The Economic and Social Impacts of Paid Family Leave in California: Report for the California Employment Development Department*

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1 Overview

1.1 Research objectives

In this study, we use detailed administrative data from the California Employment Development Department (CA EDD) to: (i) document trends in paid leave utilization and leave duration under California's Paid Family Leave (PFL) and State Disability Insurance (SDI) programs, with a focus on the possible impacts of the Great Recession; (ii) describe differences in program participation across gender, age, employer size, and employer industry; (iii) analyze the impacts of the programs on workers' leave-taking and labor market outcomes; and (iv) examine the effects of PFL on employer-level outcomes, such as total wage costs and turnover rates.

1.2 Primary conclusions

The PFL program is widely utilized, but there are some differences across groups and claim types.

- Women and men from all income and age groups, working in firms of all sizes and industries, make PFL claims for both bonding with a newborn or adopted child and caring for an ill family member.

- Bonding claims are substantially more common than caring claims. Both types of claims have risen gradually between July 2004 (the time of program implementation) and December 2014 (the last month in our data). There has been a particularly substantial rise in claim rates by men. However, claim rates do not appear to be driven by economic trends including the Great Recession.

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- For female claimants, the most common industry is health care and social assistance,[1] followed by retail trade. For male claimants, the most common industry is retail trade, followed by manufacturing.

- Women in the lowest pre-claim earnings quartile and women in the highest pre-claim earnings quartile have had the largest number of bonding claims, relative to women in the middle quartiles.

- The vast majority of PFL claimants make only a single claim.

- The majority of women who take bonding leave take the full six weeks that are provided. By contrast, about 40 percent of men take six weeks of bonding leave, while most of the remainder take between two and five weeks. There has not been much change in the distribution of bonding leave duration over time.

There are some differences in labor market attachment among claimants.

- Among bonding claimants, higher earning women are more likely to be attached to the labor market after the claim than lower earning women. Between 38 and 55 percent (between 21 and 32 percent) of high earning (low earning) women are classified as always employed post-claim.

- Among bonding claimants, higher earning men are more likely to be attached to the labor market after the claim than lower earning men. Between 49 and 64 percent (between 36 and 45 percent) of high earning (low earning) men are classified as always employed post-claim.

- Among bonding and caring claimants who remain in the labor market four quarters after the claim, all are more likely to end up at their pre-claim firm than at a different firm.

- On average, relative to bonding claimants, caring claimants are more likely to be attached to the labor market both before and after the claim.

Higher benefits lead to longer leave duration and higher earnings one year after the claim.

- Focusing on claimants close to the maximum benefit earnings threshold, there is causal evidence that higher benefit amounts lead to longer leave duration. Our results suggest that an additional $1000 in quarterly benefits is associated with a 0.02 week, 0.14 week, and 0.20 week increase in total leave duration for female bonding, female SDI, and male SDI claimants, respectively.

[1] 85 percent of this category is health care establishments, including hospitals, physician offices, and nursing care facilities. The 15 percent that is social assistance includes daycares, temporary shelters, and vocational rehabilitation services.

- Focusing on claimants close to the maximum benefit earnings threshold, there is causal evidence that higher benefit amounts increase the likelihood of employment one year after the claim. Our results suggest that an additional $1000 in quarterly benefits is associated with a 2.4, 1.9, and 1.2 percent increases in subsequent earnings for female bonding, male bonding, and male SDI claimants, respectively.

There is no evidence that firms with higher rates of PFL take-up are burdened with higher wage costs or significantly increased employee turnover rates.

- Using data on nearly all California employers that ever existed between January 2000 and December 2014, we find no evidence that firm turnover or wage costs rise when leave-taking rates rise. In fact, the average firm has a lower per worker wage bill and a lower turnover rate today than it did before PFL was introduced.

2 Background

Family leave programs provide individuals with time off work to care for their newborn or adopted children as well as for ill or aging family members. In the United States, before 1993, twenty-five states and the District of Columbia had some type of family leave provisions, which were mostly unpaid and did not offer job protection, and varied in length between six and sixteen weeks (Trzcinski and Alpert, 1994). The Family and Medical Leave Act (FMLA), enacted at the federal level in 1993, mandated that employers grant twelve weeks of unpaid job-protected family leave with continued coverage by the employer's health insurance (if such coverage was already offered at the job) to qualifying workers. However, due to firm size and work history requirements, only slightly more than half of U.S. workers in the private sector were eligible (Ruhm, 1997). By contrast, most other countries in the world have national *paid* family leave policies. In fact, the U.S. is the only OECD country that does not provide some type of paid family leave on the national level (see Ruhm, 2011 for a longer discussion of family leave policies around the world).

2.1 Family leave in California

In 2004, California became the first state in the country to implement a paid family leave program (hereafter, CA-PFL or PFL). CA-PFL provides workers with six weeks of leave, with 55 percent of usual pay replaced (up to a maximum benefit of $1,104 per week in 2015), and with almost universal eligibility among private sector workers. The program is financed through payroll taxes levied on the employees. To be eligible for the program, individuals are required to have worked at least 300 hours during a "base period" 5 to 18 months before the initiation of the leave.

CA-PFL is integrated with California's SDI system, which has the same benefit schedule as CA-PFL and provides paid leave to workers for a non-work-related illness or injury that prevents them from performing their regular job duties. Additionally, birth mothers (but not fathers) can take SDI leave around the period of childbirth. Under SDI, women who have a normal pregnancy with a vaginal delivery can get up to four weeks of leave before the expected delivery date and up to six weeks of leave after the actual delivery date. Thus, women who take both SDI and PFL can get a total of 16 weeks of paid leave. Moreover, a woman's doctor may certify for her to obtain a longer period of SDI leave if the delivery is by Cesarean section, or if there are medical complications that prohibit her from performing her regular job duties. Paid leaves under CA-PFL and SDI are not directly job-protected, although job protection is available if the job absence simultaneously qualifies under the FMLA. Additionally, workers may be eligible for job protection under the California Family Rights Act (CFRA) and/or California's Pregnancy Disability Leave law (CA-PDL). Similar to the FMLA, CFRA provides unpaid job-protected leave with continued employer-provided health insurance coverage to eligible workers. CA-PDL provides up to 16 weeks of job protected leave for those who work for an employer of 5 or more to recover from a pregnancy-related disability.[2]

2.2 What we can learn from studying CA-PFL

Studying the impacts of CA-PFL and SDI on workers and employers is important as the results may be informative both for cost-benefit calculations associated with the programs in California and for understanding the potential impacts of similar programs enacted in other states or nationally. In fact, three other states have enacted a PFL program following California's lead. The other states are New Jersey (in 2008), Rhode Island (in 2014), and most recently, New York, whose program is slated to begin in 2018. Below, we review the existing literature on this topic and discuss the contribution of our current analysis.

[2]Information on CA-PFL and SDI is available at http://www.edd.ca.gov/disability/FAQ_PFL_Benefits.htm.

2.2.1 Effects on employees

Since family leave provisions exist to provide workers with time off from work to care for their families, they are expected to increase leave-taking. However, their effects on individuals' subsequent labor market outcomes such as employment and wages are theoretically ambiguous (Klerman and Leibowitz, 1994). Following a family event (such as the birth of a child or an illness of a family member), a worker has three choices: he/she can continue to work, he/she can take leave from the job and return to work after, or he/she can become not employed. As mentioned, a family leave policy should raise (or, at least, not reduce) leave-taking on average, but this effect may come from two groups of workers: (1) those who would have otherwise remained employed and on the job, and (2) those who would have otherwise quit their jobs. For the former group, there will be an increase in leave-taking, but no change in employment in the short term; for the latter group, the higher rate of leave-taking occurs alongside a decrease in immediate non-employment. Moreover, there may be consequences on labor market outcomes in the medium- and long-term as well. If family leave encourages workers to take leave instead of quitting their jobs, then the greater job continuity may improve their labor market prospects in the future. By contrast, if family leave increases time away from the job among employees who would have otherwise kept working, then there may be negative consequences on their later employment and earnings.

Most of the early literature on the effects of family leave on employees in the United States was centered on analyzing *unpaid* leave and focused on mothers.[3] Studies have found that the FMLA leads to increased leave-taking and more time off work after childbirth for mothers, but has no detectable effects on their later employment (see, e.g.: Waldfogel, 1999; Han *et al.*, 2009). State-level unpaid leave policies have also been shown to be associated with

[3] In other countries, there is a larger literature on the impacts of *paid* leave on both women's and men's leave-taking and labor market outcomes. See, for example: Ruhm (1998) for evidence from 16 European countries; Baker and Milligan (2008); Baker and Milligan (2010); Patnaik (2015) for evidence from Canada; Lalive and Zweimüller (2009) for evidence from Austria; Liu and Skäns (2010) and Ekberg *et al.* (2013) for evidence from Sweden; Dustmann and Schönberg (2012) and Schönberg and Ludsteck (2014) for evidence from Germany; and Carneiro *et al.* (2015) and Dahl *et al.* (Forthcoming) for evidence from Norway. While there is some variation in empirical designs and results across these studies, the general finding is that the implementation and extensions of paid family leave programs increase leave-taking among both mothers and fathers (although, the effect is typically larger for mothers than for fathers). Additionally, paid family leave provisions up to one year in length have either positive or no effects on parents' subsequent labor market outcomes such as employment and earnings.

increased leave-taking among mothers, although these effects are smaller and the estimates are less consistent (Klerman and Leibowitz, 1997; Han and Waldfogel, 2003; Washbrook *et al.*, 2011). The estimated effects are largest for relatively advantaged women, who are most likely to be eligible for unpaid leave and able to afford to take unpaid time off work.

Since the enactment of CA-PFL, a small but growing literature has used survey data sets to study its effects on employees. Rossin-Slater *et al.* (2013) use data from the March Current Population Survey (CPS) and show that CA-PFL implementation nearly doubled leave-taking rates among mothers of children under 1 year old, relative to control groups of similar mothers in other states and mothers of slightly older children in California. The estimated effects are largest for the least advantaged mothers (those who are unmarried, minorities, and with low education levels). Further, they provide some evidence that CA-PFL increased the usual weekly work hours of employed mothers of one to three year-old children by 10-17 percent.[4]

Baum and Ruhm (2016) use data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY) to analyze both mothers' and fathers' leave usage during the period surrounding childbirth, as well as on the timing of mothers' return to work, the probability of their eventual return to pre-childbirth jobs, and their subsequent labor market outcomes. Baum and Ruhm (2016) find that mothers increase leave duration by approximately 5 weeks, while fathers increase their leave duration by less than one week. They also provide evidence that CA-PFL leads to higher employment probabilities for mothers nine to twelve months after childbirth, and higher work hours and wages during the child's second year of life. While this study builds on earlier work by Rossin-Slater *et al.* (2013) by studying leave duration and analyzing fathers in addition to mothers, it is limited by small sample sizes in the NLSY data—e.g., there are only 158 California fathers in the post-PFL sample.

