CONTEMPORARY ECONOMIC POLICY

UNANTICIPATED EFFECTS OF CALIFORNIA'S PAID FAMILY LEAVE PROGRAM

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We examine the effect of California paid family leave (CPFL) on young women's labor force participation and unemployment, relative to men and older women. CPFL enables workers to take at most 6 weeks of paid leave over a 12-month period in order to bond with new born or adopted children, or to care for sick family members or ailing parents. The policy benefits women, especially young women, as they are more prone to take such a leave. However, the effect of the policy on overall labor market outcomes is less clear. We apply difference-in-difference techniques to identify the effects of the CPFL legislation on young women's labor force participation and unemployment. We find that the labor force participation rate, the unemployment rate, and the duration of unemployment among young women rose in California compared to men (particularly young men) and older women in California, and to other young women, men, and older women in states that did not adopt PFL. The latter two findings regarding higher young women's unemployment and unemployment duration are unanticipated effects of the CPFL program. We utilize robustness checks as well as unique placebo tests to validate these results. (*JEL* H43, J13, J18, J48)

I. INTRODUCTION

California paid family leave (CPFL) legislation was enacted in September 2002 and went into effect in July 2004. This legislation enabled workers to take a maximum of 6 weeks leave to care for a newborn, an adopted child, or an ailing family member. It provided about 55% normal pay that was financed by the California Employment Development Department State Disability Insurance Program through a tax on *all* employees. It is distinct from other U.S. job protected family leave legislation because it provides *paid* leave, whereas others, such as the Family and Medical Leave Act (FMLA), provide unpaid leave.

Paid family leave (PFL) is becoming popular among policymakers in other states, as well. Two states, Washington and New Jersey, enacted similar PFL legislation in 2007 and 2008, respectively. PFL took effect in New Jersey in September 2009, but still has not been implemented in Washington. Other major states including Arizona, Illinois, Maine, Massachusetts, Missouri, New Hampshire, New York, Oregon, and Pennsylvania are now considering similar PFL legislation. One impetus is that a number of other nations have such programs;[1] so analysis of the effects of family leave, especially California's program, can be informative and valuable.[2]

1. According to Ray, Gornick, and Schmitt (2008), these include Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

2. There are still not enough data to test the effects of PFL in New Jersey.

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ABBREVIATIONS

AALL: American Association for Labor Legislation
CPFL: California Paid Family Leave
CPS: Current Population Survey
DID: Difference in Differences
FMLA: Family and Medical Leave Act
PFL: Paid Family Leave
SDI: State Disability Insurance
TDI: Temporary Disability Insurance

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Early studies on maternity leave indicate beneficial effects. For example, Klerman and Leibowitz (1997) use 1980 and 1990 U.S. Census data to show "maternity leave statutes increased leave, but had insignificant positive effects on employment and work." This is consistent with European studies (e.g., Bertola, Blau, and Kahn 2002; Chevalier and Viitanen 2002) that basically show that women are constrained in their work activities by the lack of childcare, and that maternity rights have induced women to return to work with a higher probability post-birth (e.g., Gregg, Gutiérrez-Domènech, and Waldfogel 2007; Ondrich et al. 1999).

While PFL policies increase parental leave-taking and subsequent labor force participation by mothers (and to a lesser extent fathers), the law can have unintended effects that, as yet, have not been studied. Although not necessarily the case, it is possible for employers' costs to increase if they need backup temporary labor to substitute for leave-takers. Temporary workers may seem like good substitutes, but they may be less productive because they often have less motivation and training. Costs also can increase if employers bear the burden of depreciation of worker skills during time out (Edin and Gustavsson 2007). Higher labor costs to support workers who make use of the legislation, even if small, can alter employer demand for labor. If such is the case, the demand for men and older women can rise, and the demand for young (child-bearing-age) women can fall. These demand shifts coupled with increases in labor force participation, especially for young women, can result in higher young women's unemployment rates, relative to other population groups, an unintended effect.

In contrast, the possibility arises that these costs can be offset. For example, if potential leaves increase retention, particularly among young women employees, labor costs can be reduced, more so for young women than other groups. Whether relative employee costs increase or decrease then becomes an empirical question.

PFL can have additional effects, some beneficial and some not so beneficial. In addition to affecting the young women target group, it is possible that those males and older females who normally do not participate in the labor force might instead do so if higher wages (brought about by an increased demand for them) drive them into the labor market. On the other hand, some young child-bearing-age women might be discouraged from labor market activity, particularly if they anticipate a shift in demand toward older women and/or men. Clearly these supply and demand shifts affect the unemployment rate of young child-bearing-age women.

Casual empiricism supports the possibility that costs have increased for hiring women relative to men. In 2010, well after CPFL's implementation, the California women's unemployment rate was the second highest in the nation. This high unemployment rate contrasts with declining California female unemployment rates *before* the CPFL law became effective. In 2000, California's unemployment rate for women was fifth highest in the nation. In 2003, just prior to the law's effective date, the California women's unemployment rate declined to ninth highest. In short, California women's unemployment rates (relative to the rest of the nation) decreased immediately *before* CPFL, but rose *afterwards*. Unlike women, men's relative unemployment in California rose over this entire period. Thus, while the position of California women (relative to men and relative to the rest of the nation) improved prior to CPFL (in terms of having a relatively low unemployment rate), it deteriorated afterwards. Though anecdotal, it is not obvious that any other factors affected California's female unemployment rate differently than California men's unemployment rate, or differently than the rest of the nation's unemployment rate. For this reason, we empirically investigate the effects of CPFL more rigorously.

The purpose of this article is to estimate effects of the CPFL on labor force participation and the incidence and duration of unemployment. Our study differs from others in that we focus on unintended outcomes. Further, we take account of other California-wide political and economic shocks that could especially affect young California women, but are unaccounted for in other studies. To estimate these, we apply difference-in-difference (DID) techniques.

The simplest identification strategy is to assess outcome changes for young California women before and after the law's implementation. However, this approach can confound measures of CPFL's effects with other independent nationwide and California trends in the outcome indicators for particular segments of the population. These trends embody movements in labor force participation and unemployment, which are coincident with the timing of CPFL, and can arise either because of, or independent of, the law. They can differ between California and the rest of the nation, they can differ between males and females, and they can differ between the young and the old. Thus, to isolate the effects of the CPFL, we examine young California women before and after the law's implementation *relative to* outcome changes for young women in the rest of the country before and after CPFL's implementation, *and* relative to older women and men in California compared to the rest of the country. This identification strategy implies a quadruple difference using data for young and old, men and women; but, to show the strength of our results, we also corroborate the findings using data solely on women, and solely on the young.[3] Finally, we adopt robustness checks as well as a set of placebo tests to ensure our results are not driven by unforeseen shocks associated with the years the CPFL was enacted, either in California or elsewhere.

For younger women, the predominant group the CPFL was designed to help, our main results indicate a net increase in labor force participation by about 1.5 percentage points. This increase in participation, coupled with likely shifts in demand, resulted in a relative increase in unemployment of between 0.3 and 1.5 percentage points, roughly 5%–22% of the young female unemployment rate in California at that time. In addition, unemployment duration increased by 4%–9%. Both these results regarding unemployment are noteworthy because they are unanticipated. Further, they counter the law's dominantly positive effects outlined in the studies cited above, and mentioned in a number of news articles and policy think-tank press releases and reports (e.g., Hollo 2012; Houser and Vartanian 2012).

