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**Policy Landscape**

Since 1993, eligible US workers have had access to 12 weeks of unpaid leave under the Family and Medical Leave Act (FMLA). However, due to firm size and work history requirements, eligibility is far from universal, and typical use is even smaller. In 2012, the Department of Labor estimated that fewer than 60% of workers nationwide were eligible for FMLA leave and only 16% of those eligible workers actually took FMLA leave (Klerman, Daley, and Pozniak 2012).

Enacted in September 2002, the California Paid Family Leave legislation (CA-PFL) went into effect July 2004. The CA-PFL grants 6 weeks of paid leave to eligible mothers and fathers, providing 55% of base pay constrained by a cap on payout ($1,075 per week in 2014 and $1,252 in 2019). Workers may take leave concurrently or intermittently in the 12 months following birth. The CA-PFL stacks with California’s preexisting Temporary Disability Insurance program (TDI) which typically provides mothers with six weeks to compensated leave to be used during pregnancy or immediately after childbirth. The CA-PFL is funded by a payroll tax on California workers.

Officially entitled the Family Temporary Disability Leave law, the New Jersey Paid Family Leave legislation (NJ-PFL) came into effect in July 2009. The NJ-PFL grants 6 weeks of paid leave to eligible mothers and fathers, providing 2/3 of average weekly pay up to a set maximum that has varied over time ($595 per week in 2014). Eligible workers are those individuals that have worked at least 20 calendar weeks in New Jersey or that have earned at least $7,150 in the 12 months preceding requested leave. Workers may take leave within 12 months of birth, and leave may be taken concurrently or intermittently. NJ-PFL is funded by a payroll tax on New Jersey workers.

**Literature Review**

Slater, Ruhm, and Waldfogel (2012) conduct a difference-in-difference analysis using yearly data from 1999 to 2010 collected in the March Current Population Survey. They use this data to estimate the effect of the CA-PFL on leave-taking of mothers following childbirth, as well as their subsequent labor market outcomes. The author find that the CA-PFL doubled overall use of maternity leave from three weeks on average to six weeks on average. Slater, Ruhm and Waldfogel also estimate that the California policy increased the usual weekly work hours of employed mothers of one-to-three year-old children by 10 to 17 percent.

Baum and Ruhm (2014) make use of the 1997 cohort of the National Longitudinal Survey of Youth to investigate the effect of the CA-PFL on various labor market outcomes. The authors find that the CA-PFL raised leave-taking on average by one week for fathers and three weeks for mothers. According to their analysis, the authors find that the largest effect of the CA-PFL on leave-taking occurs 6 to 14 weeks after birth. This corresponds with theory, as the CA-PFL stacks with California’s preexisting Temporary Disability Insurance program, which provides six weeks of paid leave following childbirth. Baum and Ruhm also find that the policy increased the rate at which mothers return to work after giving birth, but did not find a statistically significant effect upon mothers’ wages. They suggest based on the evidence that the increased rate of return to work for mothers could be due to CA-PFL lowering the probability of mothers quitting their jobs prior to giving birth.

Das and Polachek (2015) use data from the March Current Population Survey to explore the impact of the CA-PFL on labor force participation and unemployment outcomes. Utilizing a difference-in-difference framework, the authors find that the CA-PFL increased the LFP rate of young women in California relative to other states. Das and Polachek also investigate unintended negative consequences of the law, and find that the policy increased the rate and average duration of unemployment for young women relative to other states.

Curtis, Hirsch, and Schroeder (2016) use data from the Quarterly Workforce Indicators to estimate the effect of the CA-PFL on labor market outcomes by examining employment flows and wage offers among new hires. The authors find that although the CA-PFL had little effect on earnings for young women in California, the policy did result in increased labor market churn (defined by the authors as separations, hires, and recalls).

Bartel et al. (2018) use data from the 2000 Census and the 2000 to 2013 waves of the American Community Survey to investigate the effect of the California Paid Family Leave law on fathers’ leave-taking. The authors find that the policy raised leave-taking rates of fathers by 46 percent, although fathers still on average only take 1.5 weeks out of the total 6 weeks of leave for which they are eligible under CA-PFL. In contrast, mothers on average take 9 weeks out of the 12 total weeks for which they are eligible under the combined Temporary Disability Insurance policy and the CA-PFL.

**Theory**

The New Jersey and California paid family leave policies may produce both benefits and costs on a range of labor market outcomes.