Bartel *et al.* (2015) use data with a larger sample size from the American Communities Survey (ACS), and examine fathers' leave-taking as well as leave-sharing in dual-earner households. They find that CA-PFL leads to an increase in the likelihood of being on leave

[4]Related, Das and Polachek (2015) also use data from the March CPS, but study the effects of CA-PFL on all young women (and not just mothers). They find some evidence that—relative to young women in other states, older women, and men—labor force participation rates, unemployment rates, and unemployment duration among California young women have increased following the introduction of CA-PFL.

during the survey week of about 0.9 percentage points (or, 46 percent relative to the pre-treatment mean) for fathers of infants. Additionally, they demonstrate that in households where both parents work, 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).

There are several important limitations of these studies, largely due to data constraints. The CPS and ACS do not have information on leave duration; all three of the data sets (CPS, ACS, and NLSY) do not have information on the benefit amount; and all analyses with survey data are subject to measurement error and non-response bias. Moreover, existing research has focused on leave-taking associated with the birth of a child, and has not considered leave-taking for other purposes such as care for an ill relative. Finally, although there has been some exploration of heterogeneity in leave-taking by worker characteristics such as education and race, there is little evidence on heterogeneity by employer characteristics such as industry and firm size.

2.2.2 Effects on employers

As mentioned above, the CA-PFL and SDI programs are financed entirely through employee payroll taxes, so there are no direct costs to employers in terms of funding the paid leave. Yet employers whose workers take leave might face other costs due to having to hire temporary replacement workers or coordinating the schedules of their employees. Alternatively, employers may experience benefits as a result of these programs, if workers who would have otherwise quit instead return to their jobs and thus reduce overall turnover rates.

The existing literature on the effects of employee leave-taking on employers is extremely limited. To the best of our knowledge, the only evidence comes from a survey and a set of in-depth interviews conducted by Eileen Appelbaum and Ruth Milkman (Appelbaum and Milkman, 2011; Milkman and Appelbaum, 2013). Their survey included about 250 California firms in 2010, and they conducted in-depth interviews at 20 firms. Approximately 90 percent of the surveyed firms reported that CA-PFL had either a positive effect or no effect on employee productivity, morale, and costs. About two-thirds of the firms reported that they dealt with employee leave-taking by assigning work temporarily to other workers, while one-third stated that they hired temporary replacements.

While these surveys shed some light on employer experiences with CA-PFL, important questions remain. To date, there is no evidence on the consequences of PFL and SDI policies on employer turnover rates or total payroll. It is also unknown whether these effects may differ by employer industry or size.

2.2.3 Contributions of the current study

Our analysis contributes to the existing literature in the following ways. First, we use large-scale administrative data on leave-taking, leave duration, benefit amount, and reason for the leave under the CA-PFL and SDI programs to study trends in these variables over time since the implementation of CA-PFL, and to examine heterogeneity in these variables by worker and employer characteristics. We also examine the relationship between these variables and the Great Recession.

Second, we use two methods to study the effects of CA-PFL and SDI on employees' leave-taking and subsequent labor market outcomes: (i) we leverage the panel structure of our data to study changes in the labor market outcomes of individuals who take PFL, and (ii) we employ a methodology called a Regression Kink (RK) design to understand how monetary benefits provided under CA-PFL and SDI affect leave duration and workers' labor market outcomes. This method makes use of the non-linearity in the benefit schedule at the maximum benefit amount.

Third, we provide some of the first evidence on the impacts of PFL and SDI leave-taking on employer outcomes, including turnover rates and payroll. We aggregate our data to an employer-level panel, and compare the outcomes of employers with different rates of employee leave-taking, before and after the leave-taking occurs. Our models control for employer fixed effects, thereby accounting for all observable and unobservable time-invariant characteristics of the employers. Finally, we examine heterogeneity in employer effects by industry and employer size.

3 Results

To study these questions, we obtained several administrative data sets from the California EDD that are merged together. The details of the data and sample construction are discussed in Appendix A. In brief, we utilize data on: (i) the universe of PFL claims over July 2004 - December 2014, (ii) the universe of SDI claims over January 2000 - December 2014, and (iii) quarterly earnings over 2000-2014 for the universe of employees working for an employer that reports to the EDD tax branch.

3.1 Descriptive patterns in PFL and SDI utilization

We begin with a descriptive analysis of participation in the PFL and SDI programs. Additional results are presented in Appendix D. The analysis in this section is based on a total of 1,599,551 bonding claims, 175,198 caring claims, and 9,387,933 SDI claims.

Trends in the number of claims. In the top left panel of Figure 1 (page 24), we plot the trends in the annual number of PFL claims for bonding with a newborn or newly adopted child (hereafter, bonding claims) for women (in the solid blue line) and men (in the red dashed line) over 2004-2014. In 2004, the year of CA-PFL program initiation, there were just over 50,000 bonding claims among new mothers. That number approximately doubled by 2005, the first full year of the program, which is not surprising given that the program was only in effect for half a year in 2004. The annual number of female bonding claims continued to rise slowly over 2005-2008, and has remained relatively stable ever since at just under 125,000. During this time period, men have had fewer bonding claims than women, starting from about 10,000 in 2004, and rising to just over 50,000 in 2014.

The right $y-$axis shows the annual unemployment rate in California during the same time period. The Great Recession years are clearly noticeable, with a dramatic rise in the unemployment rate from about 5 percent in 2006 to a peak of 12 percent in 2010. The unemployment rate dropped to just below 8 percent by 2014. Note, however, that there are no substantial shifts in the PFL bonding claim trends during these years, suggesting that the Great Recession had little impact on PFL program participation.

One drawback of the top left panel of Figure 1 is that it does not account for changes in the underlying population of individuals eligible to take a PFL bonding claim. Ideally, we would like to know the number of new working parents in each year. However, the EDD tax branch data, which contain the universe of California employees in every year, have no information on their children's births or adoptions. Instead, we make use of data on the total number of births in California in every year from the National Center for Health Statistics (NCHS) Vital Statistics database (which, unfortunately, do not contain information on whether or not the parents are employed) to calculate the ratio of annual bonding claims to births. Trends in this ratio are shown in the top right panel of Figure 1 for women and men, respectively. Over 2004-2014, this ratio has increased from about 0.2 to 0.25 for women, and from about 0.04 to nearly 0.08 for men. Scaling these numbers by approximate employment rates of new parents from the ACS suggests that about 36.4 percent (4.4 percent) of employed new mothers (employed new fathers) made a bonding claim in 2004, while 45.4 percent (8.9 percent) of employed new mothers (employed new fathers) made a bonding claim in 2014.[5] Again, we see no noticeable shifts in these trends during the Great Recession years.

The bottom left panel of Figure 1 plots the trends in the annual number of PFL claims for caring for an ill family member (hereafter, caring claims) for women and men, with the unemployment rate again plotted on the right $y-$axis. There are substantially fewer caring claims than bonding claims in each year. For women, the number of caring claims has increased from just under 8,000 in 2004 to about 14,000 in 2012-2014. Men's caring claims have increased from around 2,000 to about 6,000 over this time period. As with the bonding claims, the increases in caring claims have been relatively gradual, and have exhibited no noticeable patterns that coincide with the Great Recession.

The bottom right panel of Figure 1 plots the trends in the annual number of SDI claims over 2001-2014. For both women and men, these numbers have been remarkably stable. Women have always had more claims than men (hovering around 425,000 per year over 2001-2012 for women, and around 225,000 per year over the same time period for men). The reason for this difference is likely due to the fact that, as noted above, women can use SDI to cover pregnancy- and childbirth-related leave-taking. There has been a slight decline in

[5]According to data from the ACS, over 2005-2014, about 55 percent of mothers with oldest children less than 1 year old and 90 percent of fathers with oldest children less than 1 year old were employed. Note that the ACS data only include parents who reside with their children.

SDI take-up over 2012-2014 for both men and women. As with the PFL claims, there seems to be no relationship between the unemployment rate and the number of SDI claims.

Characteristics of claimants. We next describe the characteristics of individuals who have claimed PFL benefits between July 2004 and December 2014. Table 1 (page 46) shows the distribution of PFL claimants by the number of claims, type of claim, and gender. The vast majority of claimants in our data are observed having only one claim—80.4 percent of female bonding claimants, 83.1 percent of male bonding claimants, 91.7 percent of female caring claimants, and 92.8 percent of male caring claimants are observed having one claim, respectively. The majority of the remainder of claimants has two claims. Less than two percent of PFL claimants in each group has three or more claims.

The distribution of bonding claims may seem surprising in light of fertility patterns in the United States, as, conditional on having at least one child, the majority of women has two or more children.[6] The fact that we observe most women with only one bonding claim in our data suggests that a non-trivial fraction of mothers exit the labor force, and are thus not eligible to take PFL for a subsequent child.[7]

In Table 2 (page 47), we provide summary statistics on the characteristics of bonding claimants by the number of claims and gender. Women who make only one claim are about 31 years old at the time of the claim, while men with only one claim are about 33 years old at the time of the claim. For both women and men, age at the time of the first claim is decreasing with the number of claims.

On average, female and male claimants with only one claim are at firms that have about 5,685 and 6,330 employees, respectively, in the quarter before the first claim. These averages are large due to a small number of very large employers. The median female (male) claimant with one claim is at a firm with 383 (639) employees. Individuals with more than one claim are on average at slightly larger firms. Women with only one claim have a pre-claim quarterly

[6]See, e.g., Table 1 of a U.S. Census Bureau report on 2012 fertility rates available here: `https://www.census.gov/content/dam/Census/library/publications/2014/demo/p20-575.pdf`.

[7]Some of the discrepancy between the distribution of bonding claims and fertility patterns is due to the fact that we only observe claims over 2004-2014. Some individuals in our data may have had children prior to 2004, while others have not finished childbearing by 2014. However, even when we limit the sample to claimants in 2007-2008, who are more likely to be having multiple children during our sample time frame, we still see that the majority of claimants only have one claim.

earnings of about $13,907, while men with only one claim have a pre-claim quarterly earnings of about $19,661, in 2014 dollars.[8] Individuals who have three or more claims have slightly higher earnings prior to the first claim, while individuals with two claims have the highest pre-claim earnings in our data.

We also show the distribution of pre-claim industries among bonding claimants. For female claimants, the most common industry is health care and social assistance, followed by retail trade. 85 percent of the health care and social assistance category is health care establishments (including hospitals, physician offices, and nursing care facilities) and 15 percent is social assistance (including daycares, temporary shelters, and vocational rehabilitation services). For male claimants, the most common industry is retail trade, followed by manufacturing.

