in wages induce a (less) more than proportionate change in employment levels. Female labor demand might be elastic if female workers are easily substituted for by male workers or if female labor costs constitute a high fraction of total costs for an employer. For instance, in occupations that are thought to be dominated by women, such as school teachers or nurses, the demand for female labor could be inelastic. Figure 3 represents the effects of maternity leave on labor demand with different elasticity. Assuming an increase in female labor supply due to the benefit, a fall in inelastic labor demand induces lower wages and a fall in female employment. A fall in elastic labor demand, with the same magnitude, induces lower wages but an increase in female employment.

**Figure 3. The Effects of a Mandated Benefit and Elasticity of Labor Demand**




Demand and supply forces do not freely shit to determine wages and employment levels in the event of market failures within labor markets, especially in the case of wage rigidities. The first example of market failure arises when there is a minimum wage in the market, such that wages cannot fall below that certain level (Summers, 1989). The new female labor market equilibrium will be at the intersection of the demand curve with the wage constraint, inducing the equilibrium quantity of labor to decline, and thus resulting in unemployment for women (Summers 1989, Zveglich et al. 2003). The second market failure emanating from mandated benefits arises when the policy is a “group-specific mandate”, disproportionately benefiting a demographically identifiable group, such as women of childbearing age in this case (Gruber, 1994; Jolls 2000, 2006). Even when restrictions on differential wages and employment are binding, as is the case because of the Employment

Non Discrimination Act in the US, Gruber (1994) finds substantial shifting of the costs of these mandates to the wages of the targeted groups, relative to the non-targeted groups.

Maternity leave benefits have an additional effect on women's future wages, in that they allow women to maintain their current jobs and give them the opportunity to earn higher wages because of the human capital they can accumulate within one firm over the long term (Spalter-Roth and Hartmann, 1990; Klerman and Leibowitz, 1999). Baum (2003) argues that maternity leave will increase wages by improving return-to-work decisions, unless there are market failures that hinder the process, such as asymmetric information and adverse selection. With asymmetric information, the employer cannot distinguish between women who will return to work after their leave and those who will not, and thus may hire another worker to the women's position permanently, and relay the women to a lower-paying position if she come back. With adverse selection, employers who offer maternity leave benefits disproportionately attract "high-risk" employees: those who are more likely to use maternity leave. To reduce the risk due to adverse selection, these employers reduce their maternity leave provisions below optimal levels (Baum, 2003; Thomas, 2015).

The theory thus predicts that the effect of maternity leave on women's employment and wages are ambiguous. On one hand, employment might decrease because the cost of the provision significantly decreases labor demand, inducing women to bear the cost associated with the benefit through lower wages. On the other hand, maternity leave benefits might facilitate and expedite return-to-work decisions of women in the absence of certain market failures, effectively increasing their labor supply and thus offsetting the downward demand pressures on employment and wage levels. Thus, ultimately, the impact of the policy on female labor market outcome is an empirical question.

## 3. Literature Review:

A broad body of literature has explored the effect of maternity leave policies on employment and wages of women across the world. One can distinguish between two aspects of such literature, those that consider the short-term effects of the legislation, and those that consider its long-term effects.

There is a general consensus in the literature that maternal leave policies increase female labor participation after childbirth, effectively shifting the female supply curve upwards. For instance, Guy Dalto (1989) finds correlation between maternity leave policies and women's return-to-work decisions. He reports that women who are currently in jobs protected by maternity leave benefits spend 1.8 years out of the labor force, compared with 5.3 years for women who lack maternity leave benefits. Spalter-Roth and Hartmann (1990) report that new mothers who had no leave were in significantly worse economic conditions than those who had access to leave. Those new mothers who had no maternal leave had a wage loss of an additional 76 cents per hour in the birth year (compared with the pre-birth year), followed by smaller additional losses in subsequent years. Women without leave also experienced even more unemployment and more hours out of the labor force. Ruhm (1998) uses variations in parental leave taking between men and women across 16 European countries and finds a positive correlation between maternal leave and total employment but a more modest effect on weekly work hours. Moreover, he finds limited evidence that maternal benefits might have depressed women's relative wages. Higuchi, Abe and Waldfogel (1999) find that family leave coverage increases the likelihood that a woman will return to her employer after childbirth in Japan, Britain and the United States, suggesting that the recent expansions in family leave coverage in the sample countries are likely to lead to increased employment of women after childbirth. Klerman and Leibowitz (1998) use data from the

1980 and 1990 censuses and find some evidence that maternity leave statuses increased leave, but had significant positive effects on employment and work.

While differential effects on employment of leave-takers may be exaggerated by biases in the data, because women who have access to maternity leaves might have had higher wages prior to giving birth or might have worked for larger employers who paid them higher wages, Walfogel (1994, 1998) stresses that the main reason why maternity leave may raise women's pay is that it increases return-to-work decisions for women. She finds statistically significant evidence from the National Longitudinal Survey of Youth (NLSY) that "67 percent of those who had formal maternity leave coverage returned to their employer after their most recent birth, as compared to only 47 percent of those lacking such coverage, and this difference was strongly significant even after controlling for preexisting differences among these women." Maternity leave, she argues, raises the likelihood that women stay with the same employer, thus raising their future earnings. Similarly, Ruhm (1998) finds positive correlation with paid parental leave in nine European countries and increases in women's employment, although extended leave periods might lead to reductions in women's wages. On the other hand, Gruber (1994) is among the few in the literature to find little correlation between female benefits and women's employment. He finds that the cost associated with a policy mandating the inclusion of pregnancy coverage in employer-provided health insurance plans is shifted to the targeted group, as predicted by the theory.

While some papers focus on the short-term effects of maternity benefits, others explore its long-term effects. For instance, Mukhopadhyay (2012) studies the impact of the Pregnancy Discrimination Act (PDA) of 1978, a policy mandate that affected the ability of women to remain in the workforce during pregnancy. Through a dynamic model and subsequent simulations of labor supply choices, he finds that the PDA increased the labor force participation rate of pregnant women by 8.2 percentage points. Erosa, Fuster and Restuccia (2010) find that leave takers lose human capital accumulation as a result of their time off the workplace, but this only accounts for a small fraction of the gender wage gap. They further find that leave policies could lead to wage gains for female workers if they encourage subsequent work. Low and Sanchez-Marcos (2013) find that a generous paid parental leave policy has a substantial effect on mothers' employment rate while accounting for a modest impact on the gender wage gap. Lalive and Zweimuller (2009) exploits variations in the duration of paid, job-protected maternity leave policies in Austria to examine the effects of such policies on fertility decisions and post-birth labor market careers. They find that these policies lead to a delay in fertility in the short run, leading to substantial increases in career earnings in years subsequent to childrearing. However, they also note that extended maternal leave significantly reduces return to work, employment and earnings, but in the short run only.

A few in the literature have examined the effect of the Family and Medical Leave Act (FMLA) of 1993 (Waldfogel, 1999; Baum, 2003) and previous or subsequent state policies (Espinola-Arredondo and Mondal, 2010; Slater, Ruhm and Waldfogel, 2013) on women's employment and wages. Using the March Current Population Survey, Waldfogel (1999) finds that while the benefit is associated with increased leave coverage and leave usage post-FMLA, it had no significant effect on women's employment and wages. Using the National Longitudinal Survey of Youth (NLSY), Baum (2003) finds that the FMLA is associated with little effect on employment and wages. He argues that this may be due to the fact that the mandated leave is short and unpaid and many employers provided maternity leave benefits prior to the statutes. Espinola-Arredondo and Mondal (2010) examine whether the FMLA disproportionately affected states that previously implemented maternity leave laws than those states which did not. They further analyze the Paid Family Leave program in California, comparing how the change in female employment and labor force participation differs from those states which have FMLA alone and those which have complemented the benefits of FMLA. Using March CPS, they find a positive and significant effect of FMLA on female employment and, a positive and significant effect on the change in female employment for some of the states that expanded the benefits and eligibility criteria of FMLA. Slater, Ruhm and Waldfogel (2013) also assess the effect of California's Paid Family Leave (PFL) on female employment and wages, and find robust evidence that the California program increased the usual weekly work hours of employed mothers of one-to-three year-old children by 6 to 9% and that their wage incomes may have risen by a similar amount.

While the effect of mandated parental leave policies in the short run are well documented, there is a growing body of research on such effects in the long run. The gender wage gap when workers are young is narrow but widens as workers progress in their careers. Much of this gender wage gap is largely associated with motherhood (Bertrand, Goldin and Katz; 2010). Thomas (2015) examines whether mandated maternity benefits account for the widening gender gap at managerial positions, as they distort employers' incentives to invest in the training of their female workers. She finds that while women hired after the FMLA passed are 5 percent more likely to remain employed, they are 8 percent less likely to be promoted than those hired before the enactment of the FMLA.

## 4. Research Design:

Variations in state policies before and after the Family Medical Leave Act of 1993, in addition to variations around eligibility requirements under the FMLA, provide us with an opportunity to treat the enactment of the FMLA as a "natural experiment" in order to study the effect of maternity leave policies on female employment and wages. In this section, I first present an overview of the law and coverage levels after its enactment. I then provide an identification strategy, and argue why the enactment of the law in 1993 can be considered a "natural experiment," that is, exogenous to the preferences and production structures of some states.

### *4.1. The Family and Medical Leave Act of 1993: An Overview*

The federal Family and Medical Leave Act of 1993 (FMLA) was signed by President Clinton on February 5, 1993. The FMLA was passed after findings of Congress that an increasing number of families were facing tradeoffs between job security and child rearing. The Law specifically states that women would disproportionately benefit from this law because of their roles in child-bearing and child-rearing. The FMLA allows eligible employees to take up to 12 workweeks of unpaid leave during any 12-month period to attend to the serious health condition of the employee, parent, spouse or child, for pregnancy or care of a newborn child, or for adoption or foster care of a child. While being the first of its kind in the US, the FMLA is limited in scope: employees are eligible for FMLA if they have been at the business at least 12 months, and if they worked at least 1,250 hours over the past 12 months, and work at a location where the company employs 50 or more employees within 75 miles. The FMLA covers both public- and private-sector employees (US Department of Labor). Following FMLA leave, employees have the right to return to their previous positions and are entitled to earn the same wages and benefits.

### *4.2. Coverage under the FMLA*

Waldfogel (1999) reports a sharp increase in maternity leave coverage for full-time employees in medium-sized and large establishments in the private sector starting in 1993 and continuing thereafter. The percentage of full-time employees in such establishments whose employers provided maternity leave (whether paid or unpaid) "increased from 39 percent in 1991 to 63 percent in 1993, 86 percent in 1995, and 95 percent in 1997." (Waldfogel, 1999) By 2000, the FMLA covered sixty percent of the nation's private sector workforce, even though only about eleven percent of the nation's employers are covered (Selmi, 2000). Women are more likely than men to take FMLA leave: 58.1% of leave-takers in 2000 were women whereas women constituted only 48.7% of all employees in the surveyed population (Selmi, 2004).

*4.3. Identification Strategy:*

Like others in the literature (Waldfogel, 1999; Baum, 2003; Espinola-Arredondo and Mondal, 2010; Slater, Ruhm and Waldfogel, 2013; Thomas, 2015), I exploit variations in state laws prior the enactment of the Family and Medical Leave Act of 1993 as a "natural experiment" in the US. In order to reduce bias and ensure the natural experiment produces "as-if random" assignments between control and treatment states, I show that the FMLA is an exogenous shock to certain states, that there is little correlation between the federal law and political preferences on the one hand, and between the law and previous market production structures within some states. Specifically, I argue that for states that are more likely to vote for a Republican representative, the law is uncorrelated to those states' political preferences. I show this by presenting a history of the bill in Congress, indicating that Republicans are more likely to oppose and veto the bill. Moreover, I show that for Republican states, market production structures did not call for the enactment of the law. Therefore, the FMLA acted as an exogenous shock to Republican states, which would allow us to consider these states as "treatment" states later in the analysis.

*4.3.1. The Law and Political Preferences*

Prior to the passing of the Family and Medical Leave Act in 1993, several iterations of the bill were introduced to Congress. Table A1 in Appendix A presents a full list of the ancestors of the FMLA, their sponsors and co-sponsors and how they failed to pass in both chambers of Congress. The first four iterations of the law failed to gain ground in Congress, in light of the Republicans' control over the House and the Senate. These bills were all introduced and overwhelmingly co-sponsored by Democrats, and encountered strong resistance from some Republicans and the National Federation of Independent Business (Elving, 1995). The Republicans' propensity to reject the law was even more pronounced in the early 1990s, when the bill passed both chambers of Congress but failed to pass President Bush's veto twice. The history of the ancestors of the FMLA in Congress not only suggests that Democrats were much more likely to co-sponsor such a law, but also that the states that are Democratic-leaning were more likely to co-sponsor the bills through their representatives. For instance, when the bill passed in 1993, 25 of the 155 cosponsors were from California, 18 were from New York and 12 from Illinois, all Democratic states (Congressional Record). The study of FMLA history reveals the propensity of Republicans to reject the bill, thus strengthening the assertion that the enactment of the FMLA did not reflect political preferences in Republican-leaning states, and thus constituted an exogenous shock to those states.

