Does Paid Family Leave Save Infant Lives? Evidence from United States

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Abstract

One goal of the paid family leave (PFL) is to help working mothers balance their careers and family responsibilities and hence improve the well-being of their infants. However, most studies of PFL on early childhood outcomes have been based on the analyses of surviving infants. If PFL reduces infant deaths, such analyses would understate the effects. Using the linked birth and infant death data in the U.S. with a difference-in-differences framework, I find that the implementation of a six-week PFL in California reduced the post-neonatal mortality rate by 0.135, or it saved approximately 339 infant lives. The effects were driven by death from internal causes, and there were larger effects for infants with married mothers and infant boys. Additional robustness checks and placebo examinations indicate that the effect is not due to confounding factors or contemporary shocks but causal.

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1. Introduction

Paid family leave (PFL), or paid parental leave, is designed to provide compensated time off from work for mothers to recover from childbirth and to care for their infants, which is essential to child development (Baker and Milligan 2008, 2010, 2015, Liu and Skans 2010, Dustmann and Schönberg 2012, Carneiro, Løken, and Salvanes 2015, Stearns 2015, Dahl et al. 2016, Danzer and Lavy 2018, Bullinger 2019, Albagli and Rau 2019). Countries have taken different avenues in the way of maternity leave legislation to improve the welfare of families. For example, 25 of 34 OECD countries guarantee at least six months of paid leave for mothers to care for their infants (Raub et al. 2018), while women in the U.S. are only entitled to twelve weeks of unpaid leave. Until 2004, California became the first state in the U.S. to offer six weeks of paid family leave (CA-PFL) for eligible workers. This paid time off increases maternal-child interactions, prolongs breastfeeding, better monitors children's health status, and thereby, benefits early childhood outcomes (Rossin‐Slater, Ruhm, and Waldfogel 2013, Huang and Yang 2015, Baum and Ruhm 2016, Lichtman‐Sadot and Bell 2017, Bartel et al. 2018, Pihl and Basso 2019, Bullinger 2019).

However, most studies of parental leave on early childhood outcomes have been based on the analyses of surviving infants, however, if parental leave significantly reduces infant deaths, then such analyses would understate the effects. Parental leave may influence infant health and ultimately reduce infant deaths through the following channels. First, paid parental leave could lead to more investment in parental care, which might lessen the need for non-parental care, and the latter is associated with increased risks of many infectious illnesses, e.g. diarrheal illness (Lu et al. 2004) and respiratory infections (Kamper-Jørgensen et al. 2006). Moreover, more time off from work may allow parents to arrange preventative care for their children more easily, such as immunizations and well-child visits (Berger, Hill, and Waldfogel 2005). Further, women with longer parental leaves can increase their breastfeeding duration (Ogbuanu et al. 2011, Huang and Yang 2015, Mirkovic, Perrine, and Scanlon 2016, Jia, Dong, and Song 2018, Pac et al. 2019), and recent studies found that longer breastfeeding duration is associated with a reduction in risk for post-neonatal death (Chen and Rogan 2004, Sankar et al. 2015). Finally, compared with unpaid leave, paid family leave provides compensating benefits, which could be used for better nutrition for kids. Evidence from studies of transfer programs in the U.S. (e.g., earned income tax credit, food stamp, and WIC[1] program) showed that transfer programs are beneficial for infant health outcomes (Moss and Carver 1998, Khanani et al. 2010, Almond, Hoynes, and Schanzenbach 2011, Hoynes, Miller, and Simon 2015).

Previous literature in economics has shown that parental leave can reduce the infant mortality rate (IMR) (Winegarden and Bracy 1995), especially for the post-neonatal mortality rate (PNMR) (Ruhm 2000, Tanaka 2005, Rossin-Slater 2011). However, most studies focused on European counties and the period in the 20th century, where there has been widespread adoption or expansion of parental leave during that time. For example, Ruhm (2000) used aggregated data on 16 European counties 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 twelve 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 the unpaid leave.

It is still unclear whether the effects of paid leave on infant mortality would change if using data from more recent years, especially in the case of the U.S. The is important because the U.S. is the largest developed country in the world, but mothers in the U.S. have limited access to pre-existing paid leave. One recent study in health service literature found PFL in California is associated with a lower PNMR, but it lacks necessary examinations to validate the causal effect

[1] 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 postpartum women, and to infants and children up to age five who are found to be at nutritional risk.

(Montoya-Williams, Passarella, and Lorch 2020). There are two obstacles in examining the causal effect of PFL on infant mortality. First, there might exist confounding factors that both correlated with the PFL policy and infant health, or the PFL policy is endogenous. For example, it might be possible that residents in states with PFL policies are more careful about infant heath than those in states without such policies. Second, if there were contemporary shocks that are beneficial for infant health (e.g., less air pollution or more clear water), then the result would be spurious rather than causal.

In this study, I examine the causal effect of CA-PFL on infant mortality using the 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 to 365 days) per 1,000 live births, which generally overlaps with the periods that CA-PFL can be taken.[2] Using 50 non-CA states as the comparison group, I find that the CA-PFL reduced PNMR by 0.135. Understanding the consequences of CA-PFL is important because it is the first PFL program in the U.S., and it shares many common elements with PFL programs in other states. It also provides a model for potential proposals in other states or at the national level.

This study makes several efforts to validate the causal effect. First, to address the concern of confounding factors, I use (1) 50 non-CA states, (2) 4 TDI states, (3) 46 non-TDI states, (4) 9 (future) PFL states, (5) 41 non-PFL states, (6) top 25 family-friendly states, (7) bottom 25 family-friendly states as the comparison group, respectively, and get consistent results. This suggests that the main result is less likely to be caused by confounding factors that both correlated with PFL policy and infant health. Second, to deal with the concern of contemporary shocks, I use fetal mortality rate and neonatal mortality rate as two placebo outcomes, this is because they are less likely to be influenced by CA-PFL but should be impacted by potential

[2] The most PFL taking time is from six weeks to 12 months after childbirth as new mothers with a pregnancy start with a State Disability Insurance (SDI) claim first, which provides six weeks paid leave. Adoptive mothers are not eligible for SDI leave, and they can start leave as soon as the time of adoption.

contemporary shocks. I find no significant impact on them, which rules out the concern of contemporary shocks. Furthermore, both additional robustness tests using 25 randomly chosen states as the comparison group (repeated 1,000 times) and placebo examinations assuming the treatment state is every other state support the main finding and make me believe that the effect is indeed not spurious but causal.

Another difficulty in conducting inference is that there is only one treated unit, which suffers from 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 would be underestimated (Bertrand, Duflo, and Mullainathan 2004, Donald and Lang 2007, Conley and Taber 2011). In this study, I follow Ferman and Pinto (2019) to deal with the few clusters problem. Ferman and Pinto's inference method first adjusts each state's residuals to eliminate heteroscedasticity, then it produces a bootstrapped distribution of the pseudo-treatment effects for determining the significance of the estimate of the treatment effect.

This article is closely related to the literature on the impact of parental leave policies on child development and extends this literature on several dimensions. First, this article examines the *causal* effect of the first PFL policy in the U.S. on PNMR and finds that a six-week PFL reduced PNMR by 0.135. Additional robustness checks and placebo examinations indicate that the effect is not due to confounding factors and contemporary shocks but causal. Findings in this study broaden our understanding of the benefits of PFL and refresh our interpretation of the effects of PFL on early childhood outcomes as most of those studies focus on surviving infants, which might understate the effects. Second, this study also examines the heterogeneous effects of PFL for different groups of mothers/infants and finds that the effects were driven by death from internal causes, and there were larger effects for infants with married mothers and infant boys. This is helpful to understand how such policies would have a different impact on infant deaths and which groups of people are more likely to be influenced. Third, to deal with the few clusters problem caused by only having one treated state, I follow Ferman and Pinto's (2019) inference method to improve the precision of inference. Forth, the findings in this study have significant policy implications as some national PFL plans are currently under review. This article further conducts a cost-benefit analysis and estimates that the reduction in infant deaths would save approximately $9.7 billion per year assuming a 12-week national PFL policy were effective in 2020.