II. BACKGROUND

Family leave legislation has a long history. In 1905, with U.S. labor unions in their infancy, a group of economists founded the American Association for Labor Legislation (AALL) to encourage the study of labor conditions and to work for protective labor legislation. Richard T. Ely was its first president and John R. Commons its early secretary (Chasse 1991). In 1917, the AALL instigated 12 state legislatures to consider compulsory disability legislation. No bill passed, but considerable debate followed (Osborn 1954). In 1942, Rhode Island was the first state to introduce compulsory disability insurance. California did so in 1946. California's temporary disability insurance (TDI) created a compulsory state fund with private insurance excluded, and did not include pregnancy or other family issues. The TDI was modified in 1973 to cover abnormal pregnancies, and in 1978, 1991, and 1992, it was again amended, first to protect pregnant women solely against job loss, then to cover spouses, and finally in 1999 to allow workers up to 50% of their annual allotment of sick leave for "kin care" (Milkman and Appelbaum 2004). The CPFL that we study in this article, passed in September 2002 and became effective in July 2004. It provided remuneration for up to 6 weeks over a 12-month period at approximately 55% of one's pay. Obviously, the big change beginning July 2004 was providing partial pay, then up to $728 per week for eligible employees who needed time off for a birth, an adoption, or a sick family member. Further, the law covers all private sector employees, including part-time employees, regardless of employer size.

In a sense, the CPFL was no real surprise given that it came about as a progression of laws each expanding the definition of family leave. On the other hand, there was sufficient initial opposition and eventual compromise so that the timing and scope was arguably unexpected. While organized labor and women's rights groups vigorously lobbied for passage, the California chamber of commerce and other business groups strongly opposed it on the grounds that it would disrupt and hurt businesses financially, especially small businesses. In the end, the direct costs of the bill were borne solely by employees through a payroll tax added to the already existing mandatory state disability insurance (SDI) fund.[4] Obviously, this payroll tax does not include employer indirect costs mentioned earlier coming about from finding substitute employees, or indirect costs based on an equilibrium change in wage structure.

Many view the CPFL as a game changer. The Economic Opportunity Institute describes the law as "the first of its kind in the nation, and [it] remains the most generous."[5] Peoples World[6] describes it as "landmark" as does Fass (2009)

3. One could also illustrate this by comparing first-difference regressions solely on young and old women, and young and old men, but these comparisons essentially amount to a quadruple difference.

4. The tax increase came about mostly by raising the taxable wage base, though the percent of salary (below the taxable wage base) also rose marginally following implementation.

5. http://washingtonpolicywatch.org/2010/02/02/new-report-details-positive-effects-of-paid-family-leave/

6. http://peoplesworld.org/california-s-paid-family-leave-a-success/

who adds that it is a model for other states to emulate. As a result, studies are just beginning to emerge on the effects of family leave. For example, from a health perspective, Guendelman et al. (2009) argue that "postpartum maternity leave may have a positive effect on breastfeeding among full-time workers, particularly those who hold non-managerial positions, lack job flexibility, or experience psychosocial distress."

With regard to utilization of family leave, some studies find an initially minimal utilization (Schuster et al. 2008). On the other hand, based on a telephone interview of 1,105 parents in Chicago and Los Angeles from November 2003 to January 2004, Chung et al. find that among the 574 full-time employed parents surveyed "parents with paid leave benefits had 2.8 times greater odds than other parents of missing work whenever their child needed them" (Chung et al. 2007). Further, Rossin-Slater, Ruhm, and Waldfogel (2011) found "robust evidence that the California program more than doubled the overall use of maternity leave," and that the increase was particularly strong for less advantaged groups. This latter study analyzes individual micro data on women workers and concentrates solely on changes in maternity leave usage relative to other leaves.[7] Baum and Ruhm (2014), using micro data from the 1997 National Longitudinal Survey, also echo this finding that the CPFL raised leave-taking by about 3 weeks for the average mother.

While most empirical research analyzes the increase in leaves young women take because of the new PFL benefit, as of now no one examined unintended consequences.[8] For example, one could easily expect the law to cause higher unemployment rates for working mothers, because more such women enter the labor market to take advantage of PFL, and because firms decrease their demand for these possibly more costly workers.[9] At the same time, shifts in demand could yield higher wages for other groups, such as men and older women, leading them to enter the labor market. Consistent with this, Curtis, Hirsch, and Schroeder (2014) use Quarterly Workforce Indictors data to show that wages of new young women hires are about 2% lower than young men and older women. In short, the CPFL could result in supply and demand shifts that might also impact unemployment rates for young women relative to other demographic groups. To our knowledge, the validity of these possible deleterious outcomes has not been tested with data.

The innovation in this article is to assess these possible unintended effects. We use March Current Population Survey (CPS) data for the entire population, not just those at work, because restricting the analysis to those at work could yield biased estimates if the law induces new workers to enter or causes existing workers to leave the labor force. From these we are able to define three outcome measures: the labor force participation rate, the unemployment rate, and unemployment duration. As already mentioned, we employ DID computations to assess these three outcome measures for young women in California relative to the rest of the United States compared to older females as well as to young and older males before and after implementation of the CPFL. Also, as already indicated, we find a relative increase in unemployment of between 0.3 and 1.5 percentage points (roughly 5%–22% of the young female unemployment rate in California at that time) and an increase in unemployment duration of 4%–9%. Further, we utilize a unique placebo test to validate our results. To the best of our knowledge, no other study assesses these unintended effects.

III. EXPERIMENTAL DESIGN

Our experiment consists of comparing how labor force participation and unemployment-related outcomes change from before to after the CPFL in California compared to the rest of the country. To do so, we use the CPS because these data represent the primary and most comprehensive information source used by the U.S. government to estimate employment and unemployment, the two outcomes we seek to analyze. They are also the data Rossin-Slater, Ruhm, and Waldfogel (2011) use to study the positive effect of the CPFL on leave-taking rates. Included in the CPS data are 60,000 households (representing 110,000 individuals) selected to characterize the entire U.S. population to within 0.2% of the true value (BLS: www.bls.gov/cps).

7. Our study uses CPS data as do Rossin-Slater, Ruhm, and Waldfogel (2011). We differ from theirs in that we examine the effect of CPFL on labor force participation and unemployment. We use data aggregated into state-year-age-gender cells whereas they use individual data only for working women. Further, we develop a more extensive placebo test. But most importantly, we examine unintended effects whereas they concentrate on maternity leave utilization.

8. Using monthly longitudinal data from the Survey of Income and Program Participation, Byker (2014) finds that paid family leave in California and New Jersey "are associated with increased labor force participation in the months directly around birth, but have little impact beyond six months."

9. Even lay policy wonks have made this prediction (Newsweek 2009).

In addition, the U.S. government uses the CPS data to compute local area employment statistics for 7,300 areas. Thus given its widespread applicability, we employ the CPS for our analysis. To put our results regarding the effects of California in proper perspective relative to the rest of the nation, we weight each observation by the weights given in the CPS, but we also repeated the analysis unweighted, and observed almost no change in our results.

To visualize this experiment, let $\overline{Y}_{i,PRE}$ and $\overline{Y}_{i,POST}$ be the outcomes of the experiment where $i = [T, C]$ for treatment (T) and control (C) groups before or after treatment. We ask whether the change in outcome in the treated group differs from the change in outcome in the control, that is, $[(\overline{Y}_{T,POST} - \overline{Y}_{T,PRE}) - (\overline{Y}_{C,POST} - \overline{Y}_{C,PRE})]$. This amounts to $(\overline{Y}_{T,POST} - \overline{Y}_{T,PRE})$ if the treatment is randomly assigned and if the control group exhibits no outcome change between *PRE* and *POST*.[10] But, in reality, the members of the treatment group (comprising all residents in California) are not chosen randomly. First, as already mentioned, Californians may differ from the rest of the nation. For example, California could have a unique factor making it different in Y (or changes in Y) than the rest of the nation, such as a charismatic governor or a distinct climate. Second, although the CPFL applies to every employer and employee, responses to the law may differ for men and women. This could be because traditional division of labor in the home impedes men from taking a leave more so than women. Third, fecundity, or other constraints, may make younger women workers different than older women workers.

