Paid Family Leave, Fathers' Leave-Taking, and Leave-Sharing in Dual-Earner Households*

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Abstract

Using difference-in-difference and difference-in-difference-in-difference designs, we study California's Paid Family Leave (CA-PFL) program, the first source of government-provided paid parental leave available to fathers in the U.S. Relative to the pre-treatment mean, fathers of infants in California are 46 percent more likely to be on leave when CA-PFL is available. In households where both parents work, we find suggestive evidence that CA-PFL increases both father-only leave-taking (i.e., father on leave while mother is at work) and joint leave-taking (i.e., both parents on leave at the same time). Effects are larger for fathers of first-born children than for fathers of later-born children.

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I. INTRODUCTION

Paid family leave (PFL) policies provide workers with paid time off from work to care for newborn or newly-adopted children, as well as seriously ill family members. PFL policies may be especially important for new parents, who often struggle to balance competing work and family responsibilities. Parents with access to PFL can stay home to care for and bond with their new children, and then return to work with minimal career interruptions. But despite the importance of these benefits, the United States is one of just a handful of countries without a national PFL policy. The U.S. offers 12 weeks of unpaid leave to some (but not all) workers through the federal Family and Medical Leave Act (FMLA).[1] However, three recent state-level PFL programs in California, New Jersey, and Rhode Island supply nearly all workers with access to paid family leave, and similar programs in New York and the District of Columbia will take effect in 2018 and 2020, respectively.

Although historically paid leave policies only applied to women, modern PFL programs typically cover (although not necessarily equally) both male and female workers. This paper uses large-scale data to study the effects of California's first-in-the-nation gender-neutral PFL (CA-PFL) policy on *paternal* leave-taking, as well as on how fathers and mothers in dual-earner households share leave-taking responsibilities.[2] CA-PFL was introduced in 2004 and offers six weeks of paid leave to nearly all new parents, with a 55 percent wage replacement rate up to a

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[1] Because of the strict eligibility requirements, less than 60 percent of private sector workers are eligible for FMLA (Klerman et al., 2012), and the impacts of the law are concentrated among relatively advantaged workers, who are more likely to be eligible and able to afford unpaid time off work.

[2] Five states, including California (as well as Hawaii, New Jersey, New York, and Rhode Island), have offered paid maternity leave to birth mothers through their Temporary Disability Insurance (TDI) systems since 1979. TDI allows pregnant and post-partum women to take 6-10 weeks of paid leave to prepare for and recover from childbirth. TDI covers birth mothers only. CA-PFL is the first source of legislation providing paid paternity leave in the U.S.

ceiling (a maximum benefit of $1,173 per week in 2017).[3] This leave is not directly job protected, but job protection is available if the job absence simultaneously qualifies under the FMLA.

Our focus on the leave-taking outcomes of fathers is particularly salient in light of recent evidence that American fathers report equal or greater levels of work-family conflict as do mothers (Auman et al., 2011; Rehel and Baxter, 2015). Understanding how PFL policies specifically affect fathers is important because they may respond to such policies differently from mothers for at least two reasons. First, despite some convergence in earnings between men and women over the last several decades, fathers continue to be the main breadwinners in many U.S. families.[4] Thus, the financial shock to the family associated with only partial wage replacement and a lack of job protection during leave (as in CA-PFL) may be more consequential when fathers take leave than when mothers do. Second, new fathers have less biological need for leave than new mothers, who need time off from work to recover from childbirth and establish breastfeeding.

Additionally, fathers' access to paid leave on the private market is very low. For instance, a 2012 report indicates that only 14 percent of U.S. employers offer paid paternity leave to most or all of their male employees (Klerman, Daley, and Pozniak, 2012). As a consequence, new fathers tend to take very little time off work when their children are born. In 2013, less than two percent of employed fathers of children under the age of one reported being on leave (versus 14 percent of employed mothers), and these rates have remained very stable over the last decade.[5] Even in California, where both mothers and fathers are covered by PFL, a large majority of parental leave

[3] CA-PFL covers essentially all private sector workers. To be eligible for the program, individuals are required to have earned at least $300 in wages during a "base period" five to eighteen months before the PFL claim begins. Additional information on the California program is available at http://www.edd.ca.gov/disability/FAQ_PFL_Benefits.htm.

[4] According to the Bureau of Labor Statistics, even in two-earner families, men bring in over half of family earnings in approximately 70 percent of households.

[5] These estimates come from the 2013 American Communities Survey. The outcome refers to individuals who are employed but absent from work in the week prior to the survey (i.e., survey reference week).

claims have been made by mothers. However, paternal take-up has increased substantially over the first decade of the policy. In 2005, only 19.6 percent of all CA-PFL claims were filed by men. By 2013, fathers were responsible for about 30 percent of claims.

Low rates of paternal leave-taking make analysis of PFL among fathers difficult because most data sets lack sufficient numbers of fathers who are on leave to produce reliable estimates of program effects. To address this issue, we use data from the 2000 Census and the 2000-2013 waves of the American Community Survey (ACS), together with difference-in-difference (DD) and difference-in-difference-in-difference (DDD) methods, to identify the causal effects of CA-PFL on paternal leave-taking. Our preferred DDD specification compares employed fathers of infants in California to employed fathers of children aged one to three, relative to corresponding fathers of the same age children in other states, before and after the introduction of CA-PFL. We perform an analogous analysis of mothers to enable comparisons of effects across parental gender within the same data set. In dual-earner households, we also separately examine impacts on joint leave-taking—where both parents are simultaneously on leave—versus "father-only" or "mother-only" leave-taking while the other parent is at work, or "either parent" leave-taking (i.e. either the mother or the father is on leave). Further, our relatively large sample sizes enable us to examine heterogeneity in the program's effects by birth order, child gender, and family income.

In our preferred specification, we find that CA-PFL raises the share of fathers of infants on leave from work in a given week by about 0.9 percentage points, or 46 percent relative to the pre-PFL mean of two percent. Among households with two married and employed parents, about half of this increase is driven by fathers taking leave at the same time as the child's mother and the other half by fathers *who take leave on their own*, while the mother is at work. The two percent baseline leave-taking rate is consistent with fathers taking about 1 week of leave on average after their child's birth, and CA-PFL increases that amount to nearly 1.5 weeks.[6] We also find some heterogeneity in parental leave-taking by birth order—the effects on leave-taking are almost entirely driven by fathers of first-born children (i.e., those with no other siblings in the household), while the corresponding differences for mothers are much smaller. We do not find robust statistically significant evidence of heterogeneity in leave-taking effects along the other dimensions that we consider (child gender and family income). The lack of significant heterogeneity by income suggests that the policy is relatively neutral with regard to distributional implications, and that our results from California may be generalizable to other states that are considering similar PFL programs but have different income distributions.

Our study is most closely related to a recent paper by Baum and Ruhm (2016), who use data from the National Longitudinal Survey of Youth (NLSY) to estimate the impacts of CA-PFL on both mothers' and fathers' leave-taking and maternal labor market outcomes. Our paper makes four contributions relative to Baum and Ruhm. First, our analysis is able to confirm Baum and Ruhm's main finding for fathers—a two to three day increase in leave-taking—using a much larger and more representative data set. Second, the larger sample size in our study permits us to examine new forms of heterogeneity in the effects of CA-PFL on paternal leave-taking.[7] Third, we provide novel insights into simultaneous versus separate leave use within households with two employed parents. Fourth, we address a critical issue affecting inference in the DD and DDD analyses commonly used in the literature on CA-PFL (including Rossin-Slater, Ruhm, and Waldfogel, 2013; Baum and Ruhm, 2016). These studies have a small number of treated groups (most often, just one) and variation in the number of observations per group, making standard errors clustered

[6] This assumes birth are uniformly distributed throughout the year. We discuss the validity of the assumption of a uniform distribution of births in Section III below.
[7] Baum and Ruhm's sample contained only 158 fathers in the post-PFL treatment group.

at the group level unsuitable (Bertrand, Duflo, and Mullainathan, 2004; Donald and Lang, 2007; MacKinnon and Webb, 2017; Ferman and Pinto, 2016). Here, we explicitly examine the sensitivity of our estimates to alternative inference methods accounting for both the small number of treatment groups and heteroskedasticity in the error structure.

II. RELATED LITERATURE AND HYPOTHESES

Understanding the extent to which CA-PFL increases paternal leave-taking is important because we know relatively little about the effects of parental leave programs on fathers.[8] While several papers study European and Canadian paternity leave reforms aimed at increasing fathers' leave-taking, this evidence may have limited relevance to the current U.S. policy landscape for a few reasons.[9] In particular, CA-PFL is much less generous in terms of the wage replacement rate and duration than many of the European polices, and does not offer job protection.[10] Additionally, the broader policy landscape could matter for understanding the impacts of PFL—a reform that expands PFL in a setting with subsidized child care and universal health insurance (e.g., as in Sweden) may be dramatically different from one where PFL is introduced for the first time and neither child care nor health insurance are guaranteed (as in the U.S. today). Finally, CA-PFL is a gender-neutral program where eligible parents are each entitled to take the same amount of leave,

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[8] The literature on the effects of leave policies for mothers typically finds large effects on paid leave take-up rates (see Olivetti and Petrongolo, 2017 and Rossin-Slater, 2017 for recent overviews), but mixed effects on subsequent labor market outcomes (Baker and Milligan, 2008; Bergemann and Riphahn, 2015; Dahl *et al.*, 2016; Stearns, 2016; Lalive *et al.*, 2014; Lequien, 2012; Schönberg and Ludsteck, 2014; Bicáková and Kalíšková, 2016).

[9] These policies are sometimes referred to as "daddy quotas" or "daddy months" and have been studied in Sweden (Duvander and Johansson, 2012; Ekberg et al., 2013), Norway (Dahl et al., 2014; Cools, Fiva, and Kirkebøen, 2015), Germany (Schober, 2014), and Canada (Patnaik, 2015).

[10] Recent work suggests that the impacts of leave are non-linear in duration (Ruhm, 1998; Olivetti and Petrongolo, 2017). Han, Ruhm and Waldfogel (2009) estimate that the unpaid leave made available to fathers under the FMLA increased their leave-taking by an average of around two days. Job protection is available in the Rhode Island and New York PFL policies, but not in California, New Jersey, or Washington, D.C.

either simultaneously or separately. In contrast, parental leave in many European countries is allocated at the household level and parents must decide how to share it.

Despite the differences between the U.S. and European context, the existing literature suggests that the introduction of CA-PFL should increase paternal leave-taking rates. Although we hypothesize that father's leave-taking should increase as a result of the policy, we expect that the effect size may be smaller than it is for mothers.[11] Because a newborn places higher biological demands on mothers, and fathers are on average higher earners, mothers may experience larger absolute increases in leave-taking than fathers. On the other hand, fathers may have larger *relative* increases in leave-taking because their baseline leave-taking rates are substantially lower than those of mothers and they are less likely to have access to employer-provided PFL.

It is less clear how CA-PFL will affect when fathers take leave relative to their spouse in dual-earner households. Baum and Ruhm (2016) show that in the absence of PFL, fathers take about a week of leave on average immediately after the child's birth. CA-PFL may increase joint leave-taking if it encourages fathers to take additional time off around the birth, rather than later in the year after the mother has returned to work. But CA-PFL gives parents access to 6 weeks of leave that can be used anytime during the first year of the child's life, and does not have to be used all at once. If dual-earner families try to maximize the total amount of time the infant spends at home with a parent, the policy may increase "father-only" leave-taking as well.