This study is also related to the literature on infant mortality. Previous literature shows that infant mortality is vulnerable to environmental factors, economic conditions, and transfer programs, such as air pollution (Chay and Greenstone 2003, Currie and Neidell 2005, Currie, Neidell, and Schmieder 2009, Tanaka 2015), clean water (Greenstone and Hanna 2014, Gamper-Rabindran, Khan, and Timmins 2010, Troesken 2008, Mettetal 2019, Heft-Neal et al. 2019) income (Baird, Friedman, and Schady 2011, Waldmann 1992), expenditure (Kiross et al. 2020), food stamps program (Almond, Hoynes, and Schanzenbach 2011), Medicaid expansion (Bhatt and Beck-Sagué 2018), WIC (Khanani et al. 2010). This study broadens our understanding of how infant mortality could be impacted in the setting of parental leave, and this could be used for comparison with effects of other shocks. For example, a six-week PFL is equivalent to 2- to 3-$\mu g/m^3$ reduction in Total suspended particles (TSPs) in terms of the effect on infant mortality, and this might be meaningful for policymakers to consider how to allocate limited resources to maximize social welfare.

The article proceeds as follows. Section 2 discusses family leave policies in the U.S. and pathways linking PFL and infant mortality rate. 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 conducts robustness checks and placebo examinations to validate the causal effect. Section 7 discusses threats to identification, interpretation, and policy implications. Finally, Section 8 concludes.

2 Paid Family Leave and Infant Mortality

2.1 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 twelve weeks of *unpaid* job-protected leave to qualified workers with a newborn or a sick child, or a personal or family illness. To be eligible for the FMLA, one must have worked at least 1,250 hours over a period of twelve months for a firm that employs at least 50 workers within 75 miles of its physical establishment. However, only 56 percent of U.S. employees are eligible for FMLA (Brown et al. 2020). This is partly due to the stringent requirements of firm size and the length of time an employee must work for the same employer, and partly because many eligible workers cannot afford to take three months off without pay (Stearns 2015).

While the U.S. lacks a national policy, the 1978 Pregnancy Discrimination Act requires that employers treat pregnancy and childbirth like any other temporary disability. Consequently, five states (California, Hawaii, New Jersey, New York, and Rhode Island) with Temporary Disability Insurance (TDI) programs have been required to provide partial wage replacement (50–66 percent) for medical leaves related to pregnancy and childbirth.[3] Workers in California and New Jersey can claim benefits for up to four weeks before the expected delivery date and six weeks after birth (eight weeks for Caesarean sections). The other TDI states provide six to eight weeks of leave that can be used on either side of birth.

Until September 23, 2002, the first PFL program in the U.S. was enacted in California and was effective on July 1, 2004. The program provides six[4] weeks of paid leave for eligible workers[5] who take time off to care for an ill family member or to bond with a new child, with benefits being equal to 55 percent of their weekly earnings up to a weekly cap of $728, as of

[3] The program in California is called State Disability Insurance (SDI).
[4] After July 1, 2020, eligible workers could have eight weeks of PFL per year.
[5] Beginning January 1, 2021, PFL will expand by adding a new claim type called Military Assist. PFL Military Assist benefits will be available to eligible Californians who need time off work to participate in a qualifying event because of the military deployment of their spouse, registered domestic partner, parent, or child to a foreign country.

2004[6]. Similar to the State Disability Insurance (SDI), the PFL program is funded by the payroll tax on employees' wages,[7] and 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 and 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 SDI, during any quarter in the 5 to 18 months prior to filing a CA-PFL claim (Appelbaum and Milkman 2015). In addition to the six weeks of PFL provision, most employed mothers in California already could qualify for up to four weeks of paid pre-birth leave and six[8] weeks of paid post-birth leave under SDI. The PFL does not include job protection unless individuals also qualify for FMLA or the California Family Rights Act (CFRA)[9]. PFL can be taken continuously or intermittently within the first twelve months of a child's birth or adoption. Since new mothers with a pregnancy start with an SDI claim first, the actual PFL taking time for mothers is from six weeks to twelve months after childbirth.

As of 2021, seven states have PFL programs in effect (California 2004, New Jersey 2009, Rhode Island 2013, New York 2018, D.C. 2020, Washington 2020, and Massachusetts 2021), and PFL programs will take effect in Connecticut (2022), Oregon (2023) and Colorado (2024) in coming years. In addition, two national PFL programs are proposed and still under review. The Family And Medical Insurance Leave Act (FAMILY Act) that was designed to provide twelve weeks of paid leave at a 66 percent wage replacement rate was introduced in 2013 but has not been enacted yet. In 2021, President Joe Biden proposed an American Families Plan (AFP) that similar to the FAMILY Act, which would guarantee twelve weeks of paid leave to new parents

[6] For claims beginning on or after Jan. 1, 2018, the weekly benefit amount is approximately 60-70 percent of weekly earnings, depending on earnings levels, and range from $50 to a maximum of approximately $1,215.

[7] Employees pay the 1 percent payroll tax on annual earnings of up to $118,371 in 2019. Earnings above that amount are not subject to the tax.

[8] Mothers who have a Cesarean section could qualify for eight weeks of post-birth leave under SDI.

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

with benefits of 66 percent to 80 percent of their wages, capped at $4,000 a month. However, the full twelve weeks of paid leave is not expected to be fully available until the 10th year of the program.[10]

Given that these PFL programs share many common elements, it seems essential to fully evaluate the effects of the first PFL program in the U.S. Recently, there are emerging studies to examine the effects of CA-PFL on various outcomes. For example, some studies found that CA-PFL increased parental leave-taking and improved early childhood outcomes. The leave-taking increased about five weeks for the average covered mother (Rossin‐Slater, Ruhm, and Waldfogel 2013, Baum and Ruhm 2016) and one week for fathers (Baum and Ruhm 2016), or fathers were 0.9 percentage 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 five percentage points. Lichtman-Sadot and Bell (2017) found evidence of improvements in health outcomes among elementary school children. Bullinger (2019) found improvements in parent-reported overall child health. Pihl and Basso (2019) reported a decline in infant admissions to hospitals and concluded that this may be due to more breastfeeding.

2.2 Pathways Linking Paid Family Leave and Infant Mortality

Previous literature suggests several mechanisms through which PFL can affect infant health, and then ultimately reduce infant deaths.

2.2.1 Parental care

Parental leave could lead to more investment in parental care, which might lessen the need for non-parental care (i.e., child care centers or family child care homes), and the latter is associated with increased risk of many infectious illnesses, such as diarrheal illness (Lu et al. 2004) and respiratory infections (Kamper-Jørgensen et al. 2006). With more time bonding with a child, parents can better monitor their kids' risk behaviors and kids are more likely to receive timely

[10] 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/

medical treatment. For example, Sudden Infant Death Syndrome (SIDS), one of the leading causes of infant death, is more than twice as common among infants who sleep prone as for those who do not, and parental leave could increase the frequency of non-prone sleeping if parents have more energy to monitor the sleeping position or are more able to directly observe it (Ruhm 2000). Compared with SIDS deaths in the care of parents, those occurring in child care settings were more likely to occur during working hours on weekdays (Moon, Patel, and Shaefer 2000).

2.2.2 Preventative care

More time off from work may allow parents to arrange appropriate preventative care for their children more easily, such as immunizations and well-child visits (Berger, Hill, and Waldfogel 2005). More timely preventative care would lead to declines among "avoidable" hospitalizations (AVH), which are a set of diagnoses that can be prevented if the condition(s) receive proper and timely care before the patient is hospitalized (Moy et al. 2013). Pihl and Basso (2019) estimated the effects of CA-PFL on infant hospital admissions and found a decline of three admissions of AVH (per 1,000 children) in the cohort following CA-PFL, which were susceptible to the improved preventative care.

2.2.3 Breastfeeding

Another potential channel could be through longer breastfeeding spans, which is associated with a reduction in risk for post-neonatal death (Chen and Rogan 2004, Sankar et al. 2015). WHO recommends that babies be breastfed exclusively through the first six months of life, followed by continued breastfeeding and complementary foods over the rest of the first year and beyond (santé et al. 2003). Women with longer parental leaves can increase their breastfeeding duration (Ogbuanu et al. 2011, Mirkovic, Perrine, and Scanlon 2016, Jia, Dong, and Song 2018). Survey evidence on users of PFL in California shows that they breastfeed longer than women who do not take the leave (Appelbaum and Milkman 2015), which is consistent with recent studies that CA-PFL increased breastfeeding by about 5 percentage points (Huang and Yang 2015, Pac et al. 2019).