*4.3.2. The Law and Labor Market Production Structures*:

In order to show that the enactment of the law did not emanate from labor market needs in Republican-leaning states, I construct an index (*leg_strength*) that assesses the strength of pre-FMLA legislation in all 50 states, assigning a lower score to a state with no or limited pre-FMLA legislation[3]. I then construct a second index (*party*) that assesses the propensity of a state to vote for a Republican or Democrat, assigning a lower score to a Republican state. I run a rank correlation analysis between *leg_strength* and *party* and find

[3] See Table A2 in Appendix A and Table B1 in Appendix B

that the two are positively correlation; that is, Republican-leaning states are more likely to have no or limited maternity leave legislation. For descriptive purposes, I construct a third index (*female_labor)* that ranks each state based on changes of female labor participation from 1988 to 1993. I run a correlation analysis between a composite of *leg_strength* and *party*, and *female_labor* and find close to 0 correlation between the two; that is, Republican states did not particularly face increased female labor participation during the years leading up to the enactment of the FMLA, a scenario which would entice them to "need", and thus be more likely to pass the FMLA. Therefore, rank correlation analysis strengthens the hypothesis that the FMLA presented exogenous shocks to Republican states.[4]

## 5. Data

The primary source of my data is the Survey of Income and Program Participation (SIPP). However, I use other complementary data sources, including the Bureau of Labor Statistics' labor force participation statistics by year and state; the Business Dynamics Statistics; the Congressional Record from the Library of Congress; and The American Presidency Project at the University of California, Santa Barbara. In this section, I focus mainly on the SIPP, its advantages over similar surveys and its limitations. I then present a description of the main variables used in my research, and present a description of data constructions and imputations.

### *5.1. Overview of SIPP*

The Survey of Income and Program Participation (SIPP) is a nationally representative survey that is administered by the US Census Bureau on a longitudinal basis. SIPP covers the period spanning 1983 to 2013. The design of the survey consists of a continuous series of

[4] Full details on how I construct each index in the Data section and in Appendix B

national panels, which each span 2.5 to 4 years. The sample size for each panel ranges from 14,000 to 52,000 interviewed households. Eligible respondents include all household members, aged 15 years and older. Each panel consists of four rotation groups, each interviewed in a separate month. Four rotations groups constitute a wave. Respondents are asked to recall information of the previous four months at each interview. SIPP information consists of two categories: the core information, and the topical modules (ICPSR; US Census Bureau, web). The core questions cover demographic characteristics, labor force participation, program participation and amounts and types of earned and unearned income received. For the purposes of this research, I only use the core information files from 1990-2013, covering the pre- and post- FMLA period. In 1996, the Census Bureau undertook a major redesign of the survey in order to improve the quality of longitudinal estimates. Specific changes included a larger initial sample than in previous panels, with a target of 37,000 households; a single 4-year panel instead of overlapping 32-month panels; twelve or thirteen waves instead of eight and oversampling of households from areas with high poverty concentrations. (ICPSR; US Census Bureau, web).

There are three panel surveys in the US that can produce nationally representative estimates: The Survey of Income and Program Participation (SIPP), the Current Population Survey (CPS) and the Panel Study of Income Dynamics (PSID). SIPP has many advantages over the CPS and the PSID. While CPS and PSID record data annually, SIPP conducts interviews and collects data every four months, thus reducing potential recall errors. Moreover, the short period between interviews reduces the problem of household composition changes. For longitudinal research purposes, SIPP and PSID have an important advantage over the CPS, because they both follow individuals as the unit of analysis, whereas the CPS follows the household address as the unit of analysis. As a result, CPS longitudinal information is very limited. Furthermore, the SIPP's income questions are more detailed and are asked more frequently than those of the CPS and PSID. Lastly, attrition is less of a problem in SIPP data than in the PSID because panels only last a few years, and because households are followed as units of analysis. Limitations of SIPP include short panels that only started in 1984 and a major re-design in 1996 that led to variable name changes and more pervasive imputations, although the CPS also underwent a major redesign in 1994 (Winship, 2010).

### *5.2. Description of main variables*

The SIPP 1996 survey redesign created several discrepancies between the pre- and post- 1996 data. The table below summarizes the variables used in my final dataset, with names in the pre- and post-1996 and their labels. It is important to note that there are two ways in which income is characterized: "*earnings*" is available for workers who are paid salaries, while "*hrlyWage1*" is only available for workers who are paid by the hour, usually working in low-paying occupations. In order to capture both demographics, I run the regression analysis on both wages and earnings.

**Table 5.2. Description of main variables**

| Pre-1996 | Post-1996 | Renaming | Label |
|---|---|---|---|
| suid | ssuid | suid | Sample Unit Identifier |
| addid | shhadid | hsld_ref | Household address ID - differentiates houeholds in sample unit |
| panel | spanel | panel | Sample code - indicates panel year |
| wave | swave | wave | Wave number |
| year | rhcalyr | year | Calendar year of the reference month |
| rot | srotaton | rot | Rotation group |
| refmth | srefmon | ref_month | Reference month |

| | | | |
|---|---|---|---|
| tfipsst | sustate | state | FIPS State code |
| pnum | eppnum | person_num | Edited person number |
| age | tage | age | Edited and imputed age as of last calendar year |
| sex | esex | sex | Sex of the respondent |
| race | erace | race | Race of the respondent |
| ms | ems | marital_status | Marital Status |
| wesr”n”l | rwkesr”n” | empStatus_wk”n” | Week “n” employment status (n=1,2,3,4,5) |
| higrade | eeducate | educ_level | What is the highest grade or year completed? |
| ws1occ | tjbocc1 | occupation1_code | Edited and imputed 3 digit occupation |
| ws1ind | ejbind1 | industry1_code | Edited and imputed 3 digit industry |
| ws1wks | rwksperm | numWksEmp | Number of weeks employed per month |
| ws1amt | tpmsum1 | earnings1 | What is the amount of earnings from this employment |
| ws12025l | ejbhrs1 | hrs_worked1 | Number of hours worked |
| ws12028l | tpyrate1 | hrlyWage1 | Hourly pay |
| - | tempall1 | firm_size | Number of employees in all locations |

### *5.3. Data Constructions and Imputations*

#### *5.3.1. Data Constructions:*

One of the most crucial variable to my analysis is *state_index*. This is the instrumental variable mentioned in Section 6 as part of the identification strategy. The *state_index* variable is an equally weighted average of two other variables: *leg_strength* and *party*. *leg_strength* records the strength of the legislation in the 11 states (and Washington D.C.) that had maternity leave legislation prior to the passing of the FMLA in 1993.[5]

The *leg_strength* variable takes values 1-5. States with scores of 4 or 5 are those that had maternity leave legislation in place prior to 1993, while states with score 3 are those that did not have maternity leave legislation prior to 1993 but had a good number of representatives in Congress advocating for the bill. States with scores 1 or 2 are those that did not have maternity leave legislation and whose representatives were not particularly enthusiastic about the FMLA and its precedents.

I construct the second variable *party* as an index from 1 to 5 that tracks the political voting history of each state in five presidential elections (from 1976 to 1992). I extract this data from the American Presidency Project at the University of California, Santa Barbara, which presents the electoral and popular vote results from 1789 to the present (Woolley and Peters, web). The lower the score is, the more likely that the state will vote for a Republican presidential candidate. For instance, a state that has voted for a Republican candidate five times is assigned a score of 1, while a state that has voted for a Democratic candidate five times is assigned a score of 5. Swing states are assigned scores 3 or 4. I run a rank correlation analysis between *leg_strength* and *party*, and I find that they are positively correlated, with a coefficient of 0.285. As mentioned in Section 5, this result strengthens the hypothesis that Republican-leaning states are less likely to support maternity leave legislation, and thus the passing of the FMLA constitutes an exogenous shock with “as-if random” effects for Republican states.

[5] The table A2 in Appendix A presents a summary of the legislation in each of these states.

To strengthen this hypothesis, I extract female labor participation levels in each state from 1988 to 1993 from the Bureau of Labor Statistics labor force participation statistics by year and state. I then calculate annual female labor participation rates for each year, and calculate the overall rate change for that time period. I construct the *female_labor* index, allocating a score from 1 to 5 to each state, from the lowest to the highest change in female labor participation rates. I then run a rank correlation analysis between *state_index* and *female_labor*, and find that they are positively correlated, although the coefficient is close to 0. This result suggests that Republican states did not particularly face increased female labor participation during the years leading up to the enactment of the FMLA, a scenario which would entice them to "need", and thus be more likely to pass the FMLA. Table B1 in Appendix B summarizes all four indices. In addition to using *state_index* as a tool to argue that the FMLA is exogenous to Republican states, I will use it as an instrumental variable in the econometrics model.

Further data constructions, related to inconsistencies between the pre-1996 and post-1996 SIPP survey re-design are described in detail in Appendix B.

*5.3.2. Data Imputations:*

One crucial variable that determines eligibility for the FMLA is the size of the firm in the location of the respondent, labeled *firm_size* in my dataset. However, this variable is missing in the pre-1996 SIPP data but exists in the post-1996 SIPP data. I use a multiple imputation technique to randomly generate the firm size variable in the pre-1996 samples: *mi impute mlogit*. This technique fills in missing values of a variable by using the multinomial (polytomous) logistic regression imputation method.[6] I regress the variable firm size in the

[6] "STATA Multiple-Imputation Reference Manual." *StataCorp. 2013. Stata: Release 13. Statistical Software. College Station, TX: StataCorp LP* (2013). Web. <https://www.stata.com/manuals13/mi.pdf>.

post-1996 data on demographic variables (age, gender, race, education level, occupation and industry) and iterate the process 10 times. This method creates 10 firm size variables in the pre-1996 data that reflect regression coefficients of the respondent's characteristics post-1996. I then create an average of the 10 variables. I round the average up to the nearest integer to obtain the final *firm_size* variable.

Another serious shortcoming of the SIPP data with regards to the firm size variable. In the survey, firm size data is collected under three categories: less than 25 employees, 25-99 employees, and more than 100 employees. The problem arises when specifying eligibility for maternity leave legislation. Prior to 1993, firm size eligibility varied widely between states, from 6 to 100 employees. The FMLA similarly mandates a minimum firm size of 50 employees. In order to move past the wide range of eligibility criteria for firm size, I use the closest (upper bound) response from the SIPP data. For instance, if eligibility is at 50 employees, then I use the third response (more than 100 employees), etc.

It is important to note that such data imputations and approximations introduce measurement errors, thus increasing standard errors of the estimates in regressions, and might lead to noisier coefficients.

*5.4. Descriptive Statistics*

The table below provides descriptive statistics for select demographic groups in the SIPP dataset. I define women of childbearing age as those who are aged 15-45 years, mothers are women who have children whose ages are less than 5, older women as those who are aged 45 and older, young men as those who are aged 15-45 years.

**Table 5.4. Descriptive Statistics for years 1990-2013**

| Variables | Treatment Groups | | Control Groups | | | All |
|---|---|---|---|---|---|---|
| | Women of childbearing age | Mothers | Older Women | Young Men | All Men | |
| **% employed (=1 if employed)** | 0.667 (0.471) | 0.607 (0.488) | 0.425 (0.494) | 0.776 (0.417) | 0.518 (0.499) | 0.474 (0.499) |
| **Wages** | 9.674 (5.361) | 9.946 (5.557) | 11.801 (6.281) | 12.179 (6.377) | 12.211 (6.438) | 11.243 (6.168) |
| **Earnings** | 1964 (1888) | 1992 (1968) | 2473 (2338) | 3156 (3235) | 3151 (3278) | 2658 (2801) |
| **Eligibility for maternity leave before FMLA[7]** | 0.1691 (0.375) | 0.1807 (0.385) | 0.1896 (0.3916) | 0.1757 (0.3806) | 0.1854 (0.389) | 0.1845 (0.387) |
| **Eligibility for maternity leave after FMLA[8]** | 0.479 (0.499) | 0.515 (0.499) | 0.605 (0.489) | 0.485 (0.499) | 0.562 (0.496) | 0.568 (0.495) |
| **Black Dummy Variable** | 0.138 (0.345) | 0.157 (0.366) | 0.118 (0.323) | 0.109 (0.3116) | 0.117 (0.321) | 0.126 (0.332) |
| **Hispanic Dummy Variable** | 0.024 (0.153) | 0.0256 (0.158) | 0.019 (0.137) | 0.0226 (0.148) | 0.0212 (0.144) | 0.022 (0.146) |
| **Age (in years)** | 30.44 (8.401) | 30.21 (7.501) | 62.29 (0.0057) | 29.62 (18.15) | 43.09 (18.147) | 35.88 (22.54) |
| **Work experience (weeks per month)** | 2.69 (2.12) | 2.27 (2.18) | 1.42 (2.05) | 3.00 (2.02) | 1.93 (2.17) | 1.79 (2.15) |
| **Number of obs.** | 4,565,889 | 2,050,837 | 4,098,363 | 5,877,023 | 7,974,491 | 21,801,879 |

## 6. Estimation Methodology

The purpose of this paper is to show whether the FMLA affected employment and wages in states with no prior maternity leave legislation more significantly than it did for states that already had similar legislation. I do so by using two estimation methods: Difference-in-Difference (DD) and Difference-in-Difference-in-Difference (DDD).