We also look for heterogeneity in the effects of CA-PFL by birth order, child gender, and family income. Recent studies suggest that there is heterogeneity in leave-taking patterns by birth order for both mothers (Han et al. 2008) and fathers (Nepomnyaschy and Waldfogel, 2007;

[11] Several studies outside the U.S. have examined the effects of gender-neutral family leave reforms on men's and women's leave-taking, finding bigger impacts on mothers than fathers (e.g. Sundström and Duvander, 2002; Kleven et al., 2017; Patnaik, 2016).

Patnaik, 2015), motivating our exploration of whether the effects of CA-PFL also vary with birth order. We hypothesize that the effects of CA-PFL will be larger for parents of first-born than later-born children. There are substantial "start-up" costs associated with having a family—both mothers and fathers must adjust to becoming a parent, and they are also typically less experienced in newborn care and may not yet have any childcare arrangements when their first child is born (Cowan and Cowan, 2000; Waldfogel, 2006). By contrast, the marginal cost of a subsequent child is arguably smaller—parents of second or higher-order children may be more prepared and their lives may be less disrupted by the birth.

Given the large literature on paternal son-preference (marriage and divorce: Bedard and Deschênes, 2005; Lundberg and Rose, 2003; Lundberg, McLanahan, and Rose, 2007; Dahl and Moretti, 2008; paternity acknowledgement: Almond and Rossin-Slater, 2013; paternity leave: Tanaka and Waldfogel, 2007), we also expect that fathers' response to CA-PFL may be greater when they have sons compared to daughters. There are at least two explanations for this phenomenon. First, it may be that fathers get more utility from spending time at home with sons rather than daughters. Second, they may perceive that paternal time spent caring for boys is relatively more productive than time spent caring for girls. While we cannot distinguish between these two channels in our data, the latter explanation seems less plausible given that it is unlikely that fathers have a relative advantage in caring for boys around the time of birth.

Finally, there are reasons to expect that the effects of CA-PFL may differ by family income.[12] The lack of job protection and the relatively low wage replacement rate available under CA-PFL may be more prohibitive for fathers in lower-income families, suggesting larger effects among higher-income families. Fathers in higher-income families are more likely to have access to

[12] We adjust family income to account for the number of adults and children in the household. This adjustment is explained in Section V.

employer-provided paid paternity leave, however, and face a higher opportunity cost of taking leave (Klerman, Daley, and Pozniak, 2012). This may mean that they have less demand for government-provided PFL than men in lower-income families. In fact, research on the effects of CA-PFL on mothers finds that the largest effects on leave-taking are concentrated among the least advantaged mothers (Rossin-Slater, Ruhm, and Waldfogel, 2013).

III. DATA

We use data from the 2000 Census and the 2000 to 2013 waves of the American Community Survey (ACS) to estimate the effects of CA-PFL on fathers' leave-taking. The ACS is conducted throughout the year and samples one percent of the population in most years; thus, it has the major advantage of providing the large samples needed to examine leave-taking behavior among fathers.[13] When weighted, the ACS is a nationally-representative survey that provides information about labor market experiences and demographic factors. For our purposes, what is particularly important is that individuals are questioned about their labor market status in the week prior to the survey—referred to as the "survey reference week"—allowing us to identify leave-taking during that week. Although the ACS does not ask about parental leave versus other specific types of leave, it does identify individuals who are temporarily absent from work during that week. The main dependent variable that we examine below is whether the father (or mother) is on leave from work in the survey reference week. This absence could be for many reasons including parental leave, vacation, or illness.[14] This lack of specificity is not a problem for our analysis because we are

[13] Data come from the Integrated Public Use Microdata Series (IPUMS) database (Ruggles et al., 2010). The ACS started in 2000, and was only a 0.13 percent sample in that year. For the next four years, it was approximately a 0.5 percent sample of the population. The questions used in this study are very comparable in the ACS and the 2000 long-form Census. This analysis combines the 2000 ACS with the 1 percent 2000 Census sample in order to increase the sample size in that year. We also show that our main results are robust to dropping the 2000 data.

[14] Specifically, the question asked is: "LAST WEEK, was this person TEMPORARILY absent from a job or business?" Respondents can answer "Yes, on vacation, temporary illness, labor dispute, etc." or "No." The Current

interested in any type of leave taken by a father of an infant, regardless of whether it is called parental leave, vacation leave, sick leave, or something else.

As detailed below, our empirical strategy focuses on whether leave-taking of any kind increases more among fathers of infants in California post-law than it does for the comparison groups. The use of appropriate control groups nets out changes in other types of leave-taking that may have occurred for reasons unrelated to the PFL law. Unfortunately the survey does not inquire about the length of the temporary work absence, so we do not know whether it lasted longer than the survey reference week.[15]

In addition to not specifying the length of leave, there are two other limitations of the ACS data. First, fathers can only be linked to children who live in the same household. The analysis therefore excludes fathers who do not live with their children.[16] Assuming that non-resident fathers are less involved with their children than resident fathers, our results will overstate the increase in leave-taking for the average new father (including those not living with their infants). Second, the ACS lacks precise information on children's birth dates, and only reports the age of the child in years. Although CA-PFL can be used at any time in the first 12 months of the child's life, as noted above, most fathers take only brief leaves that occur soon after the birth (Baum and Ruhm, 2016). Since we observe leave-taking in only a single week, we will therefore miss most of these leaves.[17]

Population Survey (CPS) asks about maternity/paternity leave specifically and is used to identify the effect of CA-PFL on mothers' leave-taking in Rossin-Slater, Ruhm, and Waldfogel (2013). However, the sample of fathers on leave in California in the CPS is too small to produce meaningful estimates.

[15] The ACS question about temporary work absences should only be answered by individuals who report not working at all during the survey reference week, and so therefore should only capture work absences that last at least a full week. Our results are likely underestimated if CA-PFL increases partial-week leave-taking. Data on hours of work during the survey reference week are not available in the ACS, so we cannot examine this. Another limitation is that the ACS does not distinguish between paid and unpaid leave.

[16] In our data, 74.5 percent of infants are identified as living with their biological father (more specifically, 67 percent live with both parents, while 7.5 percent live with only their father). 88 percent of infants are identified as living with their mother.

[17] Both of these limitations also apply to mothers, but to a lesser extent, since most children in single parent households live with mothers, and mothers typically take much longer leaves than fathers.

However, under the assumptions that births and the average length of leave are both approximately uniformly distributed throughout the year, the percentage change in leave-taking estimated to result from the policy will be accurately captured, although the levels will be understated.[18]

The analysis sample is limited to fathers who are 16-54 years old and employed in the survey reference week. We condition on employment because those who are not employed are less likely to be eligible for PFL and because we will not observe them as leave-takers in the ACS.[19] However, we show in Section VI that the results are robust to including all fathers in the analysis, regardless of employment status. We also demonstrate that CA-PFL does not affect the probability that fathers of infants are employed, which is unsurprising given the short amount of paid leave available. We do not observe CA-PFL eligibility status directly, and so our estimation procedure treats all employed fathers in California as eligible for paid leave if their youngest own child in the household is less than one year old. To the extent this assumption is incorrect (e.g., some fathers working in the public sector are not eligible), we will understate the increases in leave-taking occurring for eligible fathers.

The first five columns of Appendix Table A1 report summary statistics for the sample of fathers used in our preferred empirical specification, which compares employed fathers of infants less than one year old to employed fathers of youngest children aged one to three, in California versus corresponding fathers in other states.[20] For comparison, we also report the same summary

[18] We checked the validity of the assumption that U.S. births are uniformly distributed throughout the year using 2011 birth record data from the National Center for Health Statistics (NCHS) Vital Statistics. The shortest month, February, had the lowest number of births in 2011 (7.5 percent). April had the second lowest number of births (7.9 percent). August had the most births (9.1 percent). The ACS does not contain information about the month of the survey, so we cannot measure the timing of leave relative to birth even under these assumptions.
[19] Some non-employed fathers, who previously worked, may be eligible for CA-PFL benefits because the work history requirements for receiving it are so weak. However, we will not observe this in our data since such men will not be classified as being temporarily absent from work.
[20] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

statistics for employed mothers in the subsequent five columns. All statistics are weighted by the ACS person weights. There are several important differences between parents of infants in California and parents of infants in other states. Most notably, California parents are more likely to be Hispanic and less likely to be non-Hispanic white. Additionally, a substantially higher fraction has less than a high school education and are not citizens, although mean household income (in 2010 dollars) is somewhat higher. Finally, parents of infants in California are more likely to be on leave than those in other states, suggesting that CA-PFL may have had an effect on leave-taking.

Figure 1 plots the percentage of fathers with infants on leave in California versus all other states. After CA-PFL is implemented, there is a large increase in leave-taking in California relative to elsewhere in the U.S. in most years.[21] We explore this relationship further using regression models.

IV. EMPIRICAL STRATEGY

To identify the impact of CA-PFL on fathers' leave-taking behavior, we begin with a difference-in-differences (DD) framework, comparing leave-taking rates among fathers of infants in California before and after the implementation of CA-PFL to the same difference for a comparison group of either California fathers with slightly older children, who are not expected to be affected by the policy, or fathers of infants in other states. Specifically, we estimate:

[21] The jump in leave-taking rates between 2000 and 2001 is likely because we combine data from the Census and the ACS in 2000 and use only the ACS starting in 2001. Results are robust to dropping 2000. The national downward trend in fathers' leave-taking starting in 2008 may be due to the recession, as leave-taking is negatively correlated with the unemployment rate. Our preferred DDD specification includes state by year interactions to account for differential impacts of the Great Recession across states.

$$(1) \quad Y_{ist} = \beta_0 + \beta_1 Treat_{ist} + \beta_2 Treat_{ist} * Post_t + \gamma' X_{ist} + \rho' C_{st} + \delta_s + \phi_t + \varepsilon_{ist}$$

where the outcome Y_{ist} is an indicator equal to one if individual i living in state s who is surveyed in year t is on leave from work in the survey reference week and zero otherwise. The dummy variable $Treat_{ist}$ is equal to one for California fathers of infants and $Post_t$ is an indicator equal to one if the individual is surveyed in 2005 or later.[22] The vector X_{ist} contains the following individual-level indicator variables: father's age in bins (<20, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54), race/ethnicity (non-Hispanic white, black, Hispanic, Asian, other race), education categories (less than high school, high school, some college, 4-year degree or more), marital status, citizenship status, the age of the youngest child in the household in years, and the total number of children in the household. We also include the following state-year controls in vector C_{st} to account for labor market conditions and other state-specific factors affecting the decision to work: unemployment rate, average welfare benefit for a four-person family, poverty rate, state minimum wage, per capita income, the log of the population, and an indicator for whether or not the governor is Democratic.[23] State and year fixed effects are captured by δ_s and ϕ_t, respectively, with the $Post_t$ main effect being subsumed into the time fixed effects. The coefficient of interest, β_2, is the DD estimate of the effect of CA-PFL on fathers' leave-taking in California. We estimate (1) as a linear probability model, but results are very similar when instead estimating a probit model. These results are available upon request.

[22] CA-PFL started paying out benefits in July 2004. Because only survey year and age in years can be identified in the ACS, a reported infant in 2004 may have been born as early as January 2003. Assuming births and survey responses are both approximately uniformly distributed throughout the year, only around 12.5 percent of surveyed infants in 2004 would have been born after the implementation of CA-PFL, compared with 87.5 percent of surveyed infants in 2005. Therefore, we treat 2005 as the first year of the policy.

[23] The state-year controls come from the University of Kentucky Poverty Research Center National Welfare Data.