Table 3 (page 48) reports the corresponding summary statistics for caring claimants. Caring claimants are older than bonding claimants—women with only one claim are about 46 years old, while men are about 44 years old. For most groups, claimants' average firm sizes and quarterly earnings are also higher than those of bonding claimants. Female caring claimants are most likely to work in the health care and social assistance industry, while male caring claimants are most likely to work in manufacturing.

Differences in claim trends across sub-groups. Figures 2 and 3 (pages 25 and 26) depict trends in the annual number of bonding and caring claims, respectively, by different sub-groups of women and men. The top left panel of each figure shows heterogeneity by industry, and notes the corresponding shares of female workers in each industry for context.[9] The top right panel of each figure shows heterogeneity by firm size. The bottom left panel of each figure shows heterogeneity by the claimant's pre-claim earnings quartile, while the bottom right panel of each figure shows heterogeneity by the claimant's age group.[10]

[8] Pre-claim earnings is defined as the highest earnings in quarters 2 through 5 before the first claim.

[9] The share of female workers in each industry is calculated using 2006-2015 CPS data.

[10] Quarterly earnings quartiles are constructed as follows: We first take 2006-2014 ACS data, limiting the sample to individuals aged 21-39 with non-zero earnings. We convert quarterly earnings to 2014 dollars. We calculate the quartile thresholds separately for women and men. For women, the 25th percentile is $3,841, the 50th percentile is $8,000, and the 75th percentile is $13,750. For men, the 25th percentile is $5,165, the 50th percentile is $9,761, and the 75th percentile is $17,251. We then group the PFL claimants into earnings quartiles based on their pre-claim earnings.

The highest number of claims and the largest increases in claims over the sample time frame come from workers who are in the health care and retail industries. There does not seem to be a lot of heterogeneity by firm size, although workers in firms with 50-499 and 500-4,999 employees have had the most claims (relative to workers in both smaller and larger firms).

Interestingly, women in the lowest pre-claim earnings quartile and women in the highest pre-claim earnings quartile have had the largest number of bonding claims, relative to women in the middle quartiles. For caring claims, highest take-up seems to have occurred among women in the second and fourth quartiles of the pre-claim earnings distribution.

Finally, the number of bonding claims is largest among women aged 25-29 and 30-34, and largest for men aged 30-34 and 35 or more, consistent with individuals in these age groups being most likely to have children. Caring claims are highest for women aged 45-54, consistent with them being most likely to care for aging parents and still being in the labor force.

Distribution of PFL benefit amounts. Figure 4 (page 27) shows the distributions of weekly benefit amounts in nominal terms during four of our sample years: 2005, 2008, 2011, and 2014. The distributions of women's bonding benefit amounts in the top left panel are skewed toward the left, consistent with the fact that women with low earnings make up a large share of the bonding claims. Women's caring benefit amounts are less skewed (see the bottom left panel). Men's bonding and caring benefit amounts are also more uniformly distributed (see the top and bottom right panels, respectively). In all cases, there is substantial mass at the maximum benefit amount, which facilitates the implementation of the regression kink (RK) method described below. Further, comparing across graphs for the different years suggests that there has not been much change in the distribution of weekly benefit amounts over time.

Distribution of claim duration. Figures 5 and 6 (pages 28 and 29) plot the distributions of bonding and caring claim durations, respectively, during 2005, 2008, 2011, and 2014. The top left panel of Figure 5 shows that the majority of women who take bonding leave take the full six weeks that are provided. By contrast, as shown in the bottom left panel of Figure 5, about 40 percent of men take six weeks of bonding leave, while most of the remainder take between two and five weeks. When we consider the distribution of the total childbirth-related leave duration under SDI and PFL for women in the top right panel of Figure 5, we see a peak at 6 weeks, driven by those who only take PFL. But a substantial proportion of women take advantage of both SDI and PFL to increase their total leave duration. Consistent with women being able to get up to 16 weeks of total leave if they have a normal pregnancy and delivery, 88 percent of leaves in our data are 16 weeks or less. Ninety-four percent of leaves are 18 weeks or less, and only 2 percent of leaves are more than 20 weeks.

As for the caring claim duration, both men and women are most likely to take the full six weeks of leave, although a non-trivial proportion take less than six weeks. There is not very much change over time in these distributions.

3.2 Effects on employee outcomes

3.2.1 Labor market attachment pre- and post-claim

We study employees' labor market attachment before and after the claim. For this analysis, we use the panel structure of our data to follow employees over time, descriptively studying changes in their labor market outcomes pre- and post-claim. We calculate sub-group means of various measures of pre- and post-claim labor market attachment of individuals in our data by type of claim, gender, age, and pre-claim earnings.[11] The analysis in this section is based on a total of 122,777 individuals making bonding claims and 54,847 individuals making caring claims.

We classify individuals as attached if they had 9 or more quarters of positive employment earnings during the window of 2-13 quarters before the claim, and if they had pre-claim quarterly earnings of $2,500 or more.[12] The remainder of claimants is classified as not

[11]Since, as discussed above, the majority of claimants in our data only have one claim, and since the characteristics of individuals with only one claim are different from those with more than one claim, we focus on the labor market trajectories of claimants who make a single claim. Further, we restrict our bonding sample for this analysis to those who make a single claim between July 2007 and September 2008. This restriction makes it likely that we exclude individuals who might have made a claim before July 2004 if PFL existed or who might make a claim after the data end in December 2014. We similarly restrict our caring sample to those who make a single claim by September 2008. This restriction ensures that we have enough quarters after September 2008 to observe long-run outcomes.

[12]We exclude the quarter before the claim from this assignment rule because many women take SDI in

attached.

Post-claim labor market attachment measures are defined based on the number of quarters of employment in the window of 4-23 quarters after the claim. We classify individuals as “never employed,” having “limited employment,” having “moderate employment,” and “always employed” if they have zero, 1 to 12, 12 to 19, and 20 quarters of employment, respectively, during this window.

Lastly, we characterize individuals according to whether they change employers or exit the market after the claim. Post-claim employer change is defined as the same (different) employer if the claimant’s primary employer is the same (different) four quarters after the claim as it was one quarter before the claim. Claimants are classified as exiting the market if they have positive earnings in the quarter before the claim, but no earnings four quarters after the claim.

Table 4 (page 49) reports sub-group means of measures of labor market attachment for bonding claimants. In columns (1) and (2), we report the fraction of claimants who are attached and not attached to the labor market before the claim. Panel A demonstrates that, pre-claim, about 88 percent of high earning female claimants are attached to the labor market. Low earning women are less likely to be attached pre-claim—71 percent of low earning female claimants aged 25-34 are classified as attached, while 58 percent (72 percent) of low earning women aged less than 25 (35 or more) are attached. Men have higher labor market attachment rates pre-claim—91-93 percent of high earning men are attached, while 76-83 percent of low earning men are attached, depending on their ages.

Columns (3)-(6) present means of our four post-claim labor market attachment measures. Panel A suggests that lower earning women experience lower rates of labor market attachment after the claim relative to higher earning women. Between 21 and 32 percent (between 38 and 55 percent) of low earning (high earning) women are classified always employed post-claim, and older women are more likely to be always employed post-claim than younger women. Nearly half (between 43 and 48 percent depending on age) of low earning women are classified as either never employed or having limited employment post-claim. Between 29 and 35 percent of high earning women are never employed or have limited employment

that quarter before taking bonding leave through PFL.

after the claim.

Notably, men who take a bonding claim also have relatively low labor market attachment rates post-claim. Only 36-45 percent (49-64 percent) of low earning (high earning) men are classified as always employed post-claim. 28-29 percent of low earning men are either never employed or have limited employment post-claim, while 15-20 percent of high earning men are characterized in this way.[13]

Lastly, columns (7)-(9) characterize individuals according to whether they change employers or exit the market after the claim. Among claimants who remain in the market four quarters after the claim, all are more likely to end up at their pre-claim firm than at a different firm. However, there is substantial heterogeneity by gender, income, and age. Older and higher earning women are more likely to return to their pre-claim firms than younger and lower earning women. Across the earnings categories, men are more likely to return to their pre-claim firms than women.

Table 5 (page 50) reports the same statistics for caring claimants. In general, relative to bonding claimants, caring claimants are more likely to be attached to the labor market both before and after the claim. As with the bonding claimants, high earning caring claimants are more attached than low earning caring claimants, and return to their pre-claim employers at higher rates. However, while very few caring claimants are never employed post-claim, a non-trivial fraction of both men and women have limited employment after the claim.

3.2.2 Causal effects of benefits on employee outcomes

We also use a research design called "Regression Kink" (RK) to analyze the causal effects of PFL and SDI benefits on employee outcomes. This research design is necessary because simply comparing the outcomes of individuals who have higher benefits to those of individuals receiving lower benefits will not yield a *causal* estimate of the effect of the benefit amount. Individuals who receive higher benefits are different from those who receive lower benefits in many ways (e.g., they typically have higher education levels and longer labor market

[13]We also explored heterogeneity in pre- and post-claim labor market attachment among male bonding claimants by the duration of the claim. In general, pre-claim attachment rates are similar across men who take different lengths of bonding leave. Men who take longer leaves have lower post-claim attachment rates and are less likely to return to their pre-claim employers than men who take shorter leaves. However, sub-group sample sizes in this analysis are small and prevent us from making more definitive conclusions.

experience), and it is challenging to separate out the causal effect of the benefit from the influences of these other factors.

The RK method exploits the fact that the PFL and SDI benefit schedule is not linear. Figure 7 (page 30) depicts the 2005, 2008, 2011, and 2014 benefit schedules, where both benefits and base period earnings are presented in quarterly nominal terms. In each year, there is a linear relationship between the quarterly benefit amount and the quarterly base period earnings with a slope of about 0.55, up to a threshold at which the maximum benefit amount begins. Put differently, in each year, there is a "kink" in the relationship between the quarterly benefit amount and the quarterly base period earnings: the slope of the benefit schedule changes negatively from 0.55 to 0. The location of this kink changes over time (i.e., both the maximum benefit amount and the earnings threshold change), and the earnings threshold is labeled in each graph at the kink point.

Figure 8 (page 31) provides more details on the maximum benefit amount by showing the maximum quarterly benefit level in nominal dollars in each quarter in our sample time frame. We denote the first quarter in our data—2000q1—as quarter 1 and the last quarter in our data—2014q4—as quarter 60. CA-PFL went into effect in the 3rd quarter of 2004, which is quarter 19 on the $x-$axis in the figure. The maximum quarterly benefit has nominally increased from \$9,464 in 2004 to \$13,975 in 2014. In real 2014 dollars, this translates to an increase from \$11,860.61 to \$13,975 during this time period.

