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# Does paid family leave save infant lives? Evidence from California's paid family leave program

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**Abstract**

Paid family leave (PFL) aims to help working parents balance their careers and family responsibilities while also improving the well-being of infants. Using linked U.S. birth and infant death data with a difference-in-differences framework, I find that a 6-week PFL in California reduced the post-neonatal mortality rate by 0.135- that is, it saved approximately 339 infant lives. There were fewer deaths from health-related causes and larger effects for infants with married mothers and for infant boys. Additional checks and placebo examinations indicate that the observed effect is not due to contemporaneous shocks but rather is causal.

**KEYWORDS**

child development, infant mortality, paid family leave

**JEL CLASSIFICATION**

J13, J16, J18

## 1 | INTRODUCTION

Paid family leave (PFL), or paid parental leave, is designed to provide compensated time off from work for parents to care for their infants, which is essential to child development (Baker & Milligan, 2008, 2010, 2015; Bullinger, 2019; Carneiro et al., 2015; Dahl et al., 2016; Danzer & Lavy, 2018; Dustmann & Schönberg, 2012; Liu & Skans, 2010). Countries have taken different ways of creating maternity leave legislation to improve the welfare of families. For example, 25 of 34 Organization for Economic Cooperation and Development (OECD) countries guarantee at least 6 months of paid leave for mothers to care for their infants (Raub et al., 2018), but women in the U.S. are only entitled to 12 weeks of unpaid leave. In 2004, California became the first state in the U.S. to offer 6 weeks of paid family leave (CA-PFL) for eligible workers. The paid time off allows for increased maternal-child interactions and better monitoring of children's health status, prolongs breastfeeding, and thereby benefits early childhood outcomes (Bartel et al., 2018; Baum & Ruhm, 2016; Huang & Yang, 2015; Lichtman-Sadot & Bell, 2017; Pihl & Basso, 2019; Rossin-Slater et al., 2013).

Recent literature shows that children may benefit from parental leave if their mothers take prenatal leave. For example, Stearns (2015) found that in the U.S. paid prenatal leave through Temporary Disability Insurance (TDI)

**Abbreviations:** AFP, American Families Plan; CFRA, California Family Rights Act; CPS, Current Population Survey; DD, difference in differences; FAMILY, Family and Medical Insurance Leave; FMLA, Family and Medical Leave Act; F-P p-values, Ferman Pinto p-values; IMR, infant mortality rate; ITT, intention-to-treat; NCHS, National Center for Health Statistics; NVSS, National Vital Statistics System; OECD, Organization for Economic Cooperation and Development; PFL, Paid family leave; PNMR, post-neonatal mortality rate; SDI, State Disability Insurance; TDI, Temporary Disability Insurance; TOT, treatment-on-the-treated; VSL, value of a statistical life.

  

reduced the share of low-birth-weight births by 3.2% and decreased the likelihood of early-term births by 6.6%. In addition to the benefit to children before birth, parental leave may also influence infant health, and ultimately reduce infant deaths, through the following channels. First, paid parental leave could lead to more investment in parental care, lessening the need for non-parental care which is associated with increased risks of many infectious illnesses, for example, diarrheal illness and respiratory infections. Second, more time off from work may allow parents to arrange preventative care for their children, such as immunizations and well-child visits, more easily (Berger et al., 2005). Third, women with longer parental leaves can increase their breastfeeding duration (Huang & Yang, 2015; Pac et al., 2019), and recent studies have found that longer breastfeeding duration is associated with a reduction in the risk of post-neonatal death. Fourth, parental leave could improve parents' mental health (Bullinger, 2019), enabling them to be more attentive to an infant's needs.[1] Finally, in contrast to unpaid leave, paid family leave provides compensating benefits which could be used for better nutrition for children. Evidence from studies of transfer programs in the U.S. (e.g., earned income tax credit, food stamps, and WIC[2] program) has shown benefits for infant health outcomes (Almond et al., 2011).

Previous literature in economics has shown that parental leave can reduce the infant mortality rate (IMR), especially the post-neonatal mortality rate (PNMR) (Rossin-Slater, 2011; Ruhm, 2000; Tanaka, 2005). However, most studies focused on European countries and the 20th century, where there was widespread adoption or expansion of parental leave. For example, Ruhm (2000) used aggregated data on 16 European countries from 1969 to 1994 and found that a 10-week extension of paid leave was predicted to reduce the PNMR by 3.7%–4.6%. Similarly, Tanaka (2005) extended Ruhm (2000) by adding U.S. and Japan from 1969 to 2000 and found similar results. Both studies found little or no effect of unpaid leave. On the contrary, Rossin-Slater (2011) exclusively examined the 12 weeks unpaid leave of the 1993 Family and Medical Leave Act (FMLA) in the U.S. and found that it reduced PNMR by 10% for children with college-educated and married mothers as they were more likely eligible for the unpaid leave.

In this study, I examine the causal effect of CA-PFL on infant mortality using cohort-linked birth and infant death data from the National Vital Statistics System (NVSS) with a difference in differences (DD) framework. The outcome of interest is the PNMR, defined as infant deaths (between 28 and 365 days) per 1000 live births—this generally overlaps with the periods that CA-PFL can be taken.[3] Using all states other than California as the comparison group, I find that the CA-PFL reduced PNMR by 0.135. There were fewer deaths from health-related causes and larger effects for infants with married mothers and for infant boys. My back-of-the-envelope calculation estimates that the reduction in infant deaths would save approximately $9.7 billion per year assuming that a 12-week national PFL policy had been in effect in 2020.

There is one obstacle in examining the causal effect of PFL on PNMR. Specifically, there might exist contemporaneous shocks that are correlated with the PFL policy and are also beneficial for infant health. If so, the result would be spurious rather than causal. To address the concern of contemporaneous shocks, I use the fetal mortality rate as the placebo outcome because it is less likely to be influenced by CA-PFL but should be impacted by contemporaneous shocks. Furthermore, I performed additional robustness checks using several alternative comparison groups and found that my results are not sensitive to comparison groups consisting of states with different backgrounds of family leave policies.

Another difficulty in conducting inference is that there is only one treated unit, which suffers the few clusters problem. Typically, studies that exploit policy variation across states conduct inference using standard errors clustered at the state level. However, this approach may be challenging in cases where the number of treated clusters is small and the conventional cluster-robust standard errors may be underestimated (Bertrand et al., 2004; Conley & Taber, 2011; Donald & Lang, 2007). In this study, I follow Ferman and Pinto (2019) to deal with the few clusters problem.

This paper is closely related to the literature on the impact of parental leave policies on infant health outcomes and extends it on several dimensions. First, this paper examines the overall effect of mothers' and fathers' leave on PNMR through the first PFL policy in the U.S. and finds that a 6-week PFL program reduced PNMR by 0.135. Stearns (2015) focused on mothers' paid leave through and Rossin-Slater (2011) focused on unpaid leave which is typically taken only by mothers. Second, the findings in this study may enhance our interpretation of the effects of CA-PFL on early childhood health outcomes (e.g., Bullinger, 2019; Lichtman-Sadot & Bell, 2017; Pihl & Basso, 2019). The earlier studies focused on surviving infants, and if CA-PFL reduced deaths of the most vulnerable infants in California, then their estimates would be higher bounds of these effects. Third, this study examines the heterogeneous effects of PFL for different sub-groups of mothers/infants. This is helpful to our understanding of how such policies would have a different impact on infant deaths and which groups of people are more likely to be influenced by them.

This study is also related to the literature on infant mortality which has shown that it is vulnerable to environmental and economic factors, such as air pollution (Currie et al., 2009; Tanaka, 2015), clean water (Heft-Neal et al., 2019; Mettetal, 2019), and expenditures (Kiross et al., 2020). This study suggests that infant mortality also could be impacted by the public policy of parental leave.

There are also policy implications here for national PFL programs. Currently, two national PFL programs are under review. One is the Family and Medical Insurance Leave (FAMILY) Act, the other is the American Families Plan (AFP). Better understanding the benefits of CA-PFL may be helpful for policymakers to make their decisions for the two national PFL programs as they share many common elements with CA-PFL.

The paper proceeds as follows. Section 2 discusses family leave policies in the U.S. Section 3 describes the data and presents summary statistics. Section 4 discusses the identification strategy and inference methods. Section 5 presents the main results and the results of heterogeneous analyses. Section 6 discusses robustness checks, threats to identification, and external validity. Section 7 concludes and provides policy implications.

## 2 | FAMILY LEAVE POLICIES IN THE U.S.

The U.S. is the only developed country in the world that does not mandate paid parental leave. The only national policy, the 1993 FMLA, requires employers to provide 12 weeks of unpaid job-protected leave to qualified workers with a newborn or a sick child, or due to a personal or family illness. To be eligible for the FMLA, one must have worked at least 1250 h over 12 months for a firm that employs at least 50 workers within 75 miles of its physical establishment. Therefore, only 56% of U.S. employees are eligible for FMLA. This is partly due to the stringent requirements of firm size and the length of time an employee must work for the same employer; further, many eligible workers cannot afford to take 3 months off without pay (Stearns, 2015).

