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The Effect of Paid Family Leave on Infant and Parental Health in the United States

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Abstract. California's paid family leave (PFL) policy improved mothers' labor market outcomes, however, the health impacts of this program are less studied. I compare child and parental health of likely eligible households to a series of control groups before and after California's PFL program was implemented. I find improvements in parent-reported overall child health and suggestive improvements in maternal mental health status. Findings also suggest a reduction in asthma and a greater likelihood that parents feel they are coping well with the day-to-day demands of parenting. There are no significant effects on respiratory or food allergies, or father's mental health status. The results are robust to multiple control groups and placebo tests.

JEL codes: I18, J88, I14
Keywords: paid family leave, child health, parental mental health

1 Introduction

Calls for a national paid family leave (PFL) program in the United States have attracted serious attention in recent years. In 2011, President Obama unsuccessfully proposed to allocate $50 million in competitive grants to states that start PFL programs. More recently, the Family and Medical Insurance Leave (FAMILY) Act – proposed in 2013 and again in 2015 and 2017 – would have provided 12 weeks of paid leave at a 66 percent wage replacement rate. Despite these efforts, the U.S. remains the only developed country without a PFL program.

Six states plus the District of Columbia currently have paid family leave programs allowing employees partially paid time off work to care for a new child. For example, California's PFL program now provides six weeks of leave at 60-70 percent of weekly earnings (capped at $1,216 per week), depending on earnings levels. In August 2018 the average weekly benefit amount was $674 and total benefits paid in 2018 were nearly $864 million.

With one exception (Das and Polachek, 2015), research has shown that California's PFL program has improved mothers' labor market outcomes. The program doubled the length of leave taken from an average of three weeks to between six and eight weeks, especially among low-educated, unmarried, and minority mothers (Baum and Ruhm, 2016; Rossin-Slater, Ruhm, and Waldfogel, 2013). As a result of greater short-term labor force attachment of women who would have otherwise temporarily exited the labor force (Byker, 2016), mothers' employment and wages have improved after childbirth (Baum and Ruhm, 2016; Rossin-Slater, Ruhm, and Waldfogel, 2013). Further evidence suggests that higher benefit amounts modestly increase employment up to two years following leave (Bana, Bedard, and Rossin-Slater, 2018).

Recent research also suggests California's PFL program improved child health. Lichtman-Sadot and Pillay Bell (2017) find California's PFL program improved the health of elementary school-aged children by reducing the prevalence of overweight, ADHD, and hearing-related problems. Pihl and Basso (2019) find California's PFL reduced hospitalizations among infants for avoidable infections and illnesses. With these exceptions, little else is known about the health and human capital impacts of California's PFL program.

Several papers study the effect of expanding paid leave on child health and well-being in other countries. For example, expanding paid leave in Canada (Baker and Milligan, 2008, 2010, 2015), Germany (Dustmann and Schönberg, 2012), Sweden (Liu and Skans, 2010), Norway (Dahl et al., 2016), and Denmark (Beuchert, Humlum, and Vejlin, 2016) from between two and fifteen months had little to no significant impacts on child outcomes at various ages or maternal mental health. In these countries, however, leave lengths provided by policies were already substantially longer than the shorter leaves typically available in the United States. In contrast, for instance, in the U.S. the introduction of both twelve weeks of unpaid and six weeks of paid maternity leave for birth mothers through Temporary Disability Insurance (TDI) improved birth outcomes and reduced infant mortality rates (Rossin, 2011; Stearns, 2015). The sum of this literature then begets the question of whether a six week leave program in the U.S. has any health effects on infants or mothers.

There are several mechanisms through which paid family leave could affect children's health. For example, policies that lengthen parental leave increase the amount of time parents can spend with their infants. This extra time may affect nonparental care, breastfeeding duration, parental engagement, and parental mental health, stress and anxiety, all of which have been linked to child health. Paid leave – compared to no leave or unpaid leave – may also smooth household earnings immediately following childbirth; even slight increases in income are known to positively affect child health and development and maternal health (Milligan and Stabile, 2011).

To examine the relationship between partially paid parental leave and children's and parental health and well-being, I use data from the National Survey of Children's Health (NSCH). I compare the health of infants and their parents in California to several control groups to construct a series of difference-in-differences (DD) estimators. I also conduct within-state comparisons of infants to older children in a difference-in-difference-in-differences (DDD) analysis. I find PFL in California improved overall parent-reported infant health and likely improved respondent-reported maternal mental health. There is suggestive evidence of a reduction in parent-reported asthma, and parents are also more likely to feel they are coping well with day-to-day demands of parenting. There are no significant effects on respiratory allergies, food allergies or father's mental health. Finally, I find reductions in nonparental childcare and suggested increases in parental engagement (as measured by reading to children). In addition to improved economic well-being (Baum and Ruhm, 2016; Rossin-Slater et al., 2013; Stanzcyk, 2016), the child health improvements may be the result of better maternal mental health status and greater parental care and engagement.

2 Family Leave Policies

2.1 Parental Leave in the United States

Most developed countries provide new parents – particularly mothers – with entitlements to paid family leave (PFL).[1] These programs grant parents time off work to care for a newborn or adopted child, typically with wage replacement and a right to return to work at the conclusion of the leave. The length of leave, job protection, wage replacement rate, and payment structure differ across nations but most countries provide at least nine months of paid leave to mothers. In Germany and Canada, for example, mothers can take up to twelve months at 67 percent and 55 percent wage replacement, respectively.

Although the United States has no federal paid parental leave policy, The Family and Medical Leave Act (FMLA) of 1993 requires employers of 50 or more employees to offer at least twelve weeks of unpaid maternity leave with guaranteed health coverage. In practice, there are two primary issues related to coverage under the unpaid leave guaranteed by the FMLA; first, to be eligible for leave, a mother must work at least 1,250 hours in the past 12 months for a firm with more than 50 employees. These employer size and work history requirements result in eligibility of only slightly more than half of all private sector employees for leave under FMLA (Han, Ruhm, and Waldfogel, 2009; Ruhm, 1998). Second, college-educated and married women are more likely to be eligible for FMLA and able to afford unpaid leave than less-educated and unmarried mothers (Han et al., 2009).

In addition to FMLA, six states – California, New Jersey, Rhode Island, Washington, New York, and Massachusetts – plus the District of Columbia have laws that mandate paid family leave.[2] California was the first of these states to mandate such leave,

[1] In addition, family leave policies provide leave for medical reasons and to care for ill family members for male and female workers. This paper focuses solely on parental leave-taking for new parents, which constitute the vast majority of claims.

[2] Washington's policy will be implemented in 2019 and start paying benefits in 2020. Washington D.C.'s program will be effective in 2020. Massachusetts's program will take

where PFL took effect in 2004, and is the focus of this study. In California, New Jersey, Rhode Island, and New York birth mothers can claim PFL immediately after claiming TDI. Therefore, for most mothers PFL may be thought of as an extension of maternity leave. The state-level PFL programs differ in their lengths, eligibility requirements, wage replacement amount, and maximum benefit. Basic differences across these seven programs are outlined in Table 1. Additionally, in California, New Jersey, Washington D.C., and Washington job protection is not guaranteed unless leave under FMLA is taken simultaneously.

Research suggests that California's PFL program increased the overall use of leave-taking among mothers by three to five weeks, particularly among low-educated, unmarried, and minority mothers (Baum and Ruhm, 2016; Rossin-Slater et al. 2013). The program also increased leave-taking by nearly one week for fathers (Baum and Ruhm, 2016) and the likelihood of both parents taking leave at the same time (Bartel et al., 2018). Likely due to increased job continuity among women with relatively weak labor force attachments, PFL in California has had positive effects on labor market outcomes for women in both the short (Byker, 2016) and longer run (Baum and Ruhm, 2016; Rossin-Slater et al., 2013). As a result, PFL subsequently increased wages and household income up to three years after the child was born (Rossin-Slater et al., 2013; Stanczyk, 2016). Additionally, employers in California (Appelbaum and Milkman, 2011), New Jersey (Lerner and Appelbaum, 2014), and Rhode Island (Bartel et al., 2016) report having positive or no effects on productivity, profitability, and employee morale.

2.2 Pathways Linking Paid Family Leave and Child Health

2.2.1 Nonparental Care

Previous literature suggests several mechanisms through which paid family leave can affect child health. Developmentally, the important feature of a maternity leave mandate is the amount of parental care a child receives early in infancy. Research suggests nonparental care can negatively affect behavioral development, though the contexts are nuanced (Belsky, 2006; Loeb et al., 2007; Magnuson, Ruhm, and Waldfogel, 2007; Baker,

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effect in 2019 and begin paying benefits in 2021. Hawaii also covers postpartum women through the Temporary Disability Insurance system.

Gruber, and Milligan, 2008, 2019; Gupta and Simonsen, 2010; Bernal and Keane, 2011). For example, Baker, Gruber, and Milligan (2008) use an exogenous increase in nonparental child care in Canada as a result of a universal child care program. They find the program led to worse children's social and behavioral development among children aged 0-5, worse parental health, and less consistent parenting, on average. Though Kottelenberg and Lehrer (2017) find developmental improvements from the program among the most disadvantaged children, the average negative developmental effects persisted among children ages 5-9; in some cases, they were even worse, such as self-reported health and increased crime among teens (Baker, Gruber, and Milligan, forthcoming).

In the United States, research suggests that early entrance into a childcare center increases the likelihood that a child experiences adverse effects on behavioral health such as motivated engagement of learning activities, self-control, and several impersonal skills; the earlier a child enters center-based childcare, the larger the negative impacts on behavior (Loeb et al., 2007).[3] Although higher quality caregivers produce better developmental outcomes regardless of the child's location on the child development distribution (Araujo, Dormal, and Schady, 2018), high-quality childcare may not attenuate the negative effects of early maternal employment (Brooks-Gun, Han, and Waldfogel, 2002). Further, there is substantial variation in the quality of nonparental care in the United States (Blau, 1999).

Early exposure to group care may also affect the physical health of infants. Communicable diseases such as diarrheal illness and respiratory infections (Lu et al. 2004; Kamper-Jørgensen et al. 2006) are more prevalent in children who are in group care, such as a child care center, and asthma is often diagnosed because of the common cold or respiratory infection (Bacharier and Guilbert 2012; Busse, Lamanske, and Gern 2010; Nafstad et al. 2005). Compared to staying home, an infant receiving child care outside the home may be more prone to interacting with others and contracting upper respiratory infections.