The DD estimate in (1) will be biased if trends in leave-taking rates between the treatment and control groups would have been different in the absence of CA-PFL. Although this assumption is fundamentally untestable, we explore the robustness of our results to the use of several alternative comparison groups. First, we compare California fathers of infants to corresponding fathers in other states.[24] The key identification assumption is that of common trends in leave-taking for fathers of infants in California and in other states (in the absence of the policy). This assumption could be violated if there are differential changes in the rate of types of leave-taking that are unrelated to CA-PFL (e.g., vacation or sick days). However, as long as any such changes are not specific to fathers of infants, this concern can be addressed by instead comparing California fathers of infants to California fathers of youngest children aged 1-3 (or 2-4) at the survey date.[25] Fathers of older children in California are not eligible to receive paternity leave benefits under CA-PFL, and therefore will serve as a second control group. Interpreting the resulting treatment effect as causal requires the assumption that rates of leave-taking in California are not differentially changing among fathers of infants and of slightly older children for reasons unrelated to CA-PFL.[26]

These two sets of control groups can be combined into a difference-in-difference-in-differences (DDD) model that compares fathers with infants to fathers of older children, in California versus other states, before and after the policy. This DDD specification allows for differential trends in leave-taking across states and by age of youngest child as long as the

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[24] Individuals from New Jersey are excluded from the analysis because the state implemented its own PFL policy in 2008. Ideally we would use New Jersey as another treatment state. However, sample sizes of fathers on leave in New Jersey are too small (between 4 and 20 per year on leave) to produce meaningful estimates. Rhode Island is the only other state to have also started a PFL program, but it did so in 2014, after our sample ends.

[25] State-year controls and state fixed effects are omitted from (1) when using fathers in California with older children as the control group.

[26] CA-PFL may increase leave-taking among these fathers because the program also covers time off to care for sick family members. But fathers of older children may be less likely to take leave if they compensate for having taken leave earlier. To test this, we estimated a DD model comparing fathers of 1-3 year-olds in California to those in other states. If anything, we find evidence that fathers of 1-3 year-olds are more likely to take leave after CA-PFL, meaning our estimates may understate the effect for fathers of infants. These results are available upon request.

difference in the rate of change between fathers of infants and older children in California would have been the same as that in other states in the absence of CA-PFL. Under this assumption, we estimate the DDD equation:

$$(2)\ Y_{ist} = \beta_0 + \beta_1 Under1_{ist} + \beta_2 CA_s * Post_t + \beta_3 CA_s * Under1_{ist} + \beta_4 Post_t * Under1_{ist} + \beta_5 CA_s * Post_t * Under1_{ist} + \gamma' X_{ist} + \delta_s + \phi_t + \theta_{st} + \varepsilon_{ist}$$

where Y_{ist}, $Post_t$, X_{ist}, δ_s and ϕ_t are as above, $Under1$ is an indicator equal to 1 if the individual's youngest child is less than one year old and zero otherwise, and CA_s is an indicator for the respondent residing in California. The DDD model also allows for the estimation of state by year fixed effects (θ_{st}), which replace the state-year controls. The fixed effects make it unnecessary to include the main effects of CA_s and $Post_t$ explicitly in the model, and the DDD coefficient is β_5. This coefficient represents the effect of CA-PFL on paternity leave among fathers of infants in California. Although the outcome variable captures work absences overall and not just paternity leave, there is no reason to think that CA-PFL would differentially impact work absences for other purposes among fathers of infants.

Inference

Typically, studies that exploit policy variation across states conduct inference using standard errors clustered at the state level. However, this approach may be problematic in cases where the number of treated clusters is small (Bertrand, Duflo, and Mullainathan, 2004; Donald and Lang, 2007). Other inference methods developed to improve upon cluster robust standard errors when either the number of groups is small or there is cluster heterogeneity do not perform well when the proportion of treated groups approaches zero or one, as is true in this setting (MacKinnon and Webb, 2017). Moreover, recent work suggests that inference methods should account for the fact that there may be variation in the number of observations per group (Ferman and Pinto, 2016). As such, we explore the sensitivity of our results to alternative inference approaches.

Specifically, for both the DDD models and the DD specifications where we compare fathers in California to fathers in other states, we first present results from specifications with standard errors clustered at the state level.[27] In addition, we implement a new method of inference developed by Ferman and Pinto (2016) (hereafter, F-P) that provides an improvement in hypothesis testing for situations where there are few treated groups and many control groups in the presence of heteroskedasticity. Heteroskedastic errors are particularly likely in state-level DD and DDD models, where there is substantial variation in the number of observations used to calculate each group-time average. However, several common methods of inference, including cluster-residual bootstrapping (Cameron, Gelbach, and Miller, 2008), the Donald and Lang (2007) two-step approach, and the Conley and Taber (2011) method, all rely on a critical homoskedasticity assumption. The F-P method is an extension of the cluster-residual bootstrap with a heteroskedasticity correction applied to the residuals. F-P develop their method in a standard DD setting, and we extend it to the DDD case (see Appendix B for more details).[28] We follow F-P and assume that the heteroskedasticity is generated by the variation in group size, and present p-values calculated using this method for all results. Finally, we also present results from DD models that use the Donald and Lang (2007) two-step approach to conduct inference.

[27] DD models that compare fathers within California use heteroskedasticity-robust standard errors.

[28] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

Indirect Tests of the Identifying Assumption

To interpret the DDD effect as the causal effect of CA-PFL on fathers' leave-taking, the implementation of the policy must be uncorrelated with other time-varying determinants of leave-taking in our sample of employed fathers of young children. This assumption would be violated if the CA-PFL law induced selection into our sample through impacts on fathers' employment or fertility patterns. Moreover, since we can only observe fathers who reside with their children in our data, we face a threat to our identification assumption if the policy influences father-child cohabitation rates or is correlated with differential migration into or out of California.

To evaluate the plausibility of these concerns, Table 1 presents results from regressions that estimate the DDD model (equation (2)) using observable paternal characteristics as dependent variables (and omitting the controls in X_{ist}). Since we do not include individual-level controls in these specifications, we collapse the data to the father-group/state/year level, where father-group denotes whether the father has an infant or a child aged 1-3. Table 1—and most of the subsequent tables—shows p-values from inference with standard errors clustered at the state level in parentheses, and p-values calculated using the F-P method in brackets below.[29]

The results in columns (1) and (2) of Table 1 show that CA-PFL does not either significantly or materially affect employment status or the probability of having an infant in the household.[30] For example, the 95 percent confidence interval of the employment effect is -0.6 to 0.9 percentage

[29] The F-P method is a cluster-residual bootstrap with a correction for heteroskedasticity. The purpose of this bootstrap is to provide asymptotic refinement in the presence of clustered errors. It essentially performs a permutation test by imposing the null hypothesis and resampling the residuals—rather than re-estimating the key coefficient of interest—and then asking how likely it would be to observe the key coefficient by chance. As such, only p-values (not standard errors) are generated. See Ferman and Pinto (2016) for more details.

[30] Column (2) of Table 1 is based on a DD model comparing fathers of children age 3 and younger in California to those in other states. Using all men aged 15-55, we find a significant negative correlation between PFL and having an infant. This is driven by a relative increase in the number of single immigrants to California, and disappears when we control for the share of citizens. Our main results control for citizenship status, and we have also controlled for citizenship-year fixed effects and limited the sample to citizens, with similar results (available upon request).

points, compared to a baseline average of 89.9 percent. Given the relatively modest benefit available (up to 55 percent of wages for up to six weeks), this finding is not surprising. We also show that the policy is uncorrelated with other paternal demographic characteristics, including age, marital status, education, share of fathers who are non-Hispanic white, and share of fathers who are from an under-represented minority (URM) group, which includes blacks, Hispanics, and other non-white, non-Asian races. Finally, in the last column, we show results when "predicted leave-taking"—generated using a large set of fathers' demographic characteristics and their interactions—serves as the outcome.[31] These findings suggest that CA-PFL is uncorrelated with paternal demographics that predict leave-taking behavior. It is therefore unlikely that differential demographic trends among fathers of infants in California drive the results shown in the next section.

V. ESTIMATED EFFECTS ON LEAVE-TAKING

Table 2 shows the estimated effect of CA-PFL on parents' leave-taking behavior in California. The first six columns show results for fathers. The first three of these show the DD estimates using a control group of fathers of infants in all other states, and control groups of fathers of 1-3 and 2-4 year olds in California, respectively.[32] The fourth through sixth columns show results from DDD models, with varying sets of time and location controls, and where our preferred specification, in column 4, is the most comprehensive in that it controls for a full set of state-by-year fixed effects. The last column shows DDD result for mothers using our preferred specification. In specifications

[31] Specifically, we use the underlying individual-level data to regress leave-taking rates on paternal demographic controls for: age of youngest child, marital and citizenship status, fathers' age, and race and education, and all race-education interactions. We then use the predicted values from this regression as a "summary index" of selection.
[32] We present results with fathers of 2-4 year olds as the control group because infant age could be misreported if parents state that they are one year old instead of less than one. The data suggest that this is not an issue. In the sample of fathers with youngest children 0-3 in California, 28.04 percent have an infant less than one year old and 27.18 percent report having a one year old.

that compare across states (columns (1) and (4)-(7)), we present p-values from models with standard errors clustered at the state level in parentheses and the F-P p-values in brackets. The F-P p-values are consistently larger than the p-values from inference with clustered standard errors, due to the fact that we only have one treatment state (California), and substantial variation in group sizes (i.e., different numbers of observations across states) that results in heteroskedasticity. In specifications that compare fathers within California (columns (2) and (3)), we do not use clustered standard errors as we no longer need to account for spatial correlation in errors within states; thus we simply present p-values from models with heteroskedasticity-robust standard errors.

The DD coefficients in columns (1)-(3) suggest that CA-PFL leads to a 0.88-1.25 percentage point increase in fathers' leave-taking during the survey reference week, representing a 44 to 63 percent increase from the pre-treatment mean of 1.99 percent. Figures 2 and 3 show the corresponding event-study plots for the models using fathers of infants in other states and fathers of 1-3 year olds in California as control groups, with the coefficients normalized to zero in 2004.[33] Although the estimates are somewhat noisy, there is an indication of an upward trend after the policy takes effect. Such an increase over time (rather than an immediate jump) might occur if fathers are learning about the availability of CA-PFL; this interpretation of the figures is consistent with the 146 percent increase in male "bonding" claims (from 24,021 to 59,256) filed in California between 2005 and the 2012-2013 fiscal year.[34] However, the figures should be viewed as suggestive since they do not rule out the possibility of an upward pre-trend in leave-taking prior to 2004 among fathers of infants in California relative to those in other states. Consequently, we

[33] Appendix Figures A1 and A2 show the corresponding event studies for mothers. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[34] CA-PFL program statistics were obtained from the State of California Employment Development Department. See http://www.edd.ca.gov/about_edd/quick_statistics.htm for more information. Bonding claims are for taking leave to stay home with an infant rather than to provide care for a sick relative.

prefer the DDD specification that allows us to flexibly control for state by year fixed effects and thus account for differential trends in leave-taking across states.

The DDD specification, shown in column (4) of Table 2, suggests that the policy causes a 0.9 percentage point, or 46 percent, increase in leave-taking during the survey reference week from the pre-treatment baseline of 1.99 percent. This model compares fathers of infants to fathers of youngest children aged 1-3, in California versus other states, before and after the introduction of the policy. Results are very similar if fathers of youngest children aged 2-4 are used instead, and therefore are not shown. Columns (5) and (6) of Table 2 show that the DDD results are robust to the inclusion of state-specific linear time trends and the exclusion of state-year fixed effects. As mentioned, since the DDD model allows for both national trends in leave-taking among fathers with infants, as well as state-specific trends in leave-taking overall, subsequent results are only presented for the DDD model. However, results from the DD models are similar.