The U.S. 1978 Pregnancy Discrimination Act does require that employers treat pregnancy and childbirth like any other temporary disability. Consequently, five states (California, Hawaii, New Jersey, New York, and Rhode Island) have TDI programs that are required to provide partial wage replacement (50–66%) for medical leaves related to pregnancy and childbirth. Workers in California and New Jersey can claim benefits for up to 4 weeks before the expected delivery date and 6 weeks after birth (8 weeks for Cesarean sections). The other TDI states provide six to 8 weeks of leave that can be used on either side of birth.

On September 23, 2002, the first PFL law in the U.S. was enacted in California; it became effective on July 1, 2004. The program provides 6 weeks of paid leave for eligible workers who take time off to care for an ill family member or to bond with a new child. Benefits are equal to 55% of weekly earnings, up to a weekly cap of $728, as of 2004. The PFL program is funded by the payroll tax on employees' wages; employers make no direct financial contribution. Unlike the FMLA, the CA-PFL is nearly universal in its coverage. Apart from some self-employed persons, all private-sector and nonprofit-sector workers are included, regardless of the size of their employer (Appelbaum & Milkman, 2015). Workers need not have been with their current employer for any specific period to be eligible for the PFL; they need only to have earned at least $300 in a job that is covered by the State Disability Insurance (SDI), during any quarter in the 5–18 months prior to filing a CA-PFL claim. Most employed mothers in California already qualify for up to 4 weeks of paid pre-birth leave and 6 weeks of paid post-birth leave under SDI. Newly pregnant mothers have to start by filing an SDI claim; fathers can take leave through PFL immediately after their child's birth. The PFL does not include job protection unless individuals also qualify for FMLA or the California Family Rights Act (CFRA).[4] PFL can be taken continuously or intermittently within the first 12 months after a child's birth or adoption.

As of 2022, 11 states and the Washington, D.C. (D.C.) have enacted PFL programs. These programs are active in California (2004), New Jersey (2009), Rhode Island (2014), New York (2018), Washington (2019/2020), Massachusetts (2019/2021), the D.C. (2020), and Connecticut (2021/2022), while the programs in Delaware (2022/2023) Oregon (2023), Colorado (2023/2024), and Maryland (2023/2025) have yet to go into effect.[5] In addition, two national PFL programs are proposed and are under review. The FAMILY Act, designed to provide 12 weeks of paid leave at a 66% wage replacement rate, was introduced in 2013 but has not been enacted yet. In 2021, President Joe Biden proposed an AFP that is similar to the FAMILY Act: it would guarantee 12 weeks of paid leave to new parents with benefits of 66–80% of their wages, capped at $4000 a month. However, the full 12 weeks of paid leave is not expected to be available until the 10th year of the program.[6]

A number of studies have examined the effects of CA-PFL on various outcomes. For example, some found that CA-PFL increased parental leave-taking and improved early childhood outcomes. The leave-taking increased by about

5 weeks for the average covered mother (Baum & Ruhm, 2016; Rossin-Slater et al., 2013) and by 1 week for fathers (Baum & Ruhm, 2016). Or, fathers were 0.9% points more likely to take leave (Bartel et al., 2018). Huang and Yang (2015) and Pac et al. (2019) concluded that the CA-PFL increased breastfeeding by about 5% points. Lichtman-Sadot and Bell (2017) found improved health outcomes among elementary school children, while Bullinger (2019) found improvements in parent-reported overall child health. Pihl and Basso (2019) reported a decline in infant admissions to hospitals; they concluded that this may be due to more breastfeeding. Taken together, these studies suggest that the CA-PFL is beneficial to parents and their infants.

## 3 | DATA

This paper utilizes the cohort-linked birth and infant death data of the NVSS from the National Center for Health Statistics (NCHS, 2020). The microdata contains cohort-linked births and infant deaths occurring in a given calendar year in the U.S., which includes information on birth characteristics (e.g., birth weight, gestational age, birth order, and sex) and maternal characteristics (e.g., age, race, ethnicity, and marital status). I use the data of all singleton births and infant deaths from 2000 to 2008 for analysis. Multiple births are excluded because of the increased risk of prematurity and low birth weight associated with multiple gestations. The sample period stops in 2008 because New Jersey implemented a PFL program in 2009 and I want to have a clear comparison group of states without PFL policy changes during my sample period. The sample period starts in 2000 because I want to have a balanced length of pre- and post-treatment periods (4.5 years pre and 4.5 years post).[7]

Because there is no unique id linking individual deaths and births, I aggregate the death and birth data to state-month level and then link them by birth state and birth cohort. To reflect the underlying microdata, I use the birth counts in each cell at the aggregated level as the sample weight. The outcome of interest is the PNMR, defined as infant deaths between 28 and 365 days per 1000 live births in each month at the state level. I include birth and maternal controls in my analyses. The birth controls are birth weight, gestational age, sex at birth, and birth order.[8] The maternal controls are age, race/ethnicity, marital status, educational attainment, employment status, and family income.[9] Maternal educational attainment, employment status, and family income come from the Current Population Survey (CPS) rather than from NVSS because the NVSS data are not comparable across states and years due to the 2003 revisions of the U.S. standard certificates (NCHS, 2008).[10] To make the CPS data as representative as the NVSS data, I restrict the CPS sample to women whose youngest child is less than 1 year old. The final data are aggregated in 5508 state-month cells for 36,039,789 total births. Table 1 presents the summary statistics of outcome and the controls variables. The PNMR is lower in California than in the comparison group in both pre- and post-PFL periods. However, the PNMR was reduced by 0.12 in California after PFL was effective, while it increased by 0.04 for the comparison group.

## 4 | IDENTIFICATION STRATEGY

To identify the effects of CA-PFL on PNMR, I use the DD method that compares the PNMR in California to that of the comparison group (49 non-CA states plus D.C.) before and after the implementation of PFL. I estimate the effects based on the following equation.

$$Y_{st} = \beta CA_s \times Post_t + \gamma X_{st} + \mu_s + \lambda_t + \varepsilon_{st} \tag{1}$$

where $Y_{st}$ is the measure of the PNMR in state $s$ and time $t$ (year-by-month); $CA$ is an indicator of residence in California; $Post$ is an indicator that the birth date was after July 1, 2004; $X_{st}$ is a vector of the birth and maternal controls; $\mu_s$ is the state fixed effects; $\lambda_t$ is the time (year-by-month) fixed effects; $\varepsilon_{st}$ is the error term. The key coefficient of interest is $\beta$, which measures the DD estimate of the effect of the CA-PFL on PNMR. Standard errors are clustered at the state level.

A key assumption in the DD analysis is that the comparison group provides the appropriate counterfactuals for the trend that the treated state would have followed if it had not been treated—that is, the treated group and the comparison group would have had parallel trends. First, in Figure 1 I plot the raw trends of PNMR throughout the 2000–2008 period for California and the comparison group. The trends in PNMR are generally common for both groups before 2004; we can detect a downward trend in PNMR for California after 2004, while there is no similar pattern for the

**TABLE 1** Summary statistics

| Variable | All | Pre-CA-PFL CA | Pre-CA-PFL Comparison | Post-CA-PFL CA | Post-CA-PFL Comparison |
|---|---|---|---|---|---|
| Outcome of interest | | | | | |
| Post-neonatal mortality rate | 2.16 | 1.65 | 2.23 | 1.53 | 2.27 |
| Placebo outcome | | | | | |
| Neonatal mortality rate | 3.81 | 3.07 | 4.01 | 2.97 | 3.85 |
| Fetal mortality rate | 5.97 | 5.25 | 6.25 | 4.92 | 5.98 |
| Fertility outcome | | | | | |
| General fertility rate | 65.20 | 67.52 | 63.51 | 69.06 | 65.88 |
| Number of births | 15,798 | 43,114 | 11,202 | 45,193 | 11,751 |
| Birth control | | | | | |
| Birth weight | 3317 | 3372 | 3328 | 3338 | 3294 |
| Gestational age | 38.75 | 38.98 | 38.79 | 38.83 | 38.66 |
| Male | 0.51 | 0.51 | 0.51 | 0.51 | 0.51 |
| First born | 0.40 | 0.39 | 0.41 | 0.40 | 0.41 |
| Second born | 0.32 | 0.32 | 0.32 | 0.31 | 0.32 |
| Third or later born | 0.28 | 0.29 | 0.27 | 0.29 | 0.28 |
| Maternal control | | | | | |
| Age <= 20 | 0.16 | 0.14 | 0.16 | 0.14 | 0.15 |
| 20 < Age <= 25 | 0.26 | 0.24 | 0.26 | 0.24 | 0.27 |
| 25 < Age <= 30 | 0.27 | 0.27 | 0.27 | 0.27 | 0.28 |
| 30 < Age <= 35 | 0.21 | 0.23 | 0.21 | 0.23 | 0.20 |
| Age > 35 | 0.11 | 0.13 | 0.10 | 0.13 | 0.10 |
| Non-Hispanic black | 0.14 | 0.06 | 0.16 | 0.06 | 0.16 |
| Non-Hispanic white | 0.56 | 0.31 | 0.61 | 0.28 | 0.58 |
| Non-Hispanic other | 0.06 | 0.11 | 0.05 | 0.11 | 0.05 |
| Hispanic | 0.24 | 0.51 | 0.18 | 0.54 | 0.21 |
| Married | 0.63 | 0.67 | 0.66 | 0.62 | 0.61 |
| Less than high school completion | 0.17 | 0.23 | 0.16 | 0.23 | 0.15 |
| High school diploma | 0.28 | 0.26 | 0.29 | 0.24 | 0.28 |
| Some college | 0.26 | 0.26 | 0.26 | 0.26 | 0.27 |
| Bachelor's degree or higher | 0.29 | 0.25 | 0.29 | 0.28 | 0.30 |
| Share of employed | 0.51 | 0.45 | 0.51 | 0.44 | 0.52 |
| Family income | 47,950 | 51,274 | 47,797 | 47,956 | 47,613 |
| *N* | 5508 | 54 | 2700 | 54 | 2700 |