International examples imply that more generous paid leave improves infant and children's health (Ruhm, 2000). However, many recent papers studying the effects of parental leave expansions on child outcomes – primarily using European and Canadian

[3] In contrast, formal childcare (e.g. prekindergarten) has no adverse effects on cognitive outcomes (Bernal and Keane, 2011), and may even improve cognitive development (Magnuson, Ruhm, and Waldfogel; 2007; Loeb et al., 2007).

reforms – report no developmental advantages to extensions of maternity leave programs (see Baker 2011 for a review). For example, expanding paid leave in Canada from six to twelve months (Baker and Milligan, 2008, 2010, 2015), Germany from two to six months (Dustmann and Schönberg 2012), Sweden from twelve to fifteen months (Liu and Skans 2010), Norway from eighteen to thirty-five weeks (Dahl et al., 2016), and Denmark from six to eleven months (Beuchert, et al. 2016) had no statistically significant effects on longer term child outcomes such as physical health up to two years, childhood development between 0-5 years, grade retention, adult wages and employment, academic performance as a teen, high school graduation, or hospitalizations within one or three years. The exception is Carneiro et al. (2015) who study the effects of extensions of paid leave in Norway from zero to four months and unpaid leave from three to twelve months. Using administrative data in which they can actually identify leave eligibility, they find that children of the mothers eligible for the leave expansions were less likely to drop out of high school.

2.2.2 Parental Engagement

In addition to amount of parental care, the quality of parental care may be affected by longer parental leaves. For example, a mother with a longer maternity leave may be more likely to breastfeed, better able to recognize when an infant is ill earlier, and, in turn, seek medical attention sooner (Currie and Rossin-Slater, 2015; Berger, Hill, and Waldfogel, 2005). Breastfeeding is linked to health benefits to infants including a reduced risk of ear infections, respiratory illnesses, asthma, and obesity (American Academy of Pediatrics, 2012; Dustmann and Schönberg, 2012; Ip et al., 2007),[4] and research suggests that California's PFL program increased breastfeeding rates and durations (Huang and Yang, 2015; Appelbaum and Milkman, 2011).

Improved parental care and engagement can also improve children's health. For instance, parents may be better able to follow a routine. Predictable family routines, such as regular bedtimes, bath time, meal times and story time, are associated with better behavioral outcomes among preschoolers (Case and Paxson, 2002; Keltner, 1990). Although newborns are unlikely to follow such routines, establishing positive parenting

[4] The research on the link between breastfeeding and the timing of complementary food introduction and food/digestive allergies is mixed (e.g. see Greer et al. 2008 and Luccioli et al. 2014).

approaches when the child is an infant may increase the likelihood of persisting with these behaviors through early childhood. Indeed, recent research suggests that California's PFL program improved health outcomes among infants (Pihl and Basso, 2019) and elementary school-aged children (Lichtman-Sadot and Pillay Bell, 2017) that are linked to parental care and engagement.

2.2.3 Parental Mental Health

Having the ability to take time off work to recover from childbirth may reduce maternal stress, anxiety, and depressive symptoms during and after pregnancy. Parental stress can adversely impact a child's health and well-being from infancy through adolescence (Berger and Waldfogel, 2011). Since longer maternity leaves (more than 8 or 12 weeks) are associated with fewer depressive symptoms (Mandal, 2018; Chatterji, Markowitz, and Brooks-Gunn, 2013; Chatterji and Markowitz 2005; 2012), PFL may affect the health of parents.

Maternal mental health status in particular has important effects on child health. Psychiatrist Marilyn Essex and her colleagues (2002) studied the effect of maternal stress during a child's infancy on the child's stress and mental health symptoms during early elementary school. They measured maternal stress levels using salivary cortisol levels at children's age 1, 4, and 12 months, and 4.5 years, and then measured children's cortisol levels and mental health symptoms, such as social withdrawal, when the children were in first grade. Maternal depression during a child's infancy was the strongest predictor of children's elevated cortisol levels in first grade. Importantly, children that were exposed to high levels of concurrent stress but were not exposed to stress during infancy did not have elevated cortisol levels. Although the subjects in the current study are much younger than elementary school-aged children, these results suggest that exposure to maternal stress and depression during infancy may put children at risk of developing symptoms of mental health and behavioral problems.

Additionally, since the choices parents make regarding their children's health is in part determined by their own health and health behaviors (Case and Paxson, 2002), parental behaviors may also impact children's health. For example, if parents are more stressed, anxious, or depressed and therefore more likely to engage in alcohol and drug use, their children's health may be adversely impacted.

Previous literature on the effect of expansions on maternal health in other countries is mixed. Neither Baker and Milligan (2008) nor Beuchert et al. (2016) find an effect from adding 22-25 weeks to a 6-month leave on maternal depression. Beuchert et al. (2016) do, however, find expanding leave from 24 to 46 weeks reduced the probability of an inpatient hospital stay within one year of birth by nearly 70 percent.

2.2.4 Income

Finally, the income pathway likely affects children's health. Compared to no leave or unpaid leave, all else equal, paid leave may smooth household earnings immediately following childbirth (Rossin-Slater et al., 2013; Stanczyk, 2016). Directly, greater family resources for childrearing could translate into better nutrition (Almond, Currie, and Duque, 2017), or other goods that enhance child health and development. Greater family incomes may also have indirect effects such as reducing stress, improving family relations, increasing employment opportunities (Yeung, Linver, and Brooks-Gunn, 2002), and improving and emotional well-being of both parents and children (Milligan and Stabile, 2011). Although parental leave duration is a small portion of the earnings life course, the economic well-being of families worsens in the months surrounding a birth (Stanczyk, 2016).

2.2.5 Paid Family Leave and Child Health in the United States

Although most research on maternity leave expansions show little to no effects on child outcomes, the majority of this research comes from Europe and Canada. Using international policies as examples, however, provides little insight as to what to expect in the United States where leave programs are shorter and wage replacement rates lower. In the U.S., the introduction of both twelve weeks of unpaid and six weeks of paid maternity leave for birth mothers (through Temporary Disability Insurance) improved birth outcomes and reduced infant mortality rates (Rossin, 2011; Stearns, 2015). When coupled with the research on international expansions, these studies suggest the starting point may matter: going from no leave to any length of leave may be more important for children's health than extending existing leaves of two months or more.

The studies most similar to the current research are Lichtman-Sadot and Pillay Bell (2017) and Pihl and Basso (2019). Both studies examine the effect of California's paid family leave program on children's health. Lichtman-Sadot and Pillay Bell also use survey data and find improved health outcomes among children in elementary school that are associated with breastfeeding such as hearing problems, overweight, and attention-deficit/hyperactivity disorder (ADHD). The effects are largely driven by children from less advantaged backgrounds. Pihl and Basso (2019) use hospital admissions data and find a reduction in avoidable hospitalizations among infants, such as upper respiratory infections and gastrointestinal diseases. These authors posit the effects are driven by increases in breastfeeding duration (Huang and Yang, 2015), increased parental care in early infancy, and reduced time in group-based care.

The current study represents the first paper to assess the impact of paid family leave on parental mental health and among the first to study infant well-being in the United States. It complements Lichtman-Sadot and Pillay Bell (2017) by studying the short-run effects of paid family leave. Since early-life conditions affect long-term health and human capital (Currie et al., 2010), and investments made early are compounded throughout childhood (Cunha et al., 2006; Cunha and Heckman, 2007; Heckman, 2007), understanding the effects on infant health are independently important. This study also complements Pihl and Basso (2019). Since administrative hospitalization data only capture the most serious illnesses, survey data can provide insight into less extreme measures of health, providing a more complete picture of the health effects on children. I also explore some of the potential mechanisms through which paid family leave affects children's health, an area of research underdeveloped in the existing literature on paid family leave.

3 Data

3.1 National Survey of Children's Health

The primary data used in this study come from the National Survey of Children's Health (NSCH). The survey contains a nationally representative sample of households with children under age 18 from all states and the District of Columbia and was conducted in 2003, 2007, and 2011-2012. Over 90,000 households were surveyed in each wave, and data correspond to one focal child from each sample household. Although there are only a handful of health outcomes that are consistently measured across waves, this survey is one of few data sources that includes measures of health for both parents and children, the age of the child, waves before and after 2004, and a sample size large enough to limit to infants and their parents.

Although there are likely persisting effects of PFL (Lichtman-Sadot and Pillay Bell, 2017), I limit the sample to infants aged 0 or 1 and their parents. Since I do not know the child's date of birth, parents with children aged two or older in 2007 may have been eligible for PFL when claims were first made in July 2004, and would thereby contaminate the treatment effects. Further, there is some evidence of women shifting the timing of their births in the short-term to be eligible for PFL through November 2004 (Lichtman-Sadot, 2014), and this self-selection into the treatment group may also bias my estimates. Limiting the sample to infants aged 0 or 1 avoids including these mothers and their infants in the sample.

The Great Recession reduced fertility, particularly among women of low socioeconomic status, and especially in California (Schneider and Hastings, 2015). Positive selection into motherhood as a result of compositional and fertility changes from the Great Recession would upwardly bias estimates. Therefore, I further limit the sample to only observations from the 2003 and 2007 waves, before the effects of the Great Recession would be observed.[5]

3.2 Outcomes

The outcomes of interest are various measures of children's health and parental mental health. Child health is measured using four binary variables that equal one if: (1) the parent describes the child's health as being excellent or very good (relative to good, fair, or poor),[6] a health professional has indicated that the child has (2) asthma (3) a food or digestive allergy, and (4) a respiratory allergy. The last three outcomes have been clinically associated with breastfeeding, preventive care utilization, and childcare in a

[5] There was also a recession in 2001. Buckles et al. (2018) show that the growth rate of conceptions declines at the beginning of recessions, starting before the recession begins. For example, conceptions dropped rapidly between 2000q4 and 2001q1 (the beginning of the 2001 recession) but recovered by 2001q4 (the end of the recession), so births from mid-2002 onward are less likely to be affected by positive selection into motherhood that may have resulted from the 2001 recession. Comparatively, conceptions dropped between 2007q3 and 2007q4 (the beginning of the Great Recession), so births in 2008 onward would have been affected by the recession and are not included in my analysis.