Economic theory provides mechanisms for both a positive and negative effect of paid family leave policies on labor force participation of mothers. As paid leave can reduce career interruptions by preserving job continuity of mothers, a paid leave policy may have a positive effect on labor force participation. On the other hand, paid leave may lower the demand curve for young women in the labor market, as firms anticipate bearing higher costs compared to other workers, and discriminate accordingly.

A wrinkle in estimating the impact of paid family leave policies is the differential effects expected among different classes of workers. Among workers who would have returned to work in the absence of a paid family leave policy, the effect of the policy on work is likely to be negative as workers take advantage of the lowered cost of work interruption to lengthen their leave. However, among workers who otherwise would have ended their employment, the effect of the policy on work is likely to be positive, as the policy provides greater ability for the worker to retain employment while still taking time away from work.

Paid family leave imposes a clear monetary cost on workers and firms through the payroll tax by which the policy is funded. Firms may also bear costs through search and training costs of temporarily replacement labor. Replacement labor may also be less productive due to less accumulation of firm-specific skills.

**Data**

In this paper, I used data from four panels of the Survey of Income and Program Participation. Each panel covers a national stratified sample of the U.S. civilian non-institutionalized population and uses a 4-month recall period, with respondents divided into rotation groups with each group interviewed during one month of the four-month period. Each four-month period constitutes a wave of the survey. As respondents to the survey are recorded over different lengths of time, the dataset constitutes an unbalanced panel.

|  |  |  |  |
| --- | --- | --- | --- |
| SIPP Panel | Number of Waves | First Month | Last Month |
| 1996 | 12 | Dec 1996 | Feb 2000 |
| 2001 | 8 | Oct 2000 | Dec 2003 |
| 2004 | 12 | Oct 2003 | Dec 2007 |
| 2008 | 16 | May 2008 | Dec 2013 |

The sample used in this paper includes 2,817 unique persons and 103,624 person-month observations. This sample was constructed from all women aged 24 to 45 who gave birth during the time coverage of the SIPP panel and lived within one of the treatment or control states.

Unique Individual Counts by State and Year

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | California | Florida | New Jersey | New York | Texas |  |
| Year |  |  |  |  |  | Total |
| 1995 | 62 | 23 | 19 | 43 | 48 | 195 |
| 1996 | 319 | 105 | 76 | 166 | 211 | 873 |
| 1997 | 318 | 107 | 74 | 162 | 216 | 873 |
| 1998 | 303 | 97 | 68 | 151 | 208 | 823 |
| 1999 | 283 | 87 | 64 | 140 | 185 | 758 |
| 2000 | 282 | 95 | 58 | 145 | 207 | 787 |
| 2001 | 207 | 76 | 48 | 106 | 149 | 583 |
| 2002 | 201 | 77 | 44 | 96 | 144 | 562 |
| 2003 | 341 | 139 | 91 | 162 | 234 | 963 |
| 2004 | 204 | 99 | 59 | 103 | 143 | 604 |
| 2005 | 201 | 96 | 56 | 103 | 146 | 597 |
| 2006 | 197 | 91 | 52 | 98 | 140 | 576 |
| 2007 | 127 | 69 | 27 | 71 | 80 | 372 |
| 2008 | 222 | 86 | 74 | 86 | 150 | 618 |
| 2009 | 225 | 85 | 75 | 91 | 160 | 631 |
| 2010 | 220 | 86 | 73 | 90 | 163 | 630 |
| 2011 | 218 | 83 | 69 | 83 | 161 | 612 |
| 2012 | 148 | 51 | 41 | 52 | 103 | 395 |
| Total | 1002 | 389 | 276 | 485 | 707 | 2817 |

(Highlighted values indicate the presence of a paid family leave policy.)

Unfortunately, the variable provided by the SIPP for measurement of labor force participation does not differentiate between individuals who are employed and working, and those that are employed and away on leave. In my analysis, an individual is coded as participating in the labor force for RMESR values of 1 to 7 and not participating for an RMESR value of 8. An individual is coded as working for an RMESR value of 1. An individual is coded as looking for work for RMESR values of 5, 6, and 7.