We cannot directly translate the estimated PFL program effects into the number of additional days of leave taken, because the ACS contains only binary information about temporary absences from work during the survey reference week. However, if we assume that these men were off the job for the full week and births of infants were approximately uniformly distributed throughout the year, our preferred estimates suggest that the program added approximately 2.4 days of leave (0.00915 x 52 weeks x 5 days/week) from a pre-treatment baseline of around 5.2 days.

The last column of Table 2 shows the effect of CA-PFL on maternal leave-taking behavior using our preferred DDD specification.[35] Similar to Rossin-Slater, Ruhm, and Waldfogel (2013) and Baum and Ruhm (2016), we find that mothers are also more likely to take leave after the

[35] Appendix Table A2 shows all columns of Table 2 for mothers instead of fathers. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

introduction of CA-PFL. CA-PFL leads to a 2.3 percentage point increase in leave-taking during the survey reference week among mothers with infants, which represents a 13 percent increase from the pre-treatment baseline. In percentage terms, this is much smaller than the effect estimated for men (13 vs. 46 percent) but it is much larger in absolute terms, since new mothers are more likely to be on leave. Assuming that temporary work absences last for the full survey reference week of 5 work days, CA-PFL is estimated to increase the leave-taking of new mothers by 6 days from a base level of around 46 days.

Heterogeneity

We next examine heterogeneity by birth order, child gender, and family income. Columns (1) and (3) of Table 3 show that birth order matters more for fathers' than mothers' leave-taking. Column (1) of Table 3 indicates that CA-PFL increases the predicted leave-taking of fathers after first births by almost two percentage points during the survey reference week, or 95 percent. However, following second or higher-order births, the effect is only 0.35 percentage points (18 percent). This finding is interesting, in part, because it cannot be explained by differences in information about the policy. In supplementary analyses, we found no differences in the effect on leave-taking for the second or higher birth depending on whether the first child was born before or after the policy went into effect. The pre-policy mean rates of leave-taking do not vary significantly by birth order, so this difference is not driven by pre-existing patterns either. Interestingly, the birth order difference in the effects of CA-PFL is unique to fathers: there is a much smaller (and never significant) corresponding birth order difference in the DDD effects of the policy when looking at the probability that the mother is on leave (column 3). There are several possible explanations for the relatively stronger effect of CA-PFL on father's leave-taking after first births.

Mothers may need the most help caring for their first-born child given this is their first experience with newborn care and they do not have other child care arrangements in place, so having the father at home may be especially beneficial. Fathers may also feel they need more time off at a first birth to adjust to the changes starting a family entails. Alternatively, fathers may be more willing to take time off to be involved with the care of their first child, but revert back to more traditional gender roles with later children, particularly if the mother is no longer employed or has shifted to a part-time schedule. It is also possible that employer attitudes play a role—companies may be more accepting of a father taking leave for the birth of a first child, and less so for the birth of a subsequent child. Our data do not allow us to distinguish between these channels.[36]

To analyze whether or not fathers of boys are more likely to take PFL than fathers of girls, Column (2) of Table 3 shows the effect of CA-PFL for fathers whose youngest child is male and the differential effect for fathers whose youngest child is female. The coefficients suggest that fathers of sons are more likely to take paternity leave after CA-PFL goes into effect than fathers of daughters, although the coefficient on the interaction term is only significant with clustered standard errors and not according to the F-P method.[37] These results, while tentative, are suggestive of son preference among fathers, in line with what would be expected from related research. Interestingly, if anything, the opposite appears to be true among mothers. Column (4) of Table 3 shows that the policy may have a larger effect on mothers of daughters than it does on those with sons (although, again, the interaction coefficient is not significant with the F-P method).

[36] Appendix Table A3 shows that the effects of CA-PFL are driven by fathers of first-born children both in household where the mother does not work and in households with two employed parents. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[37] Lundberg and Rose (2002) find that fathers' labor supply and wages increase more in response to births of sons than daughters, which is in contrast to our finding that fathers spend more time at home with newborn boys than girls. However, their study covers a time period with very little availability of paid family leave for U.S. men. The patterns we find in our data could also be in part driven by selection, since fathers of sons are more likely to live with their children than fathers of daughters (Dahl and Moretti, 2008). However, this effect is relatively small.

Table 4 shows the effects of CA-PFL on fathers' and mothers' leave-taking for families in each quartile of the adjusted household income distribution. Household income is adjusted for the number of adults and number of children in the family with the equivalence scale used in the Census Bureau's supplemental poverty measure (Renwick and Fox, 2016).[38] This measure accounts for family size while also recognizing that expenses are not the same for all family members due to economies of scale (Betson and Michael, 1993). The first four columns show the effects of CA-PFL on fathers' leave-taking by quartile. The results suggest the effects of this policy are nonlinear and appear to be driven by fathers in the top and bottom quartile. The last four columns show analogous estimates for mothers' leave-taking. The effects for mothers are again non-monotonic in household income, but the effect is largest (and only statistically significant with the F-P method) for those in the 26-50th percentile of the adjusted income distribution. Interestingly, the mean leave-taking rates are also different across family income. However, while the results in Table 4 provide suggestive evidence of some heterogeneity in effects of PFL by household income, we note that the differences across groups are not statistically significant. Moreover, these results should be interpreted with caution as the measure of household income available in the ACS is endogenous to past leave-taking decisions.[39]

Finally, in exploratory analyses, we also examined heterogeneity in leave-taking by fathers' demographic characteristics. We obtain suggestive evidence that the effects are smallest among Hispanic fathers (relatively to non-Hispanic white, African-American, and Asian fathers),

[38] We divide household income by the equivalence scale, which is computed as follows: $Equivalence\ Scale = (adults + 0.8 * first\ child + 0.5 * other\ children)^{0.7}$ for single parent households, and $Equivalence\ Scale = (adults + 0.5 * children)^{0.7}$ for two parent households.
[39] Results using a measure of adjusted predicted household income are available upon request. We predict household income by regressing it on all observable demographic characteristics of the parents included in equation (1).

although small sample sizes prevent us from making definitive conclusions.[40] We also found that CA-PFL may have a larger effect on fathers with some college or a high school degree than for those with a four year degree. However, there is no corresponding positive effect for fathers who have not graduated from high school. These results are available upon request.

Household Leave-Taking

CA-PFL provides paid parental leave to any eligible parent and not just the primary caregiver. To examine household leave-taking, Table 5 explores effects on leave-taking in two-parent households. In column (1), we study households where the father is employed and the mother does not work. Columns (2)-(5) further limit the sample to households with fathers who have employed spouses, so that both parents are potentially eligible to take paid leave. Demographic controls for both spouses are included in the regressions, which are weighted by the ACS household weights.[41] The estimated coefficients suggest that fathers in both types of households are more likely to take leave after CA-PFL goes into effect. Column (1) shows that the policy increases leave-taking during the survey reference week among fathers in households where mothers do not work by 0.4 percentage points, or 25 percent at the sample mean. However, this coefficient is only significant with clustered standard errors, and not according to the F-P method. Column (2) demonstrates that, in households where both parents work, CA-PFL increases leave-taking during the survey reference week by either parent by four percentage points, or 22 percent. The increase in fathers' leave-taking is driven both by a 0.41 percentage point rise in the probability that both parents are

[40] Small sample sizes arise in part because we require the fathers in our sample to be employed and residing with their children. For example, there are only 49 black fathers of infants on leave in California in the whole sample, and only 1000 black fathers of infants in California overall.

[41] The sample is essentially the same if we condition on the mother and father of the youngest child residing in the same household (but not necessarily being married). This is a function of how IPUMS links children to parents: if both parents are present but not married to each other, the least proximate parent is unlinked. We do not distinguish between stepmothers and biological mothers.

on leave at the same time (a 28 percent increase) and a 0.53 percentage point increase in father-only leave, while the mother is at work (a 50 percent increase). Note, however, that these results are only suggestive as the F-P p-values are above 0.1.[42] The increase in father-only leave-taking indicates that providing CA-PFL to fathers—in addition to mothers—may increase the total number of days that at least one parent stays home with the infant. Married employed mothers are substantially more likely to take leave after the CA-PFL program comes into effect as well, and they are almost always on leave while the father is at work.

Finally, Appendix Tables A3 and A4 show the heterogeneous effects for the household leave-taking outcomes by birth order and gender, respectively.[43] Although the results are often imprecisely measured using the F-P method, the point estimates are consistent with the earlier results. Fathers are more likely to take leave on their own when their child is male, but no more likely to do so if the child is a girl. This gender difference is also reflected in the probability that both parents are on leave at the same time. Additionally, the increase in father-only leave-taking is driven entirely by leaves taken after first births.

VI. ROBUSTNESS

An important limitation of a difference-in-difference analysis is that one must rely on an assumption that the outcomes in treatment and control groups would have followed parallel trends in the absence of the policy reform. While this assumption is inherently untestable, the fact that our results are very consistent across the DD and DDD specifications and robust to different sets

[42] The total increase in leave-taking for fathers in households where both parents work is 0.00943 (the sum of columns 3 and 4) with an F-P p-value of 0.036. This effect is much larger than the estimated increase in leave-taking for fathers in households where the mother does not work (0.0044), but the difference is not statistically significant at conventional levels.

[43] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

of controls is reassuring. We also perform a variety of other robustness tests that lend credibility to the identifying assumption.

Table 6 shows that the findings are similar if the data are collapsed down to the state-year level or if control groups are chosen to best match pre-policy trends in fathers' leave-taking using synthetic control methods (Abadie, Diamond, and Hainmueller, 2010). The first column shows the DD estimate of the effect of the policy on the share of fathers of infants on leave in California compared to all other states. The Donald and Lang (2007) two-step approach is used to obtain the estimates and standard errors, so inference is conducted using a t-distribution with 12 degrees of freedom. The effect size is very similar to the estimate obtained using individual-level data, with CA-PFL predicted to raise paternal leave taking by 0.8 percentage points in both cases. The Donald and Lang approach for calculating standard errors is often used to conduct inference when there are a small number of clusters. While 50 clusters is normally assumed to be large enough for the asymptotic results of cluster-robust standard errors to apply, recent work shows that the "effective" number of clusters is smaller when the number of observations per cluster varies across groups, as is true in the uncollapsed data (Carter, Schnepel, and Steigerwald, 2016), so that the cluster-robust standard errors could be under-estimated. However, the fact that, for most cases, inference is the same using the Donald and Lang two-step approach and when using cluster-robust standard errors on the uncollapsed data suggests this is not a major issue.

The remaining columns of Table 6 show the DD effect when comparing California to synthetic control groups that may better match pre-policy trends in leave-taking. In each column, the synthetic control group is formed by matching on different combinations of state-year characteristics, and the treatment effect is obtained by regressing differences in the rate of leave-taking between California and the synthetic control group in each year on an indicator for years after the policy takes effect. We follow Abadie, Diamond, and Hainmueller (2015) and construct p-values by estimating placebo effects for each other state in the sample, and then calculating the fraction of placebo effects that are greater than the estimated effect for California (note that these p-values are calculated differently from the F-P p-values used in the main analysis). The effect sizes are similar across columns, and statistically significant (at least at the 10 percent level) in all but one case, suggesting that the results are not sensitive to the choice of control groups.[44]

Appendix Table A5 replicates the main results in Table 2 omitting the individual and state-year controls and dropping year 2000 from the analysis.[45] The similarity of the results with and without controls suggests that they are not driven by correlations between the policy and changing demographic trends. Because the majority of data in 2000 comes from the Census, instead of the ACS, one may be concerned about comparability between 2000 and the other years. In particular, the Census data are collected over a relatively short time span whereas the ACS is conducted throughout the year. If there are differences in leave-taking behavior across different parts of the year, this sampling design may pose a problem. However, the results are robust to both of these changes.