To account for these possibilities, we divide the population into various segments, each representing parts of the population we expect to be affected differently by the law. As explained above, if California men are not affected by CPFL, then there should be no difference between California men before and after treatment compared to men in the rest of the United States before and after treatment (of course, assuming no *other* shocks affect California men differently than the rest of the nation, or men in the rest of the nation differently than in California). Similarly, if older California women are less affected by the law than young California women, we should see greater effects for young California women (relative to young women in the rest of the country) compared to older California women (relative to older women in the rest of the country). Thus, we subdivide the population by age as well as by gender to account for these possible asymmetric effects of CPFL. As such, we rewrite the outcome Y_{it} above, as Y_{ijkt}, where now i represents the state (California being the treatment state and the other states being the controls); j represents gender; k represents the age group from which we obtain categories young (Y) and old (O); and, as described earlier, t represents year from which we define *PRE* and *POST*. We define *young* to be less than 42 because less than 0.0035 of the female population gives birth after age 39,[11] and we allow women 2 years after giving birth to take advantage of the CPFL provisions. Finally, to control for possible cohort, time, and other possible effects, we include average education, the proportion married, per capita state income, the proportion self-employed, age, and year fixed-effects, as well as a set of age–year interaction terms (to account for possible cohort effects), all of which we discuss later. As mentioned above, we weight each individual by the CPS sample weights. Our final dataset consists of 34,270 observations. The unit of observation is a state, gender, age group, and year average value. This contrasts with Rossin-Slater, Ruhm, and Waldfogel (2011), who instead use individuals as units of observation.[12] Also, they concentrate on how young mothers use the leave provision.[13]

IV. ESTIMATION

To implement our experimental strategy, we utilize DID estimation to identify CPFL's effect. As indicated above, CPFL can have differential

10. This is because random assignment of treatment implies treatment groups are comparable to control groups, that is $\overline{Y}_{T,PRE} = \overline{Y}_{C,PRE}$, and no outcome change in the control group implies $\overline{Y}_{C,POST} - \overline{Y}_{C,PRE} = 0$.

11. Computed from U.S. Census Bureau's Table 1 contained in Dye (2010).

12. Using grouped data minimizes the effect of measurement errors on coefficient standard errors, and hence coefficient significance. Nevertheless, we replicated our results (using a linear probability model) with individual (instead of grouped) data. This yielded qualitatively similar results. However, note linear probability models do not restrict the expected probability to be between 0 and 1. Further, they may be plagued by heteroskedasticity.

13. They compare young mothers in California to all California mothers; to California women with no children; to Florida, New York, and Texas young mothers; and to young mothers with infants across the country, but not to older women or men, each of whom could be affected by the law.

effects for various population subgroups. First, we expect CPFL affects inhabitants in California relative to the rest of the country. Second, we surmise CPFL affects women more than men. Third, among women, we anticipate CPFL affects the young more than the old. To test these hypotheses, we model the law's outcomes Y_{ijkt} as a function of *Cal* (California vs. all other states), *Young* (young vs. old workers), *Fem* (female compared to males), and *Post* (before and after the legislation's implementation), a set of control variables (X_{ijkt}), and interaction terms mentioned above in a year and age fixed-effects framework. This specification enables us to compare labor market outcomes for young California women (the treatment group) to the remaining population in California and the rest of the country (the control group), before and after the law. Further, this approach takes account of possible shocks affecting California (but not the rest of the country), shocks affecting the young in California but not in the rest of the country, and shocks affecting women in California but not in the rest of the country. In addition, we employ two other estimation strategies. One examines only the young. This estimation is comparable to interacting age with all independent variables. The second examines only women. This approach is comparable to interacting gender with all independent variables. Finally, later in the article, we employ a series of placebo tests to check the credibility of our results.

Our most general specification (suppressing subscripts for the obvious categorical dummy variables) is

(1)

$$\begin{aligned} Y_{ijkt} = \alpha_0 &+ \left(\alpha_1 Cal + \alpha_2 Young + \alpha_3 Fem + \alpha_4 Post\right) \\ &+ \left(\beta_1 Cal \times Young + \beta_2 Cal \times Fem \right. \\ &+ \beta_3 Cal \times Post + \beta_4 Young \times Fem \\ &\left. + \beta_5 Young \times Post + \beta_6 Fem \times Post\right) \\ &+ \left(\theta_1 Cal \times Young \times Fem \right. \\ &+ \theta_2 Cal \times Young \times Post \\ &+ \theta_3 Cal \times Fem \times Post \\ &\left. + \theta_4 Young \times Fem \times Post\right) \\ &+ \gamma\,(Cal \times Young \times Fem \times Post) \\ &+ X_{ijkt}B + X_{it}C + \varepsilon_t + \varepsilon_k + \varepsilon_{kt} + \varepsilon_{ijkt}. \end{aligned}$$

As already indicated, the variable Y_{ijkt} represents the outcome for individuals in state i, of gender j, age k, and year t. We concentrate on three outcome measures: labor force participation, unemployment rate, and unemployment duration, which as mentioned above are readily available from CPS data. Dummy control variables *Cal, Young, Fem*, and *Post* depict a California dummy categorical variable, a young (18–41) dummy categorical variable, a female dummy categorical variable, and a post-policy dummy variable. Matrix X_{ijkt} represents the set of state-age-gender-time control variables (schooling level and proportion married mentioned above) for which B is the corresponding vector of coefficients, X_{it} is a matrix of state and time-specific variables (state per capita income and state employment levels) for which C is the corresponding set of coefficients, ε_t depicts year fixed-effects, ε_k depicts cohort fixed-effects, ε_{kt} depicts cohort-year fixed-effects, and finally ε_{ijkt} depicts individual state-age-gender-year errors. The ε_t year fixed-effects enables us to discern the effect of CPFL before and after passage taking account of year-to-year changes arising from countrywide macroeconomic fluctuations not captured by state-age-gender-time-specific labor market variables contained in X_{jkt}, and the state-time variables contained in X_{it}.[14] Similarly, the ε_k cohort fixed-effect takes account of the possibility that the outcome variables vary by cohort independent of year, and the ε_{kt} cohort-year fixed-effect takes account of the possibility that cohort effects vary by year. Finally, we also assume that Equation (1) satisfies all standard assumptions (regarding ε_{ijkt}) of a classical linear regression model.