The RK method makes use of the change in the slope of the benefit function to estimate the causal effect of an additional \$1000 in benefits on the outcome of interest. Intuitively, the RK method tests for whether there is a change in the slope of the relationship between the outcome and base period earnings at the earnings threshold. Assuming that—in the absence of the kink in the benefit function—there would be a smooth (i.e., non-kinked) relationship between the outcome and earnings, evidence of a change in the slope would imply a causal effect of the benefit amount on the outcome. More details on the RK method are provided in Appendix B. The analysis in this section is based on 123,488 bonding claims for women, 65,451 bonding claims for men, 16,741 caring claims for women, 9,992 caring claims for men, 321,305 SDI claims for women, and 288,077 SDI claims for men.

Empirical evidence of a kink in the benefits schedule. We begin by describing results from the RK analysis graphically. First, in Figure 9 (page 32), we characterize the empirical distributions of PFL and SDI benefits by type of claim and gender of the claimant. Since both the maximum benefit amount and the earnings threshold associated with the maximum benefit vary across quarters, we normalize variables on the $x-$ and $y-$axes in these graphs to accommodate data from our entire sample period. Specifically, the $x-$axis plots normalized earnings, which is equal to the base period earnings divided by the earnings threshold. The data are aggregated into bins of size 0.01 in normalized earnings. The $y-$axis plots the average benefit in each bin divided by the maximum benefit. The red and green lines show linear regressions fitted to the data on the two sides of the threshold. For all types of claims (bonding, caring, and SDI) and for both men and women, there is clear evidence of a kink in the relationship between normalized earnings and the normalized benefit at the earnings threshold (i.e., at the value of 1 on the $x-$axis).

To estimate the magnitude of this slope change, we turn to the regression results in Table 6 (page 51). These specifications only include observations within a $\$5,000$ bandwidth surrounding the earnings threshold. We present results for the three types of claims—bonding (columns (1) and (2)), caring (columns (3) and (4)), and SDI (columns (5) and (6)). For each claim, we first present results for females and then for males.

Across all types of claims and for both genders, the change in the slope at the earnings threshold is large, negative, and statistically significant. Although the empirical magnitude of this slope change is not exactly -0.55 as predicted by the benefit schedule, it is reasonably close.[14] For females, the magnitudes are -0.41, -0.44, and -0.45 for bonding, caring, and SDI claims, respectively. For males, the magnitudes are -0.51, -0.53, and -0.52, respectively.

Effects on leave duration. Figure 10 (page 33) considers total leave duration in weeks (PFL+SDI) as the outcome. It plots the average weeks of leave by 0.01 bins of normalized earnings, by type of claim and gender of claimant. In all graphs, there is suggestive evidence that the slope of the relationship between leave duration and base period earnings becomes

[14]The reason that the empirical relationship between earnings and the benefit amount in our data may differ from the benefit schedule is because only earnings subject to the SDI tax are used to calculate benefit amounts. However, not all earnings are subject to the SDI tax, and we cannot distinguish between eligible and ineligible earnings.

more negative after the earnings threshold.

We quantify the magnitude of this slope change in Table 7 (page 51). Consistent with the graphical evidence, the estimated coefficient is negative for both men and women and for all types of claims. For female bonding claimants and for both male and female SDI claimants, the negative coefficient is also statistically significant.

As detailed in Appendix B, the estimate of the causal effect of an increase in benefits on total leave duration is calculated by dividing the coefficients in Table 7 by those in Table 6. Since both of these are negative, our results suggest a positive relationship between the benefit amount and leave duration. Specifically, dividing the coefficients in Tables 6 and 7 implies that each $1000 in quarterly benefits is associated with a 0.02 week, 0.14 week, and 0.20 week increase in total leave duration for female bonding, female SDI, and male SDI claimants, respectively.

Effects on employment four quarters after the claim. Figure 11 (page 34) plots the fraction of individuals who are employed four quarters after the claim by 0.01 bins of normalized earnings, by type of claim and gender of claimant. In general, higher base period earnings are associated with a greater likelihood of employment one year after the claim. There does not seem to be a noticeable change in the slope of this relationship at the earnings threshold.

Table 8 (page 52) presents estimates of the magnitude of the slope change when employment is the outcome. None of the coefficients is statistically significant at the 5% level. For male caring claimants, the coefficient is positive and marginally significant at the 10% level. Dividing by the coefficients in Table 6 implies that each $1000 in quarterly benefits is associated with a 1.5 percentage point decrease in employment four quarters after the claim. Relative to the sample mean of 0.82, this is a 2 percent decline.

Effects on earnings four quarters after the claim. Figure 12 (page 35) plots the average log earnings four quarters after the claim by 0.01 bins of normalized earnings, by type of claim and gender of claimant. As with employment, higher base period earnings are associated with higher earnings one year after the claim. The graphs do not exhibit clear evidence of a change in the slope at the earnings threshold, but, our regression results suggest that the change in slope is in fact statistically significant for some of the claimants in our data.

Table 9 (page 52) presents estimates of the change in slope for log earnings as the outcome. The coefficients are consistently negative and statistically significant at the 5% level for female and male bonding claimants as well as male SDI claimants (and marginally significant at the 10% level for female caring claimants). These negative numerators suggest that the relationship between PFL and SDI benefits and subsequent earnings is *positive*. Specifically, dividing by the coefficients in Table 6 suggests that each $1000 in quarterly benefits is associated with a 2.4, 1.9, and 1.2 percent increases in subsequent earnings for female bonding, male bonding, and male SDI claimants, respectively.

3.3 Effects on employer outcomes

To study the effects of PFL on employer-level outcomes, we aggregate our data to an employer by quarter panel. We study within-employer changes in outcomes as a function of changes in employee leave-taking rates. Our models account for all time-invariant characteristics of employers (e.g., industry or location) and all changing factors occurring in California (e.g., economic conditions or changes in population demographics). The wage analysis for this section is based on 39,942,254 firm-quarter observations and the turnover analysis is based on 36,530,145 firm-quarter observations. More details are provided in Appendix C.

We begin by describing the wage costs and turnover rates experienced by California firms from 2000-2014. Figures 13 and 14 and Panel A in Table 10 (pages 36, 37 and 53) compare the time trends for the average annual employee turnover rate (measured as the share of workers leaving firms) and the average per worker wage cost to total leave taking trends. These figures reveal no suggestion that firm turnover or wage costs rise when leave-taking rates rise. In fact, the average firm has a lower per worker wage bill and a lower turnover rate today than it did before PFL was introduced.

One might be concerned that these trends confound PFL trends with other time-varying factors affecting California, or that they partly reflect a changing composition of firms over the business cycle. We control for such confounding factors using the regression model described in Appendix C. The results are reported in Panel A in Table 11 (page 54). We find that an increase the share of employees taking leave by 1/1000 is associated with a decrease in the per worker quarterly wage bill of $1.67. Stated somewhat differently, the total quarterly wage bill for a firm with 1000 workers falls by $1,674 if one worker goes on PFL. This is consistent with firms not entirely replacing workers on leave. We similarly show that a similar increase in the share of workers on PFL is associated with a tiny increase in employee turnover. If one out of 1,000 employees takes PFL, turnover measured by the share of workers leaving (joining) firms rises by 0.000013 (0.00006) percentage points, or approximately 0.01 (0.06) percent given a base turnover rate of 10 percent per quarter.

3.3.1 Heterogeneity by firm size and industry

While the effects of PFL on firms appear very small when we look across all firms, they may mask heterogeneous effects for different sized firms or firms in different industries. We explore this issue by replicating the above analysis first for firms in a variety of size categories and then for selected industries. To provide some context, Figure 15 (page 38) displays the distribution of employees across firms size categories. Approximately 10, 20, 25, 35, and 10 percent of workers are in firms with fewer than 10 employees, 10-99, 100-999, 1,000-19,9999, and 20,000+ employees, respectively; and this distribution is stable over time. More importantly for our focus on firms, Figure 16 (page 39) shows the distribution of firms across firm size categories. While the workforce is somewhat evenly distributed across firm size categories, the vast majority of firms are small; approximately 90 percent of California firms have fewer than 10 employees.

Figures 17 and 18 and Panel B in Table 10 (pages 40, 41 and 53) compare the time trends for the average annual employee turnover rate and the average per worker wage cost to leave taking trends. There is again no suggestion that turnover is rising in any firm size category as PFL is implemented. The same is true for per worker wage costs, with one exception; average per worker wage costs at very large firms rose over the sample period. The extent to which this is due to PFL is less clear. We therefore turn to the firm fixed effects estimates reported in Panel B in Table 11. As expected, the PFL ratio point estimates for small firms are similar to those for the state as a whole. In contrast, the point estimates for large firm categories are generally statistically insignificant. This likely partially reflects the fact that there are few firms in these categories. But, taken as a whole, there is again no evidence of substantial negative effects of PFL take-up for firms. If anything, there is a small wage cost savings and a minuscule increase in employee turnover.

The results by industry generally echo the results described so far; small wage cost reductions with very small increases in turnover. Figures 19 and 20 (pages 42 and 43) show the distribution of workers and firms across industries, and Figures 21 and 22 and Panel C in Table 10 (pages 44, 45 and 53) compare the time trends for the average annual employee turnover rate and the average per worker wage cost to leave taking trends by industry. Finally, Panel C in Table 11 reports the firm fixed effect point estimates separately by industry.

Thus far we have aggregated leave taking for bonding and caring and men and women together. One might wonder if the effects differ by the reason for the leave and/or by the gender of the leave-taker. Table 12 (page 55) replicates Panel A in Table 11, but replaces the total share of PFL leave-takers with a ratio that uses total employment as the denominator and for the numerator uses either (i) women on bonding leave, (ii) men on bonding leave, (iii) women on caring leave, or (iv) men on caring leave.[15] Since women taking bonding leave constitute the majority of PFL takers, it is not surprising that the point estimates for this type of leave are similar to the overall rate reported in Table 11. While the estimates for some other types of leave are noisy, they are of a similar sign and magnitude.[16]

4 Conclusion

The California Paid Family Leave program provides eligible workers with short-term time off with partial earnings replacement to allow them to bond with their new children or care for seriously ill family members. While the primary objective of the program is to support families, it is also important to understand its possible impacts on individual claimants in terms of subsequent labor market outcomes as well as on firms in terms of their costs and

[15] We use total employees as the denominator because we do not know the gender of workers who do not claim PFL or SDI.

[16] One might also wonder how correlated these types of leave are within firms. The answer is not very; no correlation exceeds 0.03.

benefits. This study uses detailed administrative data on PFL (as well as SDI) program participants and tax data on quarterly earnings from the California Employment Development Department to explore these issues at a new level of detail.