2.2.4 Income and nutrition

Compared with unpaid leave, paid family leave provides compensating benefits, which could be used for better nutrition for kids. Evidence from studies on transfer programs in the US (e.g. earned income tax credit and food stamp program) have shown that transfer programs were beneficial for infant health outcomes (Hoynes, Miller, and Simon 2015, Almond, Hoynes, and Schanzenbach 2011), and the IMR was lower for Women, Infants, and Children (WIC) participants than for non-WIC participants (Moss and Carver 1998, Khanani et al. 2010). However, if PFL replaces time at work rather than unpaid leave, the PFL will reduce household income during leave as the PFL only has partial wage replacement.

3. DATA

This article utilizes linked birth and infant death data of the NVSS of the National Center for Health Statistics (NCHS 2020). The microdata contains all births and deaths occurring in a given calendar year. In the linked birth and infant death data set, the information from the death certificate is linked to the information from the birth certificate for each infant under one year of age who dies in the U.S. The linked files include information from the birth certificate such as age, race, and Hispanic origin of the parents, birth weight, period of gestation, plurality, prenatal care usage, maternal education, marital status, live-birth order, and maternal smoking, linked to information from the death certificate such as age at death and underlying and multiple causes of death. I use data of all singleton births and infant deaths with birth years from 2000 to 2008 for analysis. This period did not take place any PFL related policy changes except for California, which makes the 50 non-CA states a clear comparison group. Twins, triplets, and high-order multiple births[11] are excluded from analyses given the increased risk of prematurity and low birth weight associated with multiple gestations (Montoya-Williams, Passarella, and Lorch 2020). Since the birth and infant deaths data are linked by birth year and month, the infant death

[11] Twins, triplets and high-order multiple births are account for 3.3% of all birth in the sample period.

occurred in 2009 with the birth year in 2008 are included for analysis but the infant death occurred in 2000 with the birth year in 1999 are excluded for analysis.

The outcome of interest is the PNMR, define as infant death between 28 to 365 days per 1,000 live births, which generally overlaps with the periods that CA-PFL can be taken. Two alternative outcomes, fetal mortality (the death of a fetus during pregnancy) and neonatal mortality (the death of newborns within the first 28 days) are used for placebo purposes. I also include birth controls and maternal controls in analyses. The birth controls are birth weight, gestational age, sex of birth, and birth order.[12] The maternal controls are maternal characteristics at childbirth – age, race/ethnicity, marital status, educational attainment, employment status, and family income.[13] All controls are aggregated to state-month levels except for maternal educational attainment, employment status, and family income are obtained from the Current Population Survey (CPS) and are at the state-year level (Flood et al. 2020). I use educational attainment data from CPS rather than from NVSS as that from NVSS is not comparable across states and years due to the 2003 revisions of the U.S. standard certificates (NCHS 2008).[14] To make the data obtained from the CPS to be as representative as NVSS, I restrict the CPS sample to women whose youngest child less than one year old. The final data are aggregated in 5,508 state-month cells for 36,039,789 total births. I use the number of births in each cell as the sample weight for the analysis. Table 1 presents the summary statistics for the whole sample and is split according to the four groups in the DD specification.

Since 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

[12] Birth order is in three categories: first born, second born, and third born or later.
[13] 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.
[14] 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).

(TOT) effects could be estimated using the ITT effect scaled by the inverse of mothers' take-up rate of CA-PFL. One way to estimate mothers' take-up rate is the number of claims divided by the number of likely eligible mothers. Table 2 presents the estimates of mothers' and fathers' take-up rates of CA-PFL. I estimate that 44 percent (5 percent) of employed new mothers (employed new fathers) made a bonding claim in 2005, which is similar to estimates of Bana, Bedard, and Rossin-Slater (2018) – 40 percent for mothers and 4 percent for fathers. The average take-up rate is 48.58% for mothers during the sample period so that one way to estimate the TOT effects could be to scale the ITT effect by 2 (1/0.5).

4. Identification Strategy

4.1 Difference in Differences

To identify the effects of CA-PFL on PNMR, I use the DD method that compares the PNMR in California and that in the comparison group (50 non-CA states) before and after the implementation of PFL. I estimate the effects based on the following equation.

$$Y_{st}=\alpha+\beta CA_s\times Post_t+\gamma X_{st}+\mu_s+\lambda_t+\varepsilon_{st} \quad (1)$$

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; μ_s is the state fixed effects; λ_t is the time (year-by-month) fixed effects; ε_{st} is the error term. The key coefficient of interest is β, which measures the DD estimate of the effect of the CA-PFL on PNMR. Standard errors are clustered at the state level.

4.2 Parallel Trend Assumption

A key assumption in the DD analysis is that the comparison group provides the appropriate counterfactuals of 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, I plot the raw trends of PNMR throughout the 2000 to 2008 period for California and the comparison group in Figure 1 to visually inspect it. The trends in PNMR are generally in common for both groups before 2004, and we can visually detect a downward trend in PNMR for California after 2004, while there is no similar pattern for that of the comparison group. More formally, I use an event study model to test for the parallel trend 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:

$$Y_{st} = \alpha + \Sigma\, \beta_r CA \times Event_r + \gamma_4 X_{st} + \mu_s + \lambda_t + \varepsilon_{st} \quad (2)$$

In equation (2), $Event_r$ is a dummy of the r years of leads (+) or lags (-) since the implementation of PFL, 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 β_r are measures of cohort-specific effects compared with the comparison group. I plot the coefficients β_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, which suggests that the pre-treatment trends in PNMR do not differ between California and the comparison group, and the comparison states can be used as a valid comparison group for California.

4.3 Few Clusters Problem

Typically, studies that exploit policy variations across states conduct inference by using standard errors that are clustered at the state level. However, when the number of treated clusters is small, the conventional cluster-robust standard errors are underestimated (Bertrand, Duflo, and Mullainathan 2004, Donald and Lang 2007, Conley and Taber 2011). 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. This method first adjusts each state's residuals to eliminate heteroscedasticity.

Then, it randomly resamples the linear combinations of each state's adjusted residuals and the linear combination that represents the within-state differences between the average post-treatment and average pre-treatment outcomes that are used in the DD estimator. 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 and Pinto 2019). 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

Using a sample comprising all singleton births in the U.S. from 2000 to 2008, I show the estimates of the effects of CA-PFL on the PNMR in Table 3.[15] Table 3 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 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 estimate in Column 3 is my preferred result. Specifically, 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 percent reduction of its pre-treatment sample mean (1.65). According to Table 2, the estimated take-up rate for Californian mothers is about 49%. The ITT effects could be scaled to 0.27 to get the TOT effects. In addition, the event study estimates (Figure 2) show that there are no significant differences in the effects on PNMR between California and the comparison group before PFL

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

was effective but immediate and persistent negative impacts on PNMR after the effective of PFL. Overall, I find supporting evidence that the PNMR in California was reduced significantly after the implementation of PFL and no such effect prior to that date.

5.2 Heterogeneous Effects

In this section, I conduct several analyses on heterogeneous effects by cause of death, maternal race, maternal marital status, and sex of birth.

First, I follow Chay and Greenstone (2003) to separately examine infant deaths from internal health-related causes and external "non-health"-related causes (such as accidents and homicides).[16] The results in Panel A of Table 4 suggest that the reduction of PNMR is driven by internal causes rather than external causes. Even though parental leave may have some effects on the deaths from external causes if parents can better monitor their kids' risk behaviors. However, it is not surprising if remembering that the maximum length of CA-PFL is too short (only six weeks). One potential explanation could be that the death from internal causes could be anticipated compared with death from external causes, and parents can take leave as they observe some symptoms of diseases of their children.[17] The death from external causes may occur stochastically, and it is nearly impossible for parents to anticipate it and take leave in advance to avoid it. This is also consistent with Rossin-Slater's (2011) finding of FMLA that no impact on infant deaths from external causes. It is expected to see the effects of parental leave that last longer than one year (e.g., in some European countries) on infant mortality from external causes in future studies.