[6] I follow the literature and create a dichotomous variable in this way because very few parents report their children to be in poor health (Currie and Stabile, 2003; Milligan and Stabile, 2009).

group-care setting, though the causal effect is not well established. The parent-reported health of a child is a subjective measure and may suffer from systematic biases. For example, some parents might spend more time with their children and have better information about their children's health. Parental mental health is also likely to influence reports of child health. According to the National Health and Nutrition Examination Survey, however, parent-reported data on their children's health is highly correlated with doctor's reports of children's health status (Case, Lubotsky, and Paxson, 2002), and have been proven valid measures to inform the underlying concept they intend to capture (De Los Reyes and Kazdin, 2005).[7]

As noted earlier, the literature addresses at least four potential channels through which paid family leave may impact children's health: (1) more time for parental care during infancy, including healthcare utilization; (2) enhanced parental engagement; (3) improved parental health and well-being; and (4) greater income during a time in which families' economic well-being is reduced. I am able to empirically test mechanisms 1, 2, and 3. I measure parental mental and emotional health with three respondent-reported[8] variables based on a 5-point Likert scale, which I convert to binary variables that equal one if the response was either "excellent" or "very good" (relative to good, fair, or poor) to the following: (1) mother's mental and emotional health; and (2) father's mental and emotional health; and (3) how the parent feels they are coping with the day-to-day demands of parenting. I measure parental care and engagement using the following measures: a binary variable for whether the child had any nonparental child care for ten or more hours per week in the past month, a binary variable for whether a parent reads to the child four or more days per week, and the number of times a child visited a health care professional in the past 12 months.

[7] Further, Spencer and Coe (1996) find that for acute events, parent-reported measures are rated very highly. In studying the effects of a Canadian parental leave policy Baker and Milligan (2008) use similar measures for maternal and child health.
[8] In rare cases, the respondent may have answered for the mother or father if the mother or father was not present. Nearly three-fourths of respondents were the child's mother, and twenty percent of respondents were the father.

Potential channels that I cannot measure due to data limitations include income and breastfeeding.[9] Although I cannot precisely empirically test these mechanisms, previous research has shown that California's PFL increased household income among mothers of young children between nine months and three years old (Baum and Ruhm, 2016; Stanczyk, 2016; Rossin-Slater et al., 2013) and increased breastfeeding duration (Huang and Yang, 2015).

3.3 Covariates

Household-level control variables for each individual from the NSCH are limited. I disaggregate these variables to the extent that I can, including indicator variables for whether someone in the household worked 50 weeks in the last year, highest level of education of someone in the household, poverty level (eight predetermined categories),[10] and whether the primary language spoken in the household is English. I also include the total number of adults in the household, child's age, gender, birth order, and whether the child has health insurance.

The health of parents and children is also impacted by macroeconomic conditions (Dehejia and Lleras-Muney, 2004). Therefore, I also include annual state unemployment and poverty rates. Finally, since parental marital status was not measured in all years, I control for an annual state-level measure of marital status, which comes from the Outgoing Rotation Group files from the Current Population Survey.

[9] The NSCH only has a measure of a family's income as categories of percentages of the FPL. The breastfeeding duration variable is measured inconsistently in 2003 and 2007. Specifically, in 2007 the measure allows parents to report that their child "is still breastfeeding," whereas in 2003 this response was not an option. Since breastfeeding duration is measured in days and child's age is only measured in years, even a backed-out version of this measure yields a good deal of measurement error.

[10] Household income level may be endogenous. However, the income measure is categorical and is likely correlated with many relevant but unmeasured household characteristics. Although there is evidence that PFL affected household income (Rossin-Slater et al., 2013; Stanczyk, 2016), the effect is unlikely large enough for households to change income categories. Nonetheless, the DD results are robust to both fewer income categories and excluding the income level as a control variable, though the estimates are more precise when this variable is included. Further, in their study of California's PFL program on child health, Lichtman-Sadot and Pillay Bell (2017) also include a measure of socioeconomic status in their main specification. For easier comparison with their results, my preferred models include income categories.

4 Empirical Strategy

4.1 Identification

I compare changes in parental and child health for Californians surveyed before and after the implementation of PFL to corresponding differences among control groups unlikely to be affected by the program. Specifically, I estimate the following difference-in-differences (DD) equation:

$$y_{ist} = \beta_0 + \beta_1 CA_{is} * Post_t + \gamma' \boldsymbol{X_{it}} + \delta' \boldsymbol{Z_{st}} + \alpha_s + \tau_t + \varepsilon_{ist} \qquad (1)$$

The dependent variable is a measure of child or parental health as described above for each focal infant *i* in state *s* during year *t*. $Post_t$ equals one if the outcomes are measured in 2007 and zero if they are measured in 2003. CA_{is} equals one if the focal infant *i* resides in California and zero if the infant resides in a different state.

The parameter of interest is β_1, representing the effect of PFL on parents with a child one year of age or younger relative to parents of infants without access to state-provided PFL. Individual covariates are included in vector **X**, and time-varying state-level controls are in vector **Z**. I include state fixed effects, α_s, to control for any time-invariant differences in children's health that may be correlated with PFL implementation. τ_t is an indicator variable for 2007, which controls for changes in the outcome variables that occurred nationwide.

A key assumption in a DD analysis is that in the absence of PFL, trends (but not levels) in child and parental health between the treatment and control groups would have been the same, and that no other factors affecting these outcomes occurred at the same time as the PFL program. If this assumption is violated, then the DD estimates will be biased. Although I cannot directly test for "parallel trends" in health outcomes between the treatment and control groups in the pre-PFL period with the NSCH due to data limitations, I take three specific actions to address this issue; first, I examine the robustness of the results to multiple control groups. Second, I show pre-trends in self-reported maternal mental health status across these groups using an alternative data source. Third, I employ a DDD technique, using older children in California as a third within-state difference.

Although California is a diverse state in many ways, I choose control groups similar to California on a variety of dimensions.[11] Macro-level factors such as demographic composition, local economies, climate, environment, cultural values, and safety net generosity affect health (Currie and Rossin-Slater, 2015; Almond, Hoynes, Schanzenbach, 2011; Currie and Neidell, 2005; Dehejia and Lleras-Muney, 2004; Neidell, 2004). If climate and environmental factors are the most important influences on child and parental health, then nearby states with similar geographies may be a good control group. If large and diverse economies are the most important predictors, then I should compare California to other states with similarly heterogeneous economies. For these reasons, three control groups include infants aged 0 or 1 and their parents in a) neighboring states (Arizona, Oregon, Nevada, and Washington), b) other large states (Florida, New York, Pennsylvania, and Texas), and c) all states other than California plus Washington D.C.[12]

To test for parallel trends between the control groups and California in the pre-PFL period, I enlist data from the Behavioral Risk Factor Surveillance System (BRFSS) from 2001-2007 to supplement the maternal mental health analysis. By using BRFSS data starting in 2001, I can compare pre-PFL trends in parental mental health to visually examine the comparability of these groups. An additional benefit of the BRFSS is the ability to identify mothers who are employed, and therefore likely eligible for PFL. One major drawback relative to the NSCH is the ages of BRFSS respondents' children are unknown. Together, these two datasets complement one another's weaknesses.

Since the majority of PFL claims for childbirth in California come from women aged 21-40 (California Employment Development Department, 2015), I limit the BRFSS

[11] The possibility of implementing a synthetic control (Abadie et al. 2010) is inappropriate in this case. One notable limitation to constructing a synthetic control group is that the mean of the outcomes for the treatment unit in the pre-treatment period should be in the middle of the distribution (the convex hull assumption). Among all states in 2003 in the NSCH, California is the state with the worst overall child health, maternal mental health, and paternal mental health measures. The convex hull assumption is then violated, leaving no combination of states that can reproduce the outcomes in California before PFL to fulfill the requirement that pre-intervention differences between treatment and control groups be zero.

[12] Rossin-Slater et al. (2013) also use these control groups when examining the effects of California's PFL on leave-taking behaviors. Lichtman-Sadot and Pillay Bell (2017) use all other states available in their dataset as their control group. Pihl and Basso (2019) use Arizona, New York, and Washington combined as their control group.

sample to employed females aged 21-40 who have at least one child. Figure 1 plots the regression-adjusted trends in the percent of days mental health was good[13] for employed mothers in California relative to employed mothers in the control groups from 2001-2007.[14] I also formally test for equality of trends using data from January 2001 through June 2004 (the pre-PFL period) by replacing the DD interaction term with an interaction of a linear time trend and the treatment group indicator. Appendix Table 1 shows that there is no statistically detectable difference between trends in mental health status of employed mothers in California and employed mothers in any of the control groups, conditional on covariates included. This formal statistical test provides support for these control groups.

If there are changes in California other than PFL between 2003 and 2007 that are uniquely different from the comparison states that affect children's health, my results may be biased. I therefore control for within-state differences by employing a DDD technique. California's PFL program should not have affected older children and their parents in the same way that it affected infants and their parents. Indeed, in 2017 there were 227,270 claims for newborn bonding and care, compared to only 6,795 claims for older child care. Further, mothers who took PFL to care for an infant typically used all six weeks of leave time available to them. Mothers who took PFL to care for an older child typically took two-thirds of the six weeks available to them (CA EDD, 2015). To compare infants to older children in a DDD model, I estimate the following equation:

$$y_{ist} = \beta_0 + \beta_1 CA_s * Post_t * Infant_i + \beta_2 CA_s * Post_t + \beta_3 Post_t * Infant_i + \beta_4 CA_s * Infant_i + \beta_5 Infant_i + \gamma' \boldsymbol{X_{ist}} + \delta' \boldsymbol{Z_{st}} + \alpha_s + \tau_t + \varepsilon_{ist} \quad (2)$$

[13] The BRFSS questionnaire asks respondents how many days during the past 30 days was their mental health not good (including stress, depression, and problems with emotions). To compare with the NSCH data, I subtract this number from 30 to create the number of days mental health was "good," and divide by 30 to obtain a percent.

[14] The dependent variable is the percent of days of the past 30 in which mental health status was self-reported to be good. The trends are adjusted for the following covariates, which were fixed at the mean value for California: household income, education, marital status, age, age^2, race/ethnicity, self-employment status, number of children (indicators for 2 and 3+), state unemployment rate, and month of interview indicators. Trends are also weighted by sampling weights.

Where *Infant* identifies whether child *i* is aged one or younger. In this analysis, I drop children aged 2 or 3 in the 2007 wave because their parents could have been eligible for PFL when the policy was first implemented in 2004. I compare infants to children between ages 2 and 17 for most outcomes (aged 2-3 only in 2003 in California).[15]

Although there may be differences between parents with infants and parents with older children, the validity of the DDD model relies on the assumption that in the absence of PFL, the difference in outcomes between parents of infants and parents of older children in California after PFL would have been similar to the difference in outcomes between parents of infants and parents of older children in the comparison states before PFL was implemented. Appendix Table 2 shows there are very few differences in observable characteristics between these two groups. This comparison confirms that the DDD approach between these groups is likely valid.