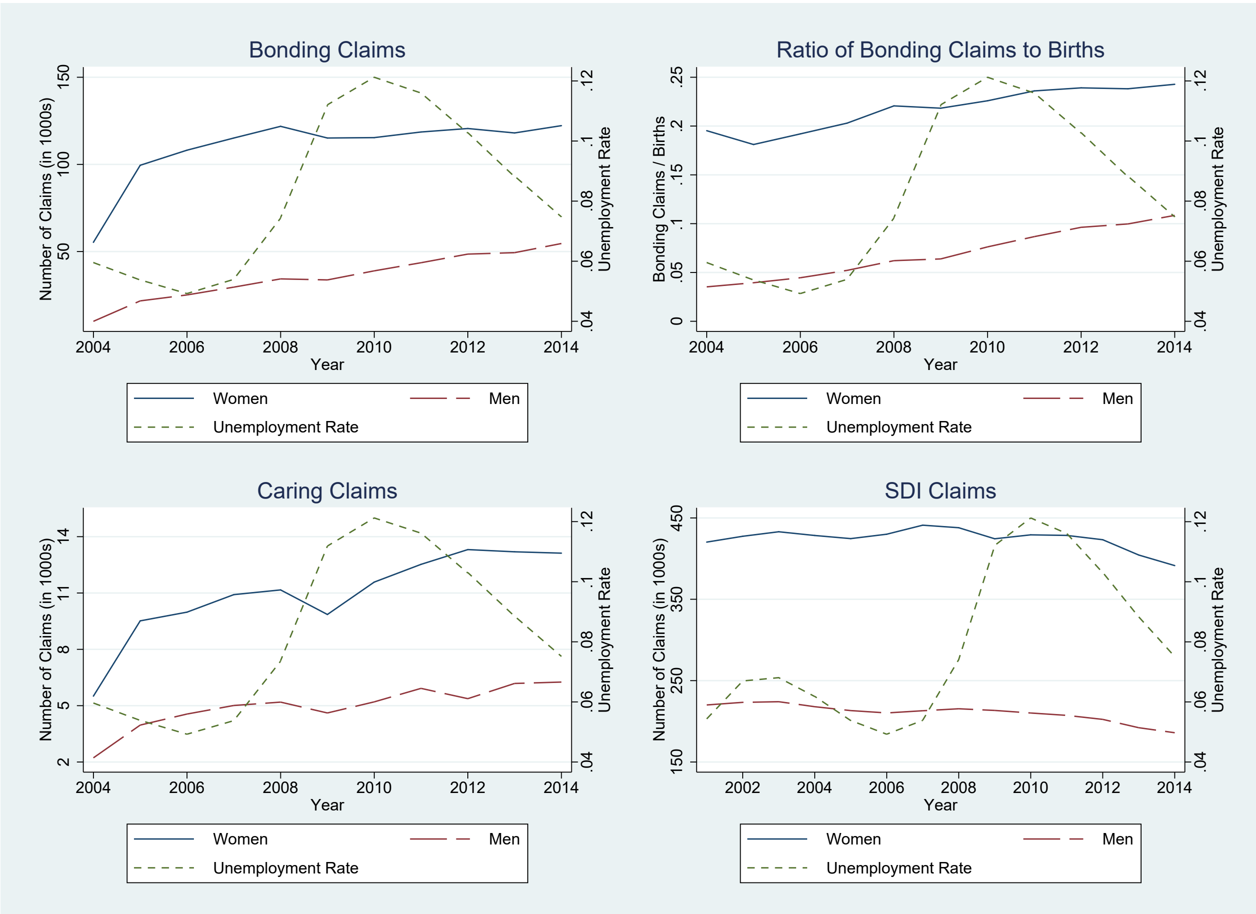
Our findings show that program utilization is widespread, across women and men from all income and age groups, working in firms of all sizes and industries. Claim rates have risen gradually over time, but do not appear to be driven by economic trends such as the Great Recession.

While there are some differences in labor market attachment rates pre- and post-claim across sub-groups, for a subset of individuals with earnings close to the maximum benefit earnings threshold, we find causal evidence that higher PFL and SDI benefit levels lead to higher earnings one year after the claim.

Finally, there is no evidence that firms with higher rates of leave-taking are burdened with higher wage costs or significantly increased employee turnover rates.

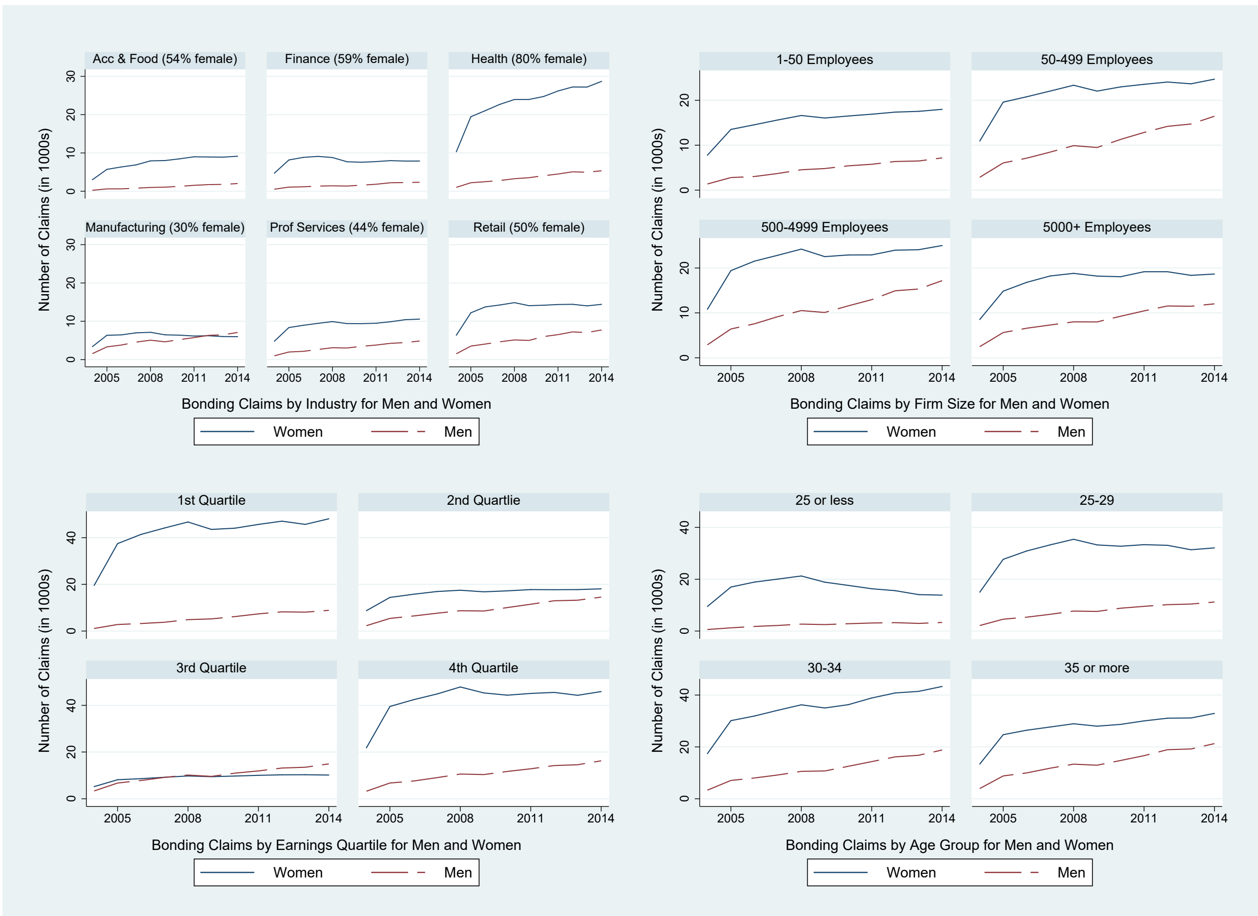
5 Figures

Figure 1: Paid Family Leave and State Disability Insurance Claim Trends



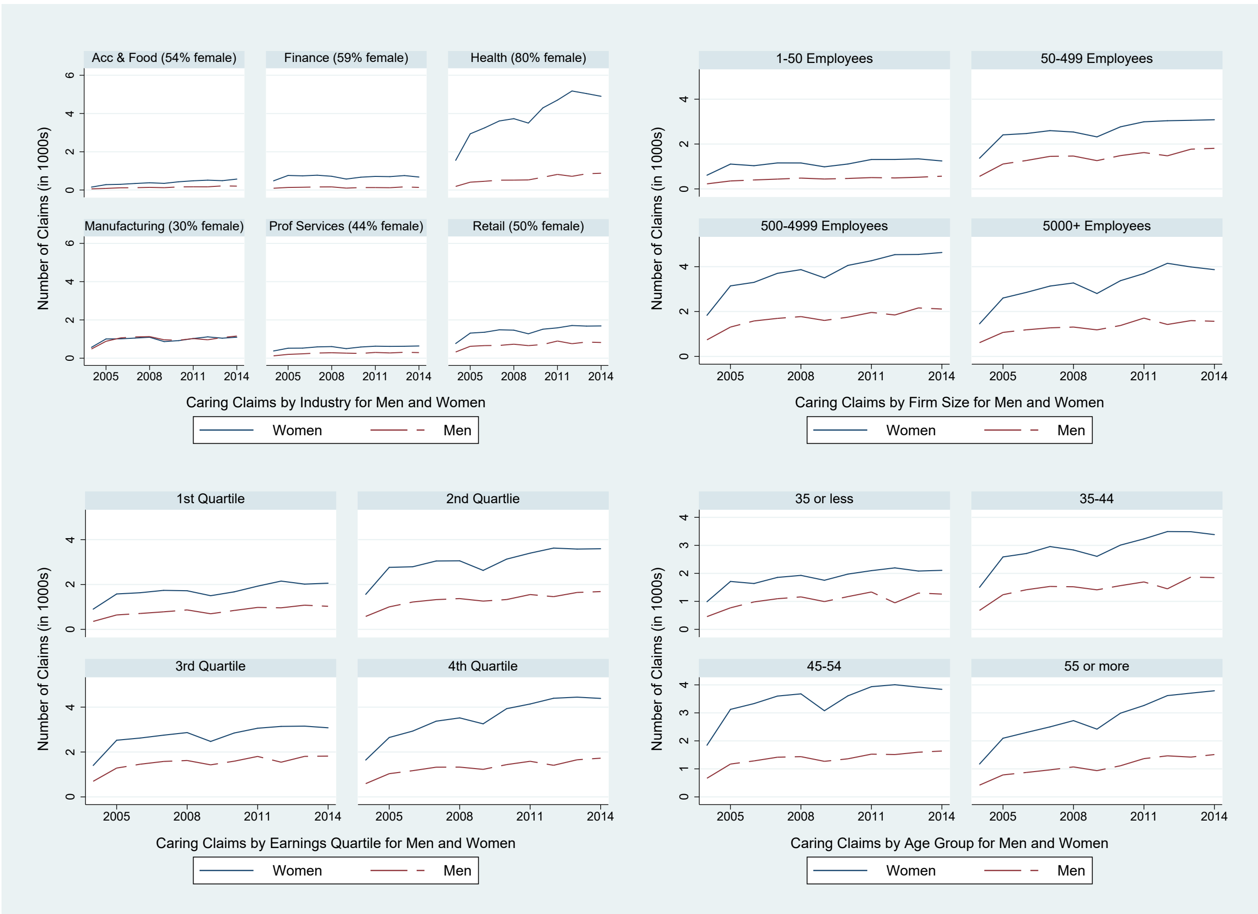
Notes: These sub-figures plot trends in the annual number of bonding claims (top left), the ratio of bonding claims to births (top right), the annual number of caring claims (bottom left), and the annual number of SDI claims (bottom right) for women (blue solid lines) and men (red dashed lines). Each sub-figure also plots the annual unemployment rate on the right axis (green dashed lines).