The effect of the law on young women is

$$\left(\partial^4 Y_{ijkt} / \partial Post\, \partial Cal\, \partial Fem\, \partial Young\right) = \gamma.$$

This amounts to the before and after CPFL law for young women taking account of possible California-specific shocks affecting the young labor market as well as California-specific shocks affecting women. More specifically, it represents the following quadruple DID

$$\gamma = \left\{ \left[\left(\overline{Y}_{CalFemYoungPost} - \overline{Y}_{CalFemYoungPre}\right) - \left(\overline{Y}_{NotCalFemYoungPost} - \overline{Y}_{NotCalFemYoungPre}\right)\right] \right.$$

14. Instead of year fixed-effects, we also model this equation with a time-trend as was done by Puhani and Sonderhof (2011) to analyze German parental leave on young women's training. We do not report these results as they were similar to the fixed-time effects results.

$$- \left[\left(\overline{Y}_{CalFemOldPost} - \overline{Y}_{CalFemOldPre} \right) - \left(\overline{Y}_{NotCalFemOldPost} - \overline{Y}_{NotCalFemOldPre} \right) \right] \Bigg\}$$

$$- \Bigg\{ \left[\left(\overline{Y}_{CalMaleYoungPost} - \overline{Y}_{CalMaleYoungPre} \right) - \left(\overline{Y}_{NotCalMaleYoungPost} - \overline{Y}_{NotCalMaleYoungPre} \right) \right]$$

$$- \left[\left(\overline{Y}_{CalMaleOldPost} - \overline{Y}^{Y}_{CalMaleOldPre} \right) - \left(\overline{Y}_{NotCalMaleoldPost} - \overline{Y}_{NotCalMaleOldPre} \right) \right] \Bigg\}.$$

Implicit in this quadruple difference is the assumption that the impact of control variables X_{ijkt} and X_{it} on outcomes are identical across age and gender groups, in other words that coefficients B and C do not vary by age and gender. To relax this assumption, one can stratify the data by gender and age. Of course, this stratification is comparable to interacting age and gender with X_{ijkt} and X_{it}. For example, the purely female case nets out any differential effects of the law by gender. Here the relevant estimating equation reduces to

$$\text{(2)} \quad Y^F_{ikt} = \alpha^F_0 + \alpha^F_1 Cal + \alpha^F_2 Young + \alpha^F_4 Post + \beta^F_1 Cal \times Young + \beta^F_3 Cal \times Post + \beta^F_5 Young \times Post + \gamma^F Cal \times Young \times Post + X_{ikt}B^F + X_{it}C^F + \varepsilon_t + \varepsilon_{ikt}$$

which is our second estimating equation, where now $\left(\partial^3 Y^F_{ikt} / \partial Post\, \partial Cal\, \partial Young\right) = \gamma^F$ represents the effect of the law. This amounts to the difference-in-difference-in-difference

$$\left[\left(\overline{Y}^F_{CalYoungPost} - \overline{Y}^F_{CalYoungPre} \right) - \left(\overline{Y}^F_{NotCalYoungPost} - \overline{Y}^F_{NotCalYoungPre} \right) \right] - \left[\left(\overline{Y}^F_{CalOldPost} - \overline{Y}^F_{CalOldPre} \right) - \left(\overline{Y}^F_{NotCalOldPost} - \overline{Y}^F_{NotCalOldPre} \right) \right].$$

It does not take account of gender-based California-specific shocks. It only measures the effect of CPFL for young California women compared to old women in California and elsewhere.

By examining the young, we net out any possibly differing effects of the CPFL by age. Here the estimating equation is

$$\text{(3)} \quad Y^Y_{ijt} = \alpha^Y_0 + \alpha^Y_1 Cal + \alpha^Y_2 Fem + \alpha^Y_4 Post + \beta^Y_1 Cal \times Fem + \beta^Y_3 Cal \times Post + \beta^Y_6 Fem \times Post + \gamma^Y Cal \times Fem \times Post + X_{ijt}B^Y + X_{it}C^Y + \varepsilon_t + \varepsilon_{ijt}.$$

The derivative $\left(\partial^3 Y^Y_{ijt} / \partial Post\, \partial Cal\, \partial Fem\right) = \gamma^Y$ amounts to the following difference-in-difference-in-difference

$$\left[\left(\overline{Y}^Y_{CalFemPost} - \overline{Y}^Y_{CalFemPre} \right) - \left(\overline{Y}^Y_{NotCalFemPost} - \overline{Y}^Y_{NotCalFemPre} \right) \right] - \left[\left(\overline{Y}^Y_{CalMalePost} - \overline{Y}^Y_{CalMalePre} \right) - \left(\overline{Y}^Y_{NotCalMalePost} - \overline{Y}^Y_{NotCalMalePre} \right) \right].$$

This is our third estimation equation. It does not take account of age-based California-specific shocks. It simply measures the effect of CPFL for young women compared to young men in California and elsewhere.

For each of these specifications, we compute clustered standard errors to account for potential serial correlation within groups. State identification codes are used as the cluster variable in each of the regressions.

V. DESCRIPTIVE STATISTICS

As discussed above, and illustrated below, one can easily argue that the CPFL affects young female workers more than other demographic groups. Table 1 summarizes worker leave behavior based on the CPS data. The top panel reports the percentage of the workforce on leave at any time. Almost twice as many young females (3.8%) are on leave as young males (2.2%), but only 30% more older females (4.3%) are on leave than older males (3.3%). Almost one-half of the male and older female workers on leave (second set of rows) give vacation as the prime reason. Not so for young females. Only slightly over one-third of them (35.7%) report vacation or personal days. Instead the preponderance of young women on leave cite maternity (33.31%) compared to only 2.1% male, who cite paternity. Among older leave-taking workers (third set of rows), women

TABLE 1
Incidence of Leave 1996–2002, by Gender[a]

	Young (18–41)	Old (42–65)
On leave (percent of total workers)		
Male	2.2	3.3
Female	3.8	4.3
Vacation/personal days (percent of workers on leave)		
Male	43.5	44.9
Female	35.7	45.6
Maternity/Paternity Leave (percent of workers on leave)		
Male	2.1	0.5
Female	33.3	2.1

[a]U.S. averages based on CPS (March round) data 1996–2002.

are four times more likely to be on maternity than men to be on paternity leave (2.1% vs. 0.5%), but these percentages are much larger for younger workers. Clearly these statistics indicate a greater preponderance of young women on maternity leave than either older women, or young or old men. Moreover, maternity leaves generally tend to be longer than other leaves.[15]

The descriptive statistics presented in Table 2 support our conjectures regarding CPFL's impact on California young women's labor market activities relative to others in California and elsewhere. The first two rows in each panel present outcome measures for young and old, males and females, before and after enactment of the CPFL. The third row gives the difference in outcome before and after the CPFL for each age-gender group. Finally, the fourth row presents the DID for each outcome between California and the rest of the country for each age-gender group. The differences specified in these latter two rows are expressed in percent terms in Rows 5 and 6 of each panel.

Noteworthy is how dissimilar young women fare compared to each other group. Take labor force participation: Young women's labor force participation declined 1.3 percentage points (rounded from 1.282 in Row 4 of Column 1) or about 1.6% (Row 6) faster nationwide outside California than in California. Further, this 1.6% more rapid decline was *not* matched by males or older females. For these, the California-non-California before–after difference was 1.37% for young men, a negative 2.13% for older women, and 0.04% for older men. In short, labor force participation increased more rapidly for California young women compared to each of the other demographic groups.

These differences are even more stark for the other outcome measures. The relative young women's unemployment rate fell by 4.7% (Row 6 of Column 1 in the unemployment panel of Table 2) in California relative to the rest of the country from before to after the enactment of the CPFL. Contrast this decline to the far greater decline of 17.8% and 14.4% for young males and older women. Similarly, for unemployment duration: From before to after the CPFL, California's young women's unemployment duration rose by 0.84%, whereas unemployment duration fell by 5.09% for older women, 0.20% for older men, and 1.38% for younger men. In short, unemployment and unemployment duration *increased* more for *young women* in California than in the rest of the country, but it *fell* more for males and older women in California compared to the rest of the country. These differences are striking, but they do not hold all factors constant. For this reason we reevaluate the law using Equations (1)–(3).

VI. AN EVALUATION OF THE CPFL

We first evaluate the CPFL program on the basis of three outcome variables by estimating Equation (1) over the time period 1996–2009. This time period comprises a period of 7 years before and 7 years after the law came into effect. As already indicated, γ is the prime coefficient of interest. It measures the difference in outcome, from before to after the law, for young California women relative to other population subgroups in California compared to the rest of the nation, holding constant measureable state differences, possible California-specific shocks for young workers, possible California-specific shocks for women, and adjusting for year fixed-effects.