Finally, I compare the effects by household income. Research suggests that California's PFL program had a larger impact on less educated, lower skilled, unmarried, and black mothers (Byker, 2016; Rossin-Slater et al., 2013). Additionally, the introduction of TDI in the United States had the largest impacts on birth outcomes for children of less advantaged populations (Stearns, 2015). For these reasons, California's PFL program may have had larger health benefits on infants from less advantaged families. To test for heterogeneous effects across socioeconomic status, I employ equation (2) on two subsamples: children in households with incomes less than/greater than 150% the federal poverty line (FPL).[16] This model captures the differential effect of PFL for infants in low-income households relative to infants in high-income households.

4.2 Interpretation

New parents are only eligible for PFL if they worked throughout most of the previous year. Unfortunately, in the NSCH I do not observe who was employed (only that someone in the household was employed for at least 50 of the last 52 weeks), a parent's employment history, whether a parent took family leave, or if leave a parent took was paid

[15] The exceptions are reading stories to children 4+ days per week and any child care in the past month, in which the comparison is children aged 2-5.

[16] I also divide this variable at other income points (e.g. <=300% FPL, <=200% FPL, and <=133% FPL). The results are substantively similar.

for through the state program. Given this lack of detailed data, the presented results represent intent-to-treat (ITT) estimates – which are informative for understanding the population-level impact of a policy change – where eligibility for PFL is having a child after PFL implementation and take-up refers to actually taking paid family leave.

Since some parents in the treatment group would not have been eligible for PFL (e.g. those not in the labor market), I understate the treatment-on-the-treated (TOT) effects. Based on previous year employment from 1999-2004, 59.6 percent of California mothers with a child under age one would have been eligible for PFL before the program's enactment (Rossin-Slater, Ruhm, and Waldfogel, 2013). About 35 percent of eligible mothers actually take paid leave.[17] The ITT effects should then be scaled by 1.67 (1/0.60) and 4.76 (1/0.60*0.35) to represent the lower and upper bound of TOT effects.

4.3 Statistical Inference

A standard approach to estimating a DD analysis is to cluster standard errors at the treatment level (Bertrand et al., 2004). In this context, I would cluster standard errors at the child age-state level. When comparing California infants to infants in neighboring or other big states, however, there are only 10 child age-state clusters (2 age groups*5 states). Therefore, clustering at the age-state level yields too few clusters for statistical inference and over-rejection of the null may still be a concern (Donald and Lang, 2007; Conley and Taber, 2011; MacKinnon and Webb 2016a; Cameron and Miller, 2015).

Instead, I calculate p-values using the wild cluster bootstrap resampling method with 1,000 replications, proposed by Cameron, Gelbach, and Miller (2008), which performs well with a small number of clusters. When there are fewer than twelve clusters, I apply the 6-point distribution suggested by Webb (2014) and MacKinnon and Webb (2016a). When comparing California infants to all other infants across the U.S., there are 102 clusters (2 age groups*51 states) so I use Rademacher weights suggested by Cameron, Gelbach, and Miller (2008). There are then two treated clusters in this analysis – California

[17] These numbers come from program statistics, which can be found on California's Employment Development Department website: http://www.edd.ca.gov/Disability/pdf/qspfl_PFL_Program_Statistics.pdf , the number of births in California from vital statistics, and California women's labor force participation rates from March Census Current Population Survey data.

infants aged 0 and California infants aged 1. With clusters approximately the same size, the problem of under-rejection with only one treated cluster (MacKinnon and Webb, 2016a) and varying cluster sizes (Carter, Schnepel, and Steigerwald, 2015; MacKinnon and Webb, 2016b) is alleviated. Taking care in these steps allows individuals to be dependent within age groups and states, relaxing the required ordinary least squares assumption that individuals are independent and identically distributed (Cameron and Miller, 2015), producing approximately valid estimates for inference.[18]

5 Results

5.1 Descriptive Statistics

Table 2 presents summary statistics of the sample. In general, infants and their households in California are worse off in both health and socioeconomic status than their neighbors, peers in other big states, and those across the country. Compared to 2003, in 2007, the NSCH sample of parents is more highly educated, higher income, and the focal child is more likely to be the oldest child in the family. Since these changes occurred across nearly all groups, it is unlikely they are the result of PFL. Indeed, Pihl and Basso (2019) and Rossin-Slater, Ruhm, and Waldfogel (2013) do not find any evidence that PFL changed overall fertility or the composition of new mothers.

5.2 Effect of PFL on Children's Health

The effects of PFL on children's health are shown in Table 3. The DD coefficients are reported first for each outcome, followed by the DDD coefficients. According to the DD coefficients (column 1), PFL improved the overall parent-reported health status of infants in California relative to infants in neighboring states, infants in other large states, and infants across the country. Specifically, the percent of parents reporting that their child is in very good or excellent overall health increased by between 4.8 (Panel B) and 8.6 (Panel A) percentage points, which is about a 5-10 percent increase relative to the pre-PFL

[18] Additionally, I estimate probit models for the binary variables and a Poisson model for the number of times a child visits a health care professional. Results are substantively similar (see Appendix Table 3).

mean. The magnitude of the coefficients is similar across all control groups, suggesting robustness in these estimates.

The DDD coefficients (column 2) are consistent with the DD estimates, albeit slightly attenuated, implying an increase of between 1.9 and 5.2 percentage points, or about 2-6 percent. To obtain the TOT effect, I scale the estimate by 1.67 and 4.76 to represent the lower and upper bound. The smallest estimates (Panel B) imply a TOT increase of between 3 and 9 percentage points. The largest estimates (Panel A) imply a TOT increase of between 8 and 25 percentage points.

Columns 3 through 8 of Table 3 suggest reductions in the rate of parent-reported asthma and respiratory allergies[19] and an increase in food allergies. The significance of these results depends, however, upon the selected control group. The large relative percent change for these outcomes is likely magnified by the small denominator.

Importantly, the improvements in children's health are not the result of better birth outcomes. In Appendix Table 4, I present results from vital statistics birth certificate data showing no effects of California's PFL on the likelihood of low birth weight and preterm birth, birth weight, or gestation length.

To put the child health findings in perspective, I compare them to previous estimates in the literature. Baker and Milligan (2008) study the effects of increasing paid parental leave from 25 weeks to 50 weeks in Canada. Although there were no statistically significant effects of the extension on children's health, the magnitude of their point estimates suggests improvements in parent-reported children's health status by about 9 percent, and reductions in the incidence of asthma by about 80 percent, allergies by about 43 percent, and bronchitis by about 75 percent. Additionally, Pihl and Basso (2019) find reductions in infant hospitalizations from upper respiratory infections – the most extreme cases – by 33 percent. The observed estimates are in line with what would be expected given these earlier results.

5.3 Effect of PFL on Potential Mechanisms

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[19] Since air pollution significantly affects asthma, particularly among children of lower socio-economic status (Neidell, 2004), the study period avoids confounding from air quality improvement regulations implemented by the California Air Resources Board in 2007 (Su et al., 2016).

I begin by examining the parental health and well-being potential mechanism. Since the causal relationship between paid family leave and parental mental health status in the United States is unknown, this mechanism is also an important health outcome of policy interest. Two data sources help study this relationship: the BRFSS and the NSCH.

Using a sample of employed females aged 21-40 with at least one child from the BRFSS, column 1 of Table 4 provides evidence of a 1-2 percent improvement in self-reported mental health. In 2006, 21.8 percent of employed mothers aged 21-40 are mothers of infants under age 2.[20] When scaling the BRFSS estimates by this figure, the BRFSS sample would then imply a 5.5 to 9 percent ITT improvement in maternal mental health.[21]

Using an arguably more appropriate group – parents of infants – from the NSCH yields stronger effects on maternal mental health. The DD estimates in column 2 show an increase of roughly 7-17 percentage points in the likelihood that maternal mental health status is in very good or excellent condition. These estimates equate to a roughly 10-24 percent ITT improvement in maternal mental health status. Though less precise and smaller in magnitude than the DD estimates, the DDD estimates in column 3 suggest positive improvements in maternal mental health status (2-4 percentage points or roughly 3-6 percent). I find no statistically significant effect on father's mental health (columns 4 and 5). PFL having an impact on mother's mental health but not father's mental health is not surprising since mothers are more likely to both take paid leave under California's PFL program and take longer leaves than fathers.[22] Finally, columns 6 and 7 report increases of between 3-5 percentage points (4-8 percent) in the likelihood that parents report they are coping very well with the day-to-day demands of parenting.

The improvements in maternal health are consistent with Chatterji and Markowitz (2012). They show that extending maternity leaves to beyond 8 or 12 weeks is associated

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[20] Author's calculations using the 2006 American Community Survey. Eleven percent of mothers in this sample are mothers of infants under age 1.

[21] I limit the BRFSS sample to employed mothers aged 21-40. Employment after PFL implementation, however, is endogenous. For this reason, and since I do not know the child's age, the BRFSS analysis is merely a supplement to the NSCH analysis. The BRFSS also allows analysis of parallel pre-trends as discussed in section 4.1.

[22] 80 percent of California's paid family leave claims were from women and 90 percent were for caring for a newborn. Mothers extended their leaves from 3 weeks, on average, to 6-8 weeks, on average (Baum and Ruhm, 2016; Rossin-Slater et al., 2013), and fathers extended their leaves by roughly one week (Baum and Ruhm, 2016).

with a reduction in the number of maternal depressive symptoms by 9-15 percent. The estimates presented here differ, however, from those found after Canada's parental leave expansion. Although statistically insignificant, Baker and Milligan's (2008) point estimates suggest Canada's paid family leave extension from 25 to 50 weeks increased mothers' scores on a depression index by about 7 percent. Cumulatively, the findings from these studies may shed light on the optimal leave length for maternal mental health.

Results for the potential mechanism of parental care and engagement are in Table 5. The survey question for nonparental care asked respondents if their child received any child care for at least ten hours in the past month. For this reason, in the childcare analysis I limit the treatment group to parents in California with infants under age 1, resulting in a smaller sample size. Overall, when comparing infants under age 1 in California to infants under age 1 in other states, I find PFL reduced nonparental child care in the past month between 3 and 6 percentage points (columns 1 and 2), or about 7-12 percent when compared to the pre-PFL mean. The DDD estimates – in which the third difference is children aged 2-5 rather than 2-17 – imply larger effects of roughly 21-35 percent, though the coefficients are imprecisely measured.

If parents have more time following the birth of a child, they may be more likely to seek medical care for their child, if necessary. To test this alternative theory, I would ideally study preventive care utilization, such as well-baby visits. Unfortunately, NSCH does not have consistently measured data on preventive care utilization, so I instead estimate the effect of PFL on the number of visits to a health professional in the past year. Columns 3 and 4 in Table 5 produce mixed results, though the DD estimates suggest a reduction in the number of visits to a health professional. This result may not be unexpected given the way this variable is measured. On one hand, PFL provides parents time off work, potentially allowing their child more frequent healthcare visits. On the other hand, if PFL improves infant health through other mechanisms, there may be fewer reasons to visit a health professional.