RMESR: Employment status recode for month

|  |  |  |
| --- | --- | --- |
| Code |  | Observations |
| 1 | With a job entire month, worked all weeks (includes individuals on paid leave) | 57,373 |
| 2 | With a job entire month, absent from work without pay 1+ weeks, absence not due to layoff | 2,595 |
| 3 | With a job entire month, absent from work without pay 1+ weeks, absence due to layoff | 450 |
| 4 | With a job at least 1 but not all weeks, no time on layoff and no time looking for work | 1148 |
| 5 | With a job at least 1 but not all weeks, remaining weeks on layoff or looking for work | 523 |
| 6 | No job all month, on layoff or looking for work all weeks | 3,323 |
| 7 | No job all month, at least one but not all weeks on layoff or looking for work | 440 |
| 8 | No job all month, no time on layoff and no time looking for work. | 37,756 |
| Nan | Missing data | 16 |

The SIPP allows for information on two possible jobs to be recorded. In the case of an individual holding multiple jobs during a reference month, the job by which the individual earned the most money over the four-month period will be listed as job 1. The job that provided the next most earnings in the four-month period will be listed as job 2. In order to simplify the analysis, only data on job 1 was used in this paper, and each individual was placed into occupations groups according to job 1.

An important aspect of the data is that the SIPP changed the encoding of occupations after the 2001 panel. The 1996 and 2001 panels of the SIPP encode occupations according to the 1990 Census Bureau occupational classification scheme, while the 2004 and 2008 panels utilize the classification scheme from the 2000 Census. This means that pre-2004 panel occupations cannot be directly matched to 2004 and later panel occupations. However, both types of occupation coding systems could still be placed into general occupation groups (specified by the Standard Occupational Classification system). Individuals were placed into occupation groups according to their most recent pre-birth occupation. I then codified each occupation group as either ‘white collar’ or ‘blue collar’. The results of this processing can be seen in the table below.

Occupation Group Counts and Encodings

|  |  |  |  |
| --- | --- | --- | --- |
| Code | Pre-birth Occupation Group | White Collar / Blue Collar | Count |
| 11 | Management | White Collar | 131 |
| 13 | Business and Finance | White Collar | 86 |
| 15 | Computer Science and Mathematics | White Collar | 38 |
| 17 | Architecture and Engineering | White Collar | 24 |
| 19 | Life, Physical, And Social Science | White Collar | 16 |
| 21 | Community and Social Service | White Collar | 43 |
| 23 | Law | White Collar | 20 |
| 25 | Education, Training, and Library | White Collar | 195 |
| 27 | Arts, Design, Entertainment, Sports | White Collar | 28 |
| 29 | Healthcare Practitioners and Technicians | White Collar | 169 |
| 31 | Healthcare Support | White Collar | 81 |
| 33 | Protective Service | Blue Collar | 78 |
| 35 | Food Preparation and Serving | Blue Collar | 89 |
| 37 | Building/Grounds Cleaning and Maintenance | Blue Collar | 54 |
| 39 | Personal Care and Service | Blue Collar | 78 |
| 41 | Sales and Related Occupations | White Collar | 190 |
| 43 | Office and Administrative Support | White Collar | 424 |
| 45 | Farming, Fishing, and Forestry | Blue Collar | 25 |
| 47 | Construction and Extraction | Blue Collar | 6 |
| 49 | Installation, Maintenance, and Repair | Blue Collar | 5 |
| 51 | Production | Blue Collar | 80 |
| 53 | Transportation and Material Moving | Blue Collar | 20 |
|  | Unclassified | N/A | 39 |
|  |  | Total Unique Individuals | 1854 |

Is the segmentation by educational attainment and the segmentation by occupation type capturing the same subpopulations? The cross tabulation below indicates that while there is overlap, the two segmentations indeed divide the sample differently.

Observation Frequency Table for Education / Employment Type

|  |  |  |  |
| --- | --- | --- | --- |
|  | White collar | Blue collar | Totals |
| Less than College | 29101 | 12722 | 41823 |
| College Educated | 25484 | 1208 | 26692 |
| Totals | 54585 | 13930 | 68515 |

Person Frequency Table for Education / Employment Type

|  |  |  |  |
| --- | --- | --- | --- |
|  | White collar | Blue collar | Totals |
| Less than College | 807 | 340 | 1147 |
| College Educated | 685 | 37 | 722 |
| Totals | 1445 | 370 | 1815 |

Summary Statistics

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | count | mean | std | min | 25% | 50% | 75% | max |
| Calendar Year | 103624 | 2002.91 | 4.93 | 1995 | 1998 | 2003 | 2007 | 2012 |
| Age | 103624 | 31.43 | 4.85 | 8.0 | 28.0 | 31.0 | 35.0 | 49.0 |
| Education | 103608 | 40.86 | 3.38 | 31.0 | 39.0 | 40.0 | 44.0 | 47.0 |
| Months Since Birth | 103624 | 2.92 | 17.01 | -47.0 | -8.0 | 3.0 | 15.0 | 47.0 |

**Methodology**

*Yits* : Labor-force outcome for woman *I* living in state *s* in period *t*

*λt* : Year Indicators

*θs* : State Indicators

: Months Since Birth Indicators

Basic Generalized Difference in Difference Estimation: Bertrand et al. (2004)

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Interacted Difference in Difference Estimation

Full Model

Assumptions:

Parallel Trends Assumption:

The parallel trends assumption is violated if there exists unobserved time-varying confounding.