*Note*: The table presents the summary statistics (means) of the outcome and control variables obtained from the NVSS for the whole sample, California (pre- and post-CA-PFL samples), and the comparison group (pre- and post- CA-PFL samples), from 2000 to 2008. The comparison group is the all non-CA states plus D.C.

comparison group. More formally, I use an event study model to test for the parallel trends assumption by regressing the outcome on the interaction of the treatment variable (CA) with a series of event-time dummies based on the following equation:

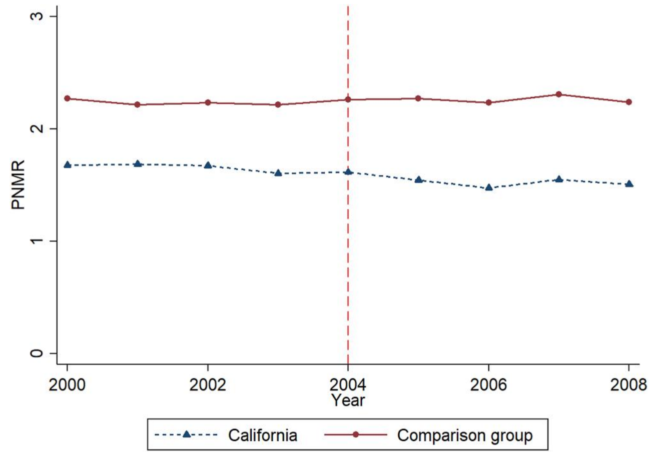


**FIGURE 1** Raw trends in PNMR in California and the comparison group, 2000–2008. This figure plots the raw trends in PNMR in California and the comparison group [Colour figure can be viewed at wileyonlinelibrary.com]

$$Y_{st} = \Sigma \beta_r CA \times Event_r + \gamma_4 X_{st} + \mu_s + \lambda_t + \varepsilon_{st} \tag{2}$$

In Equation (2), $Event_r$ is a dummy of the $r$ years of leads (+) or lags (−) since the implementation of PFL.[11] For example, $Event_{-1}$ is a dummy of the year from July 2003 to June 2004, $Event_0$ is a dummy of the year from July 2004 to June 2005, and $Event_{+1}$ is a dummy of the year from July 2005 to June 2006. The coefficients $\beta_r$ are measures of cohort-specific effects compared with the comparison group. I plot the coefficients $\beta_r$ and its 95% confidence interval in Figure 2. The coefficients of the interaction term are not statistically significant for the birth cohort prior to the implementation of PFL. This suggests that the pre-treatment trends in PNMR do not differ between California and the comparison group, and the states I have selected can be used as a valid comparison group for California.

In studies that leverage policy changes across states, the inference is usually conducted using standard errors that are clustered at the state level. However, the cluster-robust standard errors are underestimated when the number of treated clusters is small (Bertrand et al., 2004; Conley & Taber, 2011; Donald & Lang, 2007). Further, since the number of births varies greatly across states, the residuals in the regression equation tend to exhibit substantial heteroscedasticity. Accordingly, I use a method of inference, developed by Ferman and Pinto (2019), that provides an improvement in the hypothesis testing for situations where there are few or even one treated unit(s) and many control units in the presence of heteroskedasticity. It is important to note that Ferman and Pinto's method is not robust to any form of unknown heteroskedasticity, but it provides an improvement relative to existing methods that rely on homoskedasticity. Specifically, they model the heteroskedasticity of the pre-post difference in average errors. Under this assumption, they rescale the pre-post difference in average residuals of the control groups using the pre-post difference in average errors. In this way, a cluster residual bootstrap with this heteroskedasticity correction provides asymptotically valid hypothesis testing when the number of control groups goes to infinity, even when there is only one treated group. This method produces a bootstrapped distribution of the pseudo-treatment effects for determining the significance of the estimate of the treatment effects, rather than being a test statistic (Ferman & Pinto, 2019).[12] I report Ferman Pinto *p*-values (F-P *p*-values) and conventional *p*-values for all specifications. F-P *p*-values are my preferred inference results, and conventional *p*-values are listed only for reference purposes.

# 5 | RESULTS

## 5.1 | Effects of CA-PFL on PNMR

Based on a sample of all singleton births in the U.S. from 2000 to 2008, Table 2 shows the estimates of the effects of CA-PFL on the PNMR.[13] Table 2 presents estimates of Equation (1) with three model specifications. In column (1), I consider a baseline model with state and time fixed effects only. The point estimate suggests that there was a significant

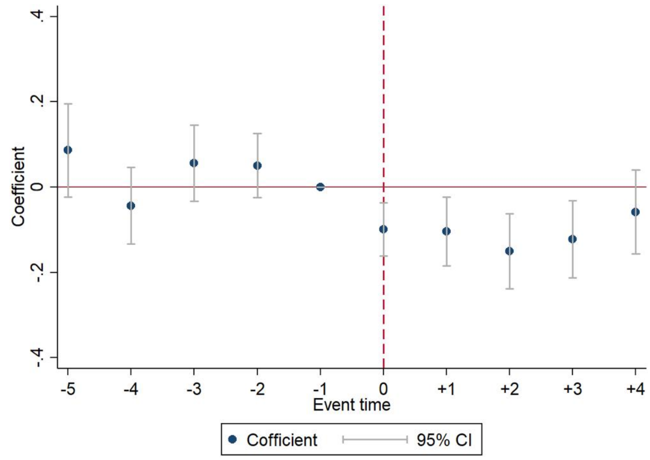


**FIGURE 2** Event study estimates of effects of CA-PFL on PNMR. This figure displays coefficients and 95% confidence intervals of event study estimates. Event time is a dummy of the year(s) of leads or lags since CA-PFL is effective, for example, the event time 0 is a dummy of the year PFL effective (July 2004 to June 2005) [Colour figure can be viewed at wileyonlinelibrary.com]

**TABLE 2** Effects of CA-PFL on the PNMR

| | (1) | (2) | (3) |
|---|---|---|---|
| CA*Post | −0.155 | −0.161 | −0.135 |
| *p*-value | (0.000) | (0.000) | (0.000) |
| F-P *p*-value | [0.098] | [0.050] | [0.008] |
| *R*-squared | 0.456 | 0.458 | 0.460 |
| Observations | 5508 | 5508 | 5508 |
| State FE, time FE | Y | Y | Y |
| Birth control | N | Y | Y |
| Maternal control | N | N | Y |

*Note*: The table presents the DD estimates of the effects of the CA-PFL on PNMR. The birth controls include birth weight, gestational age, sex of birth, and birth order; and the maternal controls include maternal age, race/ethnicity, marital status, educational attainment, employment status, and family income. All regressions are clustered at the state level and weighted by the number of births in each state-month cell. The cluster-robust *p*-values are in parentheses, and the Ferman-Pinto *p*-values are in brackets.

decrease in PNMR in California after the implementation of CA-PFL. This result hinges on the assumption that there are no omitted time-varying and state-specific factors that correlated with the PNMR. In columns (2) and (3), I relax this assumption by adding a set of time-varying state-level birth controls and maternal controls. The model in Column 3 is my preferred specification as it includes both fixed effects and time-varying controls. The magnitude of the coefficient in Column 3 indicates that the CA-PFL reduced the PNMR by 0.135 at the one percent level of significance, or about an 8% reduction of its pre-treatment sample mean (1.65).

Because the data do not contain information on who is eligible to benefit from the CA-PFL, the estimated effect will represent the intention-to-treat (ITT) effect. The treatment-on-the-treated (TOT) effects could be estimated using the ITT effect scaled by the inverse of parents' take-up rate of CA-PFL. One way to estimate the take-up rate is to consider the number of claims divided by the number of likely eligible parent. Table 3 presents the estimates of mothers' and fathers' take-up rates of CA-PFL. I estimate that 44% (5%) of employed new mothers (employed new fathers) made a bonding claim in 2005, which is similar to estimates of Bana et al. (2018)—40% for mothers and 4% for fathers. According to Table 3, the estimated take-up rate for California families is about 27.12%, and the ITT effects could be scaled to 0.5 (0.135*(1/0.27)) to get the TOT effects for both mothers and fathers taking the full length of leave.