Finally, longer maternity leaves may also improve the quality of parenting, though this is an area of research that is understudied. Since an additional year of daily mother-child reading improves children's reading test scores in elementary school (Price, 2010), I use a proxy for parental engagement by measuring whether a parent or family member reads to the child four or more days per week. Columns 5 and 6 suggest infants are 5-10 percentage points (10-20 percent) more likely to be read to four or more times per week.

I am unable to conduct a full analysis on all potential mechanisms. Nonetheless, the results from Tables 4 and 5 suggest that two possible mechanisms through which paid family leave in California improved child health and well-being are better parental mental health status and delayed entry to nonparental child care. Additionally, there may be greater parental engagement (as measured through reading) and a short-run income boost (from previous literature). Although I cannot pinpoint which of these mechanisms is responsible for the improvements in children's health – noting that it may be a combination of them or an alternative channel not examined in this study – each of these conduits is justified through evidence or the literature, and all may plausibly be behind the improvements in children's health.

5.4 Effect of PFL by Household Income

Table 6 shows the subgroup effects of PFL in California on households with high and low incomes (<=150% FPL). I find differential effects of PFL for low-income households relative to high-income households for parental well-being, nonparental childcare and reading stories. Specifically, as a result of PFL, parents in low-income households were more likely to report improvements in maternal mental health and the ability to cope with day-to-day demands of parenting. Children in low-income households were less likely to be cared for by a parent than children in high-income households,[23] but more likely to be read to four or more times per week. These results are mostly consistent with previous studies suggesting PFL in California had a stronger effect on mothers of disadvantaged socioeconomic status, who previously could not afford to take unpaid leave after the birth of a child (Byker, 2016; Rossin-Slater, Ruhm, and Waldfogel, 2013).

6 Robustness Checks

[23] Note that this measure is different than leave-taking, per se. This variable measures whether a child had any childcare for 10 or more hours per week in the past month, where the sample is limited to children under age 1.

As discussed earlier, the standard approach of clustering standard errors at the treatment level produces too few clusters. Without additional corrections, the standard errors are too small making statistical inference less straightforward. I initially control for this issue by implementing a wild cluster bootstrap. To further mitigate this concern, I use a more conservative approach to statistical inference by implementing a variation of Fisher's (1935) permutation test, suggested by Conley and Taber (2011).

I conduct this exercise by constructing a distribution of all possible values of the test statistic for many permutations of the data, which can be obtained by substituting all other states plus the District of Columbia independently into equation (1). Since no other state implemented PFL at the same time as California, the magnitude of PFL's effect on child and parental health should not be the same for other states. Instead of comparing California's estimate to its conventional asymptotic standard error, I compare California's estimate to the distribution of the 50 placebo estimates. In this way, the 50 placebo estimates are the sampling distribution for β_1. The null hypothesis is that the difference between the change in child and parental health and well-being in California during the study time period and the change in all other states is zero. This approach yields more conservative confidence intervals than those found earlier.

Each panel in Figure 2 consists of a histogram of a child health outcome of the 50 placebos and California's estimate. The dashed lines represent the 5^{th} and 95^{th} percentiles – constructing the 90 percent confidence interval – and the solid black line represents the observed estimate presented earlier for California. For both overall very good child health and food allergies, California's estimate is in the positive tail of the distribution. Although the observed reductions in asthma and respiratory allergies are in the negative end of the distribution, they are not in the tails. These results provide additional evidence that PFL in California improved overall parent-reported infant health.

The placebo tests also bolster the original findings for the mechanisms. The observed estimate for improved maternal mental health is deep in the positive tail of the placebo distribution, but father's mental health is not (Figure 3). Figure 4 provides support for a greater likelihood of being read to four or more days per week.[24] These results

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[24] For this measure, the solid black line (California) and the dashed line (90% CI) are the same line.

corroborate the original findings that – among those examined here – improved maternal mental health and greater parental care and engagement are potential mechanisms through which PFL improves children's health.

7 Conclusions

Research suggests that California's paid family leave policy – which expanded eligibility and extended the length of leave from six to twelve weeks – has improved maternal employment outcomes and wages and placed little to no financial burden on employers. This study estimates the impact of California's paid family leave program on the health and well-being of infants and their parents. Findings suggest that having access to PFL likely improves overall child health and maternal mental health status. Improvements may be a result of delayed entry to nonparental child care, greater parental care and engagement, and improved economic well-being, among other potential mechanisms not explored in this study.

The results of this study add to previous research on the effects of maternity leave on child and maternal health, largely using Europe and Canada as examples. They also contribute to a growing literature on the impacts of state-level PFL programs. By incorporating elements of both parental and infant health, this study extends our understanding of PFL beyond labor market effects and may offer a more complete cost-benefit analysis of these policies. The results also contribute to the much larger literature studying how public policies can affect early-life conditions.

Several states have legislation proposed for some kind of paid leave, and a national PFL program is almost always in public discussion. As more states become interested in adopting their own paid family leave policies and existing programs make changes, these results should prove useful in both designing a program and evaluating the costs and benefits. This research also more broadly expands our understanding of public policies that may improve maternal and child health, particularly early in life.

Data constraints limit this study to a short study period and a small set of parent-reported health measures. Insurance claims, health records, administrative data, and other, detailed non-survey data will further enhance our understanding of the health effects of PFL. Also due to data limitations, I am unable to identify a parent's employment status.

Isolating PFL eligibility based on employment history will be an important component of future PFL analyses. Finally, the health and well-being of parents during and immediately following pregnancy have a substantial causal impact on infant health, which in turn affects long-term outcomes for children (Aizer and Currie, 2014; Almond and Currie, 2011; Currie and Almond, 2011) and raises the productivity of later human capital investments (Heckman, 2007; Cunha and Heckman, 2007). The estimated benefits of PFL presented here do not include long term health and financial benefits that may accumulate as a result of improved health during infancy. Future research should determine the extent to which these health improvements may impact later-life outcomes.

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Table 1. Paid Family Leave Policy Characteristics[25]

	California[26]	New Jersey[27]	Rhode Island[28]	New York[29]	Washington D.C.	Washington	Massachusetts
Effective Year	2004	2009	2014	2018	2020	2019	2019
Maximum length for family leave	6 weeks	6 weeks	4 weeks	8 weeks in 2018; 10 weeks in 2019; 12 weeks in 2021	8 weeks	12 weeks	12 weeks
Employee eligibility	Must have been paid $300 in gross wages during the base period[30]	Must have had at least 20 calendar weeks of covered NJ employment, each being a week of being paid $168 or more, or $8,400+ during base period	Must have been paid wages in RI and paid into the TDI/TCI fund and must have been paid at least $12,120 in the base period	Must have been employed for 26 consecutive weeks	Must spend 50% of work time in DC & been employed for some of the 52 preceding weeks	Must have worked for 820 hours in 4 out of 5 quarters prior to leave	Must have earned $4,700 in the last 4 quarters and at least 30 times the weekly unemployment benefit amount
Size of employer covered	All private sector employers	Private and public sector employers covered by the NJ Unemployment Compensation Law	All private sector employers	Most private sector employers	Private sector employers covered by D.C. Unemployment Compensation Act	All employers	All private employers and the state government
Job protection for family leave	No	No	Yes	Yes	No	No	Yes
Benefit Amount	Earnings less than 1/3 state average: 70% weekly wage; More than 1/3 state	66% of worker's average weekly wage	4.62% of wages paid during highest quarter of base period	50% of worker's average weekly wage	Earnings less than 1.5 minimum wage*40: 90%	Earnings less than state average: 90% of worker's	Earnings less than state average: 80% of worker's

[25] For more details about PFL programs, see the National Partnership for Women and Families State Paid Family Leave Insurance Laws (updated July 2018): http://www.nationalpartnership.org/our-work/resources/workplace/paid-leave/state-paid-family-leave-laws.pdf
[26] More information about California's PFL program is available here: https://www.edd.ca.gov/disability/about_pfl.htm
[27] More information about New Jersey's Family Leave Insurance (FLI) program is available here: https://myleavebenefits.nj.gov/
[28] More information about Rhode Island's Temporary Caregiver Insurance (TCI) program is available here: http://www.dlt.ri.gov/tdi/
[29] More information about New York's Paid Family Leave program is available here: https://paidfamilyleave.ny.gov/
[30] The base period for California is the past four consecutive quarters (approximately 5 to 18 months before the leave begins). New Jersey defines the base period as the 52 weeks immediately before the week in which the leave begins. Rhode Island defines the base period as the first four of the last five completed calendar quarters before the leave begins.

	average: 60% weekly wage[31]			(AWW) in 2018; 55% workers' AWW in 2019; 60% worker's AWW in 2020; 67% worker's AWW in 2021	average weekly wage (AWW); More than 1.5 minimum wage*40: 90%*1.5 minimum wage*40+50% of the difference between AWW and 1.5 minimum wage*40	average weekly wage (AWW); More than state average: 90% of worker's AWW up to 50% of state AWW + 50% of worker's AWW that exceeds 50% of state AWW	average weekly wage (AWW); More than state average: 80% of worker's AWW up to 50% of state AWW + 50% of worker's AWW that exceeds 50% of state AWW
Maximum Weekly Benefit (as of January 2019)	$1,216	$650	$831	$746	$1,000	$1,000	$850
Average Weekly Benefit	$674 (August 2018)[32]	$524 (2016)[33]	$540 (November 2018)[34]	N/A	N/A	N/A	N/A

[31] When California's program was first implemented, the benefit amount was 55 percent of an employee's weekly wage.
[32]California Employment Development Department Paid Family Leave Program Statistics: https://www.edd.ca.gov/about_edd/Quick_Statistics.htm
[33] New Jersey Department of Labor and Workforce Development (2017). Family Leave Insurance Workload in 2016 Summary Report: https://www.nj.gov/labor/forms_pdfs/tdi/FLI%20Summary%20Report%20for%202016.pdf
[34]Rhode Island Department of Labor and Training TDI Annual Update: http://www.dlt.ri.gov/lmi/pdf/tdi/current.pdf