Figure 2: Bonding Claim Trends by Sub-Group



Notes: These sub-figures plot trends in the annual number of bonding claims by industry (top left), firm size (top right), earnings quartile (bottom left), and age group (bottom right) for women (solid blue lines) and men (red dashed lines). "Acc & Food" stands for accommodation and food services. Industry-level female employee percentages are calculated using 2006-2015 CPS data. Earnings quartiles are constructed as follows: We first take 2006-2014 ACS data, limiting the sample to individuals aged 21-39 with non-zero earnings. We convert earnings to 2014 dollars. We calculate the quartile thresholds separately for women and men. For women, the 25th percentile is $3,841, the 50th percentile is $8,000, and the 75th percentile is $13,750. For men, the 25th percentile is $5,165, the 50th percentile is $9,761, and the 75th percentile is $17,251. We then group the PFL claimants into earnings quartiles based on their pre-claim earnings, which is defined as their highest quarterly earnings in quarters 2 through 5 before the first claim.

Figure 3: Caring Claim Trends by Sub-Group



Notes: These sub-figures plot trends in the annual number of caring claims by industry (top left), firm size (top right), earnings quartile (bottom left), and age group (bottom right) for women (solid blue lines) and men (red dashed lines). "Acc & Food" stands for accommodation and food services. Industry-level female employee percentages are calculated using 2006-2015 CPS data. Earnings quartiles are constructed as follows: We first take 2006-2014 ACS data, limiting the sample to individuals aged 21-39 with non-zero earnings. We convert earnings to 2014 dollars. We calculate the quartile thresholds separately for women and men. For women, the 25th percentile is $3,841, the 50th percentile is $8,000, and the 75th percentile is $13,750. For men, the 25th percentile is $5,165, the 50th percentile is $9,761, and the 75th percentile is $17,251. We then group the PFL claimants into earnings quartiles based on their pre-claim earnings, which is defined as their highest quarterly earnings in quarters 2 through 5 before the first claim.

Figure 4: Distributions of Paid Family Leave Benefit Levels for Selected Years

Notes: These sub-figures plot the distributions of nominal weekly benefit amounts among PFL claimants. The top left sub-figure shows the distributions for bonding claims among women; the top right sub-figure shows the distributions for bonding claims among men; the bottom left sub-figure shows the distributions for caring claims among women; the bottom right sub-figure shows the distributions for caring claims among men. The maximum weekly benefit amount is labeled in each graph. All dollar amounts are nominal.

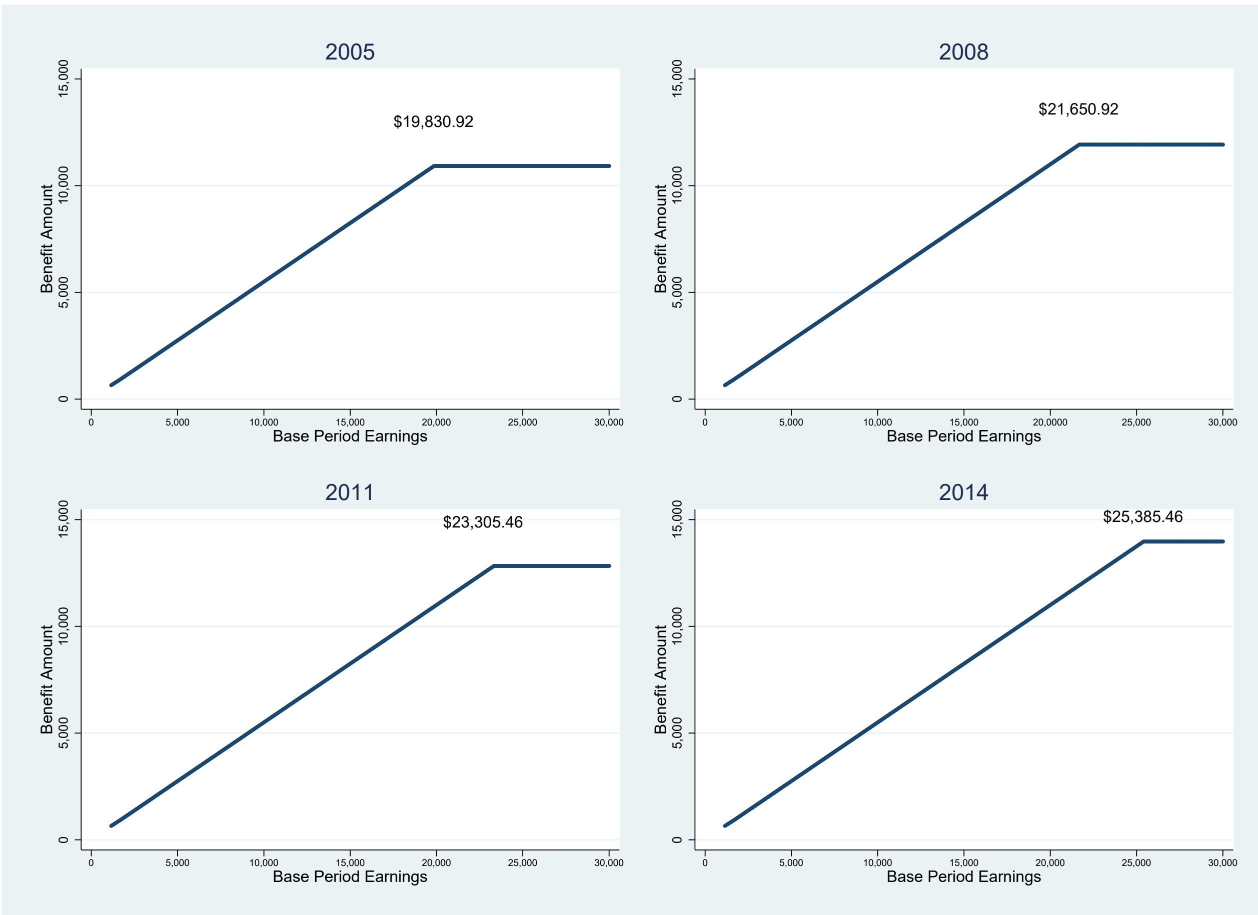
Figure 5: Distributions of Bonding Claim Durations for Selected Years

Notes: These sub-figures plot the distributions of bonding claim durations among PFL claimants. The top left sub-figure shows the distributions of bonding claim durations among women; the top right sub-figure shows the distributions of the total bonding + SDI claim durations among women who take PFL and SDI consecutively; the bottom left sub-figure shows the distributions of bonding claim durations among men.

Figure 6: Distributions of Caring Claim Durations for Selected Years

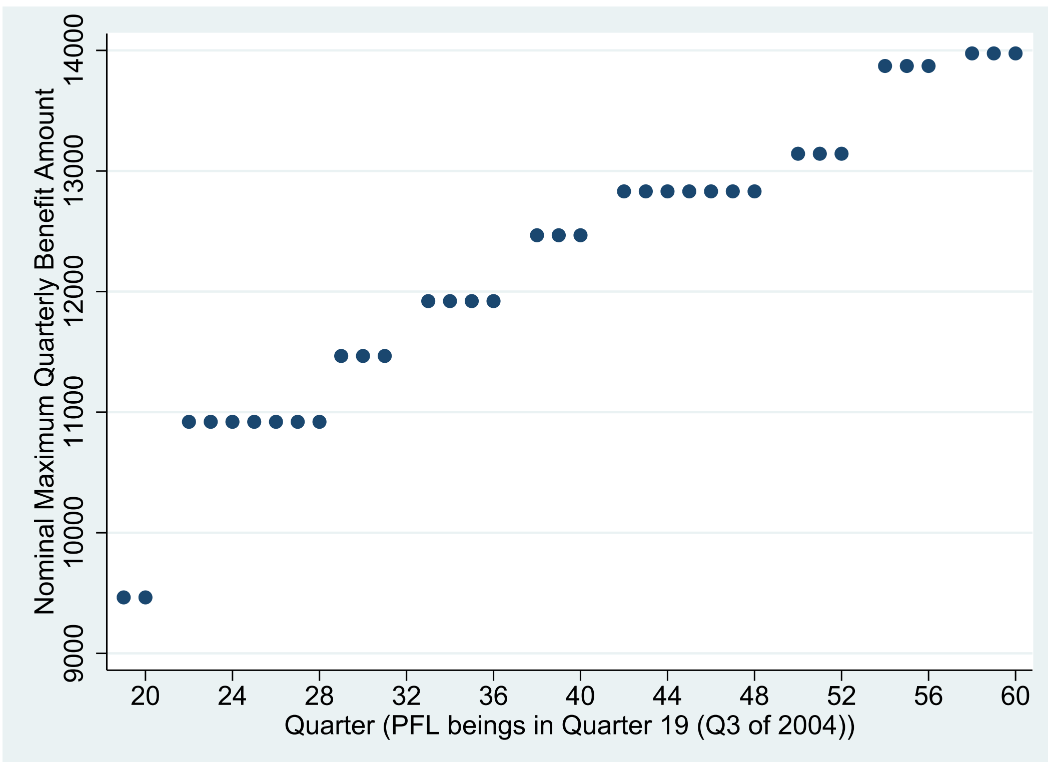
Notes: These sub-figures plot the distributions of caring claim durations among PFL claimants. The left sub-figure shows the distributions of caring claim durations among women; the right sub-figure shows the distributions of caring claim durations among men.

Figure 7: Benefit Schedule for Selected Years



Notes: This figure plots nominal quarterly base period earnings on the $x-$axis and the nominal quarterly benefit amount on the $y-$axis. The earnings threshold at which the maximum benefit begins is labeled in each sub-figure.