I also examine the heterogeneous effects of CA-PFL by maternal characteristics of race/ethnicity and marital status, Panel B and C in Table 4 presents these results. Only results of birth to married mothers are statistically significant using the Ferman-Pinto inference method,

[16] "Internal" and "external" deaths span all possible causes of infant death. Deaths with NCHS's ICD-10 130 Groups for selected causes of infant mortality codes from 001 to 137 are classified as internal, while those codes from 138 to 158 are in the external category.
[17] For example, mothers can take 4 weeks leave consecutively and wait to take the rest leave until an issue arises; or mothers take 6 weeks leave all together, and fathers only take their leave as needed.

and results of birth to mothers of non-Hispanic black and non-Hispanic white and unmarried mothers are only significant using cluster robust inference method, which is less reliable. Even though the heterogeneous effects by race are not statistically significant, it may still be worth comparing the relative magnitude of these estimates, and it is larger for birth to Non-Hispanic Black mothers (8%) and smaller for birth to Non-Hispanic White mothers (4%), which is consistent with recent studies on the CA-PFL, and they found larger effects for less advantaged families (Rossin-Slater, Ruhm, and Waldfogel 2013, Lichtman-Sadot and Bell 2017, Bullinger 2019). It might be surprising to see more effects on births with married mothers than unmarried mothers if we expect more effects on less advantaged families. However, the probability of fathers taking PFL should be higher for married couples than that for unmarried couples. For example, if both parents of one married couple take six weeks of PFL, then the total length of leave is doubled than that of one single mother could take.

Finally, I investigate the effect on PNMR by sex of births, and results in Panel D suggest that there was a larger and significant reduction in PNMR for infant boys than infant girls. Infant mortality is often higher in boys than girls, which has been explained by sex differences in genetic and biological makeup, with boys being biologically weaker and more susceptible to diseases and adverse risks (Pongou 2013). According to biological literature, boys are at higher risk of infectious diseases, and this mainly because the Y-chromosome in boys increases their vulnerability (Waldron 1983).[18] Therefore, the larger effect for infant boys may because PFL increases parental care and lessen the need for non-parental care as the latter is associated with increased risk of many infectious illnesses (Lu et al. 2004, Kamper-Jørgensen et al. 2006).

6. Correlation or Causation

6.1 Confounding Factors

[18] Biologically, males and females are differentiated by chromosomes: females have two X chromosomes (XX) and males one X and one Y chromosome (XY). Having two X chromosomes means that the newborn has a stronger immune system because X chromosomes contain a larger number of immune-related genes (Markle and Fish 2014).

All the above analysis relies on the assumption that the policy is exogenous, if there are some confounding factors that both correlated with the passage of this policy and could influence infant health, then the result would be a correlation rather than a causation. For example, it might be possible that residents in states with TDI or PFL policies are more careful about infant heath than those in states without such policies. If this were true, the results would be significantly different for different comparison groups that include states with TDI or PFL policies and exclude states with such policies. To examine if the main result is due to the confounding factors, I propose three pairs of comparison groups based on family leave related policies for robustness checks. The first pair comparison groups are states with TDI programs (Hawaii, New Jersey, New York, and Rhode Island) and states without TDI programs, and the second pair comparison groups are states with (future) PFL programs (New Jersey, Rhode Island, New York, D.C., Washington, Massachusetts, Connecticut, Oregon, and Colorado) and states without PFL programs. 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).[19] Alternatively, NPWF (2016) ranked all states based on policies that support expecting and new parents just before and soon after the arrival of a new child.[20] Then, I use the top 25 family-friendly states (other than California) and the bottom 25 family-friendly states as the third pair comparison groups.[21] Figure 3 presents the estimates using (1) 50 non-CA states, (2) 4 TDI states, (3) 46 non-TDI states, (4) 9 (future) PFL states, (5) 41 non-PFL states, (6) top 25 family-friendly states, (7) bottom 25 family-friendly states as the comparison group, respectively.[22] Results in Figure 3 indicate that estimates using all comparison groups are

[19] 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 estimates the conditional variance accurately. According to Ferman (personal communication, 2021), it is hard to tell how many control units is sufficient to use this method, but from the simulations in their paper, an N>=20 is good to use.

[20] 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. California ranked first with highest grade among all states.

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

[22] TDI comparison states are New York, New Jersey, Rhode Island, and Hawaii, and these states offer paid leave through TDI since 1978. PFL comparison states are New Jersey, Rhode Island, New York, D.C., Washington,

statistically significant and very similar in magnitude. Overall, these results do not support that the main result is due to confounding factors.

6.2 Contemporary Shocks

Another threat to identification is that the reduction in PNMR is due to contemporary shocks that coincide with the CA-PFL. For example, if there were contemporary shocks in California that also benefit infant health (e.g., less air pollution or more clear water), then the result would still be a correlation rather than a causation. Given that such shocks should also impact neonatal mortality and fetal mortality, I use the neonatal mortality rate and the fetal mortality rate as the placebo outcomes and redo the analyses. If there is no impact on neonatal mortality and fetal mortality, then I can rule out the possibility of contemporary shocks. If there are some positive effects detected, however, it is tricky and additional analyses are needed. This because there are a few reasons that access to PFL may affect neonatal or prenatal leave, at least theoretically. For example, PFL could have affected the use of prenatal leave through SDI if mothers face a binding constraint of total leave, or mothers take more leave if PFL raises awareness of SDI pregnancy-related benefits, or fathers can take leave immediately after birth. However, Bullinger (2019) found no effect of CA-PFL on birth outcomes such as low birth weight and preterm birth.

To test if the effect on PNMR was caused by contemporary shocks, I replicate the estimation of equation (1) using the neonatal mortality rate and the fetal mortality rate as the outcome, respectively. Results in Table 5 indicate that CA-PFL has no significant impact on neonatal mortality rate and the fetal mortality rate, which suggests the reduction in PNMR in California is not due to contemporary shocks.

6.3 Permutation Test

To further examine the sensitivity of the main result, I use 25 randomly chosen states as the comparison group and repeated 1,000 times. The resulting distribution of estimates is displayed

Massachusetts, Connecticut, Oregon, and Colorado, and all these states have or will have a PFL program after the years of the sample period.

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 result suggests that the main result is robust and not sensitive for using different comparison states.[23]

In addition, to check if the reduction on PNMR is exclusive for California rather than every other state, I replicate the estimation of equation (1) but assume the treatment state is a different state. I exhaustively repeat this procedure for all states other than California 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,[24] and there are six estimates with F-P p-values less than 0.1.[25] I then conduct event study analyses for the six states, respectively, and none of them show a similar pattern as that of California or display any meaningful patterns.[26] I also conduct another robustness check that excludes all these six states from the analysis, and the result is consistent with that of including them.[27] 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.

7. Discussions

7.1 Migration

The CA-PFL was announced on September 23, 2002, and became effective on July 1, 2004. Some may have concerns that the 21-months-prior announcement may make 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 $4,368 for six weeks, which is less than the average cost of an interstate move ($5,630).[28] The

[23] I also implemented a synthetic control method and got similar estimate to DD estimate, and the result is available upon request.
[24] Specifically, 6 of them in range of 0 to 0.1, 6 of them in range of 0.1 to 0.2, 4 of them in range of 0.2 to 0.3, 5 of them in range of 0.3 to 0.4, 4 of them in range of 0.4 to 0.5, 3 of them in range of 0.5 to 0.6, 8 of them in range of 0.6 to 0.7, 7 of them in range of 0.7 to 0.8, 5 of them in range of 0.8 to 0.9, and 2 of them in range of 0.9 to 1.
[25] These states are Illinois, Louisiana, Maine, Montana, North Carolina, and South Carolina.
[26] Figure A1 in the Appendix presents the figures of these event studies.
[27] Table A3 in the Appendix presents the results.
[28] According to the American Moving & Storage Association, the average cost of an interstate move is $5,630 in 2016.

relatively small financial incentive is not sufficient enough to encourage mass migration of pregnant women in other states to California.

7.2 Fertility

One 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 fertility response or changes in the composition of births after the policy (Rossin‐Slater, Ruhm, and Waldfogel 2013, Pihl and Basso 2019). However, Lichtman-Sadot (2014) found some shifts in the number of births from the earlier part of 2004 to the later part. To address the concern of fertility changes in 2004, I exclude the year 2004 and redo the analysis, and the results are consistent with that of including the year 2004.[29] To formally examine if CA-PFL impacts fertility during the sample period, I perform additional analyses using the general fertility rate[30] and the log of the number of births as the outcomes to perform the DD regressions, and results are reported in Table 6. No evidence indicates that the number of new births was changed due to the policy.