[7] Respondents were eligible for maternity leave before the FMLA if they lived in states that had similar provisions, or if their employers voluntarily provided maternity leave

[8] Respondents were eligible for maternity leave after the FMLA if their employers had at least 50 employees

*6.1. Difference-in-Difference Model*

In order to identify the effects of the FMLA on labor market outcomes such as employment, wages and earnings, I first use a difference-in-difference methodology. Outcomes are observed for two groups (control and treatment) for two time periods (pre- and post- FMLA legislation). One of the groups - the treatment group- is exposed to a treatment in the second period (post-FMLA) but not in the first period (pre-FMLA). The second group - the control group- is not exposed to the treatment during either period. The benefit of this method is that the average gain in the control group is subtracted from the average gain in the treatment group. This removes biases in post-FMLA comparisons between the treatment and control groups that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends.

In this case, the treatment group includes women of childbearing age (between 15 and 45 years old) and women who have children (less than 5 years old) who were eligible for maternity leave legislation post-1993 given the size of the firms they worked for. The control group includes men and older women. The specification is as follows:

$$Y_{ijt} = \alpha_1 + \alpha_i + \alpha_j + \alpha_t + \alpha_2 X_{it} + \alpha_3 FMLA_t + \alpha_4\, treatment_{it} + \alpha_5 (FMLA_t \times treatment_{it}) + \varepsilon_{ijt}$$

$Y_{ijt}$ is the observed outcome (employment, wages or earnings) for an individual $i$ who lives in state $j$ at year $t$, $X_{it}$ is a vector of demographic variables used as controls (age, race, education level, etc). The dummy variable for the legislation is *FMLA*, and takes value 0 during pre-1993 years and 1 during post-1993 years. The FMLA dummy captures aggregate factors that would cause changes in the outcome $Y$ even in the absence of a policy change. The dummy variable *treatment* takes value 1 if the person belongs to the treatment group, and

0 otherwise. The *treatment* variable captures aggregate factors that would cause changes in *Y* between the treatment and control groups prior to the policy change. $\varepsilon_{ijt}$ is the error term.

Given this specification, the coefficient $\alpha_i$ captures individual fixed effects, $\alpha_j$ captures state fixed effects and $\alpha_t$ captures year fixed effects. The coefficient $\alpha_3$ measures year-specific effects that are correlated with the FMLA legislation, $\alpha_4$ measures state-specific, year-specific effects that affect the treatment group. The coefficient of interest, $\alpha_5$, captures the effect of the interaction term, *(FMLA x treatment)*, which is the same as a dummy variable equal to one for those observations in the treatment group in the second period. The difference-in-difference (DD) estimator thus captures differences between eligible women and the rest of the population between pre-1993 and post-1993.

*6.2. Difference-in-Difference-in-Difference Model*

Given the specification above, the DD estimator needs further refinement, because it does not take into account variations in the legislation between states, nor does it take into account the underlying political preferences that might make the FMLA endogenous to some states' preferences. Moreover, the accuracy of the DD estimator depends on the important assumption that all regressors are uncorrelated with the error term. While I control for numerous variables, it is still possible that other factors unrelated to the federal policy might affect the labor outcomes of young women with children relative to men and older women, for instance, omitted factors that cause changes in political preferences affecting labor market production structures. To solve this double problem and eliminate such a bias, I introduce *treat_state*, an instrumental dummy variable that takes value 0 if *state_index* = {1, 1.5, 2, 2.5} and 1 if *state_index* = {3, 3.5, 4, 4.5, 5}. Recall that *state_index* is an index that measures both the strength of maternity leave legislation in a given state prior to 1993, as well as political preferences (voting history) for each state. As such, I consider Republican-leaning states with little maternity leave legislation treatment states (*treat_state* = 1) and Democratic-leaning states with strong legislation (*treat_state* = 0) control states. This variable allows for a third dimension in the analysis: variations across treatment and control states between treatment and control groups before and after 1993. I then use a difference-in-difference-in-difference estimate with the following multivariate regression model:

$$Y_{ijt} = \alpha_1 + \alpha_i + \alpha_j + \alpha_t + \alpha_2 X_{it} + \alpha_3 \text{ FMLA}_t + \alpha_4 \text{ treatment}_{it} + \alpha_5 \text{ treat\_state}_j + \alpha_6 (\text{FMLA}_t \text{ x treatment}_{it}) + \alpha_7 (\text{FMLA}_t \text{ x treat\_state}_j) + \alpha_8 (\text{treatment}_{it} \text{ x treat\_state}_j) + \alpha_9 (\text{FMLA}_t \text{ x treatment}_{it} \text{ x treat\_state}_j) + \varepsilon_{ijt}$$

Given this specification, the coefficient $\alpha_i$ captures individual fixed effects, $\alpha_j$ captures state fixed effects and $\alpha_t$ captures year fixed effects. The coefficient $\alpha_2$ measures the effect of control variables, $\alpha_3$ measures year-specific effects that are correlated with the FMLA legislation, $\alpha_4$ is the effect of changes specific to the treatment group, $\alpha_5$ measures the effects of changes in treatment states relative to control states, $\alpha_6$ is the difference-in-difference estimator between young women and the rest of the population pre- and post- FMLA, $\alpha_7$ measures the differences in trends between states pre- and post- FMLA, $\alpha_8$ is the difference-in-difference estimator between young women and the rest of the population across control and treatment states. The coefficient of interest, $\alpha_9$, captures the difference-in-difference-in-difference between young women and the rest of the population within control and treatment states between the pre- and post- FMLA period.

## 7. Results and Discussion

### *7.1. Difference-in-Difference Model*

I first estimate the effects of the FMLA on employment, the level of wages and earnings. The results (with select regressors) are shown in Table 7.1. below.[9]

The results below suggest that the DD model predicts that the FMLA had a negative and statistically significant effect on employment rates, with a coefficient of -0.092. Given the specification, the result can be interpreted such that women of childbearing age and women with children (the treatment group) benefited from 9.2% less employment after the FMLA was passed, relative to men and older women. With regards to wages, the results above suggest that the FMLA had a negative and statistically significant effect on wages: that is, women of childbearing age and women with children (the treatment group) lost 5.9% of their wages relative to older women and men after the FMLA. With regards to earnings, the passing of the FMLA is associated with strong negative and statistically significant effects between the treatment and control groups.[10]

[9] Full tables with state and year fixed effects can be found in Appendix C
[10] Full tables with state and year fixed effects can be found in Appendix C

**Table 7.1. Results of Difference-in-Difference Model with Fixed Effects (for select regressors)**

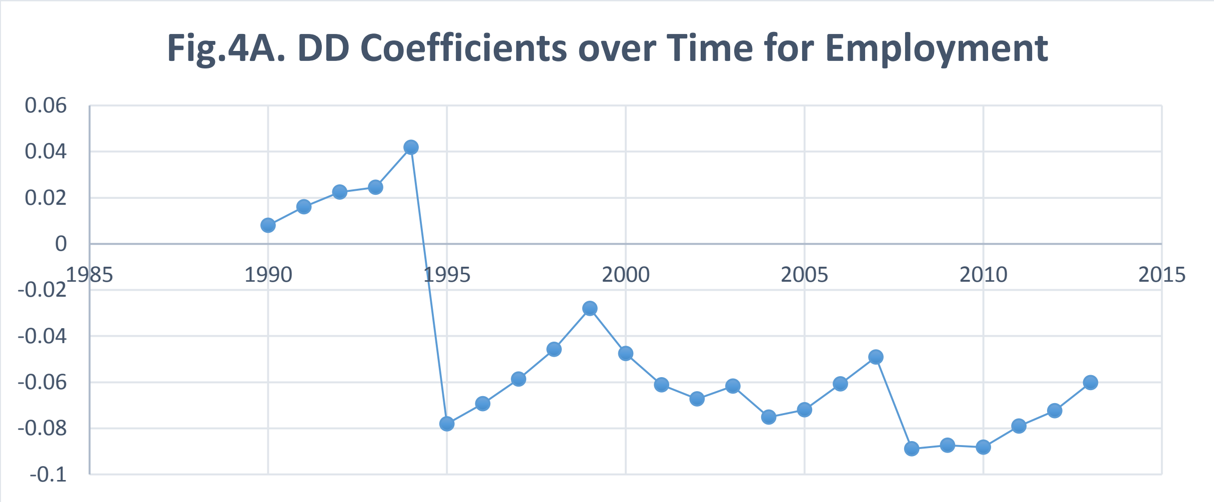
| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0455*** | 0.0919*** | 0.218*** |
| | (7.29e-05) | (0.000395) | (0.000716) |
| age_sq | -0.000690*** | -0.00159*** | -0.00374*** |
| | (1.71e-06) | (9.46e-06) | (1.67e-05) |
| age_cube | 1.55e-06*** | 8.06e-06*** | 1.80e-05*** |
| | (1.23e-08) | (7.11e-08) | (1.23e-07) |
| race | -0.0164*** | -0.0194*** | -0.0443*** |
| | (0.000205) | (0.000471) | (0.000739) |
| educ_level | 0.00578*** | 0.0330*** | 0.105*** |
| | (1.47e-05) | (0.000168) | (0.000325) |
| o.FMLA[11] | - | - | - |
| treatment | 0.0200*** | -0.0782*** | -0.163*** |
| | (0.000718) | (0.00144) | (0.00245) |
| FMLA_treatment | -0.0916*** | -0.0589*** | -0.144*** |
| | (0.000780) | (0.00156) | (0.00264) |
| Constant | -0.295*** | -0.469*** | -0.0483** |
| | (0.00339) | (0.0103) | (0.0191) |
| Observations | 21,801,879 | 5,719,113 | 8,917,420 |
| R-squared | 0.179 | 0.105 | 0.084 |
| Number of id | 704,001 | 301,446 | 387,806 |
| individual FE | YES | YES | YES |

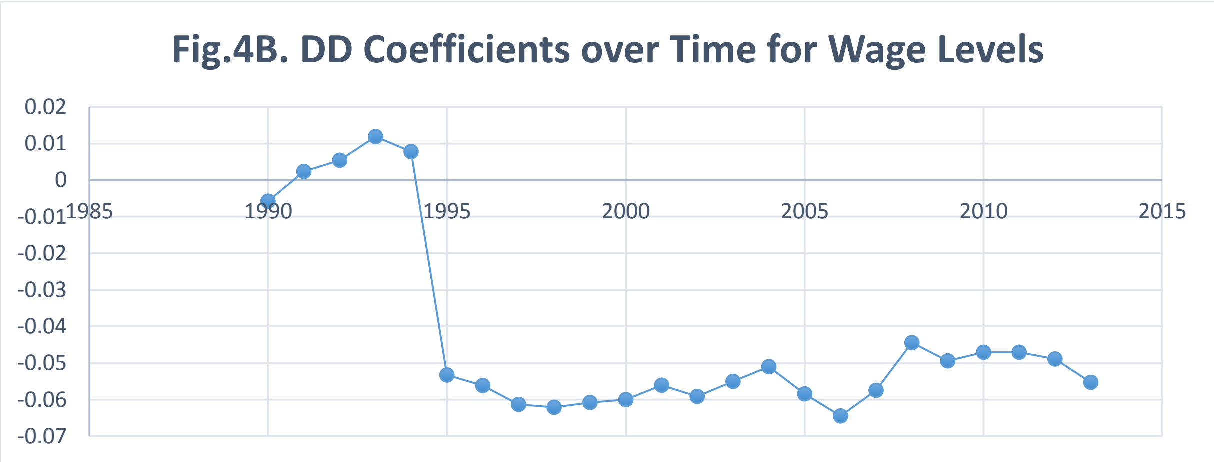
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