**TABLE 3** Estimates of the CA-PFL take-up rate

| | Number of bonding claims | | Children for bonding | | Eligible parent% | | Take-up rate | |
|---|---|---|---|---|---|---|---|---|
| **Year** | **Mother** | **Father** | **New birth** | **Adoption** | **Mother** | **Father** | **Mother** | **Father** |
| 2004 | 56,279 | 10,178 | 282,643 | 3778 | 45.09% | 91.12% | 43.57% | 3.90% |
| 2005 | 112,155 | 24,810 | 548,882 | 7556 | 44.21% | 88.29% | 45.59% | 5.05% |
| 2006 | 118,112 | 28,223 | 562,440 | 7393 | 42.13% | 90.71% | 49.19% | 5.46% |
| 2007 | 127,754 | 33,804 | 566,414 | 7622 | 43.67% | 90.54% | 50.97% | 6.50% |
| 2008 | 137,566 | 39,833 | 551,804 | 7777 | 45.91% | 90.34% | 53.55% | 7.88% |
| Total | 551,866 | 136,848 | 2,512,183 | 34,126 | 44.20% | 90.20% | 48.58% | 5.76% |

*Note*: The table presents the estimates of the CA-PFL take-up rate. The take-up rate = (number of bonding claims) ÷ (sum of new births and adoptions × eligible parent %). For example, take-up rate in 2005 for mothers: 45.59% = 112,155 ÷ ((548,882 + 7556) × 44.21%); and for fathers: 5.05% = 24,810 ÷ ((548,882 + 7556) × 88.29%). The number of bounding claims is from the California Employment Development Department (2020). The number of total births is from NCHS (2020), and the number of births in 2004 is the total births from July to December of 2004. The number of adopted children (2005–2008) is from the U.S. Department of Health and Human Services (2015), and the number of adopted children in 2004 is estimated as half of the number in 2005. The percent of eligibility is estimated as the share of the employed parent with the youngest child less than 1-year old using data from CPS.

**TABLE 4** Comparison of effect size in this study with that of previous studies

| Study | Sample period | Country | Effect | Mean | Percent change | Length (week) | 1-week effect |
|---|---|---|---|---|---|---|---|
| Ruhm (2000) | 1969–1994 | 16 European countries | 0.20 | 4.30 | 5% | 10 | 0.020 |
| Tanaka (2005) | 1969–2000 | 16 European countries, U.S., and Japan | 0.15 | 3.60 | 4% | 10 | 0.015 |
| Rossin-Slater (2011) | 1989–1997 | U.S. (FMLA) | 0.20 | 2.00 | 10% | 12 | 0.017 |
| This study | 2000–2008 | U.S. (CA-PFL) | 0.14 | 1.65 | 8% | 6 | 0.023 |

*Note*: This table presents the comparison of effect size in this study with that of previous studies. The "Effect" column is the (ITT) effect on PNMR. The "1-week effect" column is the estimate divided by leave length assuming linear effect.

## 5.2 | Interpretation

It is worthwhile to compare my estimate to studies that focus on other parental leave studies on PNMR. Table 4 presents the comparison of the effect size (ITT effects) in this study with those in related studies. Ruhm (2000) examined 16 European countries and found that the equivalent effect of a 1-week extension on PNMR is 0.020; Tanaka (2005) extended Ruhm's (2000) study by adding the U.S. and Japan and found a similar result (0.015). Rossin-Slater (2011) reported that PNMR is reduced by 0.017 (1-week equivalent effect) for infants with highly educated and married mothers after the FMLA becomes effective. In this study, I find that the 1-week equivalent effect on PNMR is 0.023, which is similar in magnitude but slightly larger than that of previous studies.

## 5.3 | Heterogeneous effects

Thus far, I have considered PNMR for all births. However, the heterogeneous effects on subgroups of infants are also important to understanding how PFL affects PNMR. In this section, I conduct several analyses according to the cause of death, maternal race, maternal marital status, and sex of birth.

First, I examine the heterogeneous effects of PFL on PNMR by causes of infant deaths which can be categorized as health-related and non-health-related causes.[14] The health-related causes include infectious diseases, nutritional diseases, respiratory diseases, and influenza. The non-health-related causes include accidents and assault, for example, The results in Panel A of Table 5 suggest that the reduction in PNMR is driven by health-related causes rather than non-health-related causes. This result is supportive of two mechanisms mentioned earlier: parental care and preventive care.

**TABLE 5** Heterogeneous effects of CA-PFL on the PNMR

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Panel A cause of death: Health-related versus non-health-related | | | | | | |
| Group (mean) | Health-related cause (1.51) | | | Non-health-related cause (0.14) | | |
| CA*Post | −0.151 | −0.160 | −0.147 | −0.004 | −0.002 | 0.012 |
| *p*-value | (0.000) | (0.000) | (0.000) | (0.754) | (0.906) | (0.452) |
| F-P *p*-value | [0.136] | [0.063] | [0.031] | [0.922] | [0.972] | [0.789] |
| R-squared | 0.394 | 0.397 | 0.398 | 0.281 | 0.283 | 0.286 |
| Panel B race: Non-Hispanic Black versus non-Hispanic White | | | | | | |
| Group (mean) | Non-Hispanic Black (3.80) | | | Non-Hispanic White (1.50) | | |
| CA*Post | −0.280 | −0.242 | −0.305 | −0.137 | −0.119 | −0.067 |
| *p*-value | (0.002) | (0.006) | (0.001) | (0.000) | (0.000) | (0.004) |
| F-P *p*-value | [0.676] | [0.710] | [0.602] | [0.163] | [0.179] | [0.333] |
| R-squared | 0.097 | 0.104 | 0.107 | 0.331 | 0.333 | 0.336 |
| Panel C Mother's marital status: Married versus unmarried | | | | | | |
| Group (mean) | Married (1.28) | | | Unmarried (2.39) | | |
| CA*Post | −0.152 | −0.176 | −0.167 | −0.050 | −0.076 | −0.064 |
| *p*-value | (0.000) | (0.000) | (0.000) | (0.363) | (0.195) | (0.310) |
| F-P *p*-value | [0.004] | [0.004] | [0.001] | [0.895] | [0.802] | [0.818] |
| R-squared | 0.273 | 0.275 | 0.277 | 0.280 | 0.286 | 0.288 |
| Panel D child sex: female versus male | | | | | | |
| Group (mean) | Female (1.48) | | | Male (1.82) | | |
| CA*Post | −0.100 | −0.101 | −0.078 | −0.207 | −0.224 | −0.201 |
| *p*-value | (0.001) | (0.001) | (0.017) | (0.000) | (0.000) | (0.000) |
| F-P *p*-value | [0.379] | [0.362] | [0.404] | [0.031] | [0.015] | [0.004] |
| R-squared | 0.271 | 0.273 | 0.274 | 0.333 | 0.336 | 0.338 |
| Observations | 5508 | 5508 | 5508 | 5508 | 5508 | 5508 |
| State FE, time FE | Y | Y | Y | Y | Y | Y |
| Birth control | N | Y | Y | N | Y | Y |
| Maternal control | N | N | Y | N | N | Y |

*Note*: The table presents the heterogeneous effects of the CA-PFL on PNMR. The pre-treatment mean of PNMR is in parentheses. The observation for the heterogeneous analysis applies to all subgroup analyses as all analyses were conducted at the state by month level. At the state by month level, each state in each month has one observation of the outcome variable for each subgroup, thus, the number of 5508 observations is applied for to subgroup analyses. See notes to Table 2 for other details.

With more time bonding with children, parents can better monitor children's health status and children are more likely to receive timely medical treatment. Also, PFL allows parents to arrange appropriate preventative care more easily for their children. Thus, PFL reduces PNMR for health-related causes rather than for non-health-related causes. Death from external causes may occur stochastically, and it is nearly impossible for parents to anticipate it and to take leave in advance to avoid it. This is also consistent with Rossin-Slater's (2011) finding that FMLA has no impact on infant deaths with non-health-related causes.

I next examine the heterogeneous effects of CA-PFL by mothers' race/ethnicity and marital status. Panel B and C in Table 5 present these results. Only the results for births to married mothers are statistically significant using the Ferman-Pinto inference method. The results for births to non-Hispanic black and non-Hispanic white mothers and for unmarried mothers are only statistically significant when using the cluster robust inference method, which is less reliable. Why are there larger effects on infants with married mothers? First, the likelihood of having more total leave per birth is higher among married couples because both parents may be eligible for leave. Second, given that the PFL only has partial wage replacement, married mothers are more likely to be able to afford the partial paid leave than single mothers because married couples may have dual incomes.

Finally, I investigate the effect on PNMR by sex of births. The results in Panel D suggest that there was a larger, and significant reduction in PNMR for infant boys than for infant girls. Infant mortality is often higher in boys than girls, which has been explained by sex differences in genetic and biological characteristics: boys are biologically weaker and more susceptible to infectious diseases and adverse risks (Pongou, 2013). This result is supportive of the mechanism that the PFL might lessen the need for non-parental care, and non-parental care is often associated with an increased risk of many infectious illnesses. It is possible that the reduction in non-parental care reduced the risk of infant deaths caused by infectious diseases, and therefore that the effect was disproportionately larger on infant boys who are more vulnerable to infectious diseases.