7.3 Birth Outcome

I also analyze the effects of CA-PFL on two measures of birth outcomes – low birth weight and preterm birth[31], as they are two of the leading causes of infant death (Ely and Driscoll 2020). As mentioned before, there are a few reasons that access to PFL may affect prenatal leave. For example, PFL could have affected the use of prenatal leave through SDI if mothers face a binding constraint of total leave, or mothers take more leave if PFL raises awareness of SDI pregnancy-related benefits. However, Bullinger (2019) found no effect of CA-PFL on birth outcomes of low birth weight and preterm birth.

[29] Table A4 in the Appendix presents the results.
[30] General fertility rate is the number of live births for every 1,000 women of childbearing age (15-44 years).
[31] Low birth weight is defined as a weight of fewer than 2,500 grams, and preterm is defined as babies born alive before 37 weeks of pregnancy are completed.

To double-check if the CA-PFL impact birth outcomes and then ultimately affect post-neonatal deaths, I report the estimates of effects of CA-PFL on birth outcomes in Table 7. There are no significant effects on both birth outcomes 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.

7.4 Interpretation

It is relevant to compare my estimate to studies that focus on other parental leave studies on PNMR. Table 8 presents the comparison of the effect size (ITT effects) in this study with those in related studies. Ruhm (2000) examined 16 European countries found that the equivalent effect of a one-week extension on PNMR is 0.020; Tanaka (2005) extended Ruhm's (2000) study by adding U.S., and Japan and found a similar result (0.015). Rossin-Slater (2011) reported that PNMR is reduced by 0.017 (one-week equivalent effect) for the infant with high educated and married mothers after the FMLA is effective. In this study, I find the one-week equivalent effect on PNMR is 0.023, which is similar in magnitude but slightly large than that of previous studies.

It also might be interesting to compare the effect of PFL on infant mortality with that of other shocks on infant mortality. For example, Chay and Greenstone (2003) use the substantial variation in air quality changes during the 1981–1982 recession to estimate the effects of particulates pollution on infant mortality. They find that a 1-µg/m^3 reduction in TSPs is associated with 0.04–0.07 fewer infant deaths per 1,000 live births. Therefore, a six-week PFL is equivalent to a 2- to 3-µg/m^3 reduction in TSPs in terms of the effect on infant mortality, and this might be meaningful for policymakers to consider how to allocate limited resources to maximize social welfare.

7.5 Policy Implication

One policy implication of this article 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.[32] Therefore, the average cost of a 12-week PFL plan would cost around 23 billion per year.

A complete analysis of a policy requires information on benefits, even though human life is priceless. The value of a statistical life (VSL) is commonly used by policy analysts and researchers to estimates life values (Chay and Greenstone 2003), and estimates of the VSL for the U.S. are around \$10 million (Kniesner and Viscusi 2019). In this study, I find that a six-week PFL reduces PNMR by 0.135. If assuming a similar effect for a national PFL policy like FAMILY Act or AFP, then the 12-week PFL plan could reduce the infant mortality rate by 0.27. In 2020, there are about 3.6 million new births, which implies that approximately 972 additional infants could survive to one 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 nearly half of the estimated cost. If the benefits are not limited to the reduction in infant mortality but also include benefits from improvements in maternal welfare and child development, the total social-economic benefits of the national PFL policy could easily beat its costs.

8. Conclusion

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 have been previously 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 six-week PFL reduced PNMR by 0.135, or it saved approximately 339 infant lives in California from 2004 to 2008.[33] To deal with the few clusters

[32] The cost of the FAMILY Act was estimates 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/

[33] 339=0.135*(the number of total births in this period)/1000.

problem caused by only having one treated state, I follow Ferman and Pinto's (2019) inference method to improve the precision of inference. Additional robustness checks and placebo examinations indicate that the effect is not due to confounding factors and contemporary shocks but causal. Further heterogeneous analyses suggest that the effects were driven by death from internal causes, and there were larger effects for infants with married mothers and infant boys.

The findings in this article broaden our understanding of the benefits of PFL and refresh our interpretation of the effects of PFL on early childhood outcomes as most of those studies focus on surviving infants, which might understate the effects. In addition, this article conducts a cost-benefit analysis and estimates that the reduction in infant deaths would save approximately $9.7 billion per year assuming a 12-week national PFL policy were effective in 2020. The results of this study are especially significant as more states in the U.S. are developing their own PFL program and some national PFL plans – FAMILY Act and AFP – are currently under review.

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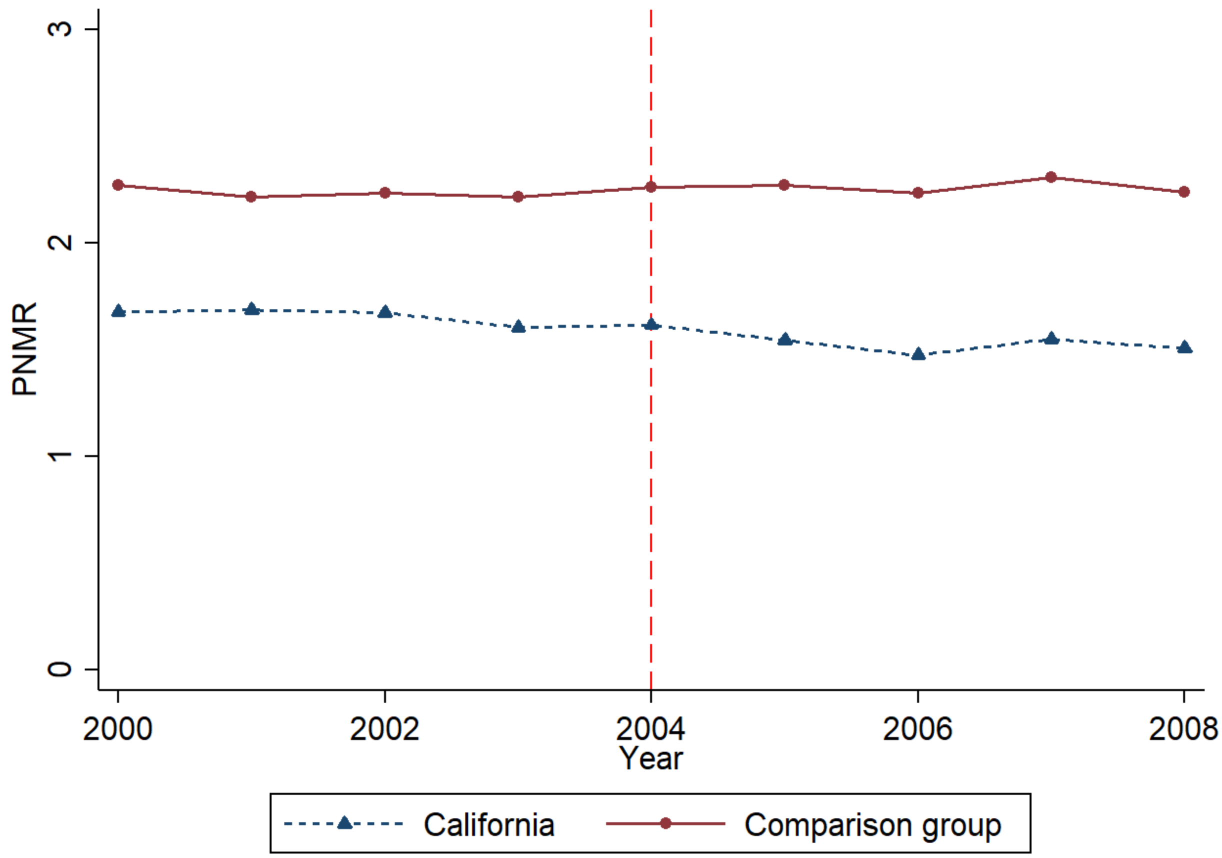
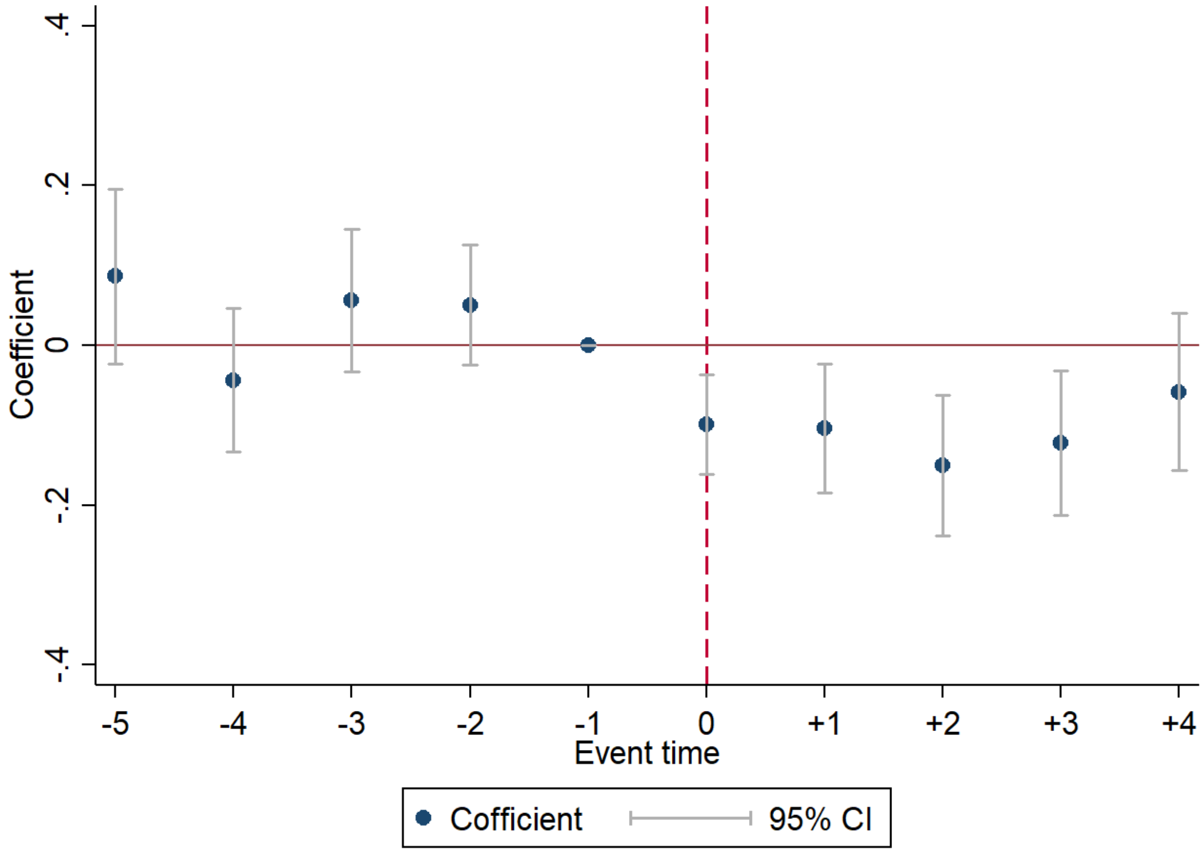