As noted above, because only fathers with some recent work experience are eligible for CA-PFL, all of our results condition on employment. However, the work history requirements are relatively weak and some fathers who report being not employed could qualify for paid leave benefits. With this in mind, Appendix Table A6 shows that the findings are robust to relaxing this

[44] We have also done a placebo analysis, in which we assign each of the other 48 states (excluding New Jersey, which implemented a PFL program during our sample time frame) to be the treatment state instead of California and run our baseline DDD model for fathers' leave-taking as the outcome. For 41 out of the 48 states, we do not find any statistically significant DDD coefficients. The states with significant DDD coefficients are: AL, AR, ID, LA, NM, RI, and VT, and only two of them (ID and LA) have a positive DDD coefficient.

[45] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

employment restriction.[46] Specifically, the results in Table 2 hold if all fathers who have worked any positive number of weeks in the previous 12 months are included in the sample, or if all fathers with age-eligible children are included in the sample, regardless of employment status. This latter specification should be expected to attenuate the results slightly, as a smaller fraction of the treated sample is eligible for leave. However, given the high employment rate among fathers, the samples do not change dramatically, and estimated CA-PFL effects remain substantial, although slightly smaller on average than previously.[47]

VII. CONCLUSION

California's PFL program is the first explicit source of government-provided paid parental leave available to fathers in the United States, and, consistent with expectations, we find that the law had a marked effect on fathers' leave-taking. Our results show that the policy raised leave-taking among fathers of infants by a substantial and statistically significant 46 percent. In relative terms, this increase is much larger than the 13 percent growth estimated for mothers of infants, although because mothers take so much more leave, the absolute rise is much smaller (at around two days). Interestingly, the predicted increase in male leave-taking is similar to the estimate found in Baum and Ruhm's (2016) analysis of CA-PFL, using a much smaller and non-representative sample, while the rise in mother's leave-taking is considerably smaller than that obtained by either Baum and Ruhm (2016) or Rossin-Slater, Ruhm and Waldfogel (2013).[48] The increases we find

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[46] All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[47] Additionally, results are robust to including only private sector (those not working for local, state, or federal government, or the military) in the analysis. Essentially all private sector workers are eligible for CA-PFL, but not all government employees participate in the program (although some do). As some government employees are not eligible, excluding them from the analysis increases the magnitude of the estimates slightly, but the results are very similar to those presented here (and are available upon request).

[48] The ACS does not report reasons for temporary work absence, so it is possible that the ACS captures less *parental* leave-taking than other data sets such as the NLSY (used by Baum and Ruhm) and the CPS (used by Rossin-Slater,

are meaningful but nevertheless suggest that fathers are taking up only about a quarter of the leave for which they are eligible—an average of 1.5 weeks out of a total of 6 possible weeks. As such, our results suggest that any possible increases in employer costs associated with fathers using CA-PFL are likely to be small. In contrast, mothers are taking up about 9 weeks on average of the 12 weeks total they are potentially eligible for (combining 6 weeks of TDI leave for birth mothers and 6 weeks of PFL for all mothers).

Our analysis goes beyond the existing studies of CA-PFL by examining novel *household-level* leave-taking outcomes. We find that the law increases both joint leave-taking and "father-only" leave-taking. In households where both parents are employed, about half of fathers' leave-taking occurs at the same time that the mother is off work and the other half takes place when she is working. This suggest that CA-PFL increases the total amount of time that a parent spends at home with a new child.

Our analysis also breaks new ground by considering heterogeneity across birth order, child gender, and family income. As hypothesized, we find that the effect of CA-PFL on fathers' leave-taking is larger for fathers of first-borns than for fathers of higher order children, while there is no such difference for mothers. These patterns may reflect joint decisions made by mothers and fathers together, if for example they feel there is less need for exclusive paternal care for a second or later child (perhaps because the family has existing child care arrangements or because the mother has stopped working or moved to part-time work), or they may reflect greater financial constraints on leave-taking by (often higher paid) fathers for later children.

Ruhm and Waldfogel). In light of this possibility, our estimates can arguably serve as lower bounds. Also, we only observe leave-taking after the birth, whereas Ruhm and Baum captured increased leave-taking *prior to the birth* as well. This is likely to explain a portion of the smaller effect we obtained for mothers.

We do not find robust evidence of heterogeneity along the other dimensions we consider. The results are suggestive of the effect on fathers' leave-taking being larger for fathers of sons than fathers of daughters, which is consistent with prior literature on son preference. We also find suggestive evidence of non-monotonic differences in the magnitude of the effects by family income, although these differences are not significant at conventional levels.

Our findings are robust across a variety of alternative DD and DDD specifications, inference methods, and to the inclusion of numerous individual-level and state-year controls. We demonstrate that there are no statistically significant pre-trends in leave-taking behavior in the years before CA-PFL and obtain similar findings when collapsing the data to the state-year level and using synthetic control methods with a variety of control groups. This consistency of estimates increases our confidence that we are accurately measuring causal effects of CA-PFL.

Our results, when combined with the relative lack of employer-provided paternity leave in the United States, indicate that new fathers respond to expanded opportunities to take paid family leave. The evidence of increased father-only leave taking, among married households where both parents work, suggests that these fathers may become more actively involved in childcare, spending more time alone with their infants than they would have in the absence of the policy. If so, such policies would have implications for reducing gender disparities.

Although women currently make up nearly half of the United States labor force, the gender wage gap still persists, with full-time female workers earning 77 percent of what their male counterparts earn.[49] Further, mothers have traditionally performed a disproportionate share of childcare and housework, and this disparity also persists today (Hochschild and Machung, 1989; Blair and Lichter, 1991; Bianchi, 2011; Bianchi et al., 2012). The unequal burden faced by women

[49] See: https://www.whitehouse.gov/issues/equal-pay#top.

in the home, combined with a lack of flexibility in work schedules at most jobs, may be an important explanation for why the gender wage gap still exists despite tremendous progress in women's educational and labor market performance over the last half century (Goldin, 2014). Increased leave-taking by fathers—including time at home while mothers work—has the potential to promote gender equality. Moreover, to the extent that gendered patterns of childcare provision develop early on, even relatively small changes in initial paternity leave decisions may have important consequences.[50]

Overall, we find that California's PFL policy has led to a large relative increase in leave-taking among fathers of infants when compared to the low pre-PFL mean. Although the average number of days spent on leave is small compared to mothers, there has been a substantial increase in the share of fathers who take at least some time off work. Results are fairly consistent across demographic groups, suggesting that the effects of the policy are likely to be generalizable across states.

However, the effects we observe for California fathers are much smaller than those found in European countries, which as discussed earlier have considerably higher rates of wage replacement than is available through CA-PFL. The low level of wage replacement and lack of job protection may be a factor in the relatively lower rates of increased take-up. If so, this would have important implications for the design of future programs whether in other states or at the national level in the U.S.

[50] The amount of time fathers spend in childcare is correlated with the generosity of paternity leave policies (Fuwa and Cohen, 2007; Boll et al., 2014) and fathers who take more leave around the time of birth may be more involved in childcare throughout the child's life (Haas, 1990; Nepomnyaschy and Waldfogel, 2007; Tanaka and Waldfogel, 2007; Haas and Hwang, 2008). There could also be other benefits related to health and well-being (Cools, Fiva, and Kirkebøen, 2015) and longer-term effects on gender norms and role models (Ray, Gornick, and Schmitt, 2008).

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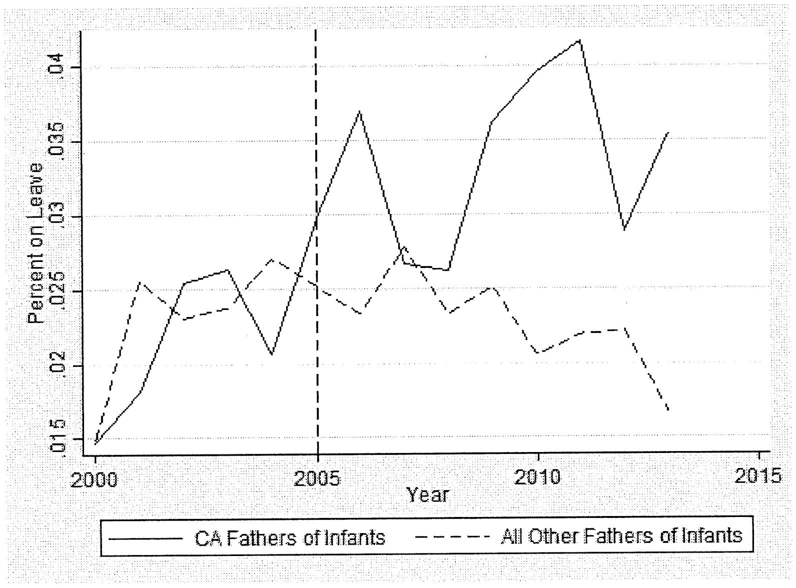
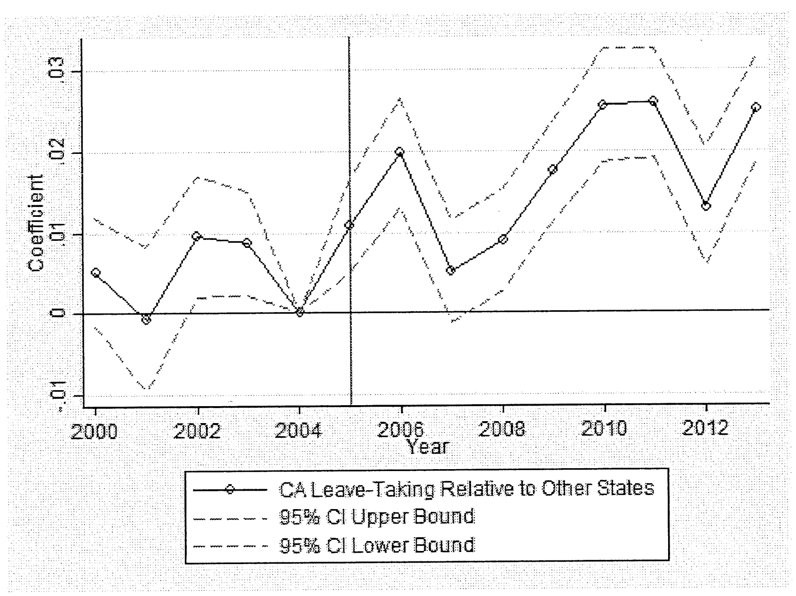
Figure 1: Fathers' Leave-Taking in CA Compared to Other States, Youngest Child Less Than Age 1



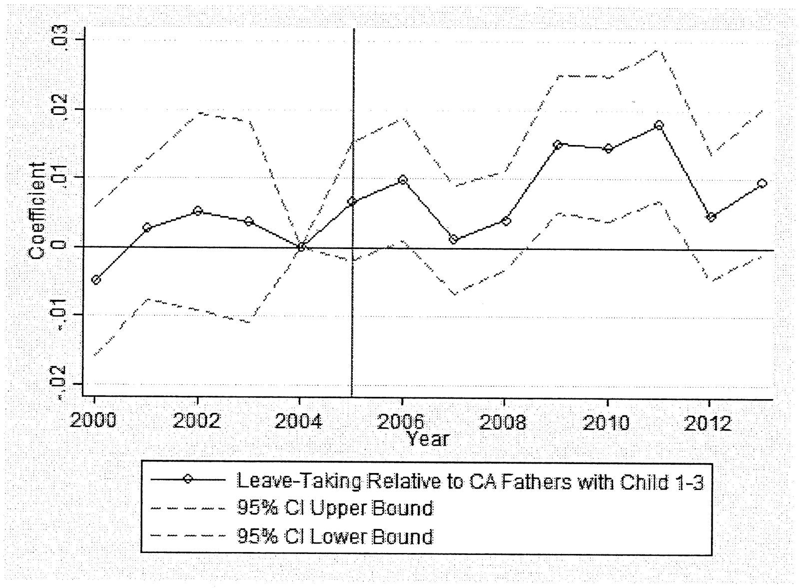
Note: This figure plots the mean leave-taking rate for California fathers of youngest children aged less than 1 year old (in the solid line) and fathers of youngest children aged less than 1 year old in all other states (in the dashed line).