# 6 | ROBUSTNESS

## 6.1 | Alternative comparison groups

So far, I used states other than California as the comparison group for the main analysis. However, some may have concerns that this is not a good comparison group because they are different from California in terms of family leave policies. Ness et al. (2016) ranked all states based on policies that support expecting and new parents, and California was ranked first.[15] To further explore the sensitivity of my estimates, I, therefore, conduct robustness checks using comparison groups based on family leave related policies. Specifically, I use: (1) states with (past) TDI programs (Hawaii, New Jersey, New York, and Rhode Island); (2) states without TDI programs; (3) states and D.C. with (future) PFL programs (New Jersey, Rhode Island, New York, D.C., Washington, Massachusetts, Connecticut, Oregon, and Colorado); (4) states without PFL programs[16]; (5) the top 25 family-friendly states (other than California); and (6) the bottom 25 family-friendly states as the alternative comparison groups.[17] Figure 3 presents the estimates using all non-CA states plus D.C. as the comparison group and then using the above-mentioned comparison groups, respectively. Figure 3 shows that the estimates using all comparison groups are statistically significant and very similar in magnitude; this indicates that my estimates are not sensitive to comparison groups having different family leave policies.

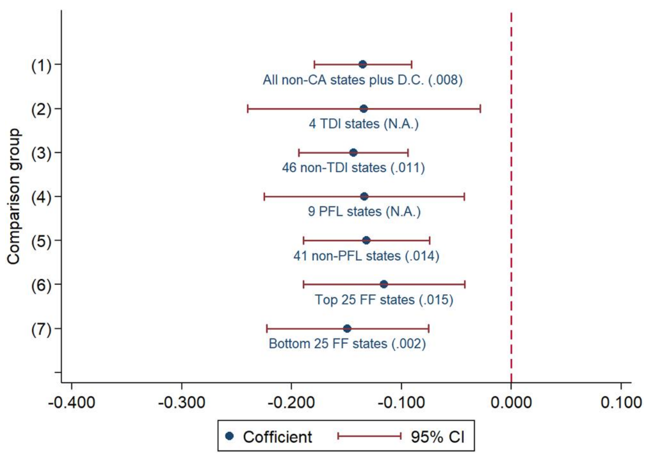


**FIGURE 3** Robustness checks: alternative comparison groups. This figure plots coefficients and 95% confidence intervals of estimates using alternative comparison groups. The 95% confidence intervals are based on the conventional cluster-robust standard errors, and F-P *p*-values are in parentheses (if applicable). Estimate (1) is the same as estimate in column (3) of Table 3. TDI comparison states are New York, New Jersey, Rhode Island, and Hawaii. PFL comparison states are New Jersey, Rhode Island, New York, D.C., Washington, Massachusetts, Connecticut, Oregon, and Colorado. See Table A2 in Appendix for the list of the top 25 family friendly (FF) states and the bottom 25 FF states [Colour figure can be viewed at wileyonlinelibrary.com]

To further examine the sensitivity of the main result, I use 25 randomly chosen states as the comparison group and repeated 1000 times. The resulting distribution of estimates is displayed in Figure 4. As it shows, all coefficients are negative and range from −0.059 to −0.125 with a mean of −0.135, and the 95% confidence interval is [−0.085, −0.185]. Overall, this suggests that the main result is robust and not sensitive to using different comparison states.

## 6.2 | Placebo check

One threat to identification is that the reduction in PNMR is due to contemporaneous shocks. For example, if there were unknown factors or contemporaneous shocks (e.g., less air pollution or more clear water) in California that also benefit infant health, then the result would be a correlation rather than a causation. To address this concern, I use the fetal mortality rate as the placebo outcome and redo the analyses. Fetal mortality is infant death during pregnancy, so it should not be influenced by CA-PFL but could be influenced by other factors or contemporaneous shocks that benefit infant health. The results in Table 6 indicate that CA-PFL has no significant impact on the fetal mortality rate, which suggests the reduction in PNMR in California is less likely due to other unknown factors or contemporaneous shocks.

One may also be interested in the effect of CA-PFL on the neonatal mortality rate. Neonatal mortality is defined as infant deaths within 28 days of birth. Recall that mothers with new births start with a 6-week SDI first and then take the PFL, so the neonatal period may less likely be influenced by the mother's leave through PFL. However, fathers can take leave immediately after birth, even though their take-up rate is only about 5%. Also, PFL may affect the mother's use of

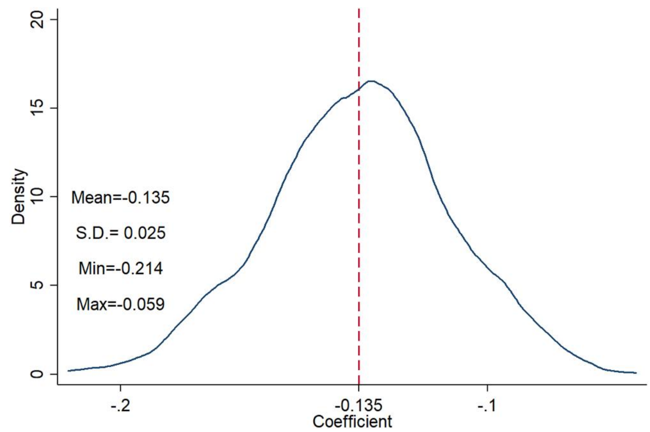


**FIGURE 4** Permutation results using 25 randomly chosen states as the comparison group. This figure plots the density distribution of estimates of using 25 randomly chosen states as the comparison group and permuted 1000 times. The vertical dashed line corresponds to −0.135, the estimate of our preferred specification in column (3) of Table 3 [Colour figure can be viewed at wileyonlinelibrary.com]

**TABLE 6** Placebo outcome: Fetal mortality

| | (1) | (2) | (3) |
|---|---|---|---|
| CA*Post | −0.049 | −0.059 | −0.027 |
| *p*-value | (0.291) | (0.231) | (0.582) |
| F-P *p*-value | [0.701] | [0.641] | [0.832] |
| *R*-squared | 0.602 | 0.604 | 0.606 |
| Observations | 5508 | 5508 | 5508 |
| State FE, time FE | Y | Y | Y |
| Birth control | N | Y | Y |
| Maternal control | N | N | Y |

*Note*: The table presents the DD estimates of the effects of the CA-PFL on fetal mortality rate. The fetal mortality rate is the number of deaths during pregnancy per 1000 live births. See notes to Table 2 for other details.

neonatal leave if it raises awareness of SDI pregnancy-related benefits. For these reasons, access to PFL may affect parents' neonatal leave; therefore, neonatal mortality may not be a clean placebo outcome. I also conducted an analysis using the neonatal mortality rate as the outcome, and the results presented in Table A3 in the Appendix suggest that CA-PFL has no significant impact on the neonatal mortality rate.

Another placebo examination assumes that the treatment state is a different state and to see if there is a similar effect. Specifically, I replicate the estimation of Equation (1) but assume that the treatment state is a different state. I repeat this procedure for all states other than California plus D.C. and then plot the coefficients and F-P *p*-values in Figure 5. As it shows, the F-P *p*-values are generally randomly distributed,[18] and there are six estimates with F-P *p*-values less than 0.1.[19] I then conduct event study analyses for the six states, respectively, and none of them show a similar pattern to that of California or display any meaningful patterns.[20] I also conduct another robustness check that excludes these six states from the analysis and the result is consistent with that of including them.[21] Overall, there is little evidence that the effects of CA-PFL on PNMR are driven by inappropriate identification assumptions, and the effect is indeed not spurious but causal.

## 6.3 | Other threats to identification: Migration, fertility, and birth outcomes

The CA-PFL was announced on September 23, 2002 and became effective on July 1, 2004. Some may have concerns that the 21-month-prior announcement may have made it possible for pregnant women in other states to migrate to California to take advantage of this policy. However, the maximum weekly benefit of the CA-PFL program was $728 before 2012, or $4368 for 6 weeks, which is less than the average cost of an interstate move ($5630).[22] The relatively small financial incentive is not sufficient enough to encourage mass migration of pregnant women in other states to California.