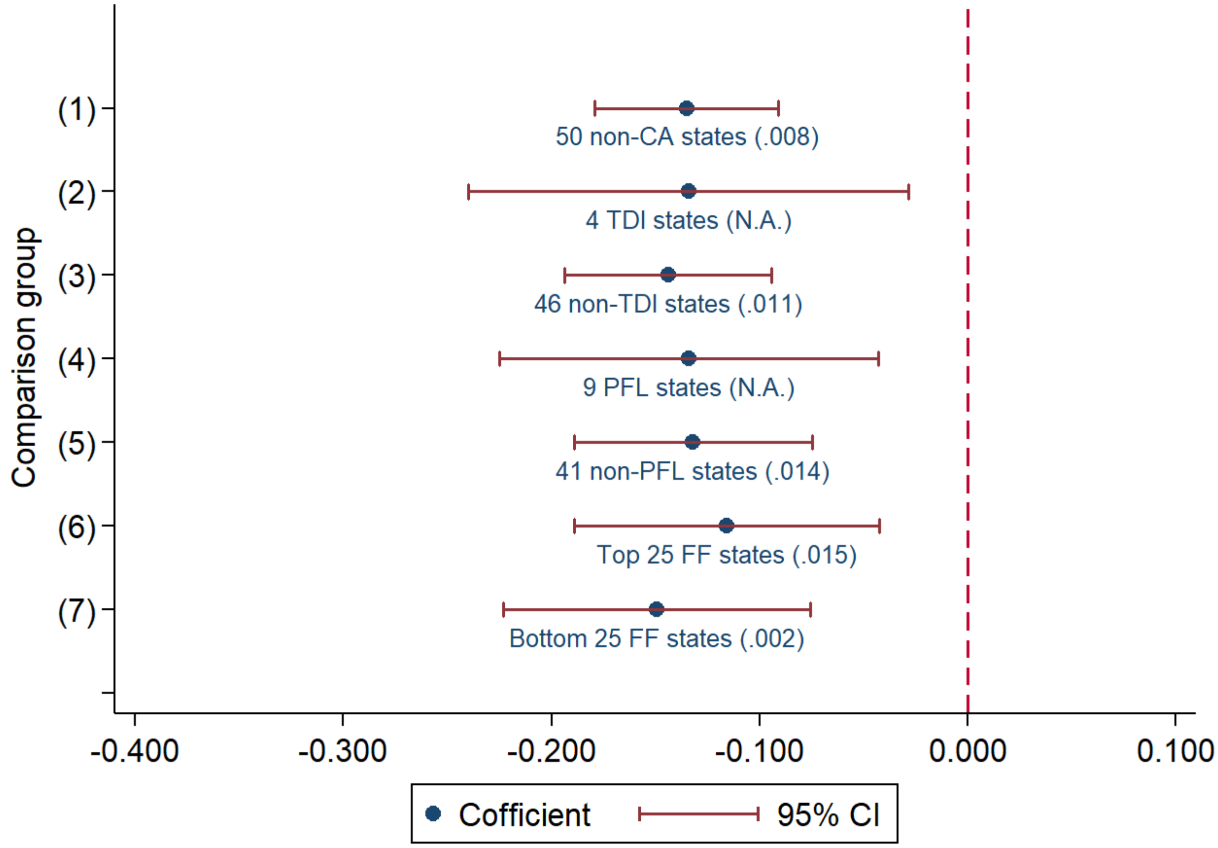
Notes: This figure plots the raw trends in PNMR in California and the comparison group.

Figure 1 Raw trends in PNMR in California and the comparison group, 2000-2008



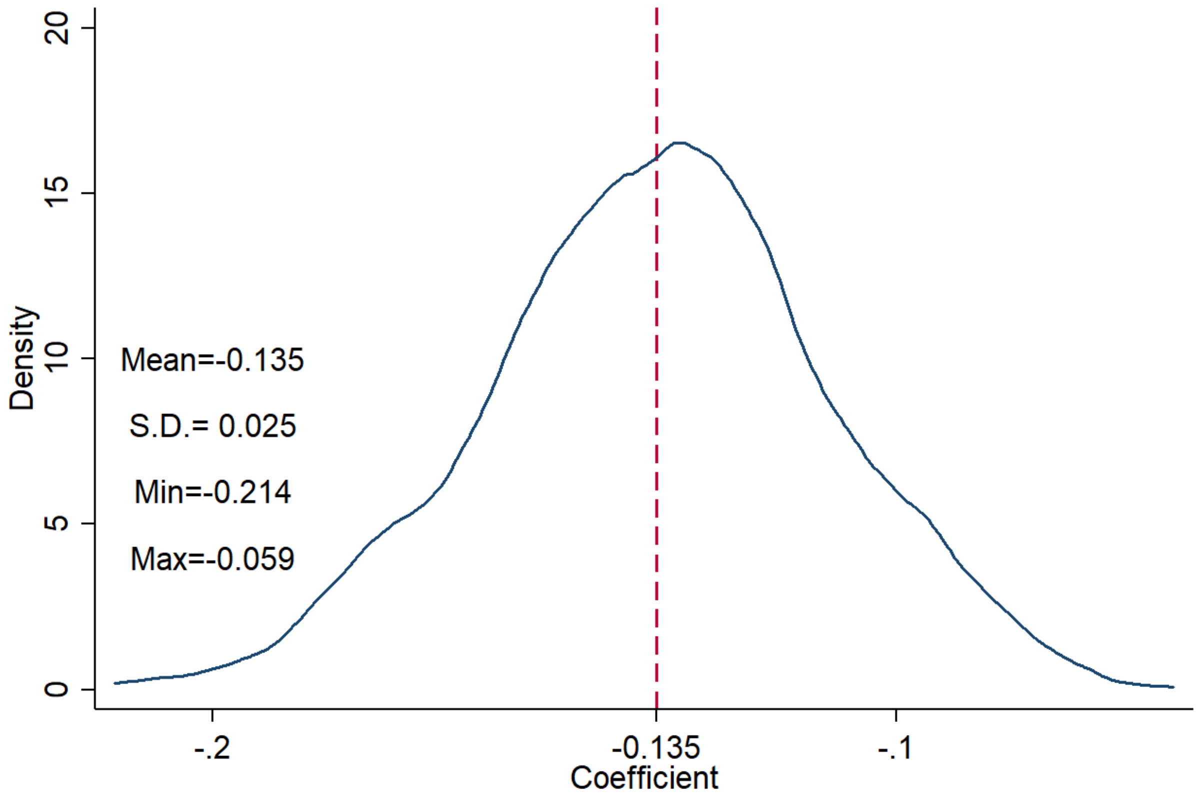
Notes: This figure displays coefficients and 95% confidence intervals of event study estimates. Event time is a dummy of the year(s) of leads or lags since CA-PFL is effective, for example, the event time 0 is a dummy of the year PFL effective (July 2004 to June 2005).