Figure 2: Event Study Graph for Leave-Taking: Fathers of Infants in CA vs. Fathers of Infants in Other States



Note: This figure plots the coefficients and 95 percent confidence intervals from an event-study regression that compares the leave-taking rate of California fathers of infants relative to fathers of infants in other states in each year before and after CA-PFL implementation. The omitted category is 2004.

Figure 3: Event Study Graph for Leave-Taking: Fathers of Infants in CA vs. Fathers of Children aged 1-3 in CA



Note: This figure plots the coefficients and 95 percent confidence intervals from an event-study regression that compares the leave-taking rate of California fathers of infants relative to California fathers of youngest children aged 1-3 years old in each year before and after CA-PFL implementation. The omitted category is 2004.

Table 1: Correlation between CA PFL and fathers' characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
						Outcome:					
	Employed	Has infant	Mean age	Married	Less than high school	High school	Some college	4-Year degree or more	White	Under-represented minority	Predicted leave
CA*Post*Under1	0.00171		-0.299	-0.00133	-0.000541	-0.00236	0.0125	-0.00961	-0.00534	-0.00294	-0.00166
	(0.6490)		(0.0010)	(0.7380)	(0.9080)	(0.7720)	(0.0988)	(0.1670)	(0.2020)	(0.5490)	(0.6520)
	[0.918]		[0.444]	[0.931]	[0.984]	[0.942]	[0.628]	[0.684]	[0.757]	[0.864]	[0.915]
CA*Post		-0.000622									
		(0.7620)									
		[0.940]									
Observations	1,400	700	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400	1,400
R-squared	0.685	0.288	0.937	0.700	0.844	0.786	0.795	0.882	0.978	0.969	0.718
Individual Controls	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
State-Year Controls	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean	0.899	0.290	32.75	0.890	0.123	0.259	0.295	0.323	0.720	0.230	0.121

Note: Cluster robust p-values in parentheses. P-values calculated using the Ferman-Pinto method are in brackets. Outcomes are shown in column headings. Data is collapsed by state, year, and whether or not the father has a child under 1. Regressions in columns (1) and (3)-(11) identify correlation between CA-PFL and the outcome shown, comparing fathers of infants to father with a youngest child 1-3 years old, in California versus other states, before and after the implementation of CA-PFL. Column (2) compares fathers in California to fathers in other states, before and after the policy. Columns (2)-(11) condition on the father being employed. Coefficient of interest (DDD or DD in column 2) is shown.

Table 2: Effects of CA-PFL on fathers' leave-taking behavior

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All parents sample						
	Father is on leave						Mother is on leave
	DD Infants in other states	DD 1-3 year olds within CA	DD 2-4 year olds within CA	DDD	DDD	DDD	DDD
CA*Post*Under1				0.00915	0.00898	0.00894	0.0233
				(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
				[0.044]	[0.049]	[0.050]	[0.000]
CA*Post	0.0088						
	(<0.0001)						
	[0.037]						
Post*Under1		0.0102	0.0125				
		(0.0016)	(0.0002)				
Observations	251,685	109,064	99,688	879,873	878,377	878,377	682,872
R-squared	0.013	0.014	0.013	0.013	0.012	0.011	0.057
Individual Controls	YES	YES	YES	YES	YES	YES	YES
State-Year Controls	YES	NO	NO	NO	YES	YES	NO
Time FE	YES	YES	YES	YES	YES	YES	YES
State FE	YES	NO	NO	YES	YES	YES	YES
State-Year FE	NO	NO	NO	YES	NO	NO	YES
State Linear Trend	NO	NO	NO	NO	YES	NO	NO
Pre-Treatment Mean for CA Parents of Infants	0.0199	0.0199	0.0199	0.0199	0.0199	0.0199	0.177

Notes: Robust p-values in parentheses. Specifications that compare across states (columns 1 and 4-7) have cluster-robust p-values, clustered at the state level. In specifications that compare across states, p-values are also calculated using the Ferman-Pinto method and are shown in brackets. P-values calculated from robust standard errors are shown in parentheses for within-California specifications (columns 2 and 3). Coefficient of interest (DD or DDD) is shown. Individual controls include dummies for age of youngest child, number of children, citizenship status, marital status, 5-year age bins, race (White, Black, Hispanic, Asian, Other), education level (less than high school, high school, some college, 4-year degree or higher), and indicators for employed and in the labor force. State-Year controls include unemployment rate, average welfare benefit for a 4 person family, poverty rate, an indicator for whether the governor is democratic, state minimum wage, log of population, and per capita income. DDD compares fathers of infants to fathers with a youngest child aged 1-3, in California versus other states, before and after the policy. The "All parents" sample includes all employed fathers or mothers.

Table 3: Heterogeneous effects of CA-PFL on parents' leave-taking behavior

	(1)	(2)	(3)	(4)
	All parents sample			
	Father is on leave		Mother is on leave	
CA*Post*Under1	0.0191	0.0116	0.0268	0.0222
(Effect for 1st parity birth or boy)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	[0.019]	[0.126]	[0.093]	[0.156]
CA*Post*Under1*HigherParity	-0.0156		-0.00728	
(Higher vs. first parity difference)	(<0.0001)		(0.2770)	
	[0.033]		[0.561]	
CA*Post*Under1*Girl		-0.00536		0.0156
(Girl vs. boy difference)		(0.0347)		(0.0006)
		[0.568]		[0.465]
Observations	879,873	874,759	682,872	637,774
R-squared	0.013	0.013	0.057	0.058
Pre-Treatment Mean for CA Parents of Infants	0.0199	0.0199	0.177	0.177

Note: Cluster-robust p-values in parentheses. P-values calculated using the Ferman-Pinto method are in brackets. The coefficient in the first row is the DDD effect of CA-PFL on fathers' (or mothers') leave taking, comparing fathers (or mothers) of infants to those of 1-3 year olds, in California versus other states, before and after the introduction of CA-PFL for fathers (or mothers) with a first parity birth (Columns 1 and 3) or whose youngest child is a boy (Columns 2 and 4); the second coefficient is the differential effect for fathers (or mothers) whose youngest child is a higher parity birth (Columns 1 and 3) or whose youngest child is a girl compared to those with a boy (Columns 2 and 4). All models also include controls for individual and spouse characteristics, state and time dummy variables, and state-year fixed-effects.

Table 4: Heterogeneous effects of CA-PFL on fathers' leave-taking behavior by adjusted household income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Sample: Adjusted household income quartile of parent							
	1	2	3	4	1	2	3	4
	Father is on leave				Mother is on leave			
CA*Post*Under1	0.0123	0.00413	0.00710	0.0167	0.0171	0.0378	0.00198	0.0286
	(<0.0001)	(0.122)	(0.0057)	(<0.0001)	(0.005)	(<0.0001)	(0.692)	(<0.0001)
	[0.041]	[0.534]	[0.290]	[0.031]	[0.257]	[0.032]	[0.868]	[0.312]
Observations	220,018	219,940	219,994	219,921	170,721	170,718	170,716	170,717
R-squared	0.020	0.020	0.012	0.013	0.048	0.055	0.066	0.082
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
State-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Pre-Treatment Mean for CA Parents of Infants	0.0128	0.0264	0.0190	0.0228	0.155	0.137	0.192	0.213

Note: Cluster-robust p-values in parentheses. P-values calculated using the Ferman-Pinto method are in brackets. The coefficient is the DDD effect of CA-PFL on fathers' (or mothers') leave taking, comparing fathers (or mothers) of infants to those of 1-3 year olds, in California versus other states, before and after the introduction of CA-PFL for fathers (or mothers). Each column limits the sample to parents in the specified quartile of the adjusted household income distribution, where household income is adjusted for family size using the equivalence scale used in the supplemental poverty measure.

Table 5: Effects of CA-PFL on household leave-taking behavior

	(1)	(2)	(3)	(4)	(5)
	Two parent households sample:				
	Mother not employed	Both parents employed			
	Father is on leave	Either parent is on leave	Both parents are on leave	Father only is on leave	Mother only is on leave
CA*Post*Under1	0.00424	0.0404	0.00412	0.0053	0.0309
	(0.0040)	(<0.0001)	(0.0009)	(<0.0001)	(<0.0001)
	[0.318]	[0.027]	[0.263]	[0.168]	[0.073]
Observations	343,184	468,134	468,134	468,134	468,134
R-squared	0.016	0.055	0.007	0.012	0.063
Pre-Treatment Mean for CA Parents of Infants	0.0167	0.187	0.0149	0.0105	0.162

Note: Cluster-robust p-values in parentheses. P-values calculated using the Ferman-Pinto method are in brackets. The "Two Parent Households" sample is conditional on the father being married. The "Mother Not Employed" sample in the first column is conditional on only the father (and not the mother) being employed. The "Both Parents Employed" sample in columns 2-5 is conditional on both parents being employed (such that the leave variable is non-missing for both). The DDD specification is estimated in all columns, comparing fathers of infants to those with a youngest child 1-3 years old, in California versus other states, before and after the implementation of CA-PFL. The DDD coefficient is shown. All models also include controls for individual characteristics, state and time dummy variables, and state-year fixed-effects.

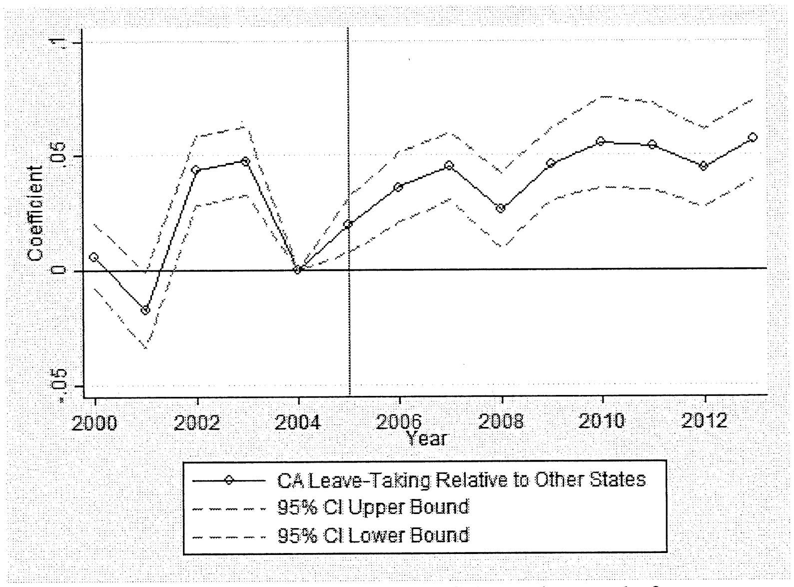
Table 6: Estimates based on collapsed data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Outcome: Father is on leave										
	Not matched	Synthetic 1	Synthetic 2	Synthetic 3	Synthetic 4	Synthetic 5	Synthetic 6	Synthetic 7	Synthetic 8	Synthetic 9	Synthetic 10
CA*Post	0.00809	0.00968	0.0107	0.0107	0.0137	0.0139	0.0144	0.0133	0.0107	0.0134	0.0132
	(0.0608)	[0.0625]	[0.0625]	[0.104]	[0.0208]	[0.0208]	[0.0208]	[0.0208]	[0.0625]	[0.0417]	[0.0417]
Observations	14	14	14	14	14	14	14	14	14	14	14
R-squared	0.324	0.330	0.310	0.195	0.388	0.405	0.433	0.399	0.310	0.430	0.353
Individual Controls	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Time FE	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
State FE	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Pre-Treatment Mean in CA	0.0203	0.0211	0.0211	0.0211	0.0211	0.0211	0.0211	0.0211	0.0211	0.0211	0.0211