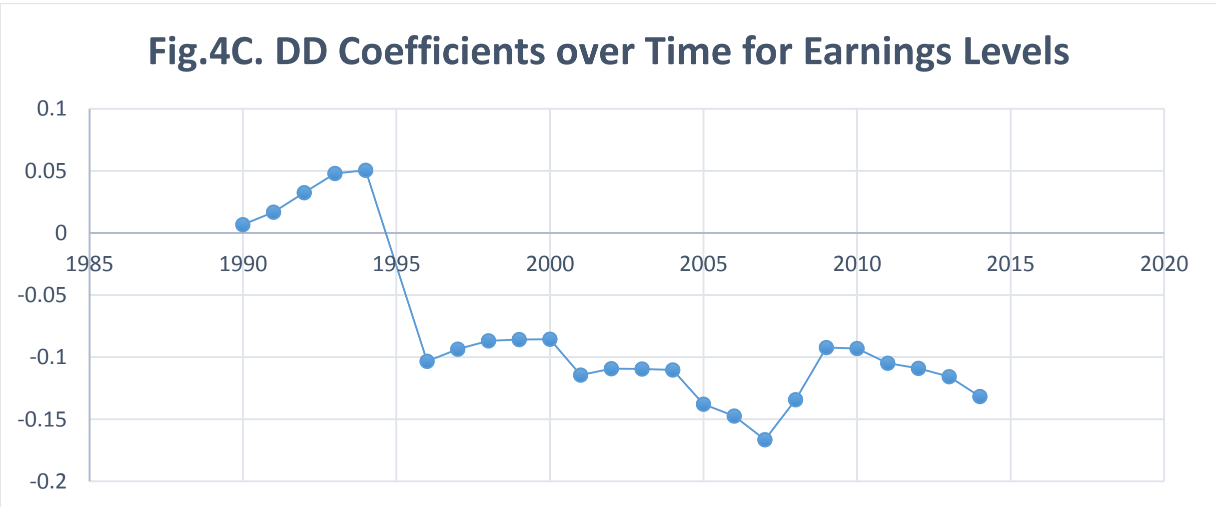
[11] The FMLA coefficient is omitted by the statistical software because it is collinear with year fixed effects

In order to assess the short term vs. the long term effect of the policy, I run a second DD regression analysis (with the interaction term as $year_t$ x $treatment_{it}$), and I plot the coefficient of this interaction term over the period 1990-2013 (Figure 4). The figure below suggests that the FMLA (enacted in 1993) disrupted a trend of growing female employment rates, wages and earnings, and thus had a significant impact on these labor market outcomes, as the DD coefficients fell sharply between 1993 and 1994. Employment rates started to increase after their sharp drop in the mid-1990s, before falling again from 1999 until 2003, picking up again until 2007 and then sharply declining that year. These episodes of declines in employment rates coincide with US recessions, such as the Dotcom bubble and the Great Recession, which may also account for declines in female employment relative to other demographic groups. When comparing wage and earnings levels over time, we observe that wages fell much more sharply than earnings after the enactment of the FMLA in 1993. Given the type of worker who might be paid a salary over an hourly wage, we can speculate that highly-paid workers (those who are paid salaries), are more likely to have access to maternity leave through their employer prior to the FMLA, or had more bargaining power to negotiate their return-to-work conditions after a sustained leave. The same cannot be sustained for employees who are paid hourly wages, for whom the enactment of the FMLA might have been more of a shock to their ability to take maternity leave.

**Figure 4. DD Coefficients for Labor Outcomes over Time**



### 7.2. Difference-in-Difference-in-Difference Model

As mentioned in Section 6, the difference-in-difference is further refined by including the effect of being in a control or treatment state through difference-in-difference-in-difference (DDD) estimators. I first present DDD results for employment and levels of wages and earnings. I then isolate wages by types of industries and occupations and present DDD results for levels of wages of these industries.

#### 7.2.1 Employment, Levels of Wages and Earnings

Table 8.2.1 below summarizes the main results of the DDD model. Adding additional treatment and control states in the DDD model significantly reduces the effects of the FMLA on employment, wages and earnings, while still being statistically significant. With regards to employment, the table below suggests that women of childbearing age and women with children (the treatment group) in states that had no or little maternity leave provision (treatment states) encountered a fall in employment rates by about 2.57%, a fall in wages by about 0.07% and a fall in earnings by about 4.2%, relative to similar women in states that did have provisions prior to 1993.

All three coefficients are statistically significant, and present a non-negligible difference from what the DD model predicts, thus suggesting that state trends captured by the instrumental variable *treat_state* used in the DDD model account for some of the changes reported by the DD model. The DDD model thus presents a more precise prediction of the effects of the FMLA by isolating and controlling for state trends. However, both models are consistent in how they relate to the theory presented in Section 2. As predicted by the theory, the DD and DDD estimation methods both predict a fall in young female wages in treatment states relative to those of older women and men in control states, while it predicts a fall in employment, consistent with predictions of the theory in Figure 1 of section 2. The fall in female employment relative to the control groups suggests that the increase in female labor supply was not large enough to offset the fall in female labor demand after the enactment of the FMLA in 1993. Another explanation could be that the demand for female labor is elastic with respect to wages, as represented by Figure 3 in Section 2. A fall in wages due to the FMLA thus effectively induces a fall in female employment.

**Table 7.2.1 Results of Difference-in-Difference-in-Difference Model with Fixed Effects**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0455*** | 0.0919*** | 0.218*** |
| | (7.29e-05) | (0.000395) | (0.000716) |
| age_sq | -0.000690*** | -0.00159*** | -0.00374*** |
| | (1.71e-06) | (9.46e-06) | (1.67e-05) |
| age_cube | 1.55e-06*** | 8.06e-06*** | 1.80e-05*** |
| | (1.23e-08) | (7.11e-08) | (1.23e-07) |
| race | -0.0164*** | -0.0193*** | -0.0443*** |
| | (0.000205) | (0.000471) | (0.000739) |
| educ_level | 0.00578*** | 0.0330*** | 0.105*** |
| | (1.47e-05) | (0.000168) | (0.000325) |
| o.FMLA | - | - | - |
| treatment | 0.00179* | -0.0715*** | -0.176*** |
| | (0.00108) | (0.00217) | (0.00373) |
| o.treat_state | - | - | - |
| FMLA_treatment | -0.0778*** | -0.0513*** | -0.117*** |
| | (0.00123) | (0.00247) | (0.00418) |
| o.FMLA_treat_state | -0.248*** | - | - |
| | (0.0634) | | |
| treatment_treat_state | 0.0320*** | -0.0119*** | 0.0214*** |
| | (0.00143) | (0.00288) | (0.00491) |
| FMLA_treatment_treat_state | -0.0257*** | -0.00774** | -0.0420*** |
| | (0.00159) | (0.00319) | (0.00539) |

| | | | |
|---|---|---|---|
| Constant | -0.0915* | -0.467*** | -0.0466** |
| | (0.0524) | (0.0103) | (0.0191) |
| | | | |
| Observations | 21,801,879 | 5,719,113 | 8,917,420 |
| R-squared | 704,001 | 0.105 | 0.084 |
| Number of id | 0.179 | 301,446 | 387,806 |
| individual FE | YES | YES | YES |

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

*7.2.2. Employment, Levels of Wages and Earnings by Industry*

Table 7.2.2 summarizes the coefficient of the DDD interaction term *(FMLA x treatment x treat_state)*, denoted DDD interaction in the table, for select industries[12]. Complete regression tables for each industry can be found in Appendix C.

The table below shows that the FMLA induced a 2% (statistically significant) increase in female employment for the manufacturing industry and a 0.9% increase (statistically insignificant) for the health industry, while the Law induced a 1.7% (statistically significant) and 2.2% (statistically insignificant) fall in female employment in the services and the education industry, respectively. With regards to wages, the table below suggests that the FMLA mostly induced a statistically significant fall in wages, with the strongest change in the services industry (14.5% decrease), followed by manufacturing (5.67% decreased), then health (5.18% decrease), and lastly education (0.86% decrease). With regards to earnings, the FMLA is correlated with a 16.9% fall in earnings in the manufacturing industry, a 8.04% fall in the health industry, a 7.56% decrease in the education industry, and a 4.5% fall in the services industry. All coefficients are statistically significant.

The results below suggest that the impact of the FMLA impacted different industries to varying degrees. A reason for this disparity is that in some industries, employers tend to be larger in size, and are thus disproportionately more likely to have eligible employees for

[12] This list of industries is not exhaustive

maternity leave. This is the case for the manufacturing industry, compared with health or education, for instance. Another reason for such disparities could be that in some industries, such as services, the cost of providing maternity leave is small relative to the total cost of employment.

**Table 7.2.2 Results of Difference-in-Difference-in-Difference by Select Industries**

| DDD Interaction Term | **Employment** | **Wages** | **Earnings** |
|---|---|---|---|
| **Manufacturing** | 0.0205***<br>(0.00651) | -0.0567***<br>(0.00958) | -0.169***<br>(0.0173) |
| **White-collar Services** | -0.0172*<br>(0.00912) | -0.145***<br>(0.0153) | -0.0452*<br>(0.0247) |
| **Health** | 0.00997<br>(0.00687) | 0.0518***<br>(0.0102) | -0.0804***<br>(0.0203) |
| **Education** | -0.0222***<br>(0.00666) | -0.00861<br>(0.0161) | -0.0756***<br>(0.0218) |

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

*7.2.3. Employment, Levels of Wages and Earnings by Occupation*

Table 7.2.3 summarizes the coefficient of the DDD interaction term *(FMLA x treatment x treat_state)*, denoted DDD interaction in the table, for select occupations. Complete regression tables for each industry can be found in Appendix C.

With regards to employment rates, the table below suggests that the FMLA induced a 0.02% (statistically insignificant) fall in employment rates for high-paying occupations, a 1.97% fall for medium-paying occupations and 0.13% fall in employment for low-paying occupations. With regards to income, the table below shows that the FMLA increased wages for high-paying occupations by 3.23% (statistically significant) and increased earnings for the same category by 3.11%. As for medium-paying occupations, the FMLA is associated with a 13.3% (statistically significant) increase in wages and 3.08% (statistically insignificant) fall in earnings for the same group. Lastly, the FMLA is associated with a 1.3% (statistically significant) fall in wages and a 3.08% (statistically insignificant) fall in earnings for low-paying occupations.

The results below suggests that the FMLA did not have a significant impact on the employment of high-paying occupations, relative to that of low- and medium-paying occupations. This is intuitively plausible, as employees in high-paying occupations might already have access to maternity leave provisions, as provided by their employees, or they might have more bargaining power to request maternity leave prior to the enactment of the policy as part of their compensation package. Similarly, the FMLA is associated with an increase of income for high-paying and medium-paying occupations, while it is associated with a decrease in income for low-paying occupations. This could be explained by the fact that highly-paid employees are more productive, and thus more desirable to hire, regardless of the enactment of the FMLA, and thus leading employers to demand more of them, pushing their wages up.

**Table 7.2.3 Results of Difference-in-Difference-in-Difference by Types of Occupations**

| DDD Interaction Term | **Employment** | **Wages** | **Earnings** |
|---|---|---|---|
| **High-paying Occupation** | -0.000227<br>(0.00348) | 0.0323***<br>(0.0112) | 0.0311**<br>(0.0124) |
| **Medium-paying Occupation** | -0.0197***<br>(0.00743) | 0.133***<br>(0.0305) | -0.0308<br>(0.0239) |
| **Low-paying Occupation** | -0.00137<br>(0.00269) | -0.0129***<br>(0.00383) | -0.0121<br>(0.00738) |

## 8. Conclusion:

This paper exploits variations in state policies prior to the enactment of a federal law, the Family and Medical Leave Act of 1993, to test the effects of maternity leave on female employment and labor outcomes in the US. I argued that the enactment of the FMLA represented an exogenous shock to some states relative to others, and thus could be considered as a “natural experiment” with “as-if random” effects. Results from two estimation methods, using data from the Survey of Income and Program Participation between 1990 and 2013, suggest that the FMLA disrupted a trend of growing female employment rates and wages. In effect, the FMLA had a negative, albeit small, statistically significant effect on female employment, wages and earnings. Moreover, the FMLA impacted different industries to varying degrees, causing a larger fall of employment rates in the education sector than in the services sector, for example. Similarly, the FMLA impacted different occupations differently: while it had little impact on employment rates in high-paying occupations, it had a more pronounced effect on employment rates in low-paying occupations.

The results of this paper support the hypothesis that taking time off for the purposes of childbearing and childrearing reduces female employment rates and depresses wage levels, despite procurements that legally ease women's return to work decisions after a sustained leave. As more states in the United States continue to enact more generous parental leave policies, and as men become more involved in childrearing, there is an increasing opportunity to further study the effects of such policies on labor markets, in order to study which policies account for the narrowing or widening of the widely debased gender wage gap.