We present the γ coefficient in Table 3 (top panel) for each of the three outcome measures.[16] We find that the increase in the labor force participation rate (from before to after the law) is 1.37 percentage points higher for young California women compared to the rest of the population. This is consistent with Rossin-Slater,

15. Average maternity leave duration is about 10.3 weeks (http://www.mchb.hrsa.gov/whusa11/hstat/hsrmh/downloads/pdf/233ml.pdf). The maximum holiday and vacation time for workers having accumulated 20 or more years of seniority in large (100+ employee) firms is at most 6.4 weeks (United States Bureau of Labor Statistics, 2009).

16. The complete regression results for each row are available upon request.

TABLE 2
Descriptive Statistics

	18–41				42–65			
	Female		Male		Female		Male	
	Non-California	California	Non-California	California	Non-California	California	Non-California	California
Labor force participation								
Before: 1996–2002	77.26	71.01	91.99	91.01	68.09	67.05	81.22	82.31
After: 2003–2009	75.20	70.23	90.43	90.70	69.22	66.72	80.44	81.54
Arithmetic difference	−2.05	−0.77	−1.56	−0.31	1.13	−0.33	−0.78	−0.76
California–non-California	1.282		1.247		−1.454		0.020	
Percent change (before/after)	−2.70	−1.09	−1.71	−0.34	1.64	−0.49	−0.97	−0.93
California–non-California percent difference	1.60		1.37		−2.13		0.04	
Unemployment rate								
Before: 1996–2002	5.42	6.63	5.95	7.48	2.86	4.32	3.59	4.62
After: 2003–2009	6.24	7.28	7.68	8.09	3.73	4.87	4.71	5.93
Arithmetic difference	0.815	0.645	1.732	0.603	0.868	0.556	1.121	1.317
California–non-California percent difference	−0.170		−1.129		−0.312		0.196	
Percent change (before/after)	14.00	9.28	25.55	7.75	26.52	12.12	27.19	25.10
California–non-California percent difference	−4.73		−17.80		−14.39		−2.09	
Weeks unemployed (only for unemployed)								
Before: 1996–2002	16.48	17.69	17.10	17.64	17.32	19.34	18.12	18.36
After: 2003–2009	18.21	19.72	18.89	19.22	19.59	20.79	19.65	19.87
Arithmetic difference	1.73	2.03	1.79	1.58	2.27	1.45	1.53	1.51
California–non-California percent difference	0.293		−0.210		−0.821		−0.019	
Percent change (before/after)	10.00	10.84	9.95	8.57	12.30	7.21	8.10	7.91
California–non-California percent difference	0.84		−1.38		−5.09		−0.20	

Note: Computed from CPS (March round) for indicated years.

Ruhm, and Waldfogel (2011) who find hours of work increase after the law for young (at work) mothers in California relative to similar young mothers throughout the rest of the country. However, we find the unemployment rate increased 1.48 percentage points *more* for young California women compared to other population groups. And similarly, we find the unemployment duration 1.57 weeks *more* for young California women relative to the other demographic groups. These latter two results regarding increased unemployment of young women are unintended effects of the CPFL.[17]

Row (2) presents estimates of γ^F from Equation (2), a similar regression, but limited only to women. As such this regression measures the impact of CPFL on young women relative to old women in California, but does not account for the gender-specific shocks facing women and not men. The γ^F coefficient measures the difference in outcome from before to after the law for young California women compared to non-California and old women throughout. Again, the results show that CPFL has a positive significant effect on young women's relative labor force participation change in California compared to other demographic groups. Similarly, CPFL's effect on the unemployment rate and unemployment duration is significant. We find the young California female unemployment rate increases 0.346 percentage points (about a 5% increase) relative to older California women and all women in the rest of the United States. The duration of unemployment for California young women rises by 0.729 weeks in the post-CPFL period.

Row (3) corresponds to regression Equation (3) run only for young men and young women. As such, γ^Y measures the impact of CPFL on young California women relative to young men in California and young men and women elsewhere, but does not account for age-specific shocks, namely the possibility young women and young men can differ from old men and old women. The labor force participation coefficient is insignificant, indicting no greater rise in labor force participation of young California women compared to young California men or young men and women elsewhere. However,

17. The sign and magnitude of the control variables are also consistent with the intuition. Schooling increases the LFPR, reduces the unemployment rate, increases the labor force participation propensity, and reduces the tendency to leave the labor market. Also economic environment affects these variables by a great margin. Higher state unemployment rates reduce the LFPR (decline of 7 percentage point due to 10 percentage point increase in unemployment). States with higher unemployment rates increase group-specific unemployment rates by the same proportion and increase duration of unemployment by 6.5 weeks (for a 10 percentage point increase). State unemployment induces less workers to join the labor market and induces more workers to leave the labor market.

TABLE 3
The Effect of California Paid Family Leave on Labor Force Participation and Unemployment

Sample	Coefficient	Derivative	(1) LFPR	(2) Unemployment Rate	(3) Unemployment Duration
All	γ in Equation (1)	$\partial^4 Y/\partial Cal\ \partial Fem\ \partial Young\ \partial Post$	0.0137***	0.0148***	1.572***
			(0.00365)	(0.00195)	(0.483)
Female	γ^F in Equation (2)	$\partial^3 Y/\partial Cal\ \partial Young\ \partial Post$	0.0159***	0.00346**	0.729*
			(0.00277)	(0.00144)	(0.434)
Young	γ^Y in Equation (3)	$\partial^3 Y/\partial Cal\ \partial Fem\ \partial Post$	−0.00116	0.0101***	0.969***
			(0.00379)	(0.00210)	(0.238)

Notes: Indicated interaction term coefficient for Models (1), (2), and (3) using CPS data (March round) data, 1996–2009. Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.
$^{**}p<.05$, $^{***}p<.01$.

unemployment levels and duration significantly increased, again substantiating the unanticipated effects found above.

VII. ROBUSTNESS CHECK

One way to test the strength of our findings is to compare the outcomes in California (before and after the CPFL) to outcomes in similar states that did not pass PFL legislation. If CPFL had an effect, the results observed for California's outcome variables should mimic those observed in Table 3, though given fewer observations, statistical significance levels might be lower. One possibility is to compare California with Massachusetts and New York because both have high population densities (as does California) and because both are contemplating family paid leave legislation. Alternatively, Rossin-Slater, Ruhm, and Waldfogel (2011), in their analysis, choose Florida, New York, and Texas because they are "the next three largest states" (p. 229) to California. To be most general, we do both.

Table 4 replicates Table 3 but confines the control states to Massachusetts and New York, and Table 5 replicates Table 3 but confines the control states to Florida, New York, and Texas. As in Table 3, from before to after CPFL, California's young female unemployment rate rose more compared to Massachusetts and New York (Row 1, Column 2 of Table 4) and compared to Florida and New York (Row 1, Column 2 of Table 5). This was also true when limiting the sample to women (Row 2 of Tables 4 and 5) and the young (Row 3 of Tables 4 and 5). Also, as in Table 3, unemployment duration rose more in California from before to after CPFL compared to Massachusetts and New York (Column 3 of Table 4) and compared to Florida, Texas, and New York (Column 3 of Table 5).

VIII. PLACEBO TESTS

To further check the credibility of our results, we perform a series of placebo tests. One set involves choosing states that we assume implement PFL, but which in reality did not. Another set involves the chronological timing of the CPFL's implementation. Here we assume California implemented PFL when in reality it did not. In both we verify that placebo states and placebo years are not related to outcome variables.