Note: Donald-Lang p-values in parentheses (column 1). P-values constructed by estimating "in-space" placebo effects as in Abadie, Diamond, and Hainmueller (2015) in brackets (note these p-values are not the F-P p-values used in the main analysis). The samples compare fathers of infants in California to fathers of infants in other states. The first column shows the specification from Column 1, Table 3 using the Donald-Lang method to adjust the standard errors. Columns 2-11 show the raw DD effect of fathers of infants in California compared to fathers of infants in the synthetic control state, matched on different sets of variables. Synthetic 1 matches on the share of fathers on leave averaged over the pre-treatment period; Synthetic 2 matches on share on leave in each year of the pre-treatment period; Synthetic 3 matches on leave, share employed, and share in the labor force averaged over the pre-treatment period; Synthetic 4 matches on share on leave, employed, labor force, and race in the pre-treatment period; Synthetic 5 matches on share on leave in the pre-treatment period and share employed, in the labor force, and race averaged over the whole period; Synthetic 6 matches on the share on leave, employed, in labor force, race, and education averaged over the pre-treatment period; Synthetic 7 matches on share on leave in the pre-treatment period and share employed, in the labor force, race, and education averaged over the whole period; Synthetic 8 matches on share on leave in each year of the pre-treatment period and race and education averaged over the whole period; Synthetic 9 matches on 2 year averages of the share on leave in the pre-treatment period and race and education averaged over the whole period; and Synthetic 10 matches on share on leave averaged over the pre-treatment period and race and education averaged over the whole period.

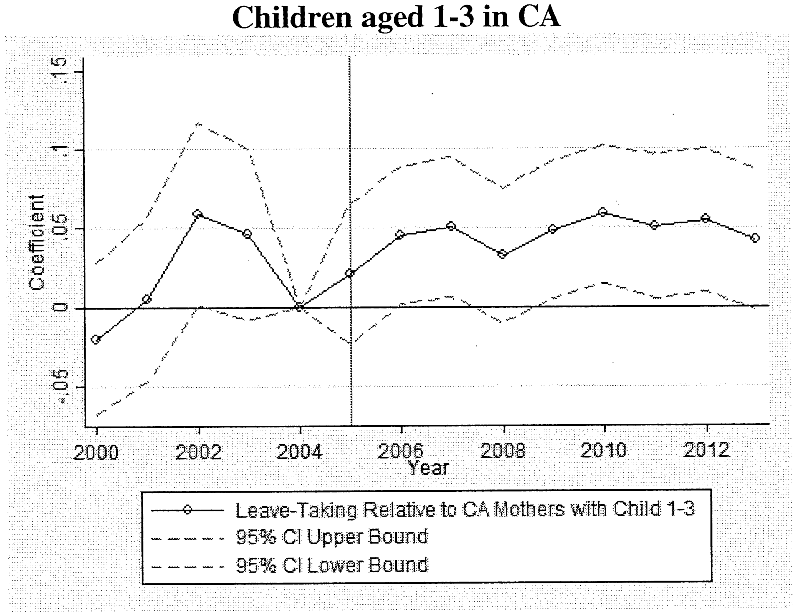
APPENDIX A

Figure A1: Event Study Graph for Leave-Taking: Mothers of Infants in CA vs. Mothers of Infants in Other States



Note: This figure plots the coefficients and 95 percent confidence intervals from an event-study regression that compares the leave-taking rate of California mothers of infants relative to mothers of infants in other states in each year before and after CA-PFL implementation. The omitted category is 2004.

Figure A2: Event Study Graph for Leave-Taking: Mothers of Infants in CA vs. Mothers of Children aged 1-3 in CA



Note: This figure plots the coefficients and 95 percent confidence intervals from an event-study regression that compares the leave-taking rate of California mothers of infants relative to California mothers of youngest children aged 1-3 years old in each year before and after CA-PFL implementation. The omitted category is 2004.

Appendix Table A1: Summary statistics

	Employed fathers					Employed mothers				
	Youngest child 0-3, all states	Youngest child <1, CA	Youngest child <1, other states	Youngest child 1-3, CA	Youngest child 1-3, other states	Youngest child 0-3, all states	Youngest child <1, CA	Youngest child <1, other states	Youngest child 1-3, CA	Youngest child 1-3, other states
Age	33.554	33.061	32.002	34.762	34.019	30.848	30.836	29.612	32.107	31.114
	(0.007)	(0.037)	(0.013)	(0.024)	(0.009)	(0.007)	(0.042)	(0.015)	(0.027)	(0.009)
Married	0.909	0.895	0.905	0.902	0.914	0.706	0.760	0.735	0.724	0.692
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Citizen	0.850	0.695	0.874	0.685	0.875	0.909	0.799	0.927	0.790	0.922
	(0.000)	(0.003)	(0.001)	(0.002)	(0.000)	(0.000)	(0.003)	(0.001)	(0.002)	(0.000)
White	0.653	0.378	0.700	0.360	0.697	0.633	0.388	0.685	0.360	0.660
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Black	0.077	0.037	0.081	0.041	0.083	0.141	0.060	0.139	0.071	0.154
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)
Hispanic	0.199	0.437	0.160	0.452	0.161	0.160	0.382	0.121	0.404	0.132
	(0.000)	(0.003)	(0.001)	(0.002)	(0.000)	(0.000)	(0.003)	(0.001)	(0.002)	(0.001)
Asian	0.060	0.136	0.047	0.138	0.048	0.054	0.155	0.042	0.153	0.040
	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)	(0.002)	(0.000)
Less than high school	0.133	0.213	0.121	0.228	0.119	0.090	0.122	0.079	0.145	0.086
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)
High School Diploma	0.245	0.203	0.246	0.206	0.253	0.223	0.185	0.212	0.204	0.231
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Some College	0.283	0.259	0.285	0.258	0.287	0.338	0.321	0.324	0.329	0.345
	(0.000)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
BA or higher	0.339	0.325	0.348	0.308	0.341	0.349	0.372	0.385	0.323	0.338
	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
Usual Hours Worked	44.852	43.670	44.837	43.739	45.101	35.759	36.144	35.998	35.838	35.649

	(0.011)	(0.059)	(0.023)	(0.037)	(0.014)	(0.014)	(0.078)	(0.028)	(0.048)	(0.017)
On Leave	0.021	0.028	0.022	0.024	0.019	0.064	0.199	0.148	0.040	0.032
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.000)
Total Household Income	86,122.59	93,164.62	82,412.74	94,140.33	85,947.91	81,607.77	100,429.75	81,544.49	95,840.09	78,968.89
	(82.515)	(494.842)	(157.089)	(310.324)	(103.203)	(89.094)	(646.093)	(181.592)	(364.376)	(106.213)
Total Personal Income	59,926.93	61,722.46	56,407.75	64,420.77	60,536.90	33,305.20	39,925.57	33,056.39	38,288.22	32,458.47
	(67.567)	(384.039)	(125.602)	(252.047)	(85.744)	(44.094)	(325.882)	(89.542)	(179.229)	(52.753)
N	879,873	30,534	221,664	78,530	549,145	682,872	19,428	159,961	55,390	448,093

Note: Standard errors in parentheses. In the first 5 columns, the sample is limited to employed fathers 16-54 years old. In the subsequent 5 columns, the sample is limited to employed mothers 16-54 years old. Statistics are weighted by the ACS person weights.

Appendix Table A2: Effects of CA-PFL on mothers' leave-taking behavior

	(1)	(2)	(3)	(4)	(5)	(6)
	Mother is on leave					
	DD state	DD 1-3	DD 2-4	DDD 1-3	DDD 1-3	DDD 1-3
CA*Post*Under1				0.0233	0.0233	0.0231
				(<0.0001)	(<0.0001)	(<0.0001)
				[0.000]	[0.024]	[0.029]
CA*Post	0.0267					
	(<0.0001)					
	[0.000]					
Post*Under1		0.0329	0.0302			
		(0.0005)	(0.0094)			
Observations	178,934	74,818	71,208	682,872	681,354	681,354
R-squared	0.014	0.074	0.078	0.057	0.055	0.055
Individual Controls	YES	YES	YES	YES	YES	YES
State-Year Controls	YES	NO	NO	NO	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
State FE	YES	NO	NO	YES	YES	YES
State-Year FE	NO	NO	NO	YES	NO	NO
State Linear Trend	NO	NO	NO	NO	YES	NO
Pre-Treatment Mean for CA Mothers of Infants	0.177	0.177	0.177	0.177	0.177	0.177

Note: Robust p-values in parentheses. Specifications that compare across states (columns 1 and 4-7) have cluster-robust p-values, clustered at the state level. In specifications that compare across states, p-values are also calculated using the Ferman-Pinto method and are shown in brackets. P-values calculated from robust standard errors are shown in parentheses for within-California specifications (columns 2 and 3). This table replicates Table 2, looking at the effect of CA-PFL on mothers instead of fathers. The sample includes all employed mothers.

Table A3: Heterogeneous effects by child parity—Two parent household sample

	(1)	(2)	(3)	(4)	(5)
	Two parent households				
		Both parents employed			
	Father is on leave, mother does not work	Either parent is on leave	Both parents are on leave	Father only is on leave	Mother only is on leave
CA*Post*Under1	0.011	0.0456	0.00726	0.0132	0.0251
	(0.00161)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	[0.198]	[0.159]	[0.290]	[0.001]	[0.346]
CA*Post*Under1* HigherParity	-0.00973	-0.0103	-0.00558	-0.0131	0.00838
	(0.0191)	(0.164)	(0.0134)	(<0.0001)	(0.257)
	[0.375]	[0.771]	[0.486]	[0.000]	[0.719]
Observations	343,184	468,134	468,134	468,134	468,134
R-squared	0.016	0.055	0.007	0.012	0.063
Pre-Treatment Mean for CA Parents of Infants	0.0169	0.188	0.0143	0.0106	0.164

Note: Cluster-robust p-values in parentheses. P-values calculated using the Ferman-Pinto method are in brackets. The "Two Parent Households" sample is conditional on the father being married. The "Both Parents Employed" sample is conditional on both parents being employed (such that the leave variable is non-missing for both). The coefficient in the first row is the DDD effect of CA-PFL on the leave taking outcome, comparing fathers (or mothers) of infants to those of 1-3 year olds, in California versus other states, before and after the introduction of CA-PFL for fathers (or mothers) whose youngest child is a first parity birth (within the household); the second coefficient is the differential effect for fathers (or mothers) whose youngest child is a higher parity birth. All models also include controls for individual characteristics, state and time dummy variables and state-year fixed-effects.