Figure 8: Maximum Quarterly PFL Benefit Amount



Notes: This figure plots the maximum quarterly PFL benefit level by quarter in nominal dollars. The first quarter of 2000 is quarter 1, so CA-PFL goes into effect in quarter 19 (quarter 3 of 2004). The last quarter in our data—quarter 60—is quarter 4 of 2014.

Figure 9: Empirical Distributions of PFL and SDI Benefits

Notes: These sub-figures show the distributions of PFL and SDI benefits by type of claim and gender of the claimant. The $x-$axis plots normalized quarterly earnings, which is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The data are binned into 0.01 bins of normalized earnings. The $y-$axis plots the average normalized quarterly benefit amount, which is equal to the average quarterly benefit amount in each bin divided by the maximum benefit amount (in real 2014 dollars). The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.

Figure 10: Effects of PFL and SDI Benefits on the Total Duration of Leave

Notes: These sub-figures show the average weeks of total PFL+SDI leave by 0.01 bins of normalized earnings, by type of claim and gender of claimant. Normalized quarterly earnings is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.

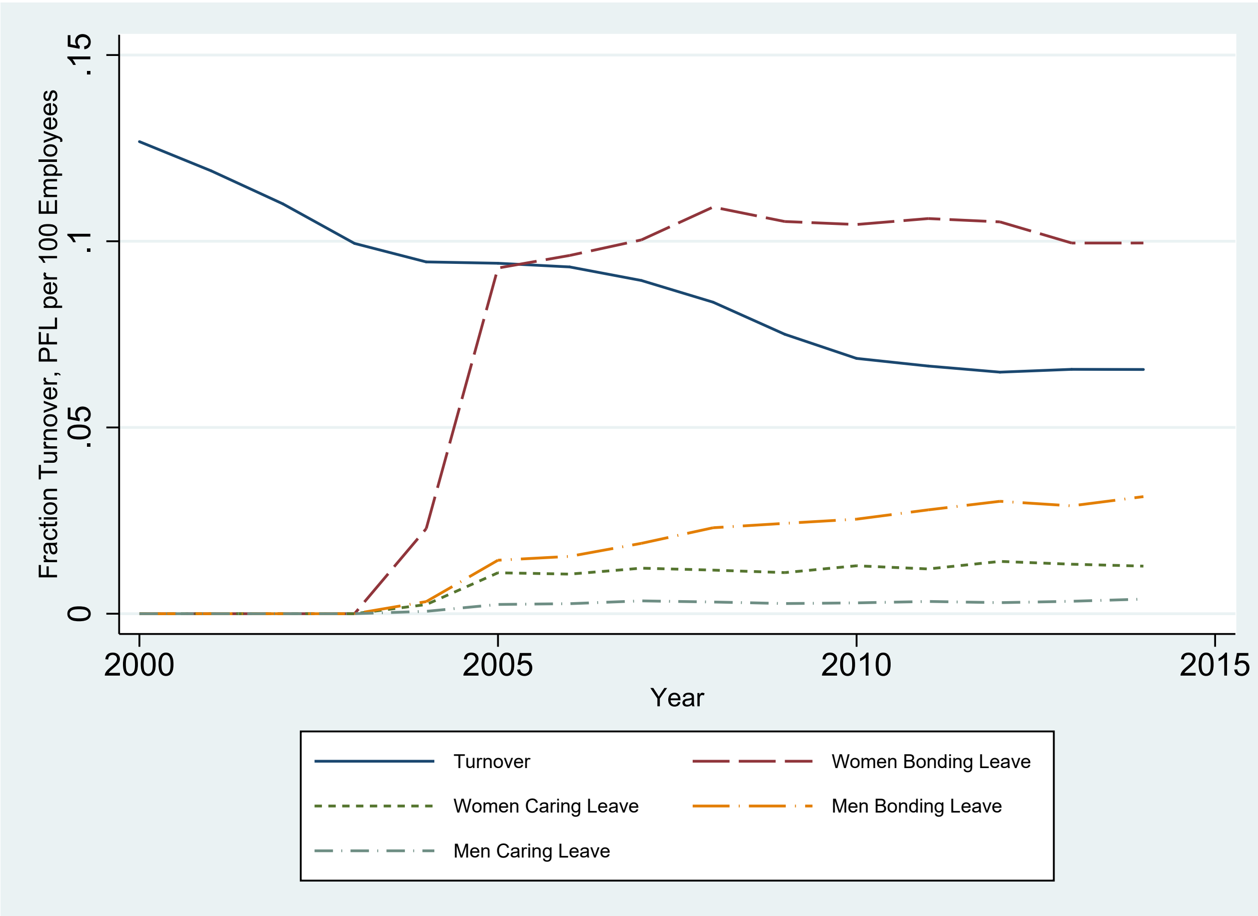
Figure 11: Effects of PFL and SDI Benefits on the Employment Four Quarters After the Claim

Notes: These sub-figures show the fraction of individuals employed four quarters after the date of the claim by 0.01 bins of normalized earnings, by type of claim and gender of claimant. Normalized quarterly earnings is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.

Figure 12: Effects of PFL and SDI Benefits on the Log Earnings Four Quarters After the Claim

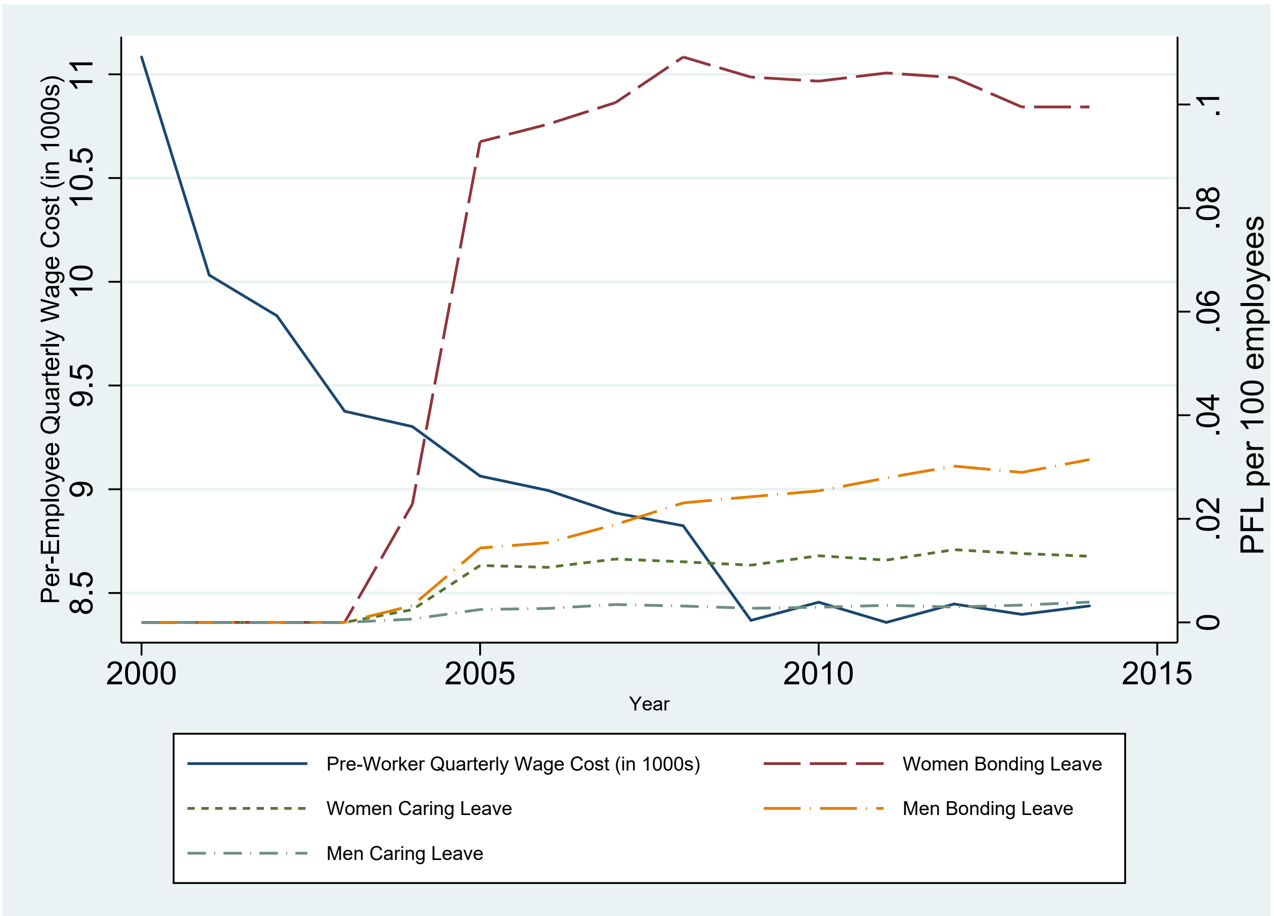
Notes: These sub-figures show the average log quarterly earnings four quarters after the date of the claim by 0.01 bins of normalized earnings, by type of claim and gender of claimant. Normalized quarterly earnings is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.