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# Appendix A
## The Family and Medical Leave Act of 1993

**Table A1. History of the Law**

| **Name of the Bill** | **Sponsor** | **Number of Cosponsors** | **% of sponsors - Democrats** | **Status of the Bill** |
|---|---|---|---|---|
| The Parental and Disability Act of 1985 | P. Schroeder (D) | 41 | 91% | Not passed |
| The Parental and Medical Leave Act of 1987 | C. Dodd (D) | 13 | 92% | Not passed |
| The Parental and Medical Leave Act of 1988 | C. Dodd (D) | 28 | 75% | Not passed |
| The Family and Medical Leave Act of 1989 | C. Dodd (D) | 25 | 92% | Not passed |
| The Family and Medical Leave Act of 1990 | B. Clay (D) | 151 | 89% | Passed Congress. Vetoed by President Bush (R) |
| The Family and Medical Leave Act of 1991 | C. Dodd (D) | 39 | 90% | Passed Congress. Vetoed by President Bush (R) |
| The Family and Medical Leave Act of 1993 | W. Ford (D) | 170 | 91% | Passed Congress. Signed by President Clinton (D). Became Law. |

*Source: Congressional Record*. Library of Congress. Web. Feb.-Mar. 2016.

**Table A2. State and federal maternity leave legislation prior to FMLA**

| **States** | **Weeks of leave** | **Employer size** | **Tenure required** | **Date of enforcement** | **Work requirement** |
|---|---|---|---|---|---|
| California | 17 | no minimum | 1 year | 1/92 | no minimum |
| Connecticut | 12 | 75 employees | 1 year | 7/90 | 1000 h in prior year |
| District of Columbia | 16 | 50 employees | 1 year | 4/91 | 1000 h in prior year |
| Federal FMLA | 12 | 50 employees | 1 year | 7/93 | 1250 h in prior year |
| Maine | 8 | 25 employees | 1 year | 4/88 | no minimum |

| | | | | | |
|---|---|---|---|---|---|
| Minnesota | 6 | 21 employees | 1 year | 7/87 | 20 h per week |
| Massachusetts | 8 | 6 employees | 3 months | 10/72 | full-time |
| New Jersey | 12 | 75 employees | 1 year | 4/90 | 1000 h in prior year |
| Oregon | 12 | 25 employees | 90 days | 1/88 | no minimum |
| Rhode Island | 13 | 50 employees | 1 year | 7/87 | full-time |
| Tennessee | 16 | 100 employees | 1 year | 1/88 | full-time |
| Vermont | 12 | 10 employees | 1 year | 7/92 | 30 h per week |
| Washington | 12 | 100 employees | 1 year | 9/89 | 35 h per week |
| Wisconsin | 6 | 50 employees | 1 year | 4/88 | 1000 h in prior year |

Source: Klerman and Leibowitz (1997), the Women's Legal Defense Fund (1994), Bond (1991), and the Bureau of National Affairs (1987), as cited by Baum (2003) in his paper under Table1.

# Appendix B
# Data

## B1. Data Constructions

### a. Rank Correlation Variables

**Table B1. Data indices by state**

| US State | leg_strength | party | state_index | Female_labor |
|---|---|---|---|---|
| Alabama | 1 | 2 | 1,50 | 4 |
| Alaska | 3 | 1 | 2,00 | 1 |
| Arizona | 1 | 1 | 1,00 | 2 |
| Arkansas | 1 | 3 | 2,00 | 5 |
| California* | 5 | 2 | 3,50 | 3 |
| Colorado | 3 | 2 | 2,50 | 1 |
| Connecticut* | 5 | 2 | 3,50 | 3 |
| Delaware | 1 | 3 | 2,00 | 2 |
| Florida | 1 | 2 | 1,50 | 1 |
| Georgia | 1 | 4 | 2,50 | 2 |
| Idaho | 1 | 1 | 1,00 | 3 |
| Illinois | 1 | 2 | 1,50 | 2 |
| Indiana | 1 | 1 | 1,00 | 4 |
| Iowa | 3 | 3 | 3,00 | 2 |
| Kansas | 3 | 1 | 2,00 | 3 |
| Kentucky | 3 | 3 | 3,00 | 4 |
| Louisiana | 3 | 3 | 3,00 | 4 |
| Maine* | 4 | 2 | 3,00 | 5 |
| Maryland | 1 | 4 | 2,50 | 2 |
| Massachussets* | 4 | 4 | 4,00 | 3 |
| Michigan | 1 | 2 | 1,50 | 1 |
| Minnesota* | 4 | 5 | 4,50 | 2 |
| Mississipi | 1 | 2 | 1,50 | 4 |
| Missouri | 1 | 3 | 2,00 | 5 |
| Montana | 3 | 2 | 2,50 | 1 |
| Nebraska | 1 | 2 | 1,50 | 3 |

| | | | | |
|---|---|---|---|---|
| Nevada | 1 | 2 | 1,50 | 3 |
| New Hampshire | 3 | 2 | 2,50 | 2 |
| New Jersey* | 5 | 2 | 3,50 | 5 |
| New Mexico | 1 | 2 | 1,50 | 4 |
| New York | 3 | 4 | 3,50 | 4 |
| North Carolina | 1 | 2 | 1,50 | 5 |
| North Dakota | 1 | 1 | 1,00 | 2 |
| Ohio | 1 | 3 | 2,00 | 5 |
| Oklahoma | 1 | 1 | 1,00 | 5 |
| Oregon* | 5 | 3 | 4,00 | 3 |
| Pennsylvania | 1 | 3 | 2,00 | 1 |
| Rhode Island* | 5 | 4 | 4,50 | 5 |
| South Carolina | 1 | 2 | 1,50 | 3 |
| South Dakota | 1 | 1 | 1,00 | 1 |
| Tennessee* | 5 | 3 | 4,00 | 4 |
| Texas | 1 | 2 | 1,50 | 5 |
| Utah | 1 | 1 | 1,00 | 2 |
| Vermont* | 5 | 2 | 3,50 | 4 |
| Virginia | 1 | 1 | 1,00 | 4 |
| Washington* | 5 | 3 | 4,00 | |
| West Virginnia | 1 | 4 | 2,50 | 1 |
| Wisconsin* | 4 | 4 | 4,00 | 5 |
| Wyoming | 1 | 1 | 1,00 | 5 |
| D.C* | 5 | 5 | 5,00 | 3 |

**B2. Constructions of Other variables**

***Id* variable:** a unique panel identifier for each respondent using the command: *concat(suid hsld_ref person_number)*

***Education level*:** Due to the 1996 survey redesign, the coding for the education level variable is not consistent between pre- and post-1996 data.

In pre-1996, the variable is named *HIGRADE*. The question asks: "What is the highest grade or year of regular school this person attended?" The answer codes are as follows:

- 00 - Not applicable if under 15, or if only attended kindergarten

- 01-08 - Elementary school
- 09-12 -  High school
- 21-26 - College

In post-1996, the variable is named EEDUCATE. The question asks: “What is the highest level of school this person has completed or the highest degree this person has received?”  The answer codes are as follows:

- 31 - less than 1st grade
- 32 - 1st, 2nd, 3rd or 4th grade
- 33 - 5th or 6th grade
- 34 - 7th or 8th grade
- 35 - 9th grade
- 36 - 10th grade
- 37 - 11th grade
- 38 - High school graduate
- > 39 - Attended college

In my final merged dataset, I rename both datasets EDUC_LEVEL and I re-code the pre-1996 data to make it consistent with post-1996 data. See below:

```
replace educ_level=31 if educ_level==.
replace educ_level=32 if educ_level<5
replace educ_level=33 if educ_level==5 | educ_level==6
replace educ_level=34 if educ_level==7 | educ_level==8
replace educ_level=35 if educ_level==9
replace educ_level=36 if educ_level==10
replace educ_level=37 if educ_level==11
replace educ_level=38 if educ_level==12
replace educ_level=39 if educ_level==13
replace educ_level=40 if educ_level>20 //attended college
```

***treatment*** **variable:** a dummy variable containing women of childbearing age and women with children, who lived in states that did not have maternity leave legislation. I thus construct the control states variable: *cntrl_state*, a dummy variable taking the value 1 for states that had maternity leave legislation prior to 1993. I then construct two women variables:

- *Women_childbearing*: women aged 15 to 45 years old.
- *Women_children*: women who have children less than 5 years of age. I use the household id to match children and their mothers using the following code:

```
egen hhid = concat (suid hsld_ref)
gen aged = (age<5)
egen sumchildren = sum (aged), by (hhid year month)
gen children = (sumchildren>0)
```

*The treatment* variable consists of observations with firmsize_main=3 and (women_childbearing=1 or women_children=1).

**Industry_code variable:**

I re-code industry codes from 1-5 (originally ranging from 1 to 989) in order to aggregate under umbrella industries. For instance:

- Agriculture, forestry, fishing, hunting and mining are assigned code 1 under the re-coding (ranging from 9 to 51 in the original dataset)
- Manufacturing is assigned code 2 (ranging from 99 to 393 in the original dataset)
- White-collar services are assigned code 3 (ranging from 700 to 741 in the original dataset)
- Health is assigned code 4 (ranging from 812 to 840 in the original dataset)
- Education is assigned code 5 (ranging from 842 to 860 in the original dataset)

**Occupation_code variable:**

I determine a pattern between codes of occupations in the dataset: the lower codes are associated with high-paying occupations. I thus distinguish between low-, medium- and high-paying occupations and re-code them as follows:

- High-paying occupations are assigned code 1 (ranging from 4 to 105 in the original dataset)
- Medium-paying occupations are assigned code 2 (ranging from 113 to 176 in the original dataset)
- Low-paying occupations are assigned code 3 (ranging from 203 to 906 in the original dataset)

**Appendix C**
**Full Results**
**Table C1. Difference-in-Difference Model for levels of wages and earnings**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0455*** | 0.0919*** | 0.218*** |
| | (7.29e-05) | (0.000395) | (0.000716) |
| age_sq | -0.000690*** | -0.00159*** | -0.00374*** |
| | (1.71e-06) | (9.46e-06) | (1.67e-05) |
| age_cube | 1.55e-06*** | 8.06e-06*** | 1.80e-05*** |
| | (1.23e-08) | (7.11e-08) | (1.23e-07) |
| race | -0.0164*** | -0.0194*** | -0.0443*** |
| | (0.000205) | (0.000471) | (0.000739) |
| educ_level | 0.00578*** | 0.0330*** | 0.105*** |
| | (1.47e-05) | (0.000168) | (0.000325) |
| _Iyear_90 | 0.00149 | 0.0252*** | 0.0183*** |
| | (0.000937) | (0.00162) | (0.00299) |
| _Iyear_91 | -0.00685*** | 0.0605*** | 0.0406*** |
| | (0.000941) | (0.00165) | (0.00303) |
| _Iyear_92 | -0.0116*** | 0.0817*** | 0.0694*** |
| | (0.000947) | (0.00168) | (0.00306) |
| _Iyear_93 | -0.0142*** | 0.102*** | 0.0923*** |
| | (0.000954) | (0.00171) | (0.00310) |
| _Iyear_94 | -0.0102*** | 0.128*** | 0.125*** |
| | (0.000971) | (0.00175) | (0.00317) |
| _Iyear_95 | -0.00758*** | 0.159*** | 0.160*** |
| | (0.00103) | (0.00187) | (0.00336) |
| _Iyear_1995 | 0.0190*** | -0.410*** | -0.474*** |
| | (0.00175) | (0.00304) | (0.00570) |
| _Iyear_1996 | 0.0317*** | -0.398*** | -0.477*** |
| | (0.000594) | (0.00123) | (0.00205) |
| _Iyear_1997 | 0.0289*** | -0.357*** | -0.422*** |
| | (0.000597) | (0.00123) | (0.00205) |
| _Iyear_1998 | 0.0272*** | -0.310*** | -0.357*** |
| | (0.000602) | (0.00124) | (0.00206) |
| _Iyear_1999 | 0.0259*** | -0.271*** | -0.301*** |
| | (0.000608) | (0.00125) | (0.00208) |
| _Iyear_2000 | 0.0320*** | -0.234*** | -0.297*** |
| | (0.000797) | (0.00149) | (0.00262) |
| _Iyear_2001 | 0.0357*** | -0.211*** | -0.287*** |
| | (0.000604) | (0.00123) | (0.00206) |
| _Iyear_2002 | 0.0220*** | -0.185*** | -0.247*** |
| | (0.000611) | (0.00124) | (0.00208) |