Another threat to the identification is that the CA-PFL may induce a change in fertility and, thereby affect the PNMR by changing the number of new births. This could happen if some women find that motherhood would be more appealing when they have access to PFL. Previous studies have examined the impacts of the CA-PFL on fertility and found no evidence of a response or in changes in the composition of births after the policy (Pihl & Basso, 2019; Rossin-Slater et al., 2013). However, Lichtman-Sadot (2014) found some shifts in the number of births from the earlier part of 2004 to the latter part. To address the concern over fertility changes in 2004, I exclude that year and redo the analysis; the results are consistent with those that include 2004.[23] To formally examine whether CA-PFL impacts fertility during the sample period, I perform additional analyses using the general fertility rate and the log of the number of births

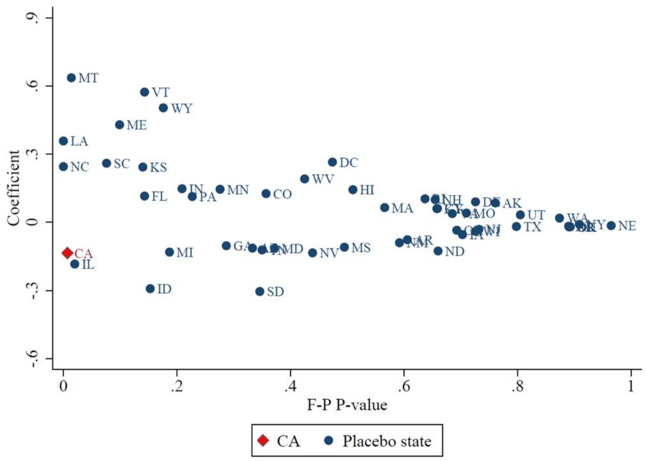


**FIGURE 5** Results of placebo tests using every other state as the treated state. This figure plots coefficients and F-P *p*-values of placebo tests using every other state as the treated state. The solid diamond dot is the main result that using California as the treated state, and the solid circle dots are results of placebo tests using every other state as the treated state. The F-P *p*-values are generally randomly distributed: 6 of them in range of 0–0.1, 6 of them in range of 0.1–0.2, 4 of them in range of 0.2–0.3, 5 of them in range of 0.3–0.4, 4 of them in range of 0.4–0.5, 3 of them in range of 0.5–0.6, 8 of them in range of 0.6–0.7, 7 of them in range of 0.7–0.8, 5 of them in range of 0.8–0.9, and 2 of them in range of 0.9–1 [Colour figure can be viewed at wileyonlinelibrary.com]

as the outcomes in the DD regressions, and the results are reported in Table 7. There is little evidence indicating that there is a fertility change in new births due to the CA-PFL.

I also analyze the effects of CA-PFL on two measures of birth outcomes—low birth weight and preterm birth, two of the leading causes of infant death (Ely & Driscoll, 2020). To examine if the CA-PFL impacts birth outcomes and then ultimately affects post-neonatal deaths, Table 7 reports the estimates of the effects of CA-PFL on birth outcomes. There are no significant effects on either birth outcome using the Ferman-Pinto inference method, which is consistent with Bullinger (2019). Overall, the reduction in PNMR is less likely to be explained by better health outcomes at birth.

## 6.4 | External validity

So far, I have evaluated the effect of PFL on PNMR in CA, but it is also important to know if a similar effect would be expected for other states with similar programs. Given that New Jersey (in 2009) and Rhode Island (in 2014) also implemented a similar PFL program, and that the data is also available to evaluate them, I followed Callaway and Sant'Anna (2021)'s method of staggered DD to explore the effect of PFL in CA, NJ, and RI on PNMR. I did two different

**TABLE 7** Effects of CA-PFL on fertility and birth outcomes

| | (1) | (2) | (3) |
|---|---|---|---|
| Panel A general fertility rate | | | |
| CA*Post | −0.632 | −0.553 | 0.047 |
| *p*-value | (0.017) | (0.035) | (0.831) |
| F-P *p*-value | [0.310] | [0.308] | [0.923] |
| R-squared | 0.977 | 0.977 | 0.982 |
| Panel B log of N(birth) | | | |
| CA*Post | −0.002 | 0.002 | 0.002 |
| *p*-value | (0.844) | (0.875) | (0.785) |
| F-P *p*-value | [0.959] | [0.968] | [0.891] |
| R-squared | 0.999 | 0.999 | 0.999 |
| Panel C low birth weight | | | |
| CA*Post | −0.001 | −0.001 | −0.001 |
| *p*-value | (0.004) | (0.008) | (0.001) |
| F-P *p*-value | [0.371] | [0.403] | [0.403] |
| R-squared | 0.910 | 0.911 | 0.913 |
| Panel D preterm birth | | | |
| CA*Post | 0.000 | 0.001 | 0.001 |
| *p*-value | (0.608) | (0.399) | (0.309) |
| F-P *p*-value | [0.910] | [0.805] | [0.735] |
| R-squared | 0.909 | 0.909 | 0.911 |
| Observations | 5508 | 5508 | 5508 |
| State FE, time FE | Y | Y | Y |
| Birth control | N | Y | Y |
| Maternal control | N | N | Y |

*Note*: The table presents the DD estimates of the effects of the CA-PFL on fertility and birth outcomes. The general fertility rate is the number of live births per 1000 females of childbearing age between the ages of 15–44 years. Low birth weight is defined as a weight of fewer than 2500 g, and preterm is defined as babies born alive before 37 weeks of pregnancy are completed. See notes to Table 2 for other details, except for the birth controls exclude birth weight and gestational age.

**TABLE 8** Results of staggered DD

| | (1) | (2) | (3) |
|---|---|---|---|
| Panel A balanced panel (1999–2017) | | | |
| Estimate | −0.098 | −0.193 | −0.090 |
| *p*-value | (0.000) | (0.000) | (0.429) |
| Panel B balanced pre- and post-period | | | |
| Estimate | −0.120 | −0.165 | −0.101 |
| *p*-value | (0.000) | (0.000) | (0.522) |
| State, time FE | Y | Y | Y |
| Birth control | N | Y | Y |
| Maternal control | N | N | Y |

*Note*: This table presents the results of staggered DD on the effect of PFL of CA, NJ, and RI on PNMR. Panel A shows the results using the balanced panel from 1999 to 2017, and Panel B shows the results using the balanced pre- and post-period, 4 years before and after.

versions of the staggered DD. One uses the balanced panel data from 1999 to 2017; the other uses the balanced pre-and post-period data, 4 years before and after implementation. Table 8 presents the estimates of the overall effect. The estimates are only statistically significant in specifications without controls or with birth controls. However, the parallel trend assumption does not hold for NJ and RI; thus, these estimates would be more like suggestive evidence.

Alternatively, the synthetic control method is useful for constructing a comparison group with parallel trends when there is only one treated unit and many control units. Thus, I estimate the effect of PFL on PNMR in CA, NJ, and RI using that method. The result, as Figure 6 presents, is that the synthetic state shares parallel trends in PNMR with the treated state before the effects of the PFL program. The PNMR in all three states was reduced after the implementation of the PFL program, and this was especially true for CA and NJ. Galiani and Quistorff (2017) proposed a method for inference for the synthetic control method by comparing the estimated main effect with the distribution of placebo effects (estimations for the same treatment period but on all the control units). It could also provide inference for several units that received treatment at different times. I followed their method for inference and the results are in Table 9. As shown, the overall estimates and the estimates for all states are negative. However, the estimates are only statistically significant for CA and the overall effect of the three programs but are not statistically significant for NJ and RI individually.

Overall, the results of the staggered DD and synthetic control methods provide suggestive evidence that PFL also reduced PNMR in NJ and RI; along with the solid evidence in CA, it is supportive that we should expect a similar effect for a national PFL program.

## 7 | CONCLUSION AND POLICY IMPLICATION

The PFL aims to help working parents balance their careers and family responsibilities, which is essential to child development. The benefits of PFL on infant mortality previously have been documented in large cohort studies using data from European countries, where there has been widespread adoption of paid family leave at a national level. This study examines the first PFL program in the U.S. and finds that a 6-week PFL reduced PNMR by 0.135, saving approximately 339 infant lives in California from 2004 to 2008.[24] Heterogeneous analyses suggest that there were fewer deaths from health-related causes and larger effects for infants with married mothers and for infant boys.

One policy implication of this study is that the benefits of the PFL program may be understated if the effects on infant mortality are not taken into account. This is especially significant as more states in the U.S. are developing their own PFL program and the national PFL plans, FAMILY Act and AFP, are currently under review. The FAMILY Act and AFP were estimated to cost approximately $228 billion and $225 billion across 10 years, respectively.[25] Therefore, the average cost of a 12-week PFL plan would cost around 23 billion per year. The value of a statistical life (VSL) is commonly used by policy analysts and researchers to estimate life values, even though human life is priceless—estimates of the VSL for the U.S. are around $10 million (Kniesner & Viscusi, 2019). In this study, I find that a 6-week PFL reduces PNMR by 0.135. Assuming a similar effect for a national PFL policy like FAMILY Act or AFP, the 12-week PFL plan could reduce the infant mortality