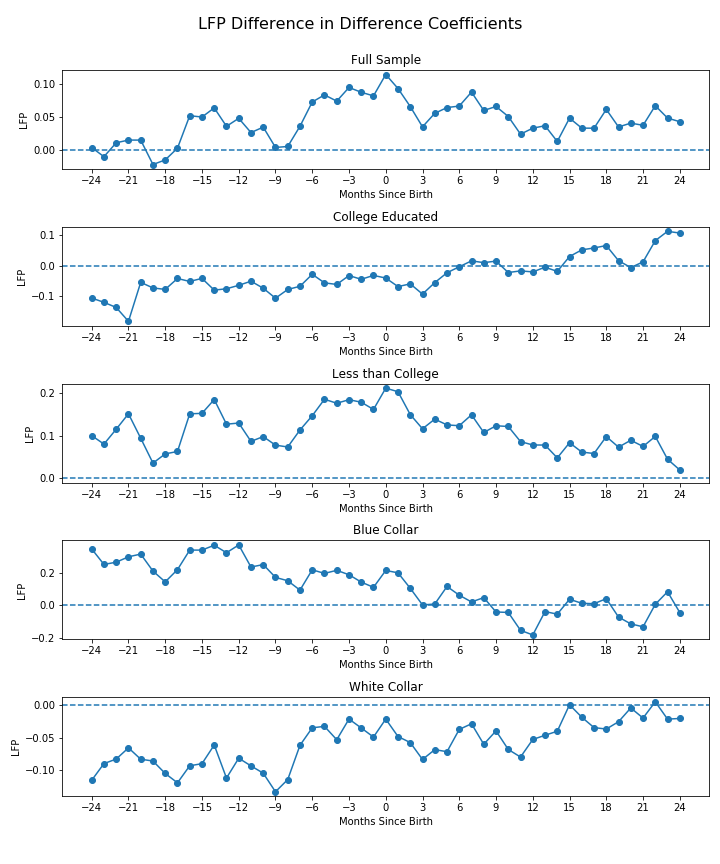
Exogeneity of Treatment:

Unbiased difference-in-difference estimation requires the assumption that the assignment of treatment is not caused in any way by the outcome variable. In this case, it is likely that the assumption holds, as is unlikely that policy-makers enacted paid leave policies as a result of any particular pattern of mothers’ labor force participation.

No Effect of Treatment on pre-Treatment Population:

Unbiased difference-in-difference estimation requires the assumption that pre-treatment outcomes are not affected by treatment. That is, we assume that mothers do not anticipate the implementation of a paid leave policy and adjust their labor force participation accordingly. It is quite possible that this assumption is violated in this analysis. Mothers expecting shortly before the implementation of a paid leave policy, who would otherwise have dropped out of the labor-force, may have stayed in the labor-force anticipating eligibility for paid leave once the policy came into effect. However, as the proportion of mothers who were pregnant in the 9 months before the implementation of a paid leave policy is small compared to the total sample, the effect on the DiD coefficients is likely to also be small.

**Results**



P-Values of Joint Tests for Significance: Months Since Birth \* Policy Coefficients

|  |  |  |  |
| --- | --- | --- | --- |
| Months Since Birth | -3 to +3 | 0 to + 6 | +6 to +14 |
| Full Sample | 0.12 | 0.33 | .78 |
| College Educated | 0.78 | 0.36 | .97 |
| Less Than College | 0.02 | 0.045 | .43 |
| Blue Collar | 0.17 | 0.17 | .28 |
| White Collar | 0.53 | 0.62 | .71 |

**Limitations**

Empirical analysis of employer mandates is often difficult to examine with rigor due to the limitations of available data. Segmenting individual level data like the Survey of Income and Program Participation by geographical location and time period leads to small sample sizes and low statistical power. Aggregate data, on the other hand, lacks the granularity necessary to estimate the effect of the mandate on the subpopulations that are likely to be affect most by the mandate.

**References**

Klerman, J. A., Daley, K., & Pozniak, A. (2012). Family and Medical Leave in 2012: Technical Report (contract #GS10FOO86K). Cambridge, MA: Abt Associates. Retrieved from U.S. Department of Labor website: http://www.dol.gov/asp/evaluation/fmla/FMLATechnicalReport.pdf