| | | | |
|---|---|---|---|
| _Iyear_2003 | 0.0196*** | -0.164*** | -0.204*** |
| | (0.000584) | (0.00118) | (0.00198) |
| _Iyear_2004 | 0.0336*** | -0.158*** | -0.156*** |
| | (0.000522) | (0.00107) | (0.00178) |
| _Iyear_2005 | 0.0316*** | -0.135*** | -0.118*** |
| | (0.000532) | (0.00109) | (0.00182) |
| _Iyear_2006 | 0.0319*** | -0.105*** | -0.0768*** |
| | (0.000569) | (0.00115) | (0.00193) |
| _Iyear_2007 | 0.0285*** | -0.0751*** | -0.0467*** |
| | (0.000628) | (0.00126) | (0.00212) |
| _Iyear_2008 | 0.0304*** | -0.0371*** | -0.0504*** |
| | (0.000530) | (0.00101) | (0.00175) |
| _Iyear_2009 | 0.0171*** | -0.0365*** | -0.0689*** |
| | (0.000486) | (0.000933) | (0.00162) |
| _Iyear_2010 | 0.00511*** | -0.0313*** | -0.0607*** |
| | (0.000488) | (0.000933) | (0.00162) |
| _Iyear_2011 | 0.00131*** | -0.0207*** | -0.0391*** |
| | (0.000489) | (0.000928) | (0.00163) |
| _Iyear_2012 | 0.000965** | -0.00784*** | -0.0123*** |
| | (0.000487) | (0.000908) | (0.00161) |
| o._Iyear_2013 | - | - | - |
| _Istate_2 | 0.115*** | 0.243*** | 0.198*** |
| | (0.00737) | (0.0160) | (0.0253) |
| _Istate_4 | 0.0438*** | 0.0556*** | 0.0987*** |
| | (0.00406) | (0.00834) | (0.0143) |
| _Istate_5 | 0.0189*** | 0.0820*** | 0.0168 |
| | (0.00494) | (0.0101) | (0.0180) |
| _Istate_6 | 0.0377*** | 0.142*** | 0.0418*** |
| | (0.00369) | (0.00774) | (0.0131) |
| _Istate_8 | 0.0251*** | 0.138*** | 0.00785 |
| | (0.00430) | (0.00893) | (0.0149) |
| _Istate_9 | 0.0423*** | 0.130*** | 0.0880*** |
| | (0.00479) | (0.0105) | (0.0167) |
| _Istate_10 | 0.0436*** | 0.128*** | 0.209*** |
| | (0.00659) | (0.0152) | (0.0232) |
| _Istate_11 | 0.0693*** | 0.115*** | 0.209*** |
| | (0.00648) | (0.0147) | (0.0203) |
| _Istate_12 | 0.0225*** | 0.0901*** | 0.0473*** |
| | (0.00364) | (0.00758) | (0.0129) |
| _Istate_13 | 0.0362*** | 0.0637*** | 0.0452*** |
| | (0.00386) | (0.00805) | (0.0136) |
| _Istate_15 | 0.0449*** | 0.0603*** | -0.0268 |
| | (0.00584) | (0.0128) | (0.0210) |
| _Istate_16 | 0.0306*** | 0.0613*** | -0.124*** |
| | (0.00536) | (0.0107) | (0.0195) |
| _Istate_17 | 0.0612*** | 0.185*** | 0.0574*** |

| | | | |
|---|---|---|---|
| | (0.00401) | (0.00835) | (0.0139) |
| _Istate_18 | 0.0442*** | 0.0248*** | -0.0678*** |
| | (0.00430) | (0.00877) | (0.0149) |
| _Istate_19 | 0.0524*** | 0.0998*** | -0.131*** |
| | (0.00513) | (0.0102) | (0.0171) |
| _Istate_20 | 0.0452*** | 0.0977*** | -0.00269 |
| | (0.00521) | (0.0105) | (0.0178) |
| _Istate_21 | 0.0196*** | 0.0264*** | 0.0231 |
| | (0.00488) | (0.0100) | (0.0172) |
| _Istate_22 | 0.0222*** | 0.0412*** | -0.0538*** |
| | (0.00444) | (0.00921) | (0.0157) |
| _Istate_23 | 0.0490*** | 0.0345** | -0.228*** |
| | (0.00799) | (0.0157) | (0.0270) |
| _Istate_24 | 0.0558*** | 0.170*** | 0.149*** |
| | (0.00439) | (0.00974) | (0.0149) |
| _Istate_25 | 0.0579*** | 0.107*** | -0.0469*** |
| | (0.00460) | (0.00978) | (0.0155) |
| _Istate_26 | 0.0182*** | 0.0552*** | 0.0237 |
| | (0.00438) | (0.00904) | (0.0153) |
| _Istate_27 | 0.0164*** | 0.107*** | -0.0395** |
| | (0.00454) | (0.00928) | (0.0155) |
| _Istate_28 | 0.0104** | 0.0203** | -0.0496*** |
| | (0.00461) | (0.00940) | (0.0169) |
| _Istate_29 | 0.0441*** | 0.0825*** | -0.0225 |
| | (0.00426) | (0.00871) | (0.0149) |
| _Istate_30 | 0.0533*** | 0.0549*** | -0.137*** |
| | (0.00632) | (0.0120) | (0.0221) |
| _Istate_31 | 0.106*** | 0.00478 | -0.206*** |
| | (0.00580) | (0.0113) | (0.0188) |
| _Istate_32 | 0.0652*** | 0.165*** | 0.152*** |
| | (0.00479) | (0.00950) | (0.0167) |
| _Istate_33 | 0.0431*** | 0.153*** | 0.0749*** |
| | (0.00609) | (0.0128) | (0.0201) |
| _Istate_34 | 0.0669*** | 0.132*** | 0.0211 |
| | (0.00430) | (0.00985) | (0.0149) |
| _Istate_35 | -0.0151*** | -0.0117 | -0.0785*** |
| | (0.00558) | (0.0110) | (0.0196) |
| _Istate_36 | 0.0590*** | 0.164*** | 0.135*** |
| | (0.00394) | (0.00830) | (0.0138) |
| _Istate_37 | 0.0291*** | 0.0343*** | -0.0277* |
| | (0.00404) | (0.00853) | (0.0141) |
| _Istate_38 | 0.0973*** | 0.161*** | -0.104*** |
| | (0.00835) | (0.0158) | (0.0289) |
| _Istate_39 | 0.0423*** | 0.105*** | 0.0748*** |
| | (0.00424) | (0.00871) | (0.0147) |
| _Istate_40 | 0.0468*** | 0.0731*** | -0.0362** |
| | (0.00469) | (0.00969) | (0.0164) |

| | | | |
|---|---|---|---|
| _Istate_41 | -0.000330 | 0.0668*** | -0.172*** |
| | (0.00456) | (0.00896) | (0.0156) |
| _Istate_42 | 0.0252*** | 0.150*** | 0.0304** |
| | (0.00415) | (0.00880) | (0.0143) |
| _Istate_44 | 0.0111* | 0.168*** | 0.0200 |
| | (0.00665) | (0.0137) | (0.0241) |
| _Istate_45 | 0.0355*** | 0.0331*** | -0.0763*** |
| | (0.00445) | (0.00941) | (0.0159) |
| _Istate_46 | -0.000629 | 0.0273* | -0.0966*** |
| | (0.00731) | (0.0148) | (0.0276) |
| _Istate_47 | 0.0187*** | 0.0513*** | 0.0251* |
| | (0.00402) | (0.00848) | (0.0145) |
| _Istate_48 | 0.0279*** | 0.0519*** | 0.0361*** |
| | (0.00358) | (0.00750) | (0.0127) |
| _Istate_49 | 0.0692*** | 0.0845*** | -0.0143 |
| | (0.00482) | (0.0103) | (0.0172) |
| _Istate_50 | 0.0755*** | 0.169*** | -0.0394 |
| | (0.0101) | (0.0206) | (0.0376) |
| _Istate_51 | 0.0565*** | 0.0680*** | 0.100*** |
| | (0.00394) | (0.00868) | (0.0138) |
| _Istate_53 | 0.0461*** | 0.184*** | 0.0121 |
| | (0.00416) | (0.00864) | (0.0145) |
| _Istate_54 | 0.0357*** | 0.0618*** | 0.101*** |
| | (0.00644) | (0.0135) | (0.0248) |
| _Istate_55 | 0.0170*** | 0.127*** | -0.00310 |
| | (0.00440) | (0.00895) | (0.0153) |
| _Istate_56 | 0.0170** | 0.0146 | 0.113*** |
| | (0.00708) | (0.0136) | (0.0246) |
| _Istate_61 | 0.0767*** | -0.0499*** | -0.374*** |
| | (0.00801) | (0.0141) | (0.0260) |
| _Istate_62 | 0.0483*** | 0.0912*** | 0.0255 |
| | (0.00612) | (0.0119) | (0.0210) |
| o._Istate_63 | - | - | - |
| o.FMLA | - | - | - |
| treatment | 0.0200*** | -0.0782*** | -0.163*** |
| | (0.000718) | (0.00144) | (0.00245) |
| FMLA_treatment | -0.0916*** | -0.0589*** | -0.144*** |
| | (0.000780) | (0.00156) | (0.00264) |
| Constant | -0.295*** | -0.469*** | -0.0483** |
| | (0.00339) | (0.0103) | (0.0191) |
| Observations | 21,801,879 | 5,719,113 | 8,917,420 |
| R-squared | 0.179 | 0.105 | 0.084 |
| Number of id | 704,001 | 301,446 | 387,806 |
| individual FE | YES | YES | YES |

Standard errors in parentheses

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

**Table C2. Difference-in-Difference-in-Difference Model for levels of wages and earnings**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0455*** | 0.0919*** | 0.218*** |
| | (7.29e-05) | (0.000395) | (0.000716) |
| age_sq | -0.000690*** | -0.00159*** | -0.00374*** |
| | (1.71e-06) | (9.46e-06) | (1.67e-05) |
| age_cube | 1.55e-06*** | 8.06e-06*** | 1.80e-05*** |
| | (1.23e-08) | (7.11e-08) | (1.23e-07) |
| race | -0.0164*** | -0.0193*** | -0.0443*** |
| | (0.000205) | (0.000471) | (0.000739) |
| educ_level | 0.00578*** | 0.0330*** | 0.105*** |
| | (1.47e-05) | (0.000168) | (0.000325) |
| _Iyear_90 | 0.00148 | 0.0252*** | 0.0183*** |
| | (0.000937) | (0.00162) | (0.00299) |
| _Iyear_91 | -0.00686*** | 0.0605*** | 0.0406*** |
| | (0.000941) | (0.00165) | (0.00303) |
| _Iyear_92 | -0.0116*** | 0.0817*** | 0.0694*** |
| | (0.000947) | (0.00168) | (0.00306) |
| _Iyear_93 | -0.0142*** | 0.102*** | 0.0922*** |
| | (0.000954) | (0.00171) | (0.00310) |
| _Iyear_94 | -0.0102*** | 0.128*** | 0.125*** |
| | (0.000971) | (0.00175) | (0.00317) |
| _Iyear_95 | -0.00765*** | 0.159*** | 0.160*** |
| | (0.00103) | (0.00187) | (0.00336) |
| _Iyear_1995 | 0.0190*** | -0.410*** | -0.474*** |
| | (0.00175) | (0.00304) | (0.00570) |
| _Iyear_1996 | 0.0317*** | -0.398*** | -0.477*** |
| | (0.000594) | (0.00123) | (0.00205) |
| _Iyear_1997 | 0.0289*** | -0.357*** | -0.422*** |
| | (0.000597) | (0.00123) | (0.00205) |
| _Iyear_1998 | 0.0272*** | -0.310*** | -0.357*** |
| | (0.000602) | (0.00124) | (0.00206) |
| _Iyear_1999 | 0.0260*** | -0.271*** | -0.301*** |
| | (0.000608) | (0.00125) | (0.00208) |
| _Iyear_2000 | 0.0320*** | -0.234*** | -0.297*** |
| | (0.000797) | (0.00149) | (0.00262) |
| _Iyear_2001 | 0.0357*** | -0.211*** | -0.287*** |