Table A4: Heterogeneous effects by gender of youngest child—Two parent household sample

	(1)	(2)	(3)	(4)	(5)
	Two parent households				
		Both parents employed			
	Father is on leave, mother does not work	Either parent is on leave	Both parents are on leave	Father only is on leave	Mother only is on leave
CA*Post*Under1	0.000358	0.0433	0.00833	0.0103	0.0247
	(0.0820)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
	[0.956]	[0.175]	[0.085]	[0.021]	[0.320]
CA*Post*Under1*Girl	0.00674	-0.00715	-0.00762	-0.0104	0.0109
	(0.0138)	(0.1980)	(<0.0001)	(<0.0001)	(0.0574)
	[0.408]	[0.752]	[0.312]	[0.148]	[0.696]
Observations	340,838	466,661	466,661	466,661	466,661
R-squared	0.016	0.055	0.007	0.012	0.063
Pre-Treatment Mean for CA Parents of Infants	0.0169	0.188	0.0143	0.0106	0.164

Note: Cluster-robust p-values in parentheses. P-values calculated using the Ferman-Pinto method are in brackets. The "Two Parent Households" sample is conditional on the father being married. The "Both Parents Employed" sample is conditional on both parents being employed (such that the leave variable is non-missing for both). The coefficient in the first row is the DDD effect of CA-PFL on the leave taking outcome, comparing fathers (or mothers) of infants to those of 1-3 year olds, in California versus other states, before and after the introduction of CA-PFL for fathers (or mothers) whose youngest child is a boy; the second coefficient is the differential effect for fathers (or mothers) whose youngest child is a girl compared to those with a boy. All models also include controls for individual characteristics, state and time dummy variables and state-year fixed-effects.

Appendix Table A5: Results excluding controls and excluding year 2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcome: Father is on leave, all parents sample							
	Excluding controls				Excluding year 2000			
	DD state	DD 1-3	DD 2-4	DDD 1-3	DD state	DD 1-3	DD 2-4	DDD 1-3
CA*Post*Under1				0.00882				0.00731
				(<0.0001)				(<0.0001)
				[0.055]				[0.154]
CA*Post	0.0117				0.00945			
	(<0.0001)				(<0.0001)			
	[0.034]				[0.030]			
Post*Under1		0.01	0.0122			0.0083	0.00997	
		(0.0022)	(0.0004)			(0.0204)	(0.0066)	
Observations	252,198	109,064	99,688	879,873	224,937	97,683	89,427	789,026
R-squared	0.002	0.001	0.001	0.002	0.010	0.009	0.008	0.009
Individual Controls	NO	NO	NO	NO	YES	YES	YES	YES
State-Year Controls	NO	NO	NO	NO	YES	NO	NO	NO
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	NO	NO	YES	YES	NO	NO	YES
State-Year FE	NO	NO	NO	YES	NO	NO	NO	YES
Pre-Treatment Mean for CA Fathers of Infants	0.0199	0.0199	0.0199	0.0199	0.0226	0.0226	0.0226	0.0226

Note: Robust p-values in parentheses. Specifications that compare across states (columns 1, 4, 5, and 8) have cluster-robust p-values, clustered at the state level. In specifications that compare across states, p-values calculated using the Ferman-Pinto method are shown in brackets. P-values calculated from robust standard errors in parentheses for within-California specifications (columns 2 and 3). This table replicates the first four columns of Table 2, but Columns (1)-(4) omit individual and state-year controls and columns (5)-(8) exclude observations from 2000 because the Census might be different from the ACS. The sample includes all employed fathers.

Appendix Table A6: Estimates based on alternative samples of fathers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Outcome: Father is on leave							
	Father worked at least one week last year				All fathers			
	DD state	DD 1-3	DD 2-4	DDD 1-3	DD state	DD 1-3	DD 2-4	DDD 1-3
CA*Post*Under1				0.00804				0.00755
				(<0.0001)				(<0.0001)
				[0.060]				[0.048]
CA*Post	0.00769				0.00735			
	(<0.0001)				(<0.0001)			
	[0.061]				[0.073]			
Post*Under1		0.00907	0.0112			0.00857	0.0108	
		(0.0024)	(0.0003)			(0.0029)	(0.0003)	
Observations	269,010	117,707	107,542	937,452	279,603	123,769	113,194	976,475
R-squared	0.003	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Individual Controls	YES	YES	YES	YES	YES	YES	YES	YES
State-Year Controls	YES	NO	NO	NO	YES	NO	NO	NO
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	NO	NO	YES	YES	NO	NO	YES
State-Year FE	NO	NO	NO	YES	NO	NO	NO	YES
Pre-Treatment Mean for CA Fathers of Infants	0.0181	0.0181	0.0181	0.0181	0.0176	0.0176	0.0176	0.0176

Note: Robust p-values in parentheses. Specifications that compare across states (columns 1, 4, 5, and 8) have cluster-robust p-values, clustered at the state level. In specifications that compare across states, p-values calculated using the Ferman-Pinto method are shown in brackets. P-values calculated from robust standard errors in parentheses for within-California specifications (columns 2 and 3). This table replicates the first four columns of Table 2, but includes all fathers who worked at least one week in the previous year in columns (1)-(4), instead of conditioning on employed fathers. Columns (5)-(8) include all fathers, regardless of employment status.

APPENDIX B

This appendix derives the formulas for W and $G(M)$ needed to perform inference on a DDD coefficient (β_5 in equation 2). These estimates are used to implement Ferman and Pinto (2016) method of inference. See Ferman and Pinto (2016) for more details on the full implementation of their method.

We start with a standard DDD model collapsed down to the group level, where s is state, t is year, and a is age of the father's youngest child:[51]

$$Y_{sat} = \beta_0 + \beta_1 CA + \beta_2 Treat + \beta_3 Under1 + \beta_4 CA * Post + \beta_5 CA_s * Under1 + \beta_6 Post * Under1 + \alpha CA * Post * Under1 + \eta_{sat}$$

The estimated DDD coefficient, $\hat{\alpha}$, can be written as:

$$\begin{aligned}\hat{\alpha} = \alpha + \frac{1}{S_1}\sum_{s=s^*}^{S}\Bigg[&\left(\frac{1}{A_1}\frac{1}{T_1}\sum_{a=0}^{0}\sum_{t=t^*}^{T}\eta_{sat} - \frac{1}{A_1}\frac{1}{T_0}\sum_{a=0}^{0}\sum_{t=1}^{t^*-1}\eta_{sat}\right)\\ &-\left(\frac{1}{A_0}\frac{1}{T_1}\sum_{a=1}^{A}\sum_{t=t^*}^{T}\eta_{sat} - \frac{1}{A_0}\frac{1}{T_0}\sum_{a=1}^{A}\sum_{t=1}^{t^*-1}\eta_{sat}\right)\Bigg]\\ -\frac{1}{S_0}\sum_{s=1}^{s^*-1}\Bigg[&\left(\frac{1}{A_1}\frac{1}{T_1}\sum_{a=0}^{0}\sum_{t=t^*}^{T}\eta_{sat} - \frac{1}{A_1}\frac{1}{T_0}\sum_{a=0}^{0}\sum_{t=1}^{t^*-1}\eta_{sat}\right)\\ &-\left(\frac{1}{A_0}\frac{1}{T_1}\sum_{a=1}^{A}\sum_{t=t^*}^{T}\eta_{sat} - \frac{1}{A_0}\frac{1}{T_0}\sum_{a=1}^{A}\sum_{t=1}^{t^*-1}\eta_{sat}\right)\Bigg]\end{aligned}$$

where S_1 is the number of treated states, S_0 is the number of control states, S is the total number of states, s^* is the first treated state, A_1 is the number of infant groups, A_0 is the number of non-infant groups, A is the maximum age of children in the sample, T_1 is the number of treated periods, T_0 is the number of untreated periods, T is the total number of periods, and t^* is the first treated period. Here we assume there is only one infant group, $a = 0$, but this can easily be generalized to allow for multiple treated ages.

We can write this as:

[51] In implementation, we first regress out the individual level controls as recommended in F-P.

$$\hat{\alpha} = \alpha + \frac{1}{S_1}\sum_{s=s^*}^{S} W_s - \frac{1}{S_0}\sum_{s=1}^{s^*-1} W_s$$

where[52]

$$W_s = \left(\frac{1}{A_1}\frac{1}{T_1}\sum_{a=0}^{0}\sum_{t=t^*}^{T}\eta_{sat} - \frac{1}{A_1}\frac{1}{T_0}\sum_{a=0}^{0}\sum_{t=1}^{t^*-1}\eta_{sat}\right) - \left(\frac{1}{A_0}\frac{1}{T_1}\sum_{a=1}^{A}\sum_{t=t^*}^{T}\eta_{sat} - \frac{1}{A_0}\frac{1}{T_0}\sum_{a=1}^{A}\sum_{t=1}^{t^*-1}\eta_{sat}\right)$$

Assuming that errors are correlated within states and $M(s,a,t)$ is the number of individual-level observations in cell s,a,t,

$$\eta_{sat} = \nu_{st} + \frac{1}{M(s,a,t)}\sum_{i=1}^{M(s,a,t)} \varepsilon_{isat}$$

so:

$$\begin{aligned} var(W_s) = var\Bigg[&\left(\frac{1}{T_1}\sum_{a=0}^{0}\sum_{t=t^*}^{T}\nu_{st} - \frac{1}{T_0}\sum_{a=0}^{0}\sum_{t=1}^{t^*-1}\nu_{st}\right) - \left(\frac{1}{T_1}\sum_{a=1}^{A}\sum_{t=t^*}^{T}\nu_{st} - \frac{1}{T_0}\sum_{a=1}^{A}\sum_{t=1}^{t^*-1}\nu_{st}\right) \\ &+\left(\frac{1}{T_1}\sum_{a=0}^{0}\sum_{t=t^*}^{T}\left[\frac{1}{M(s,a,t)}\sum_{i=1}^{M(s,a,t)}\varepsilon_{isat}\right] - \frac{1}{T_0}\sum_{a=0}^{0}\sum_{t=1}^{t^*-1}\left[\frac{1}{M(s,a,t)}\sum_{i=1}^{M(s,a,t)}\varepsilon_{isat}\right]\right) \\ &-\left(\frac{1}{T_1}\sum_{a=1}^{A}\sum_{t=t^*}^{T}\left[\frac{1}{M(s,a,t)}\sum_{i=1}^{M(s,a,t)}\varepsilon_{isat}\right] - \frac{1}{T_0}\sum_{a=1}^{A}\sum_{t=1}^{t^*-1}\left[\frac{1}{M(s,a,t)}\sum_{i=1}^{M(s,a,t)}\varepsilon_{isat}\right]\right)\Bigg] \end{aligned}$$

This can be expressed as:

$$\begin{aligned} var(W_s) = A + B\Bigg[&\left(\frac{1}{T_1}\right)^2\sum_{a=0}^{0}\sum_{t=t^*}^{T}\frac{1}{M(s,a,t)} \\ &+\left(\frac{1}{T_0}\right)^2\sum_{a=0}^{0}\sum_{t=1}^{t^*-1}\frac{1}{M(s,a,t)} + \left(\frac{1}{T_1}\right)^2\sum_{a=1}^{A}\sum_{t=t^*}^{T}\frac{1}{M(s,a,t)} + \left(\frac{1}{T_0}\right)^2\sum_{a=1}^{A}\sum_{t=1}^{t^*-1}\frac{1}{M(s,a,t)}\Bigg] \end{aligned}$$

[52] W_s is referred to as W_j in F-P.

where A and B are constants.

Let

$$q = \left(\frac{1}{T_1}\right)^2 \sum_{a=0}^{0} \sum_{t=t^*}^{T} \frac{1}{M(s,a,t)} + \left(\frac{1}{T_0}\right)^2 \sum_{a=0}^{0} \sum_{t=1}^{t^*-1} \frac{1}{M(s,a,t)} + \left(\frac{1}{T_1}\right)^2 \sum_{a=1}^{A} \sum_{t=t^*}^{T} \frac{1}{M(s,a,t)} + \left(\frac{1}{T_0}\right)^2 \sum_{a=1}^{A} \sum_{t=1}^{t^*-1} \frac{1}{M(s,a,t)}$$

Following F-P, the predicted $G(M)$ is obtained by regressing $\widehat{W}_s$ on q and a constant, and then $\widehat{G(M)}$ is a consistent estimator for $var(W_s)$.