Table 2. Descriptive Statistics

	Treatment (California)		Control A (Neighboring States)		Control B (Other Big States)		Control C (All Other States)	
	Pre-PFL (2003)	Post-PFL (2007)	Pre-PFL (2003)	Post-PFL (2007)	Pre-PFL (2003)	Post-PFL (2007)	Pre-PFL (2003)	Post-PFL (2007)
Outcomes								
Very Good Overall Child Health	82.2%	90.9%	88.4%	88.8%	90.2%	92.7%	91.3%	91.9%
Asthma	5.8%	3.0%	2.5%	2.9%	4.7%	5.1%	3.6%	3.7%
Has a Food Allergy	3.1%	7.4%	6.8%	6.5%	5.9%	6.6%	6.4%	6.7%
Has a Respiratory Allergy	3.1%	0.6%	5.2%	4.4%	5.9%	5.6%	5.9%	6.1%
Parental Health								
Very Good Mental Health - Mother	71.6%	80.5%	78.8%	78.9%	81.2%	77.2%	81.7%	80.9%
Very Good Mental Health - Father	76.7%	82.2%	83.1%	82.1%	85.3%	83.3%	86.1%	86.2%
Coping Very Well with Day-to-Day Demands	66.7%	70.1%	72.9%	70.9%	72.4%	72.1%	74.5%	72.4%
Child Rearing								
Any Nonparental Childcare in Past Month	52.0%	40.9%	42.9%	41.0%	52.0%	50.7%	52.4%	50.9%
Visits to Health Professional in Last Year	4.6	4.3	4.5	4.4	5.0	4.8	4.7	4.7
Read Stories To 4+ Days Per Week	54.2%	65.2%	59.6%	63.6%	62.6%	63.6%	65.3%	67.7%
Household Characteristics								
Household Income Under 150% FPL	36.9%	29.3%	28.2%	25.6%	29.8%	27.5%	25.3%	22.7%
Someone in Household Employed	87.6%	86.6%	90.9%	88.7%	92.0%	89.7%	91.7%	91.2%
Highest Grade: Less than High School	12.0%	12.8%	5.7%	8.6%	5.3%	8.1%	3.9%	6.0%
Highest Grade: High School Graduate	24.0%	12.8%	21.6%	15.5%	19.6%	14.8%	19.2%	14.0%
Highest Grade: Greater than High School	64.0%	74.4%	72.7%	76.0%	75.1%	77.1%	76.9%	80.0%
Primary Language at Home Not English	31.6%	29.3%	18.3%	15.3%	16.0%	20.4%	8.9%	8.6%
Number of Adults in Household	2.2	2.2	2.1	2.1	2.1	2.2	2.1	2.1
Child Characteristics								
Child Age (Years)	0.6	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Child is the Oldest	54.2%	60.4%	55.1%	52.9%	55.3%	55.4%	57.8%	55.0%
Child is Male	48.9%	57.3%	51.8%	53.9%	48.1%	54.2%	51.3%	51.8%
Child has Health Insurance	94.7%	92.1%	90.3%	91.7%	95.9%	92.8%	95.2%	95.0%
State Characteristics								
Unemployment Rate	6.8%	5.4%	6.6%	4.5%	6.0%	4.4%	5.6%	4.3%
Poverty Rate	13.1%	12.7%	12.4%	11.6%	13.6%	13.5%	11.8%	11.8%
Percent Married	53.7%	52.9%	56.4%	54.8%	55.0%	54.1%	56.3%	55.3%
Percent Divorced	9.0%	9.3%	12.2%	12.3%	9.3%	9.5%	10.2%	10.5%
Percent Single	29.6%	30.1%	24.1%	25.6%	26.0%	27.0%	25.1%	26.0%
Percent Other Marital Status	7.7%	7.7%	7.2%	7.3%	9.7%	9.5%	8.4%	8.2%
N	389		1,581		1,511		18,569	

Notes: Data from National Survey of Children's Health, 2003 and 2007 waves. The sample is limited to children aged 0-1 and their parents. The sample size for father's mental health in the treatment group is 335, and 1377, 1241, and 15920, respectively in each control group.

Table 3. Effect of PFL on Child Health and Well-being

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Very Good Overall Children's Health		Asthma		Food Allergy		Respiratory Allergy	
Sample	≤ Age 1	Age 0-17	≤ Age 1	Age 0-17	≤ Age 1	Age 0-17	≤ Age 1	Age 0-17
Mean Y for Treat in Pre	82.2%		5.8%		3.1%		3.1%	
Model	DD	DDD	DD	DDD	DD	DDD	DD	DDD
Panel A: Infants (0-1) in Neighboring States								
DD or DDD Coefficient	0.086	0.052	-0.029	-0.047	0.053	0.042	-0.007	-0.011
Cluster Robust P-value	(0.000)	(0.006)	(0.173)	(0.044)	(0.086)	(0.128)	(0.558)	(0.570)
Wild Cluster Bootstrap P-value	[0.016]	[0.018]	[0.232]	[0.025]	[0.106]	[0.193]	[0.337]	[0.278]
Number of Clusters	10	90	10	90	10	90	10	90
Relative Percent Change	10.5%	6.3%	-50.2%	-81.3%	169.6%	134.4%	-22.5%	-35.4%
N	1970	15218	1970	15218	1961	15190	1965	15189
Panel B: Infants (0-1) in Other Large States								
DD or DDD Coefficient	0.048	0.019	0.021	-0.057	0.019	0.032	-0.024	-0.045
Cluster Robust P-value	(0.169)	(0.366)	(0.594)	(0.030)	(0.586)	(0.258)	(0.031)	(0.044)
Wild Cluster Bootstrap P-value	[0.070]	[0.208]	[0.275]	[0.023]	[0.223]	[0.201]	[0.015]	[0.025]
Number of Clusters	10	90	10	90	10	90	10	10
Relative Percent Change	5.8%	2.3%	36.3%	-98.7%	60.8%	102.4%	-77.1%	-144.6%
N	1900	15588	1900	15588	1894	15560	1899	15557
Panel C: Infants (0-1) in All States Except California								
DD or DDD Coefficient	0.074	0.050	-0.027	-0.050	0.039	0.033	-0.025	-0.020
Cluster Robust P-value	(0.000)	(0.003)	(0.013)	(0.007)	(0.090)	(0.158)	(0.004)	(0.248)
Wild Cluster Bootstrap P-value	[0.012]	[0.026]	[0.253]	[0.017]	[0.244]	[0.258]	[0.152]	[0.143]
Number of Clusters	102	918	102	918	102	918	102	918
Relative Percent Change	9.0%	6.1%	-46.7%	-86.5%	124.8%	105.6%	-80.4%	-64.3%
N	18958	157161	18958	157161	18902	156938	18925	156839

Notes: Data from National Survey of Children's Health, 2003 and 2007 waves. Models include state FE, year FE, individual-level covariates, and state-level covariates. In all cases, the treatment group consists of infants aged 0-1 in California. In the DD analysis, the control group is infants aged 0-1 in other states. In the DDD analysis, the third difference is older children aged 2-17. Neighboring states include: Nevada, Oregon, Arizona, and Washington. Other large states include Texas, Florida, New York, and Pennsylvania. I use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values in brackets clustered at child age-state level. For models with more than 12 clusters, I use Rademacher weights suggested by Cameron, Gelbach, and Miller (2008). For models with fewer than 12 clusters, I use the 6-point distribution recommended by Webb (2014). Relative percent changes are calculated by dividing the coefficient estimate by the mean of the dependent variable pre-policy. Significance stars omitted due to differing results depending on p-values used.

Table 4. Effect of PFL on Parental Health

	BRFSS	NSCH					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome	Percent Days Mental Health Was Good	Very Good Mental Health - Mother		Very Good Mental Health - Father		Coping Very Well with Day-to-Day Demands	
Sample	Employed Mothers Aged 21-40	Parents of Infants (0-1)	Parents of Children (0-17)	Parents of Infants (0-1)	Parents of Children (0-17)	Parents of Infants (0-1)	Parents of Children (0-17)
Mean Y for Treat in Pre	84.4%	71.6%		76.7%		66.7%	
Model	DD	DD	DDD	DD	DDD	DD	DDD
Panel A: Neighboring States							
DD or DDD Coefficient	0.0099	0.076	0.019	0.043	-0.008	0.042	0.053
Cluster Robust P-value	(0.232)	(0.003)	(0.472)	(0.257)	(0.883)	(0.195)	(0.110)
Wild Cluster Bootstrap P-value	[0.142]	[0.043]	[0.238]	[0.257]	[0.457]	[0.333]	[0.066]
Number of Clusters	35	10	90	10	90	10	90
Relative Percent Change	1.2%	10.6%	2.7%	5.6%	-1.0%	6.3%	7.9%
N	15139	1970	15218	1712	12193	1970	15218
Panel B: Other Large States							
DD or DDD Coefficient	0.0170	0.177	0.043	0.053	0.001	0.056	0.028
Cluster Robust P-value	(0.030)	(0.002)	(0.116)	(0.298)	(0.986)	(0.065)	(0.403)
Wild Cluster Bootstrap P-value	[0.026]	[0.000]	[0.071]	[0.186]	[0.505]	[0.380]	[0.201]
Number of Clusters	35	10	90	10	90	10	90
Relative Percent Change	2.0%	24.7%	6.0%	6.9%	0.1%	8.4%	4.2%
N	17606	1900	15588	1576	11846	1900	15588
Panel C: All States Except California							
DD or DDD Coefficient	0.0109	0.086	0.019	0.036	-0.017	0.053	0.051
Cluster Robust P-value	(0.087)	(0.000)	(0.386)	(0.421)	(0.723)	(0.000)	(0.043)
Wild Cluster Bootstrap P-value	[0.094]	[0.000]	[0.196]	[0.258]	[0.352]	[0.000]	[0.029]
Number of Clusters	357	102	918	102	918	102	918
Relative Percent Change	1.3%	12.0%	2.7%	4.7%	-2.2%	7.9%	7.6%
N	143092	18958	157161	16255	125576	18958	157161

Notes: Data from Behavioral Risk Factor Surveillance System 2001-2007 and National Survey of Children's Health, 2003 and 2007 waves. Models include state FE, year FE, individual-level covariates, and state-level covariates. Using the BRFSS data, the treatment group consists of employed mothers aged 21-40 in California. Using the NSCH, the treatment group consists of parents with infants aged 0-1 in California. In the DD analysis, the control group is parents with infants aged 0-1 in other states. In the DDD analysis, the third difference is parents of older children aged 2-17. Neighboring states include: Nevada, Oregon, Arizona, and Washington. Other large states include Texas, Florida, New York, and Pennsylvania. I use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values in brackets clustered at the state-year level in BRFSS and the child age-state level in NSCH. For models with more than 12 clusters, I use Rademacher weights suggested by Cameron, Gelbach, and Miller (2008). For models with fewer than 12 clusters, I use the 6-point distribution recommended by Webb (2014). Relative percent changes are calculated by dividing the coefficient estimate by the mean of the dependent variable pre-policy. Significance stars omitted due to differing results depending on p-values used.