A. State Placebo Tests

To perform state placebo tests, we omit California from the analysis and choose states comparable to California, but which did not as yet pass PFL. We choose New York and Massachusetts as the placebo treatment states because both are heavily populated and both are contemplating PFL legislation. We report the results in Table 6. In addition, we perform a strong state-based placebo test, which we explain in the next subsection.

Row 1 (Columns 1–3) reports estimates for Equation (1). These correspond to Row 1 of Table 3, except we choose New York and Massachusetts as the states to have implemented PFL, when in reality they did not. The results are consistent with CPFL's unanticipated effects obtained above. Young female labor force participation in Massachusetts and New York increased at a greater rate than California relative to other demographic groups before and after the implementation of California's law. Yet unemployment in each decreased significantly. This means that CPFL did not increase young women's labor force participation more than comparable states, but it did increase unemployment by a greater amount.

TABLE 4

Replicating Results with Massachusetts and New York as Control States

Sample	Coefficient	Derivative	(1) LFPR	(2) Unemployment Rate	(3) Unemployment Duration
All	γ in Equation (1)	$\partial^4 Y/\partial Cal\ \partial Fem\ \partial Young\ \partial 2004$	−0.00522	0.0290**	2.052*
			(0.00434)	(0.00504)	(0.599)
Female	γ^F in Equation (2)	$\partial^3 Y/\partial Cal\ \partial Young\ \partial 2004$	9.16e-05	0.00600**	0.367
			(0.00149)	(0.000681)	(0.144)
Young	γ^Y in Equation (3)	$\partial^3 Y/\partial Cal\ \partial Fem\ \partial 2004$	−0.0252*	0.0229*	2.209*
			(0.00596)	(0.00626)	(0.563)

Notes: Indicated interaction term coefficient for Models (1), (2), and (3) using CPS data (March round) 1996–2009. Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.

$^{**}p < .05$, $^{*}p < .1$.

TABLE 5

Replicating Results with Florida, New York, Texas as Control States

Sample	Coefficient	Derivative	(1) LFPR	(2) Unemployment Rate	(3) Unemployment Duration
All	γ in Equation (1)	$\partial^4 Y/\partial Cal\ \partial Fem\ \partial Young\ \partial 2004$	0.0135	0.0191***	0.398
			(0.0106)	(0.00295)	(0.524)
Female	γ^F in Equation (2)	$\partial^3 Y/\partial Cal\ \partial Young\ \partial 2004$	0.0133	0.00576***	−0.318
			(0.00870)	(0.000519)	(0.504)
Young	γ^Y in Equation (3)	$\partial^3 Y/\partial Cal\ \partial Fem\ \partial 2004$	−0.00552	0.0134**	1.292**
			(0.0117)	(0.00372)	(0.292)

Notes: Indicated interaction term coefficient for Models (1), (2), and (3) using CPS data (March rounds) 1996–2009. Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.

$***p < .01$, $**p < .05$.

Row 2 (Columns 1–3) of Table 6 corresponds to Row 2 of Table 3, where we limit our analysis to females. Again, the results suggest that placebo treatment states (New York and Massachusetts) increased labor force participation and decreased unemployment more than California, again consistent with unintended CPFL effects. The same can be said of Row 3, which reports results comparable to Row 3 of Table 3, but for placebo states.

B. Strong State Placebo Test

Some may question whether New York and Massachusetts, as well as Florida, Texas, and New York, are comparable to California. If these two sets of states are not similar enough to California, the above placebo test would be meaningless. A more stringent placebo test is to consider *each* state other than California, New Jersey, and Washington as *possible* placebos, since each of these states passed PFL. Here one asks whether young women's labor force participation and unemployment would increase in *any* state that presumably passed a law comparable to California's Paid Family Leave Act effective as of July 2004. We test this by rerunning Equations (1)–(3) first using Alabama, then using Alaska, then Arizona, and so on for each of the 47 possible placebo states, instead of California. One can then compile the number of such placebo states in which the labor force participation rate, the unemployment rate, and the unemployment duration rose for young women relative to other demographic groups in the placebo state compared to the rest of the country. Clearly, if no placebo state is associated with higher values for these young women's labor force participation and unemployment effects, then California is unique, and the CPFL must have had an effect because no similar effects occurred in states that did not pass the law. Of course, the strength of the test is mitigated the more states we observe with effects similar to California.

We perform this strong placebo test by running Equations (1)–(3) forty-seven times, each time choosing a state other than California, New Jersey, or Washington as the state that passed the parental leave act. Column 4 of Table 6 gives the number of states with significantly positive

TABLE 6
Placebo Estimates of the Effect of Paid Family Leave

			Outcome Measure			Strong Placebo
Sample	Coefficient	Derivative	(1) LFPR	(2) Unemployment Rate	(3) Unemployment Duration	(4) Number of States Same Signs as California
All	γ in Equation (1)	$\partial^4 Y/\partial Placebo\ \partial Fem\ \partial Young\ \partial Post$	0.0213***	−0.0156***	−0.573	2
			(0.00439)	(0.00441)	(0.668)	
Female	γ^F in Equation (2)	$\partial^3 Y/\partial Placebo\ \partial Young\ \partial Post$	0.0268***	−0.0139***	−1.394***	2
			(0.00488)	(0.00513)	(0.509)	
Young	γ^Y in Equation (3)	$\partial^3 Y/\partial Placebo\ \partial Fem\ \partial Post$	0.0184***	−0.00280*	0.445	1
			(0.00284)	(0.00160)	(0.491)	

Notes: Indicated interaction term coefficient for Models (1), (2), and (3), but with placebo states using CPS data (March round) 1996–2009. Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.
***p<.01, *p<.1.

coefficients for the labor force participation rate, the unemployment rate, and unemployment duration for Equations (1)–(3). These are reported in Column (4) for Rows (1), (2), and (3), respectively. As illustrated, only two states (Missouri and Ohio) are comparable to California when testing the effects of PFL for the entire population of males and females. Similarly, only two states (Montana and Ohio) behave comparably to California when using the female-only sample, and only one state (Kentucky) when restricting the sample to young men and women. In short, the effects found for California are virtually unique.[18] This result validates our assessment of the CPFL.

C. Time-Based Placebo Test

An alternative placebo test entails chronological time, rather than location. This type of test determines whether the previously observed CPFL effects (on labor force participation, unemployment, and unemployment duration) are also obtained when pretending the CPFL was implemented prior to the actual implementation date, when in reality it was not initiated then. Clearly, in this case, the CPFL has no effect if we estimate the same CPFL impact as was observed when CPFL was actually implemented, when in fact it was not. On the other hand, credence is established that the CPFL had no statistically significant outcome for the placebo years.

To construct such a test we consider time periods prior to the actual CPFL policy year, and arbitrarily designate one of these years as a pseudo policy year. Based on this classification, we then perform pre- and post-policy analyses to assess the effects of an "imaginary" CPFL on the treatment group. The problem is how to choose a placebo year.[19] Given the cyclical economic fluctuations, it is not easy to find a "comparable" year to the actual time when CPFL was implemented. As such, we consider *each* pair of consecutive years prior to the 2002 policy year. We take 1996–2001 as pre-policy years and perform the analyses with each pair of years (1996–1997, 1997–1998, 1998–1999, 1999–2000, and 2000–2001), with the later year in each pair as the pseudo policy year.[20] Testing that the sum of the effects equals zero is equivalent to a test that overall placebo effects during the pre-CPFL time period are zero.