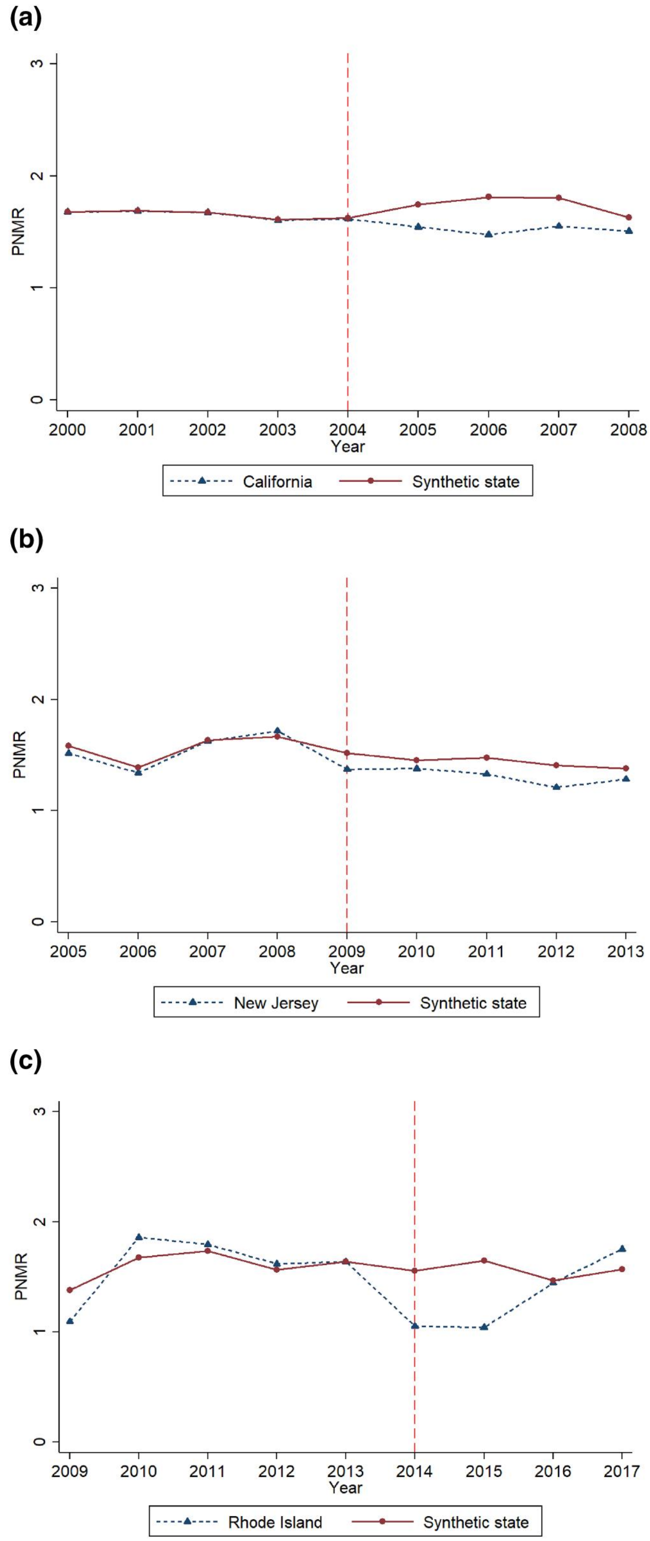


**FIGURE 6** Results of the synthetic control method for CA, NJ, and RI. (a) California. (b) New Jersey. (c) Rhode Island. This figure presents the synthetic control results for CA, NJ, and RI. The red vertical line is the year that the PFL policy was effective [Colour figure can be viewed at wileyonlinelibrary.com]

rate by 0.27. In 2020, there were about 3.6 million new births, which implies that approximately 972 additional infants could survive to 1 year of age if the FAMILY Act or AFP were effective. When a statistical life is valued at $10 million, the reduction in infant mortality is worth approximately $9.7 billion per year. The estimated dollar benefit is substantial and is

TABLE 9 Synthetic control results

| State | CA | | NJ | | RI | | Overall | |
|---|---|---|---|---|---|---|---|---|
| Post-period | Coef. | *p*-value | Coef. | *p*-value | Coef. | *p*-value | Coef. | *p*-value |
| 1 | −0.008 | 0.340 | −0.149 | 0.720 | −0.502 | 0.700 | −0.145 | 0.298 |
| 2 | −0.201 | 0.020 | −0.075 | 0.920 | −0.610 | 0.700 | −0.203 | 0.005 |
| 3 | −0.336 | 0.040 | −0.145 | 0.760 | −0.020 | 0.960 | −0.106 | 0.023 |
| 4 | −0.256 | 0.000 | −0.199 | 0.800 | 0.184 | 0.840 | −0.074 | 0.017 |
| 5 | −0.121 | 0.040 | −0.096 | 0.820 | NA | NA | NA | NA |
| Average | −0.184 | | −0.133 | | −0.237 | | −0.132 | |

*Note*: This table presents the inference for the synthetic control results. The inference was conducted using Galiani and Quistorff (2017) proposed a synth runner package by comparing the estimated main effect with the distribution of placebo effects (estimations for the same treatment period but on all the control units).

nearly half of the estimated cost. The back-of-the-envelope calculations of benefits associated with the reduction in infant deaths might be helpful for policymakers to make decisions on the national PFL programs.

## ACKNOWLEDGMENTS

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## ENDNOTES

[1] I thank one anonymous reviewer for reminding me of this mechanism.

[2] WIC is the special supplemental nutrition program for Women, Infants, and Children (WIC), which provides federal grants to states for supplemental foods, health care referrals, and nutrition education for low-income pregnant, breastfeeding, and non-breastfeeding post-partum women, and to infants and children up to age five who are found to be at nutritional risk.

[3] The PFL for new mothers runs from 6 weeks to 12 months after childbirth—new mothers with pregnancy have to start with State Disability Insurance (SDI) first, which provides them 6 weeks paid leave.

[4] CFRA generally requires employers with 50 or more employees to provide eligible workers unpaid time off to attend to the medical needs of themselves or certain family members.

[5] Numbers in parentheses are years that PFL program in effect. Multiple effective dates denote effective dates for premiums/benefits. Sources: https://bipartisanpolicy.org/download/?file=/wp-content/uploads/2022/05/2022-05-Features-of-State-PFL-Programs.pdf

[6] Fact Sheet: The American Families Plan, retrieved from https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/28/fact-sheet-the-american-families-plan.

[7] Results using extended periods are similar to my main result and are available upon request.

[8] Birth order is in three categories: first born, second born, and third born or later.

[9] Mother's age is in five categories: 20 years old or less, 21–25 years, 26–30 years, 30–35 years, 36 or more; Mother's race/ethnicity is in four categories: non-Hispanic white, non-Hispanic black, non-Hispanic other, and Hispanic. Education attainment is in four categories: less than high school diploma, high school diploma, some college, college degree and more.

[10] States implemented the 2003 revision of the birth certificate across different years that range from 2003 to 2016. Many data items are common to both the 1989 and 2003 standard birth certificates and are considered directly comparable between revisions. Several key items, however (i.e., educational attainment, tobacco use during pregnancy, month prenatal care began and type of vaginal or cesarean delivery), are not considered comparable between revisions (NCHS, 2008).

[11] The PNMR is noisy at shorter periods (e.g., monthly). Conducting event study analysis at the yearly level would use 12 months before the implementation of the policy as the reference period, which is more reliable. Event study results at monthly, quarterly, and semiyearly levels are available upon request.

[12] The purpose of this bootstrap is to provide asymptotic refinement in the presence of clustered errors. It essentially performs a permutation test by imposing the null hypothesis and resampling the residuals—rather than re-estimating the key coefficient of interest—and then asking how likely it would be to observe the key coefficient by chance. As such, only *p*-values (not standard errors and R-squared) are generated.

[13] I present a version of estimates using all births in the U.S. during 2000–2008 in Table A1 in the Appendix.

[14] Deaths with NCHS's ICD-10 130 Groups for selected causes of infant mortality codes from 001 to 137 are classified as health related, while those codes from 138 to 158 are in the non-health related category.

[15] They assess state laws and policies that guarantee access to family or medical leave to expecting and new parents, paid sick days, reasonable accommodations for pregnant workers and support for breastfeeding mothers.

[16] However, one drawback of using TDI states and PFL states as the comparison groups is that Ferman and Pinto's inference method is not applicable as there are only very limited control units ($N < 10$). Ferman-Pinto inference method works well for cases of few treated units and many control units, however, when the number of control units is small (e.g., $N < 10$), it is difficult to estimate the conditional variance accurately. According to Ferman (personal communication, 2021), it is hard to tell how many control units are sufficient to use this method, but from the simulations in their paper, an $N >= 20$ is good to use.

[17] Table A2 in the Appendix lists ranks of all states based on the assessment of family-friendly policies.

[18] Specifically, 6 of them in range of 0–0.1, 6 of them in range of 0.1–0.2, 4 of them in range of 0.2–0.3, 5 of them in range of 0.3–0.4, 4 of them in range of 0.4–0.5, 3 of them in range of 0.5–0.6, 8 of them in range of 0.6–0.7, 7 of them in range of 0.7–0.8, 5 of them in range of 0.8–0.9, and 2 of them in range of 0.9–1.

[19] These states are Illinois, Louisiana, Maine, Montana, North Carolina, and South Carolina.

[20] Figure A1 in the Appendix presents the figures of these event studies.

[21] Table A4 in the Appendix presents the results.

[22] According to the American Moving & Storage Association, the average cost of an interstate move is $5630 in 2016.

[23] Table A5 in the Appendix presents the results.

[24] 339 = 0.135*(the number of total births in this period)/1000.

[25] The cost of the FAMILY Act was estimated by the Congressional Budget Office. https://www.cbo.gov/publication/56129 The cost of the AFP is from the *Fact Sheet: The American Families Plan*, retrieved from https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/28/fact-sheet-the-american-families-plan.

## REFERENCES


Almond, D., Hoynes, H.W. & Whitmore Schanzenbach, D. (2011) Inside the war on poverty: the impact of food stamps on birth outcomes. *The Review of Economics and Statistics*, 93(2), 387–403. Available from: https://doi.org/10.1162/rest_a_00089

Appelbaum, E. & Milkman, R. (2015) *Leaves that pay: employer and worker experiences with paid family leave in California*. Washington: Center for Economic and Policy Research.