Figure 2 Event study estimates of effects of CA-PFL on PNMR



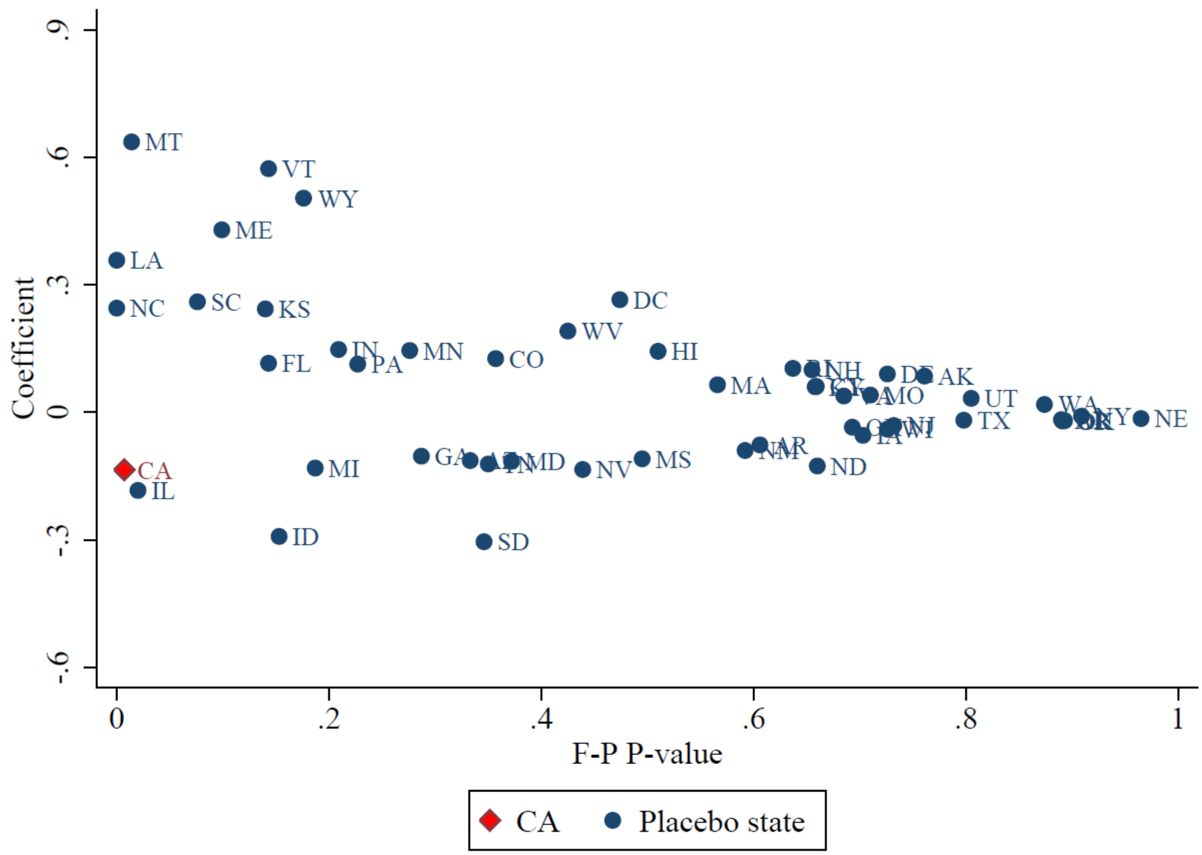
Notes: This figure plots coefficients and 95% confidence intervals of estimates using alternative comparison groups. The 95% confidence intervals are based on the conventional cluster-robust standard errors, and F-P p-values are in parentheses (if applicable). Estimate (1) is the same as estimate in 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.

Figure 3 Robustness checks: alternative comparison groups



Notes. This figure plots the density distribution of estimates of using 25 randomly chosen states as the comparison group and permuted 1,000 times. The vertical dashed line corresponds to -0.135, the estimate of our preferred specification in column (3) of Table 3.

Figure 4 Permutation results using 25 randomly chosen states as the comparison group



Notes: 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 to 0.1, 6 of them in range of 0.1 to 0.2, 4 of them in range of 0.2 to 0.3, 5 of them in range of 0.3 to 0.4, 4 of them in range of 0.4 to 0.5, 3 of them in range of 0.5 to 0.6, 8 of them in range of 0.6 to 0.7, 7 of them in range of 0.7 to 0.8, 5 of them in range of 0.8 to 0.9, and 2 of them in range of 0.9 to 1.

Figure 5 Results of placebo tests using every other state as the treated state

Table 1 Summary statistics

Variable	All	Pre-CA-PFL		Post-CA-PFL	
		CA	Comparison	CA	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	3,317	3,372	3,328	3,338	3,294
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	5,508	54	2,700	54	2,700

Notes: 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 50 non-CA states.

Table 2 Estimates of the CA-PFL take-up rate

Year	Number of bonding claims		Children for bonding		Eligible parent%		Take-up rate	
	Mother	Father	New birth	Adoption	Mother	Father	Mother	Father
2004	56,279	10,178	282,643	3,778	45.09%	91.12%	43.57%	3.90%
2005	112,155	24,810	548,882	7,556	44.21%	88.29%	45.59%	5.05%
2006	118,112	28,223	562,440	7,393	42.13%	90.71%	49.19%	5.46%
2007	127,754	33,804	566,414	7,622	43.67%	90.54%	50.97%	6.50%
2008	137,566	39,833	551,804	7,777	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%

Notes: 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 + 7,556) × 44.21%); and for fathers: 5.05%=24,810 ÷ ((548,882 + 7,556) × 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 one-year old using data from CPS.

Table 3 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	5,508	5,508	5,508
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

Notes: 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.

Table 4 Heterogeneous effects of CA-PFL on the PNMR

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A Cause of death: internal vs external						
Group (mean)	Internal Cause (1.51)			External 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 vs 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 vs 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 vs 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	5,508	5,508	5,508	5,508	5,508	5,508
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

Notes: The table presents the heterogeneous effects of the CA-PFL on PNMR. The pre-treatment mean of PNMR is in parentheses. See notes to table 3 for details.

Table 5 Placebo outcomes: neonatal mortality & fetal mortality

	(1)	(2)	(3)
Panel A Neonatal mortality (0-28 days)			
CA*Post	0.059	0.004	0.031
P-value	(0.118)	(0.919)	(0.555)
F-P p-value	[0.704]	[0.984]	[0.857]
R-squared	0.470	0.498	0.499
Panel B Fetal mortality (in pregnancy)			
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	5,508	5,508	5,508
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

Notes: The table presents the DD estimates of the effects of the CA-PFL on neonatal mortality rate and fetal mortality rate. The neonatal mortality rate is the number of deaths during the first 28 days of life per 1,000 live births, and the fetal mortality rate is the number of deaths during pregnancy per 1,000 live births. See notes to table 3 for details.