Table 7 presents results from this placebo exercise. It tests the hypothesis that the average effect of the "imaginary" CPFL based on time-based placebo tests is zero. There are three panels. The top is for the whole population, the second for females, and the third for young males and females. The three columns present the results for each outcome variable. Each pair of numbers represents a χ^2 value and a probability of obtaining a χ^2 value greater than what is observed. Row 3 of each panel indicates the probability exceeds 0.05. Thus, we accept the null hypothesis that the average effect based on

18. Coefficients and standard errors for each state are contained in the Appendix.

19. Recall, for the state placebo experiments, described above, we chose "comparable" states based on population and size, but in the strong state placebo test we used all states.

20. We take pairs in order to have the same number of years before and after the law.

TABLE 7

Time-Based Placebo Test[a]

	LFPR	Unemployment Rate	Unemployment Duration
All			
χ^2	0.29	0.77	0.27
Prob > χ^2	0.59	0.38	0.60
Female			
χ^2	0.07	0.59	0.31
Prob > χ^2	0.78	0.44	0.58
Young			
χ^2	0.00	0.40	0.11
Prob > χ^2	1.00	0.53	0.74

[a]Test of the hypothesis that the sum of the placebo test coefficients is zero. The top row in each panel contains the calculated χ^2 value. The bottom row in each panel is probability of obtaining a χ^2 value greater than observed. Probabilities exceeding 0.05 are consistent with a zero average placebo effect.

the placebo test is zero. The validity of our measured effects of the actual CPFL is consistent with this result.

IX. CONCLUSIONS

Our analyses clearly suggest that the CPFL induced young women to participate somewhat more in the labor market than the typical state, but not necessarily more than comparable states. As a result the labor force participation rate for young women in California grew more than labor force participation rates of other states after CPFL became effective. But further analysis indicates additional effects. Among young women, relative to other states, California's unemployment rate and unemployment duration increased after the law, two unintended effects. This is consistent with firms increasing their demand for men and older women at the expense of young women. Re-estimation using several placebo methods verifies these findings.

These results have implications beyond California and beyond PFL legislation. One implication is that such a law, if passed in other states, could increase women's labor force participation rates. However, another implication is that laws (even those that benefit one aspect of women's wellbeing by providing a better safety net resulting in a greater incentive to participate in the labor market) could have unintended effects. In the case of California, we observe a higher incidence of unemployment and unemployment duration, and these adverse effects are significant and substantial. In California, as many as 75,000 young women entered the workforce that otherwise would not have. On the other hand, about 80,000 young women suffered spells of unemployment amounting to as much as 2 weeks longer than in other states.

APPENDIX: STATE-SPECIFIC PLACEBO TESTS

TABLE A1

State Coefficients for Equation (1), Strong Placebo Test

	Sample: All					
	LFPR		Unemployment Rate		Unemployment Duration	
State	Coef[a]	SE	Coef[a]	SE	Coef[a]	SE
Alabama	−0.029	0.004	0.011	0.002	0.146	0.575
Alaska	−0.030	0.004	0.012	0.002	−0.716	0.527
Arizona	−0.013	0.003	0.012	0.002	−2.766	0.511
Arkansas	0.005	0.004	0.009	0.002	−1.289	0.644
Colorado	0.006	0.004	0.004	0.002	0.855	0.557
Connecticut	−0.039	0.004	0.029	0.002	0.540	0.577
Delaware	−0.042	0.004	0.012	0.002	−1.649	0.477
District of Columbia	0.013	0.004	0.004	0.002	−1.494	0.512
Florida	−0.016	0.004	−0.001	0.002	1.748	0.494
Georgia	−0.025	0.004	0.009	0.002	−3.912	0.547
Hawaii	0.031	0.004	0.029	0.002	−3.976	0.568
Idaho	0.001	0.004	−0.037	0.002	−2.193	0.527
Illinois	0.005	0.004	0.005	0.002	0.433	0.527
Indiana	0.000	0.003	0.003	0.002	−2.425	0.573
Iowa	−0.043	0.004	0.017	0.002	−1.999	0.512
Kansas	0.053	0.004	0.003	0.002	0.407	0.602
Kentucky	0.004	0.004	0.007	0.002	−2.977	0.483
Louisiana	−0.040	0.004	−0.015	0.002	−0.589	0.621
Maine	0.009	0.004	0.002	0.002	−3.478	0.492

TABLE A1
Continued

	Sample: All					
	LFPR		Unemployment Rate		Unemployment Duration	
State	Coef[a]	SE	Coef[a]	SE	Coef[a]	SE
Maryland	0.007	0.004	0.010	0.002	1.239	0.495
Massachusetts	0.013	0.004	−0.026	0.002	−1.699	0.456
Michigan	0.023	0.004	0.011	0.002	−2.495	0.532
Minnesota	0.019	0.004	−0.005	0.002	−2.825	0.517
Mississippi	−0.019	0.004	0.002	0.002	−8.591	0.604
Missouri	0.022	0.003	0.008	0.002	4.277	0.561
Montana	0.035	0.004	0.028	0.002	0.108	0.461
Nebraska	−0.017	0.004	0.008	0.002	0.664	0.530
Nevada	−0.023	0.004	0.002	0.002	0.606	0.552
New Hampshire	−0.021	0.004	0.004	0.002	−0.068	0.454
New Mexico	0.017	0.004	−0.001	0.002	3.091	0.543
New York	0.023	0.003	−0.011	0.002	−0.166	0.524
North Carolina	−0.005	0.004	−0.009	0.002	−0.843	0.510
North Dakota	−0.014	0.004	−0.014	0.002	0.409	0.552
Ohio	0.025	0.004	0.006	0.002	5.292	0.495
Oklahoma	−0.043	0.004	−0.034	0.002	−6.212	0.505
Oregon	0.010	0.004	−0.030	0.002	0.467	0.517
Pennsylvania	0.009	0.004	0.018	0.002	0.107	0.542
Rhode Island	−0.010	0.004	−0.004	0.002	−0.230	0.535
South Carolina	0.061	0.003	−0.008	0.002	−4.103	0.484
South Dakota	0.032	0.004	0.002	0.002	−1.070	0.598
Tennessee	−0.008	0.004	0.008	0.002	−2.360	0.608
Texas	−0.006	0.004	−0.004	0.002	2.054	0.532
Utah	−0.003	0.005	0.006	0.002	−3.085	0.468
Vermont	−0.011	0.003	−0.012	0.002	−2.178	0.554
Virginia	−0.048	0.004	−0.005	0.002	9.139	0.506
West Virginia	0.002	0.004	−0.014	0.002	1.299	0.487
Wisconsin	0.002	0.004	0.002	0.002	−5.009	0.523
Wyoming	−0.078	0.004	0.009	0.002	2.095	0.492

Notes: Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.
[a]Coef depicts γ in Equation (1) representing $\partial^4 Y_{ijkt}/\partial Placebo\ \partial Fem\ \partial Young\ \partial Post$.