| | | | |
|---|---|---|---|
| | (0.000604) | (0.00123) | (0.00206) |
| _Iyear_2002 | 0.0220*** | -0.185*** | -0.247*** |
| | (0.000611) | (0.00124) | (0.00208) |
| _Iyear_2003 | 0.0196*** | -0.164*** | -0.204*** |
| | (0.000584) | (0.00118) | (0.00198) |
| _Iyear_2004 | 0.0337*** | -0.158*** | -0.156*** |
| | (0.000522) | (0.00107) | (0.00178) |
| _Iyear_2005 | 0.0316*** | -0.135*** | -0.118*** |
| | (0.000532) | (0.00109) | (0.00182) |
| _Iyear_2006 | 0.0319*** | -0.106*** | -0.0769*** |
| | (0.000569) | (0.00115) | (0.00193) |
| _Iyear_2007 | 0.0285*** | -0.0752*** | -0.0468*** |
| | (0.000628) | (0.00126) | (0.00212) |
| _Iyear_2008 | 0.0304*** | -0.0372*** | -0.0505*** |
| | (0.000530) | (0.00101) | (0.00175) |
| _Iyear_2009 | 0.0171*** | -0.0366*** | -0.0690*** |
| | (0.000486) | (0.000933) | (0.00162) |
| _Iyear_2010 | 0.00512*** | -0.0314*** | -0.0608*** |
| | (0.000488) | (0.000933) | (0.00162) |
| _Iyear_2011 | 0.00132*** | -0.0208*** | -0.0391*** |
| | (0.000489) | (0.000928) | (0.00163) |
| _Iyear_2012 | 0.000966** | -0.00784*** | -0.0123*** |
| | (0.000487) | (0.000908) | (0.00161) |
| o._Iyear_2013 | - | - | - |
| _Istate_2 | 0.115*** | 0.243*** | 0.197*** |
| | (0.00737) | (0.0160) | (0.0253) |
| _Istate_4 | 0.0437*** | 0.0557*** | 0.0988*** |
| | (0.00406) | (0.00834) | (0.0143) |
| _Istate_5 | 0.0188*** | 0.0820*** | 0.0176 |
| | (0.00494) | (0.0101) | (0.0180) |
| _Istate_6 | -0.209*** | 0.140*** | 0.0401*** |
| | (0.0635) | (0.00774) | (0.0131) |
| _Istate_8 | 0.0250*** | 0.139*** | 0.00813 |
| | (0.00430) | (0.00893) | (0.0149) |
| _Istate_9 | -0.204*** | 0.122*** | 0.0822*** |
| | (0.0635) | (0.0105) | (0.0167) |
| _Istate_10 | 0.0435*** | 0.127*** | 0.209*** |
| | (0.00659) | (0.0152) | (0.0232) |
| _Istate_11 | -0.176*** | 0.105*** | 0.201*** |
| | (0.0637) | (0.0147) | (0.0204) |
| _Istate_12 | 0.0225*** | 0.0899*** | 0.0475*** |
| | (0.00364) | (0.00758) | (0.0129) |
| _Istate_13 | 0.0361*** | 0.0639*** | 0.0451*** |
| | (0.00386) | (0.00805) | (0.0136) |
| _Istate_15 | 0.0448*** | 0.0606*** | -0.0262 |
| | (0.00584) | (0.0128) | (0.0210) |

| | | | |
|---|---|---|---|
| _Istate_16 | 0.0306*** | 0.0608*** | -0.123*** |
| | (0.00536) | (0.0107) | (0.0195) |
| _Istate_17 | 0.0611*** | 0.185*** | 0.0576*** |
| | (0.00401) | (0.00835) | (0.0139) |
| _Istate_18 | 0.0442*** | 0.0250*** | -0.0677*** |
| | (0.00430) | (0.00877) | (0.0149) |
| _Istate_19 | -0.193*** | 0.0916*** | -0.139*** |
| | (0.0636) | (0.0102) | (0.0171) |
| _Istate_20 | 0.0441*** | 0.0977*** | -0.00253 |
| | (0.00522) | (0.0105) | (0.0178) |
| _Istate_21 | -0.226*** | 0.0175* | 0.0157 |
| | (0.0636) | (0.0100) | (0.0172) |
| _Istate_22 | -0.224*** | 0.0329*** | -0.0606*** |
| | (0.0635) | (0.00923) | (0.0157) |
| _Istate_23 | 0.0489*** | 0.0347** | -0.228*** |
| | (0.00799) | (0.0157) | (0.0270) |
| _Istate_24 | 0.0557*** | 0.169*** | 0.149*** |
| | (0.00439) | (0.00974) | (0.0149) |
| _Istate_25 | -0.189*** | 0.106*** | -0.0481*** |
| | (0.0635) | (0.00978) | (0.0155) |
| _Istate_26 | 0.0181*** | 0.0554*** | 0.0239 |
| | (0.00438) | (0.00904) | (0.0153) |
| _Istate_27 | -0.230*** | 0.105*** | -0.0412*** |
| | (0.0634) | (0.00928) | (0.0155) |
| _Istate_28 | 0.0103** | 0.0204** | -0.0489*** |
| | (0.00461) | (0.00940) | (0.0169) |
| _Istate_29 | 0.0439*** | 0.0823*** | -0.0225 |
| | (0.00426) | (0.00871) | (0.0149) |
| _Istate_30 | 0.0531*** | 0.0551*** | -0.137*** |
| | (0.00632) | (0.0120) | (0.0221) |
| _Istate_31 | 0.106*** | 0.00502 | -0.205*** |
| | (0.00580) | (0.0113) | (0.0188) |
| _Istate_32 | 0.0652*** | 0.165*** | 0.152*** |
| | (0.00479) | (0.00950) | (0.0167) |
| _Istate_33 | 0.0431*** | 0.153*** | 0.0752*** |
| | (0.00609) | (0.0128) | (0.0201) |
| _Istate_34 | -0.179*** | 0.124*** | 0.0149 |
| | (0.0635) | (0.00987) | (0.0149) |
| _Istate_35 | -0.0151*** | -0.0115 | -0.0780*** |
| | (0.00558) | (0.0110) | (0.0196) |
| _Istate_36 | -0.187*** | 0.156*** | 0.127*** |
| | (0.0635) | (0.00832) | (0.0138) |
| _Istate_37 | 0.0290*** | 0.0347*** | -0.0273* |
| | (0.00404) | (0.00853) | (0.0141) |
| _Istate_38 | 0.0974*** | 0.161*** | -0.104*** |
| | (0.00835) | (0.0158) | (0.0289) |
| _Istate_39 | 0.0422*** | 0.105*** | 0.0752*** |

| | | | |
|---|---|---|---|
| | (0.00424) | (0.00871) | (0.0147) |
| _Istate_40 | 0.0467*** | 0.0729*** | -0.0363** |
| | (0.00469) | (0.00969) | (0.0164) |
| _Istate_41 | -0.247*** | 0.0648*** | -0.173*** |
| | (0.0635) | (0.00896) | (0.0156) |
| _Istate_42 | 0.0251*** | 0.150*** | 0.0306** |
| | (0.00415) | (0.00880) | (0.0143) |
| _Istate_44 | -0.235*** | 0.160*** | 0.0139 |
| | (0.0637) | (0.0137) | (0.0241) |
| _Istate_45 | 0.0354*** | 0.0334*** | -0.0758*** |
| | (0.00445) | (0.00941) | (0.0159) |
| _Istate_46 | -0.000821 | 0.0291** | -0.0956*** |
| | (0.00731) | (0.0148) | (0.0276) |
| _Istate_47 | -0.227*** | 0.0431*** | 0.0185 |
| | (0.0635) | (0.00850) | (0.0145) |
| _Istate_48 | 0.0278*** | 0.0516*** | 0.0362*** |
| | (0.00358) | (0.00750) | (0.0127) |
| _Istate_49 | 0.0691*** | 0.0846*** | -0.0142 |
| | (0.00482) | (0.0103) | (0.0172) |
| _Istate_50 | 0.0755*** | 0.171*** | -0.0376 |
| | (0.0101) | (0.0206) | (0.0376) |
| _Istate_51 | 0.0564*** | 0.0686*** | 0.101*** |
| | (0.00394) | (0.00868) | (0.0138) |
| _Istate_53 | -0.200*** | 0.176*** | 0.00578 |
| | (0.0635) | (0.00866) | (0.0145) |
| _Istate_54 | 0.0356*** | 0.0618*** | 0.101*** |
| | (0.00644) | (0.0135) | (0.0248) |
| _Istate_55 | -0.229*** | 0.118*** | -0.0106 |
| | (0.0635) | (0.00897) | (0.0153) |
| _Istate_56 | 0.0169** | 0.0145 | 0.113*** |
| | (0.00708) | (0.0136) | (0.0246) |
| _Istate_61 | -0.170*** | -0.0509*** | -0.375*** |
| | (0.0639) | (0.0141) | (0.0260) |
| _Istate_62 | 0.0483*** | 0.0917*** | 0.0260 |
| | (0.00612) | (0.0119) | (0.0210) |
| o._Istate_63 | - | - | - |
| o.FMLA | - | - | - |
| treatment | 0.00179* | -0.0715*** | -0.176*** |
| | (0.00108) | (0.00217) | (0.00373) |
| o.treat_state | - | - | - |
| FMLA_treatment | -0.0778*** | -0.0513*** | -0.117*** |
| | (0.00123) | (0.00247) | (0.00418) |
| o.FMLA_treat_state | -0.248*** | - | - |

| | | | |
|---|---|---|---|
| | (0.0634) | | |
| treatment_treat_state | 0.0320*** | -0.0119*** | 0.0214*** |
| | (0.00143) | (0.00288) | (0.00491) |
| FMLA_treatment_treat_state | -0.0257*** | -0.00774** | -0.0420*** |
| | (0.00159) | (0.00319) | (0.00539) |
| Constant | -0.0915* | -0.467*** | -0.0466** |
| | (0.0524) | (0.0103) | (0.0191) |
| | | | |
| Observations | 21,801,879 | 5,719,113 | 8,917,420 |
| R-squared | 704,001 | 0.105 | 0.084 |
| Number of id | 0.179 | 301,446 | 387,806 |
| individual FE | YES | YES | YES |

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

**Table C3. Difference-in-Difference-in-Difference Model for the Agriculture, Fishing and Mining Industry**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0313*** | 0.0603*** | 0.218*** |
| | (0.00469) | (0.00522) | (0.0128) |
| age_sq | -0.000594*** | -0.000989*** | -0.00385*** |
| | (0.000110) | (0.000136) | (0.000317) |
| age_cube | 3.17e-06*** | 5.20e-06*** | 2.09e-05*** |
| | (8.31e-07) | (1.15e-06) | (2.51e-06) |
| race | 0.0283*** | -0.179*** | -0.227*** |
| | (0.0105) | (0.0168) | (0.0236) |
| educ_level | -0.00938*** | 0.000464 | 0.0991*** |
| | (0.00255) | (0.00249) | (0.00693) |
| year | 0.00144* | 0.0349*** | 0.0313*** |
| | (0.000815) | (0.000816) | (0.00194) |
| o.FMLA | - | - | - |
| | | | |
| treatment | -0.0137 | -0.0258 | -0.108 |
| | (0.164) | (0.149) | (0.461) |
| treat_state | -0.0188 | -0.0783** | -0.308*** |
| | (0.0357) | (0.0310) | (0.0811) |
| FMLA_treatment | -0.00603 | 0.0102 | 0.0104 |
| | (0.162) | (0.148) | (0.459) |
| FMLA_treat_state | 0.0395 | 0.0620* | 0.0136 |

| | | | |
|---|---|---|---|
| | (0.0396) | (0.0355) | (0.0928) |
| treatment_treat_state | 0.0148 | 0.0525** | 0.149** |
| | (0.0271) | (0.0232) | (0.0600) |
| o.FMLA_treatment_treat_state | - | - | - |
| o.FMLA_treat_state | | | |
| FMLA_treatment_treat_state | | | |
| Constant | -0.877 | -37.13*** | -34.18*** |
| | (0.935) | (0.885) | (2.125) |
| Observations | 136,429 | 77,604 | 107,232 |
| R-squared | 0.001 | 0.055 | 0.022 |
| Number of id | 10,111 | 6,969 | 9,059 |
| individual FE | YES | YES | YES |

**Table C4. Difference-in-Difference-in-Difference Model for the Manufacturing Industry**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0256*** | 0.0798*** | 0.121*** |
| | (0.00124) | (0.00191) | (0.00360) |
| age_sq | -0.000494*** | -0.00148*** | -0.00206*** |
| | (2.92e-05) | (4.59e-05) | (8.52e-05) |
| age_cube | 2.93e-06*** | 8.90e-06*** | 1.03e-05*** |
| | (2.19e-07) | (3.52e-07) | (6.48e-07) |
| race | -0.000197 | 0.00501* | -0.0391*** |
| | (0.00165) | (0.00260) | (0.00450) |
| educ_level | 0.00612*** | 0.0242*** | 0.0539*** |
| | (0.000539) | (0.000755) | (0.00151) |
| year | -0.00144*** | 0.0265*** | 0.0238*** |
| | (0.000165) | (0.000247) | (0.000438) |
| o.FMLA | - | - | - |
| treatment | -0.00473 | -0.0751*** | -0.141*** |
| | (0.00380) | (0.00559) | (0.0100) |
| treat_state | -0.00852** | -0.00859 | -0.0258** |
| | (0.00433) | (0.00799) | (0.0117) |
| FMLA_treatment | -0.0233*** | -0.0228*** | 0.00931 |

| | | | |
|---|---|---|---|
| | (0.00517) | (0.00762) | (0.0138) |
| FMLA_treat_state | | | |
| treatment_treat_state | 0.00136 | 0.0453*** | 0.142*** |
| | (0.00505) | (0.00743) | (0.0133) |
| o.FMLA_treatment_treat_state | | | |
| o.FMLA_treat_state | - | - | - |
| FMLA_treatment_treat_state | 0.0205*** | -0.0567*** | -0.169*** |
| | (0.00651) | (0.00958) | (0.0173) |
| Constant | 1.831*** | -27.42*** | -20.90*** |
| | (0.170) | (0.253) | (0.446) |
| Observations | 1,029,756 | 690,530 | 968,260 |
| R-squared | 0.001 | 0.042 | 0.013 |
| Number of id | 60,213 | 45,570 | 58,644 |
| individual FE | YES | YES | YES |