Baker, M. & Milligan, K. (2008) Maternal employment, breastfeeding, and health: evidence from maternity leave mandates. *Journal of Health Economics*, 27(4), 871–887. Available from: https://doi.org/10.1016/j.jhealeco.2008.02.006

Baker, M. & Milligan, K. (2010) Evidence from maternity leave expansions of the impact of maternal care on early child development. *Journal of Human Resources*, 45(1), 1–32. Available from: https://doi.org/10.1353/jhr.2010.0007

Baker, M. & Milligan, K. (2015) Maternity leave and children's cognitive and behavioral development. *Journal of Population Economics*, 28(2), 373–391. Available from: https://doi.org/10.1007/s00148-014-0529-5

Bana, S., Kelly, B. & Rossin-Slater, M. (2018) Trends and disparities in leave use under California's paid family leave program: new evidence from administrative data. *AEA Papers and Proceedings*, 108, 388–391. Available from: https://doi.org/10.1257/pandp.20181113

Bartel, A.P., Rossin-Slater, M., Ruhm, C.J., Stearns, J. & Waldfogel, J. (2018) Paid family leave, fathers' leave-taking, and leave-sharing in dual-earner households. *Journal of Policy Analysis and Management*, 37(1), 10–37. Available from: https://doi.org/10.1002/pam.22030

Baum, C.L. & Ruhm, C.J. (2016) The effects of paid family leave in California on labor market outcomes. *Journal of Policy Analysis and Management*, 35(2), 333–356. Available from: https://doi.org/10.1002/pam.21894

Berger, L.M., Hill, J. & Waldfogel, J. (2005) Maternity leave, early maternal employment and child health and development in the US. *Economic Journal*, 115(501), F29–F47. Available from: https://doi.org/10.1111/j.0013-0133.2005.00971.x

Bertrand, M., Duflo, E. & Mullainathan, S. (2004) How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics*, 119(1), 249–275. Available from: https://doi.org/10.1162/003355304772839588

Bullinger, L.R. (2019) The effect of paid family leave on infant and parental health in the United States. *Journal of Health Economics*, 66, 101–116. Available from: https://doi.org/10.1016/j.jhealeco.2019.05.006

Callaway, B. & Sant'Anna, P.H.C. (2021) Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230. Available from: https://doi.org/10.1016/j.jeconom.2020.12.001

Carneiro, P., Løken, K.V. & Salvanes, K.G. (2015) A flying start? Maternity leave benefits and long-run outcomes of children. *Journal of Political Economy*, 123(2), 365–412. Available from: https://doi.org/10.1086/679627

Conley, T.G. & Taber, C.R. (2011) Inference with "difference in differences" with a small number of policy changes. *The Review of Economics and Statistics*, 93(1), 113–125. Available from: https://doi.org/10.1162/rest_a_00049

Currie, J., Neidell, M. & Schmieder, J.F. (2009) Air pollution and infant health: lessons from New Jersey. *Journal of Health Economics*, 28(3), 688–703. Available from: https://doi.org/10.1016/j.jhealeco.2009.02.001

Dahl, G.B., Løken, K.V., Mogstad, M. & Vea Salvanes, K. (2016) What is the case for paid maternity leave? *The Review of Economics and Statistics*, 98(4), 655–670. Available from: https://doi.org/10.1162/REST_a_00602

Danzer, N. & Lavy, V. (2018) Paid parental leave and children's schooling outcomes. *Economic Journal*, 128(608), 81–117. Available from: https://doi.org/10.1111/ecoj.12493

Donald, S.G. & Lang, K. (2007) Inference with difference-in-differences and other panel data. *The Review of Economics and Statistics*, 89(2), 221–233. Available from: https://doi.org/10.1162/rest.89.2.221

Dustmann, C. & Schönberg, U. (2012) Expansions in maternity leave coverage and children's long-term outcomes. *American Economic Journal: Applied Economics*, 4(3), 190–224. Available from: https://doi.org/10.1257/app.4.3.190

Ely, D.M. & Driscoll, A.K. (2020) Infant mortality in the United States, 2018: data from the period linked birth/infant death file. *National Vital Statistics Reports: From the Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System*, 69(7), 1–18.

Ferman, B. & Pinto, C. (2019) Inference in differences-in-differences with few treated groups and heteroskedasticity. *The Review of Economics and Statistics*, 101(3), 452–467. Available from: https://doi.org/10.1162/rest_a_00759

Galiani, S. & Quistorff, B. (2017) The synth_runner package: utilities to automate synthetic control estimation using synth. *STATA Journal*, 17(4), 834–849. Available from: https://doi.org/10.1177/1536867x1801700404

Heft-Neal, S., Burney, J., Bendavid, E., Voss, K. & Burke, M. (2019) *Air pollution and infant mortality: evidence from Saharan dust*. National Bureau of Economic Research.

Huang, R. & Yang, M. (2015) Paid maternity leave and breastfeeding practice before and after California's implementation of the nation's first paid family leave program. *Economics and Human Biology*, 16, 45–59. Available from: https://doi.org/10.1016/j.ehb.2013.12.009

Kiross, G.T., Tsegay, G., Chojenta, C., Barker, D. & Loxton, D. (2020) The effects of health expenditure on infant mortality in sub-Saharan Africa: evidence from panel data analysis. *Health Economics Review*, 10(1), 1–9. Available from: https://doi.org/10.1186/s13561-020-00262-3

Kniesner, T.J. & Viscusi, W.K. (2019) *The value of a statistical life*. Oxford University Press.

Lichtman-Sadot, S. (2014) The value of postponing pregnancy: California's paid family leave and the timing of pregnancies. *The B.E. Journal of Economic Analysis & Policy*, 14(4), 1467–1499. Available from: https://doi.org/10.1515/bejeap-2013-0141

Lichtman-Sadot, S. & Bell, N.P. (2017) Child health in elementary school following California's paid family leave program. *Journal of Policy Analysis and Management*, 36(4), 790–827. Available from: https://doi.org/10.1002/pam.22012

Liu, Q. & Skans, O.N. (2010) The duration of paid parental leave and children's scholastic performance. *The B.E. Journal of Economic Analysis & Policy*, 10(1). Available from: https://doi.org/10.2202/1935-1682.2329

Mettetal, E. (2019) Irrigation dams, water and infant mortality: evidence from South Africa. *Journal of Development Economics*, 138, 17–40. Available from: https://doi.org/10.1016/j.jdeveco.2018.11.002

NCHS, NVSS. (2008) *User guide to the natality public use file*. National Center for Health Statistics.

NCHS, NVSS. (2020) *Linked birth and infant death data 2000–2008*. National Center for Health Statistics.

Ness, D.L., Shabo, V. & Fink, S.F. (2016) *Expecting better: a state-by-state analysis of laws that help new parents*. Washington: National Partnership for Women & Families.

Pac, J.E., Bartel, A.P., Ruhm, C.J. & Waldfogel, J. (2019) *Paid family leave and breastfeeding: evidence from California*. National Bureau of Economic Research.

Pihl, A.M. & Basso, G. (2019) Did California paid family leave impact infant health? *Journal of Policy Analysis and Management*, 38(1), 155–180. Available from: https://doi.org/10.1002/pam.22101

Pongou, R. (2013) Why is infant mortality higher in boys than in girls? A new hypothesis based on preconception environment and evidence from a large sample of twins. *Demography*, 50(2), 421–444. Available from: https://doi.org/10.1007/s13524-012-0161-5

Raub, A., Nandi, A., Earle, A., De Guzman Chorny, N., Wong, E., Chung, P. et al. (2018) *Paid parental leave: a detailed look at approaches across OECD countries*. WORLD Policy Analysis Center.

Rossin-Slater, M. (2011) The effects of maternity leave on children's birth and infant health outcomes in the United States. *Journal of Health Economics*, 30(2), 221–239. Available from: https://doi.org/10.1016/j.jhealeco.2011.01.005

Rossin-Slater, M., Ruhm, C.J. & Waldfogel, J. (2013) The effects of California's paid family leave program on mothers' leave-taking and subsequent labor market outcomes. *Journal of Policy Analysis and Management*, 32(2), 224–245. Available from: https://doi.org/10.1002/pam.21676

Ruhm, C.J. (2000) Parental leave and child health. *Journal of Health Economics*, 19(6), 931–960. Available from: https://doi.org/10.1016/s0167-6296(00)00047-3

Stearns, J. (2015) The effects of paid maternity leave: evidence from Temporary Disability Insurance. *Journal of Health Economics*, 43, 85–102. Available from: https://doi.org/10.1016/j.jhealeco.2015.04.005

Tanaka, S. (2005) Parental leave and child health across OECD countries. *Economic Journal*, 115(501), F7–F28. Available from: https://doi.org/10.1111/j.0013-0133.2005.00970.x

Tanaka, S. (2015) Environmental regulations on air pollution in China and their impact on infant mortality. *Journal of Health Economics*, 42, 90–103. Available from: https://doi.org/10.1016/j.jhealeco.2015.02.004

## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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