TABLE A2
State Coefficients for Equation (2), Strong Placebo Test

	Sample: Female					
	LFPR		Unemployment Rate		Unemployment Duration	
State	Coef[a]	SE	Coef[a]	SE	Coef[a]	SE
Alabama	−0.004	0.003	0.012	0.001	1.840	0.466
Alaska	−0.007	0.003	0.012	0.002	−0.209	0.479
Arizona	−0.020	0.003	0.004	0.001	−2.287	0.505
Arkansas	−0.013	0.003	0.011	0.001	−1.535	0.528
Colorado	−0.005	0.003	0.002	0.001	0.671	0.478
Connecticut	−0.021	0.003	0.022	0.001	1.908	0.468
Delaware	−0.014	0.004	0.006	0.001	1.093	0.455
District of Columbia	0.018	0.005	−0.035	0.002	−1.686	0.514
Florida	−0.015	0.003	−0.002	0.002	0.586	0.483
Georgia	−0.012	0.003	0.001	0.002		
Hawaii	0.045	0.003	0.015	0.001	−0.282	0.479
Idaho	0.011	0.004	−0.018	0.002	−0.710	0.488
Illinois	0.008	0.003	−0.006	0.001	−2.234	0.440
Indiana	−0.016	0.003	−0.004	0.002	−0.772	0.448
Iowa	−0.025	0.003	0.013	0.001	−1.538	0.498
Kansas	0.035	0.003	0.004	0.002	0.013	0.449
Kentucky	0.019	0.003	0.022	0.001	1.901	0.478
Louisiana	−0.010	0.003	−0.009	0.002	−2.254	0.540
Maine	−0.006	0.003	0.001	0.001	−1.314	0.452
Maryland	0.010	0.003	0.003	0.001	−2.026	0.469

TABLE A2

Continued

	Sample: Female					
	LFPR		Unemployment Rate		Unemployment Duration	
State	Coef[a]	SE	Coef[a]	SE	Coef[a]	SE
Massachusetts	0.016	0.003	−0.003	0.001	0.037	0.447
Michigan	0.015	0.003	0.019	0.001	−4.213	0.409
Minnesota	−0.007	0.003	0.001	0.002	−1.077	0.505
Mississippi	−0.003	0.003	−0.002	0.002	−3.648	0.528
Missouri	0.024	0.003			−0.026	0.565
Montana	0.016	0.003	0.003	0.001	−1.558	0.448
Nebraska	−0.016	0.003	0.007	0.001	4.845	0.506
Nevada	−0.011	0.003	−0.010	0.001	0.135	0.525
New Hampshire	−0.037	0.003	−0.001	0.001	0.111	0.392
New Mexico	−0.016	0.003	0.008	0.002	4.808	0.434
New York	0.018	0.003	−0.002	0.002	0.458	0.484
North Carolina	0.001	0.003	−0.007	0.001	−0.207	0.550
North Dakota	−0.026	0.003	−0.001	0.001	2.356	0.480
Ohio	0.022	0.003	0.001	0.002	3.872	0.470
Oklahoma	−0.035	0.004	−0.019	0.001	−0.360	0.529
Oregon	0.004	0.003	−0.020	0.001	1.370	0.528
Pennsylvania	−0.022	0.003	0.005	0.002	0.604	0.467
Rhode Island	−0.025	0.003	0.011	0.002	1.867	0.396
South Carolina	−0.016	0.003	−0.006	0.002	−3.233	0.393
South Dakota	0.026	0.003	0.001	0.001	4.219	0.421
Tennessee	−0.001	0.003	0.011	0.002	−0.079	0.466
Texas	0.010	0.003	−0.003	0.002	2.508	0.403
Utah	−0.031	0.003	0.028	0.002	0.928	0.506
Vermont	−0.025	0.003	0.001	0.002	0.666	0.447
Virginia	−0.024	0.003	0.002	0.001	3.898	0.460
West Virginia	0.013	0.003	−0.005	0.002	2.847	0.367
Wisconsin	0.020	0.003	0.014	0.001	−4.627	0.424
Wyoming	−0.080	0.003	0.000	0.002	0.752	0.500

Notes: Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.
[a]Coef depicts γ^F in Equation (2) representing $\partial^3 Y_{ikt}/\partial Placebo\ \partial Young\ \partial Post$.

TABLE A3

State Coefficients for Equation (3), Strong Placebo Test

	Sample: Young					
	LFPR		Unemployment Rate		Unemployment Duration	
State	Coef[a]	SE	Coef[a]	SE	Coef[a]	SE
Alabama	−0.019	0.005	0.009	0.002	−0.605	0.259
Alaska	−0.012	0.004	0.024	0.002	0.168	0.248
Arizona	−0.020	0.004	−0.007	0.002	−0.575	0.267
Arkansas	−0.016	0.004	0.026	0.002	−0.005	0.255
Colorado	−0.031	0.003	0.002	0.002	0.756	0.247
Connecticut	−0.031	0.004	0.030	0.002	4.912	0.277
Delaware	−0.039	0.004	0.018	0.002	1.327	0.288
District of Columbia	−0.022	0.004	0.003	0.002	1.229	0.246
Florida	−0.005	0.004	−0.007	0.002	−0.300	0.254
Georgia	−0.008	0.004	0.010	0.002	1.410	0.254
Idaho	−0.001	0.004	−0.013	0.002	−0.478	0.260
Illinois	−0.005	0.004	0.003	0.002	−0.257	0.258
Indiana	0.000	0.003	−0.007	0.002	−2.307	0.229
Iowa	−0.023	0.004	0.014	0.002	−2.024	0.262
Kansas	0.013	0.003	0.000	0.002	1.941	0.267
Kentucky	0.029	0.003	0.007	0.002	−1.710	0.270
Louisiana	−0.028	0.004	−0.016	0.002	−4.764	0.244
Maine	0.011	0.004	−0.002	0.002	−0.073	0.227
Maryland	−0.010	0.004	0.011	0.002	0.795	0.239
Massachusetts	0.015	0.003	−0.026	0.002	−2.441	0.233

TABLE A3
Continued

	Sample: Young					
	LFPR		Unemployment Rate		Unemployment Duration	
State	Coef[a]	SE	Coef[a]	SE	Coef[a]	SE
Michigan	0.038	0.003	−0.010	0.002	−0.676	0.253
Minnesota	0.017	0.004	−0.013	0.002	−2.660	0.237
Mississippi	0.024	0.005	−0.010	0.002	−3.842	0.331
Missouri	−0.015	0.003	0.007	0.002	0.879	0.299
Montana	0.009	0.004	0.026	0.002	1.168	0.233
Nebraska	0.000	0.004	0.014	0.002	2.250	0.285
Nevada	−0.005	0.004	−0.003	0.002	0.268	0.256
New Hampshire	0.007	0.004	−0.009	0.002	−0.374	0.235
New Mexico	0.024	0.004	0.003	0.002	2.399	0.254
New York	0.030	0.003	−0.009	0.002	−0.901	0.244
North Carolina	−0.012	0.004	−0.008	0.002	1.316	0.267
North Dakota	−0.012	0.004	−0.017	0.002	−1.441	0.241
Ohio	0.030	0.004	0.006	0.002	1.798	0.239
Oklahoma	−0.030	0.004	−0.021	0.002	−3.789	0.279
Oregon	0.017	0.004	−0.025	0.002	0.379	0.252
Pennsylvania	−0.003	0.004	0.028	0.002	1.763	0.254
Rhode Island	−0.028	0.004	−0.014	0.002	−0.567	0.230
South Carolina	0.036	0.004	−0.013	0.002	−3.581	0.210
South Dakota	0.001	0.003	0.002	0.002	2.392	0.245
Tennessee	−0.020	0.004	0.017	0.002	0.135	0.275
Texas	−0.009	0.004	0.003	0.002	0.094	0.264
Utah	0.005	0.004	0.006	0.002	0.343	0.268
Vermont	0.014	0.004	−0.007	0.002	−0.920	0.252
Virginia	−0.036	0.004	−0.015	0.002	2.783	0.235
Wisconsin	0.008	0.004	−0.009	0.002	−0.909	0.279
Wyoming	−0.022	0.004	0.013	0.002	−0.319	0.252

Notes: Reported standard errors are cluster standard errors. State identification codes are used as the cluster variable.
[a]Coef depicts γ^Y in Equation (3) representing $\partial^3 Y_{ijt}/\partial Placebo\ \partial Fem\ \partial Post$.

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