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

**Table C5. Difference-in-Difference-in-Difference Model for the Services Industry**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0185*** | 0.0719*** | 0.133*** |
| | (0.00200) | (0.00288) | (0.00556) |
| age_sq | -0.000343*** | -0.00144*** | -0.00227*** |
| | (4.70e-05) | (7.07e-05) | (0.000131) |
| age_cube | 1.85e-06*** | 9.37e-06*** | 1.04e-05*** |
| | (3.51e-07) | (5.45e-07) | (9.82e-07) |
| race | -0.00394* | -0.0319*** | 0.00990 |
| | (0.00236) | (0.00416) | (0.00653) |
| educ_level | 0.00786*** | 0.0231*** | 0.106*** |
| | (0.00136) | (0.00167) | (0.00379) |
| year | 0.000651** | 0.0382*** | 0.0458*** |

| | | | |
|---|---|---|---|
| | (0.000286) | (0.000461) | (0.000773) |
| o.FMLA | - | - | - |
| treatment | 0.00456 | -0.0426*** | -0.0823*** |
| | (0.00576) | (0.0105) | (0.0157) |
| treat_state | 0.0229*** | -0.0227** | -0.00367 |
| | (0.00562) | (0.00882) | (0.0157) |
| FMLA_treatment | 0.00294 | 0.0600*** | -0.0251 |
| | (0.00716) | (0.0124) | (0.0195) |
| FMLA_treat_state | | | |
| treatment_treat_state | -0.00236 | 0.0823*** | 0.0270 |
| | (0.00745) | (0.0130) | (0.0202) |
| o.FMLA_treatment_treat_state | | | |
| o.FMLA_treat_state | - | - | - |
| FMLA_treatment_treat_state | -0.0172* | -0.145*** | -0.0452* |
| | (0.00912) | (0.0153) | (0.0247) |
| Constant | -0.367 | -43.62*** | -49.23*** |
| | (0.312) | (0.520) | (0.840) |
| Observations | 589,139 | 278,293 | 544,922 |
| R-squared | 0.001 | 0.051 | 0.018 |
| Number of id | 40,793 | 25,997 | 39,773 |
| individual FE | YES | YES | YES |

**Table C6. Difference-in-Difference-in-Difference Model for the Health Industry**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0190*** | 0.0761*** | 0.139*** |
| | (0.00201) | (0.00282) | (0.00602) |
| age_sq | -0.000318*** | -0.00132*** | -0.00244*** |
| | (4.73e-05) | (6.67e-05) | (0.000141) |
| age_cube | 1.46e-06*** | 7.64e-06*** | 1.38e-05*** |
| | (3.56e-07) | (5.04e-07) | (1.06e-06) |
| race | 0.00854*** | -0.0198*** | -0.00439 |
| | (0.00268) | (0.00479) | (0.00788) |

| | | | |
|---|---|---|---|
| educ_level | 0.00302** | 0.0274*** | 0.0641*** |
| | (0.00130) | (0.00181) | (0.00392) |
| year | 0.000255 | 0.0343*** | 0.0342*** |
| | (0.000260) | (0.000383) | (0.000768) |
| o.FMLA | - | - | - |
| treatment | 0.00189 | 0.0230*** | 0.0182 |
| | (0.00399) | (0.00576) | (0.0117) |
| treat_state | -0.0151*** | -0.0557*** | 0.0387** |
| | (0.00539) | (0.00903) | (0.0164) |
| FMLA_treatment | -0.00717 | -0.0312*** | 0.0589*** |
| | (0.00533) | (0.00777) | (0.0157) |
| FMLA_treat_state | | | |
| treatment_treat_state | -0.00495 | -0.00814 | -0.0100 |
| | (0.00536) | (0.00785) | (0.0158) |
| o.FMLA_treatment_ treat_state | | | |
| o.FMLA_treat_state | - | - | - |
| FMLA_treatment_tr eat_state | 0.00997 | 0.0518*** | -0.0804*** |
| | (0.00687) | (0.0102) | (0.0203) |
| Constant | 0.260 | -36.67*** | -33.75*** |
| | (0.272) | (0.405) | (0.805) |
| Observations | 525,560 | 392,273 | 501,139 |
| R-squared | 0.001 | 0.052 | 0.015 |
| Number of id | 31,056 | 25,803 | 30,524 |
| individual FE | YES | YES | YES |

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

**Table C7. Difference-in-Difference-in-Difference Model for the Education Industry**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0231*** | 0.0680*** | 0.192*** |
| | (0.00193) | (0.00391) | (0.00646) |
| age_sq | -0.000408*** | -0.00106*** | -0.00284*** |

| | | | |
|---|---|---|---|
| | (4.42e-05) | (9.34e-05) | (0.000147) |
| age_cube | 2.11e-06*** | 4.94e-06*** | 1.14e-05*** |
| | (3.23e-07) | (7.07e-07) | (1.08e-06) |
| race | 0.00106 | -0.0984*** | 0.0113 |
| | (0.00266) | (0.00875) | (0.00880) |
| educ_level | 0.00694*** | 0.0262*** | 0.131*** |
| | (0.00160) | (0.00253) | (0.00533) |
| year | 0.00178*** | 0.0296*** | 0.0465*** |
| | (0.000244) | (0.000612) | (0.000795) |
| o.FMLA | - | - | - |
| treatment | -0.00875** | -0.0265*** | -0.0331*** |
| | (0.00382) | (0.00911) | (0.0125) |
| treat_state | -0.0245*** | -0.0779*** | 0.0691*** |
| | (0.00530) | (0.0141) | (0.0183) |
| FMLA_treatment | 0.0154*** | -0.00200 | 0.0698*** |
| | (0.00547) | (0.0130) | (0.0179) |
| FMLA_treat_state | | | |
| treatment_treat_state | 0.0109** | -0.0169 | -0.00368 |
| | (0.00486) | (0.0118) | (0.0158) |
| o.FMLA_treatment_treat_state | | | |
| o.FMLA_treat_state | - | - | - |
| FMLA_treatment_treat_state | -0.0222*** | -0.00861 | -0.0756*** |
| | (0.00666) | (0.0161) | (0.0218) |
| Constant | -1.607*** | -32.43*** | -52.10*** |
| | (0.270) | (0.664) | (0.880) |
| Observations | 531,050 | 181,357 | 495,863 |
| R-squared | 0.001 | 0.036 | 0.025 |
| Number of id | 29,267 | 15,197 | 28,772 |
| individual FE | YES | YES | YES |

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

**Table C8. Difference-in-Difference-in-Difference Model for High-Paying Occupations**

| VARIABLES | (Employment) Fixed Effects DDD | (logWages) Fixed Effects DDD | (logEarnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.00769*** | 0.0831*** | 0.138*** |
| | (0.00105) | (0.00403) | (0.00380) |
| age_sq | -0.000129*** | -0.00136*** | -0.00205*** |
| | (2.33e-05) | (9.53e-05) | (8.45e-05) |
| age_cube | 5.30e-07*** | 7.25e-06*** | 7.27e-06*** |
| | (1.67e-07) | (7.23e-07) | (6.07e-07) |
| race | 0.00212** | 0.00242 | -0.00500 |
| | (0.000935) | (0.00628) | (0.00332) |
| educ_level | 0.00561*** | 0.0284*** | 0.0751*** |
| | (0.00120) | (0.00329) | (0.00443) |
| year | -0.000751*** | 0.0261*** | 0.0331*** |
| | (0.000114) | (0.000463) | (0.000406) |
| o.FMLA | - | - | - |
| treatment | -0.00261 | -0.0188** | -0.104*** |
| | (0.00259) | (0.00818) | (0.00921) |
| treat_state | -0.00584*** | -0.00917 | 0.0277*** |
| | (0.00225) | (0.00999) | (0.00814) |
| FMLA_treatment | 0.000226 | 0.00976 | 0.0559*** |
| | (0.00325) | (0.0104) | (0.0116) |
| o.FMLA_treat_state | - | - | - |
| treatment_treat_state | -0.000227 | 0.0323*** | 0.0311** |
| | (0.00348) | (0.0112) | (0.0124) |
| FMLA_treatment_treat_state | -0.00211 | -0.0710*** | -0.115*** |
| | (0.00420) | (0.0138) | (0.0150) |
| Constant | 1.510*** | -29.67*** | -36.06*** |
| | (0.138) | (0.530) | (0.495) |
| Observations | 1,112,506 | 325,589 | 1,071,126 |
| R-squared | 0.000 | 0.032 | 0.019 |
| Number of id | 60,500 | 26,351 | 59,587 |
| individual FE | YES | YES | YES |

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

**Table C9. Difference-in-Difference-in-Difference Model for Medium-Paying Occupations**

| VARIABLES | (Employment) Fixed Effects DDD | (Wages) Fixed Effects DDD | (Earnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0243*** | 0.0949*** | 0.0890*** |
| | (0.00219) | (0.00671) | (0.00728) |
| age_sq | -0.000483*** | -0.00160*** | -0.000748*** |
| | (4.93e-05) | (0.000159) | (0.000164) |
| age_cube | 2.88e-06*** | 8.53e-06*** | -3.07e-06*** |
| | (3.55e-07) | (1.20e-06) | (1.18e-06) |
| race | -0.0143*** | -0.0944*** | -0.0686*** |
| | (0.00357) | (0.0246) | (0.0119) |
| educ_level | 0.00172 | 0.0238*** | 0.107*** |
| | (0.00262) | (0.00500) | (0.00891) |
| year | 0.00113*** | 0.0193*** | 0.0415*** |
| | (0.000241) | (0.000963) | (0.000777) |
| o.FMLA | - | - | - |
| treatment | -0.00348 | 0.0652*** | -0.0404*** |
| | (0.00456) | (0.0186) | (0.0146) |
| treat_state | -0.0103** | -0.0866*** | 0.00474 |
| | (0.00488) | (0.0209) | (0.0164) |
| FMLA_treatment | 0.0116* | -0.125*** | 0.0211 |
| | (0.00600) | (0.0243) | (0.0193) |
| o.FMLA_treat_state | - | - | - |
| treatment_treat_state | 0.00798 | -0.0929*** | -0.0229 |
| | (0.00585) | (0.0243) | (0.0188) |
| FMLA_treatment_treat_state | -0.0197*** | 0.133*** | -0.0308 |
| | (0.00743) | (0.0305) | (0.0239) |
| Constant | -0.823*** | -24.89*** | -49.50*** |
| | (0.311) | (1.234) | (1.013) |
| Observations | 437,878 | 94,504 | 411,743 |
| R-squared | 0.001 | 0.023 | 0.019 |
| Number of id | 24,865 | 9,267 | 24,481 |
| individual FE | YES | YES | YES |

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

**Table C10. Difference-in-Difference-in-Difference Model for Low-Paying Occupations**

| VARIABLES | (Employment) Fixed Effects DDD | (Wages) Fixed Effects DDD | (Earnings) Fixed Effects DDD |
|---|---|---|---|
| age | 0.0349*** | 0.0846*** | 0.218*** |
| | (0.000444) | (0.000638) | (0.00126) |
| age_sq | -0.000695*** | -0.00143*** | -0.00389*** |
| | (1.06e-05) | (1.57e-05) | (3.01e-05) |
| age_cube | 4.29e-06*** | 6.76e-06*** | 1.97e-05*** |
| | (8.03e-08) | (1.21e-07) | (2.28e-07) |
| race | -0.00206*** | -0.0164*** | -0.0309*** |
| | (0.000598) | (0.000951) | (0.00163) |
| educ_level | 0.00615*** | 0.0274*** | 0.0974*** |
| | (0.000218) | (0.000300) | (0.000613) |
| year | 0.00110*** | 0.0340*** | 0.0489*** |
| | (7.28e-05) | (0.000114) | (0.000198) |
| o.FMLA | - | - | - |
| treatment | -0.00192 | -0.0875*** | -0.167*** |
| | (0.00164) | (0.00229) | (0.00450) |
| treat_state | 9.92e-05 | -0.0206*** | -0.00564 |
| | (0.00209) | (0.00320) | (0.00585) |
| FMLA_treatment | -0.00738*** | -0.0372*** | -0.122*** |
| | (0.00214) | (0.00306) | (0.00589) |
| o.FMLA_treat_state | - | - | - |
| treatment_treat_state | -0.00189 | -0.0149*** | -0.00371 |
| | (0.00214) | (0.00300) | (0.00588) |
| FMLA_treatment_treat_state | -0.00137 | -0.0129*** | -0.0121 |
| | (0.00269) | (0.00383) | (0.00738) |
| Constant | -1.032*** | -36.95*** | -54.26*** |
| | (0.0801) | (0.122) | (0.217) |
| Observations | 4,520,144 | 3,150,020 | 4,158,522 |
| R-squared | 0.004 | 0.078 | 0.063 |
| Number of id | 231,348 | 185,747 | 226,580 |
| individual FE | YES | YES | YES |

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