Table 5. Effect of PFL on Other Potential Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
Potential Mechanism	Non-Parental Childcare		Healthcare Utilization		Parental Engagement	
Measurement	Any Child Care in Past Month		Visits to Health Professional in Past Year		Read Stories 4+ Days	
Sample	< Age 1	Age 0, 2-5	≤ Age 1	Age 0-17	≤ Age 1	Age 0-5
Mean Y for Treat in Pre	52.0%		4.6		54.2%	
Model	DD	DDD	DD	DDD	DD	DDD
Panel A: Neighboring States						
DD or DDD Coefficient	-0.056	-0.186	-0.007	-0.187	0.106	0.058
Cluster Robust P-value	(0.000)	(0.055)	(0.979)	(0.371)	(0.013)	(0.292)
Wild Cluster Bootstrap P-value	[0.056]	[0.229]	[0.483]	[0.237]	[0.263]	[0.195]
Number of Clusters	5	25	10	90	10	30
Relative Percent Change	-10.8%	-35.8%	-0.2%	-4.0%	19.5%	10.7%
N	961	4616	1892	13724	1965	4599
Panel B: Other Large States						
DD or DDD Coefficient	-0.035	-0.112	-0.541	0.112	0.090	0.068
Cluster Robust P-value	(0.015)	(0.244)	(0.080)	(0.531)	(0.054)	(0.176)
Wild Cluster Bootstrap P-value	[0.000]	[0.276]	[0.068]	[0.278]	[0.004]	[0.188]
Number of Clusters	5	25	10	90	10	30
Relative Percent Change	-6.7%	-21.5%	-11.7%	2.4%	16.6%	12.5%
N	913	4575	1820	14399	1891	4554
Panel C: All States Except California						
DD or DDD Coefficient	-0.063	-0.128	-0.291	-0.076	0.082	0.076
Cluster Robust P-value	(0.000)	(0.134)	(0.007)	(0.588)	(0.023)	(0.075)
Wild Cluster Bootstrap P-value	[0.000]	[0.463]	[0.090]	[0.330]	[0.276]	[0.220]
Number of Clusters	51	255	102	918	102	306
Relative Percent Change	-12.1%	-24.6%	-6.3%	-1.6%	15.1%	14.0%
N	9260	45076	18362	145659	18874	44901

Notes: Data from National Survey of Children's Health, 2003 and 2007 waves. Models include state FE, year FE, individual-level covariates, and state-level covariates. For visits to a health professional and reading, the treatment group consists of children aged 0-1 in California. For child care, the treatment group consists of children under age 1 in California. In the DD analysis, the control group is infants aged 0-1 in other states. In the DDD analysis, the third difference is older children aged 2-17. Neighboring states include: Nevada, Oregon, Arizona, and Washington. Other large states include Texas, Florida, New York, and Pennsylvania. I use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values in brackets clustered at child age-state level. For models with more than 12 clusters, I use Rademacher weights suggested by Cameron, Gelbach, and Miller (2008). For models with fewer than 12 clusters, I use the 6-point distribution recommended by Webb (2014). Relative percent changes are calculated by dividing the coefficient estimate by the mean of the dependent variable pre-policy. Significance stars omitted due to differing results depending on p-values used.

Table 6. Effect of PFL on California Parents with Infants by Income Level

Child Health and Well-being

	Very Good Overall Children's Health			Asthma			Food Allergy			Respiratory Allergy		
	(1) <=150% FPL	(2) >150% FPL	(3) P-value for Difference	(4) <=150% FPL	(5) >150% FPL	(6) P-value for Difference	(7) <=150% FPL	(8) >150% FPL	(9) P-value for Difference	(10) <=150% FPL	(11) >150% FPL	(12) P-value for Difference
Panel A: Neighboring States												
DDD Coef	0.037	0.065	0.729	-0.039	-0.043	0.933	0.031	0.050	0.716	-0.004	-0.016	0.752
Cluster Robust P-value	(0.607)	(0.001)		(0.362)	(0.108)		(0.245)	(0.206)		(0.897)	(0.519)	
N	3579	11639		3579	11639		3576	11614		3574	11615	
Panel B: Other Large States												
DDD Coef	0.149	-0.006	0.293	-0.217	0.118	0.447	0.156	-0.106	0.004	-0.184	-0.118	0.635
Cluster Robust P-value	(0.213)	(0.959)		(0.592)	(0.421)		(0.266)	(0.347)		(0.028)	(0.376)	
N	565	1335		565	1335		565	1329		565	1334	
Panel C: All Other States												
DDD Coef	0.069	0.074	0.944	-0.044	-0.022	0.108	0.016	0.052	0.351	0.005	-0.040	0.000
Cluster Robust P-value	(0.264)	(0.000)		(0.000)	(0.127)		(0.093)	(0.123)		(0.527)	(0.001)	
N	4611	14347		4611	14347		4602	14300		4602	14323	

Parental Well-being

	Very Good Mental Health - Mother			Very Good Mental Health - Father			Coping Very Well with Day-to-Day Demands		
	(1) <=150% FPL	(2) >150% FPL	(3) P-value for Difference	(4) <=150% FPL	(5) >150% FPL	(6) P-value for Difference	(7) <=150% FPL	(8) >150% FPL	(9) P-value for Difference
Panel D: Neighboring States									
DDD Coef	0.103	-0.015	0.044	0.138	-0.050	0.085	-0.050	0.090	0.021
Cluster Robust P-value	(0.057)	(0.586)		(0.263)	(0.128)		(0.336)	(0.024)	
N	3579	11639		2240	9953		3579	11639	
Panel E: Other Large States									
DDD Coef	0.349	-0.245	0.207	0.875	-0.191	0.117	1.138	-0.126	0.000
Cluster Robust P-value	(0.378)	(0.071)		(0.160)	(0.185)		(0.001)	(0.364)	
N	565	1335		374	1202		565	1335	
Panel F: All Other States									

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DDD Coef	0.179	0.049	0.000	0.150	0.003	0.034	0.090	0.034	0.091
Cluster Robust P-value	(0.000)	(0.000)		(0.105)	(0.902)		(0.002)	(0.000)	
N	4611	14347		3078	13177		4611	14347	

	Other Potential Mechanisms								
	Any Child Care in Past Month			Visits to Health Professional in Past Year			Read Stories 4+ Days		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	<=150% FPL	>150% FPL	P-value for Difference	<=150% FPL	>150% FPL	P-value for Difference	<=150% FPL	>150% FPL	P-value for Difference
Panel G: Neighboring States									
DDD Coef	0.205	-0.285	0.000	-0.574	-0.047	0.364	0.202	-0.008	0.018
Cluster Robust P-value	(0.144)	(0.002)		(0.171)	(0.880)		(0.015)	(0.893)	
N	979	2628		3026	10698		1266	3333	
Panel H: Other Large States									
DDD Coef	-1.271	-0.299	0.000	-2.686	-0.078	0.079	0.495	-0.133	0.007
Cluster Robust P-value	(0.011)	(0.006)		(0.209)	(0.917)		(0.019)	(0.190)	
N	258	655		520	1300		563	1328	
Panel I: All Other States									
DDD Coef	0.213	-0.170	0.000	-0.426	-0.194	0.494	0.206	0.031	0.000
Cluster Robust P-value	(0.121)	(0.061)		(0.011)	(0.363)		(0.000)	(0.464)	
N	2247	7013		4298	14064		4576	14298	

Notes: Data from National Survey of Children's Health, 2003 and 2007 waves. Models include state FE, year FE, individual-level covariates, and state-level covariates. For visits to a health professional and reading, the treatment group consists of children aged 0-1 in California. For child care, the treatment group consists of children under age 1 in California. The parameter of interest is a triple interaction between CA*Post*Infant. The bottom half of the income distribution in this sample is a child's household income <=300% FPL. Neighboring states include: Nevada, Oregon, Arizona, and Washington. Other large states include Texas, Florida, New York, and Pennsylvania. P-values testing the significance of the difference in outcomes are corrected at the age-state level and displayed in columns 3, 6, 9, and 12.

Figure Legend

Figure 1. Percent of Days with Good Mental Health Among Employed Mothers
Notes: Data are from 2001-2007 Behavioral Risk Factor Surveillance System. N=168,867. The sample includes employed females aged 21-40 who have at least one child. The dependent variable is the percent of days of the past 30 in which mental health status was self-reported to be good. The trends are adjusted for the following covariates, which were fixed at the mean value for California: household income, education, marital status, age, age^2, race/ethnicity, self-employment status, number of children (indicators for 2 and 3+), state unemployment rate, and month of interview indicators. Trends are also weighted by sampling weights. Pre-July 2004 trends are not statistically significantly different between California and any of the control groups (see Appendix Table 1).

Figure 2. DD Estimates on Child Health from Placebo Tests
Notes: Data from the National Survey of Children's Health 2003 and 2007 waves. The figures plot the distribution of DD estimates from equation (1) on child health outcomes using each state as the placebo treatment state. The observed estimate from California is bolded. The dashed lines represent the 5th and 95th percentiles, constructing a 90 percent confidence interval.

Figure 3. DD Estimates on Parental Mental Health from Placebo Tests
Notes: Data from the National Survey of Children's Health 2003 and 2007 waves. The figures plot the distribution of DD estimates from equation (1) on parental health outcomes using each state as the placebo treatment state. The observed estimate from California is bolded. The dashed lines represent the 5th and 95th percentiles, constructing a 90 percent confidence interval.

Figure 4. DD Estimates on Other Potential Mechanisms from Placebo Tests
Notes: Data from the National Survey of Children's Health 2003 and 2007 waves. The figures plot the distribution of DD estimates from equation (1) on potential mechanisms using each state as the placebo treatment state. The observed estimate from California is bolded. The dashed lines represent the 5th and 95th percentiles, constructing a 90 percent confidence interval.