Table 6 Effects of CA-PFL on fertility

	(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
Observations	5,508	5,508	5,508
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

Notes: The table presents the DD estimates of the effects of the CA-PFL on fertility. The general fertility rate is the number of live births per 1,000 females of childbearing age between the ages of 15-44 years. See notes to table 3 for details.

Table 7 Effects of CA-PFL on birth outcome

	(1)	(2)	(3)
Panel A 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 B 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	5,508	5,508	5,508
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

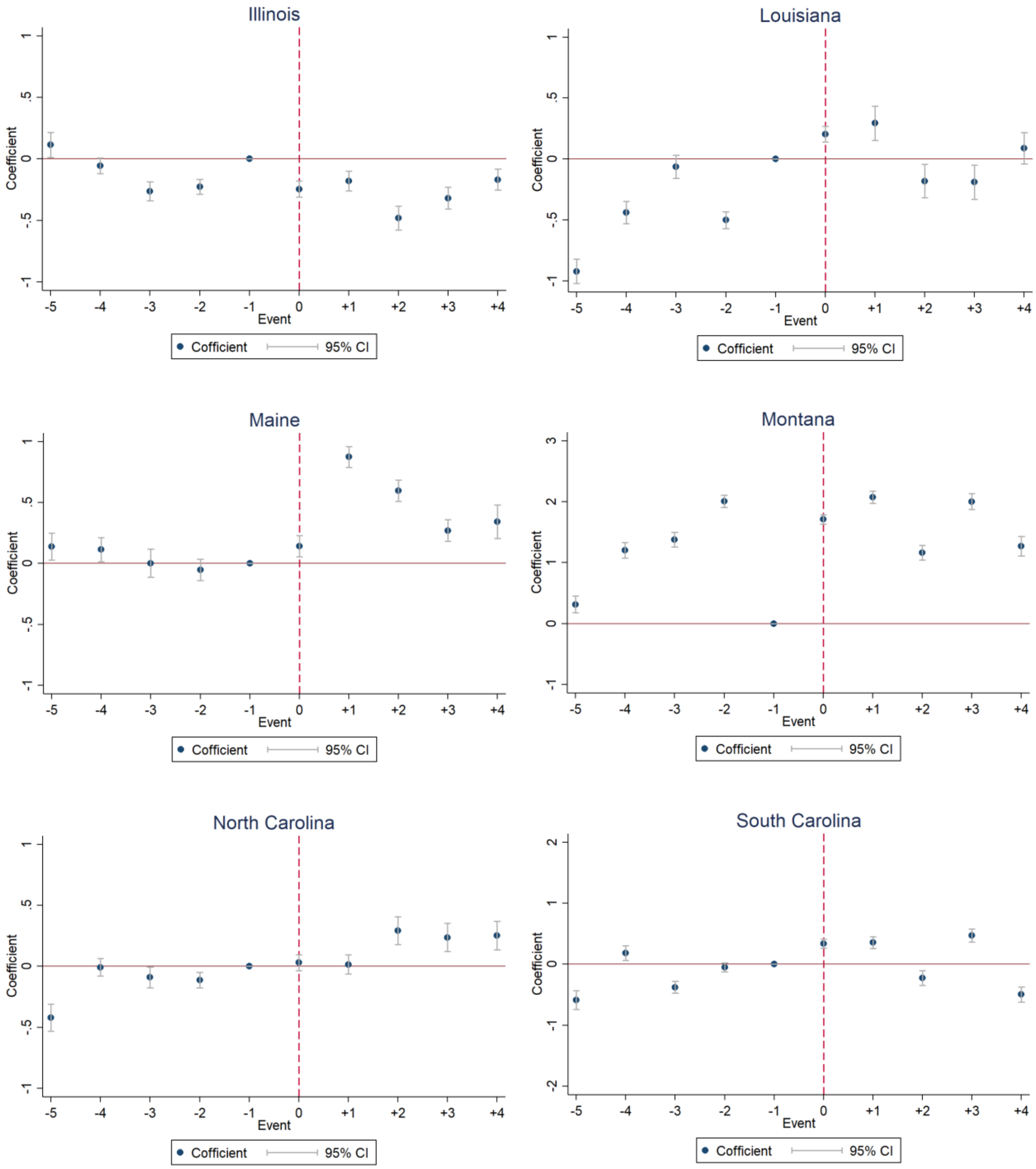
Notes: The table presents the DD estimates of the effects of the CA-PFL on birth outcomes. Low birth weight is defined as a weight of fewer than 2,500 grams, and preterm is defined as babies born alive before 37 weeks of pregnancy are completed. See notes to table 3 for details, except for the birth controls exclude birth weight and gestational age.

Table 8 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.

Appendix



Notes: This figure displays coefficients from event study regressions of selected placebo tests with F-P p-values less than 0.1. Event time is a dummy of the year(s) of leads or lags since the CA-PFL is effective, for example, the event time 0 is a dummy of the year PFL effective (July 2004 to June 2005).

Figure A1 Event study estimates of selected placebo tests

Table A1 Effects of CA-PFL for all plurality

	(1)	(2)	(3)
CA*Post	-0.147	-0.161	-0.137
P-value	0.000	0.000	0.000
F-P p-value	0.175	0.098	0.016
R-squared	0.474	0.477	0.479
Observations	5,508	5,508	5,508
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

Notes: The table presents the DD estimates of the effects of the CA-PFL on PNMR for all plurality. See notes to table 3 for details.

Table A2 List of states of two alternative comparison groups

Top 25 family-friendly states			Bottom 25 family-friendly states		
Rank	State	Grade	Rank	State	Grade
2	District of Columbia	140	27	Florida	20
3	New York	135	27	Iowa	20
4	Rhode Island	125	27	Kansas	20
5	Connecticut	120	27	New Hampshire	20
6	Hawaii	110	27	North Carolina	20
7	New Jersey	100	27	Ohio	20
8	Oregon	95	27	Virginia	20
9	Vermont	85	34	Indiana	15
10	Illinois	70	34	New Mexico	15
10	Massachusetts	70	34	North Dakota	15
12	Minnesota	65	37	Kentucky	10
12	Washington	65	37	Pennsylvania	10
14	Maine	60	37	Texas	10
15	Colorado	50	40	Alabama	0
16	Louisiana	45	40	Arizona	0
16	Wisconsin	45	40	Georgia	0
18	Maryland	40	40	Idaho	0
19	Arkansas	35	40	Michigan	0
20	Alaska	30	40	Mississippi	0
20	Delaware	30	40	Missouri	0
20	Montana	30	40	Nevada	0
20	Nebraska	30	40	Oklahoma	0
20	Utah	30	40	South Carolina	0
25	Tennessee	25	40	South Dakota	0
25	West Virginia	25	40	Wyoming	0

Note: This table presents grades of state policies that support expecting and new parents just before and soon after the arrival of a new child. California ranked first with a grade of 155. See NPWF (2016) for detailed methodologies that they used to calculate the grades. The top 25 family-friendly states (other than California) and the bottom 25 family-friendly states are two alternative comparison groups used in this article.

Table A3 Robustness check: exclude IL, LA, ME, MT, NC, and SC

	(1)	(2)	(3)
CA*Post	-0.143	-0.153	-0.129
P-value	0.000	0.000	0.000
F-P p-value	0.044	0.002	0.000
R-squared	0.453	0.456	0.457
Observations	4,860	4,860	4,860
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

Notes: The table presents the DD estimates of the effects of the CA-PFL on PNMR excluding states IL, LA, ME, MT, NC, and SC from the analysis. See notes to table 3 for details.

Table A4 Robustness check: exclude the year 2004

	(1)	(2)	(3)
CA*Post	-0.162	-0.171	-0.142
P-value	0.000	0.000	0.000
F-P p-value	0.108	0.066	0.005
R-squared	0.450	0.453	0.455
Observations	4,896	4,896	4,896
State FE, Time FE	Y	Y	Y
Birth control	N	Y	Y
Maternal control	N	N	Y

Notes: The table presents the DD estimates of the effects of the CA-PFL on PNMR excluding the year 2004 from the analysis. See notes to table 3 for details.