Fig 1

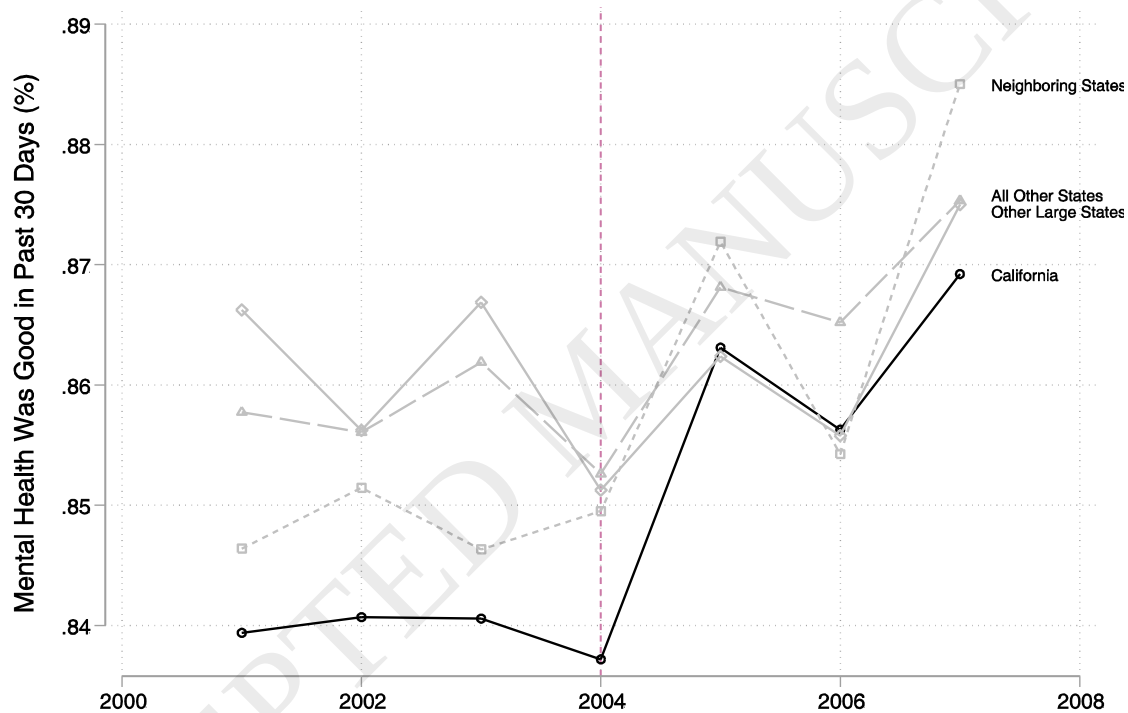

Mental Health Was Good in Past 30 Days (%)
.89
.88
.87
.86
.85
.84
2000
2002
2004
2006
2008
Neighboring States
All Other States
Other Large States
California

Fig 2

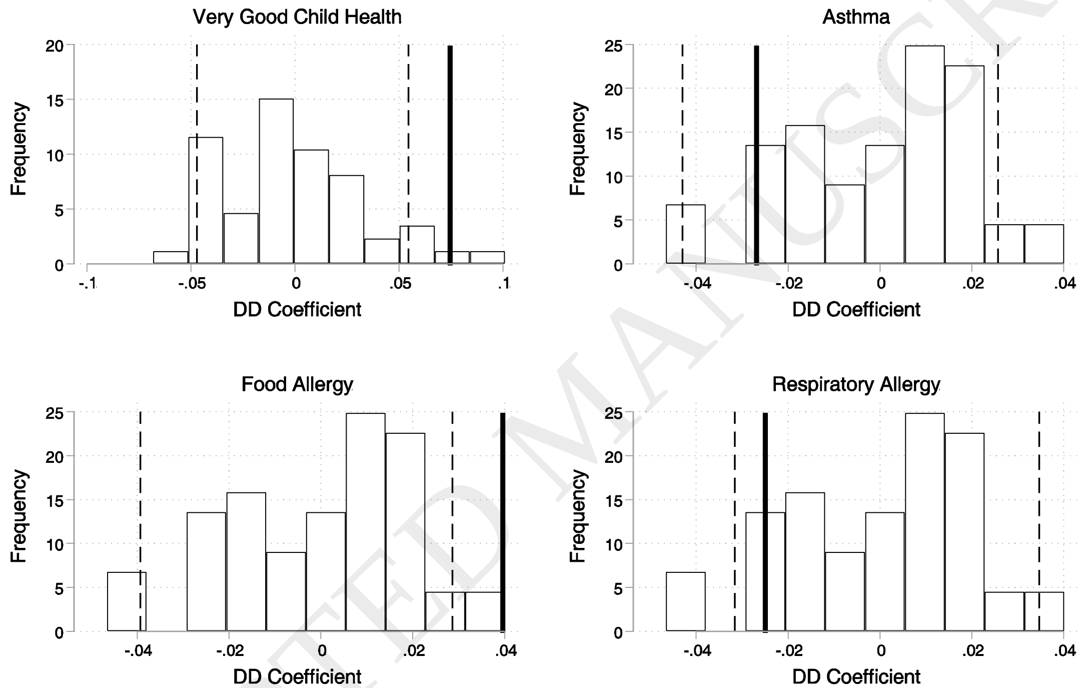

Very Good Child Health
Frequency
20
15
10
5
0
-.1
-.05
0
.05
.1
DD Coefficient
Asthma
Frequency
25
20
15
10
5
0
-.04
-.02
0
.02
.04
DD Coefficient
Food Allergy
Frequency
25
20
15
10
5
0
-.04
-.02
0
.02
.04
DD Coefficient
Respiratory Allergy
Frequency
25
20
15
10
5
0
-.04
-.02
0
.02
.04
DD Coefficient

Fig 3

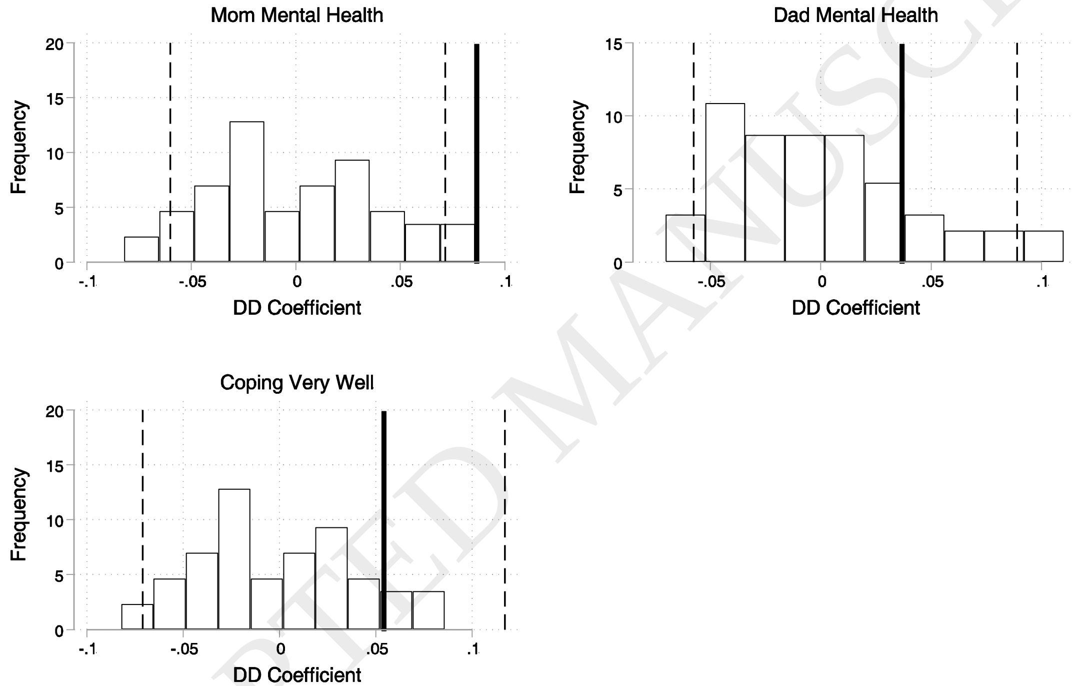
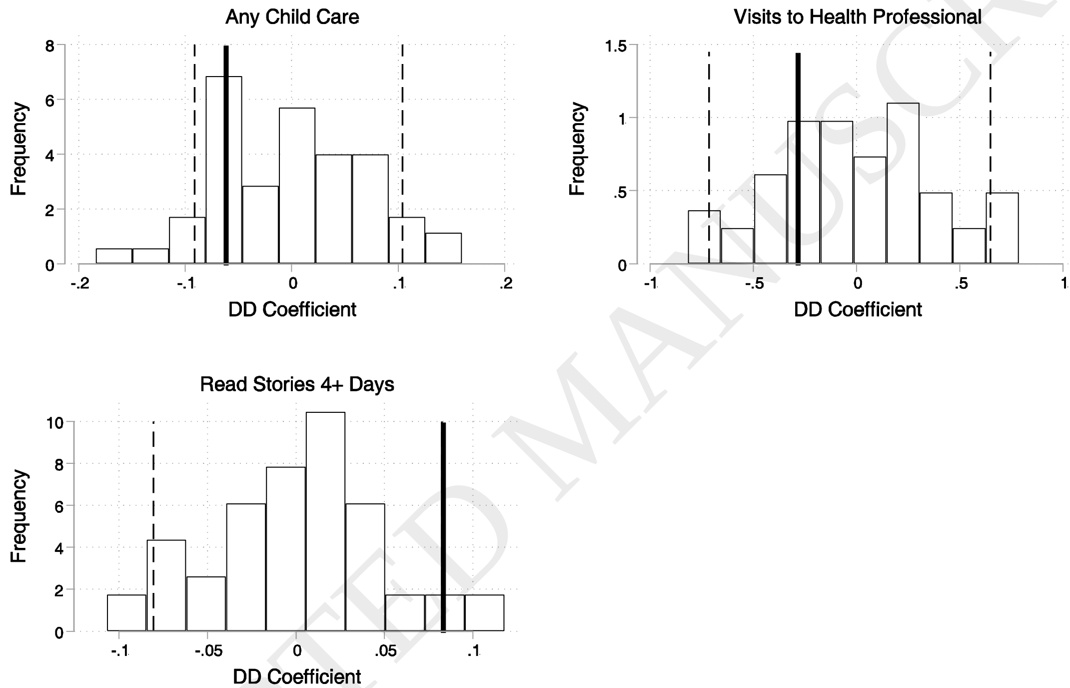

Mom Mental Health
Frequency
20
15
10
5
0
-.1
-.05
0
.05
.1
DD Coefficient
Dad Mental Health
Frequency
15
10
5
0
-.05
0
.05
.1
DD Coefficient
Coping Very Well
Frequency
20
15
10
5
0
-.1
-.05
0
.05
.1
DD Coefficient

Fig 4


Any Child Care
Frequency
DD Coefficient
0
2
4
6
8
-.2
-.1
0
.1
.2
Visits to Health Professional
Frequency
DD Coefficient
0
.5
1
1.5
-1
-.5
0
.5
1
Read Stories 4+ Days
Frequency
DD Coefficient
0
2
4
6
8
10
-.1
-.05
0
.05
.1