Figure 13: PFL and Turnover



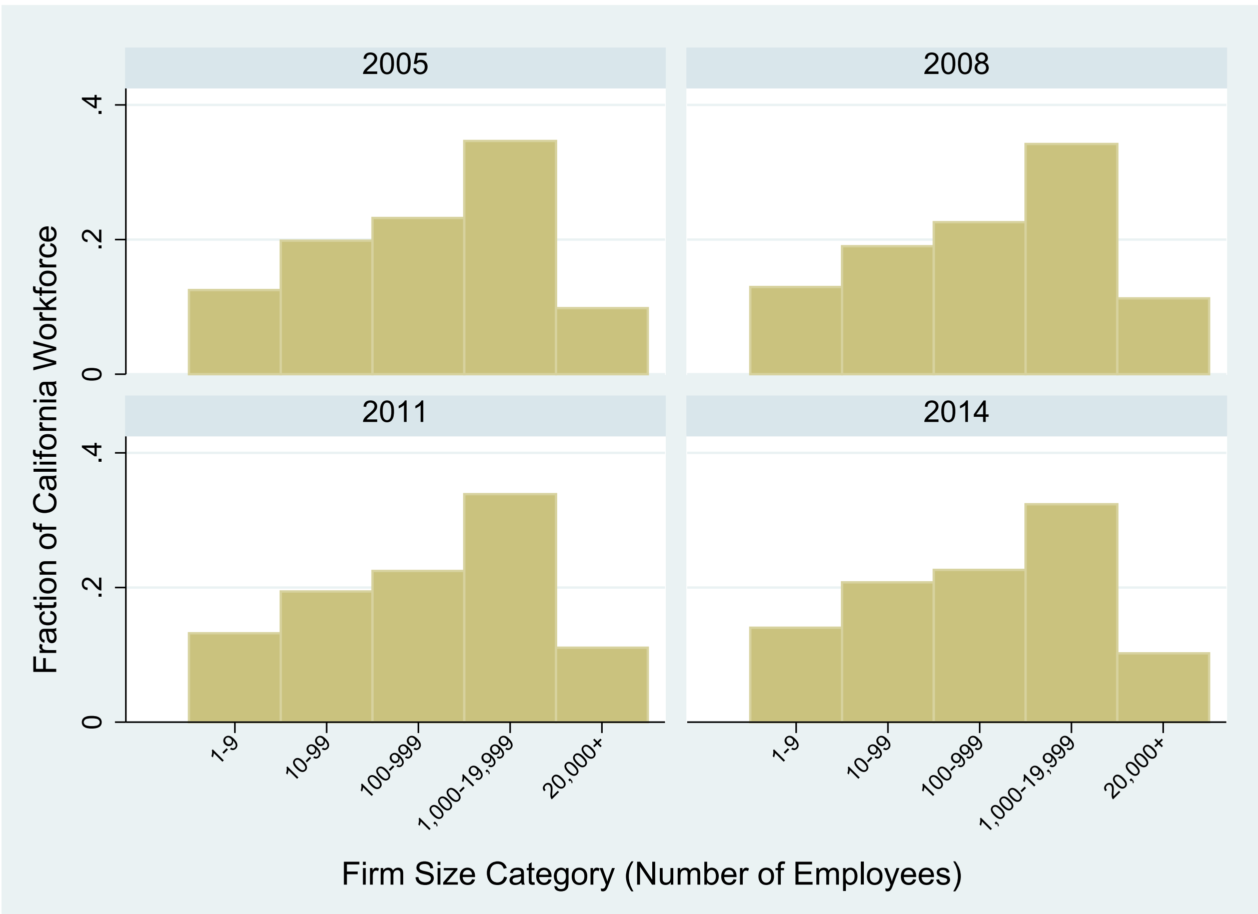
Notes: This figure shows average quarterly employee turnover for California firms and leave-taking of different types over time. All variables are quarterly values averaged at the annual level. Turnover is defined as the fraction of employees who exited the firm (had positive earnings at the firm last quarter but have no earnings this quarter). Firms are excluded in quarters in which they first appear in the data or in which they leave the data. They are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. Turnover is the solid blue line. The leave types are shown separately by gender: women's bonding leave (red dashed line), men's bonding leave (orange dashed line), women's caring leave (green dotted line), and men's caring leave (teal dashed line).

Figure 14: PFL and Employee Wage Cost



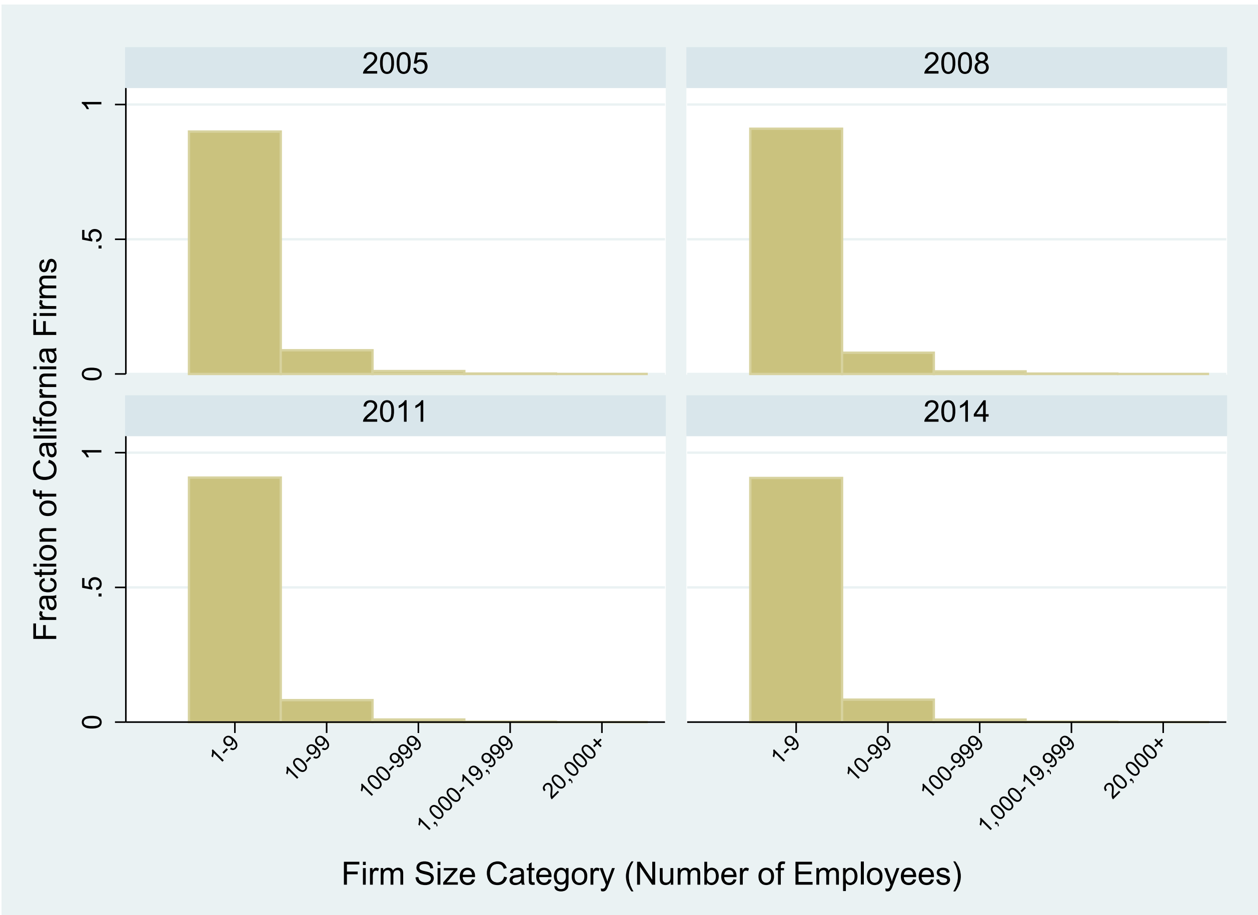
Notes: This figure shows the average per employee quarterly wage cost for California firms and the leave-taking of different types over time. All variables are quarterly values averaged at the annual level. Firms are excluded in quarters in which they first appear in the data or in which they leave the data. They are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. The wage cost is in thousands of 2014 dollars, shown as a solid blue line. The leave types are shown separately by gender: women's bonding leave (red dashed line), men's bonding leave (orange dashed line), women's caring leave (green dotted line), and men's caring leave (teal dashed line).

Figure 15: Employees by Firm Size



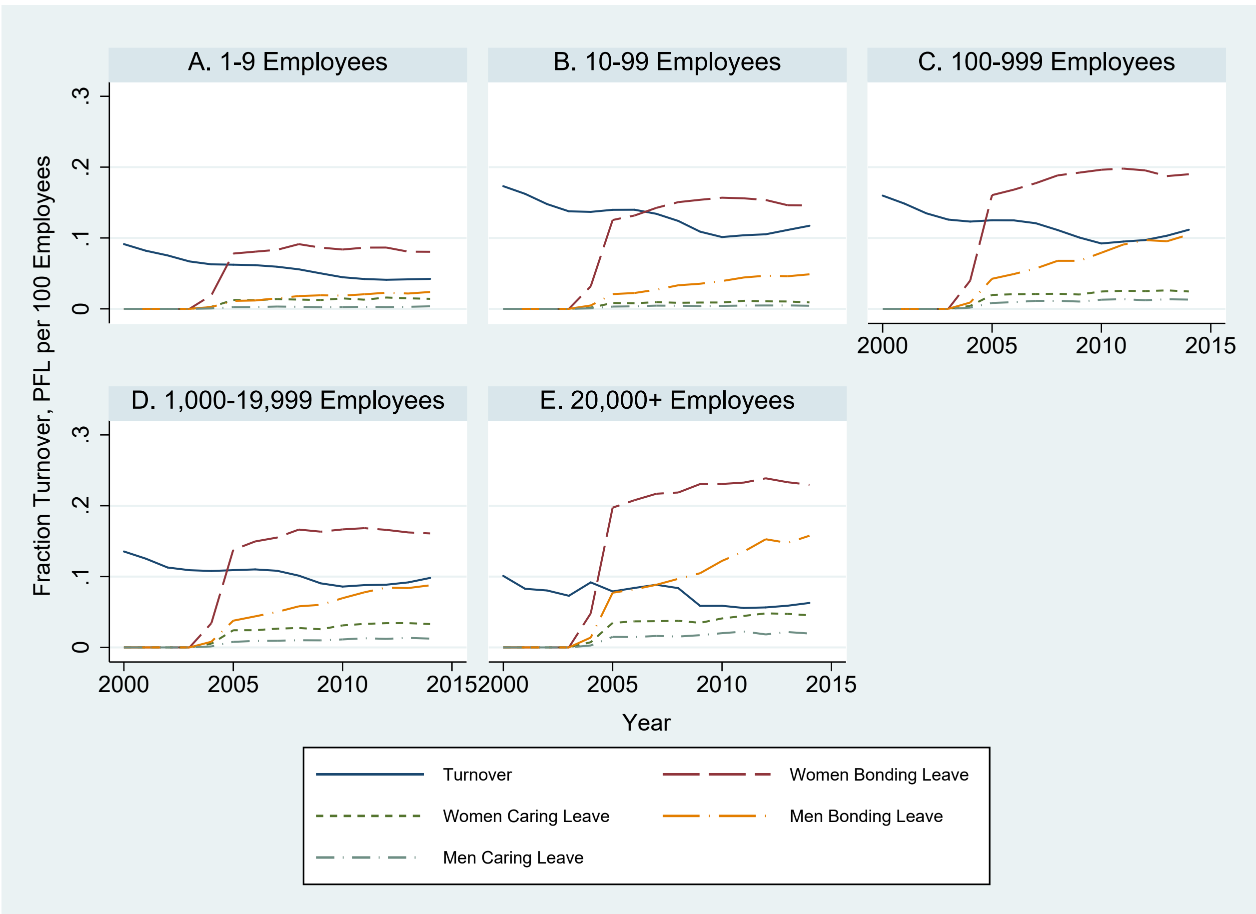
Notes: This figure shows the distribution of the California workforce by firm size category for selected years. Firm size categories are fewer than 10 employees, Firms are excluded in quarters in which they first appear in the data or in which they leave the data. They are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. Firms are included in a firm size category if their minimum and maximum size always fall within the category.

Figure 16: Fraction Firms by Firm Size



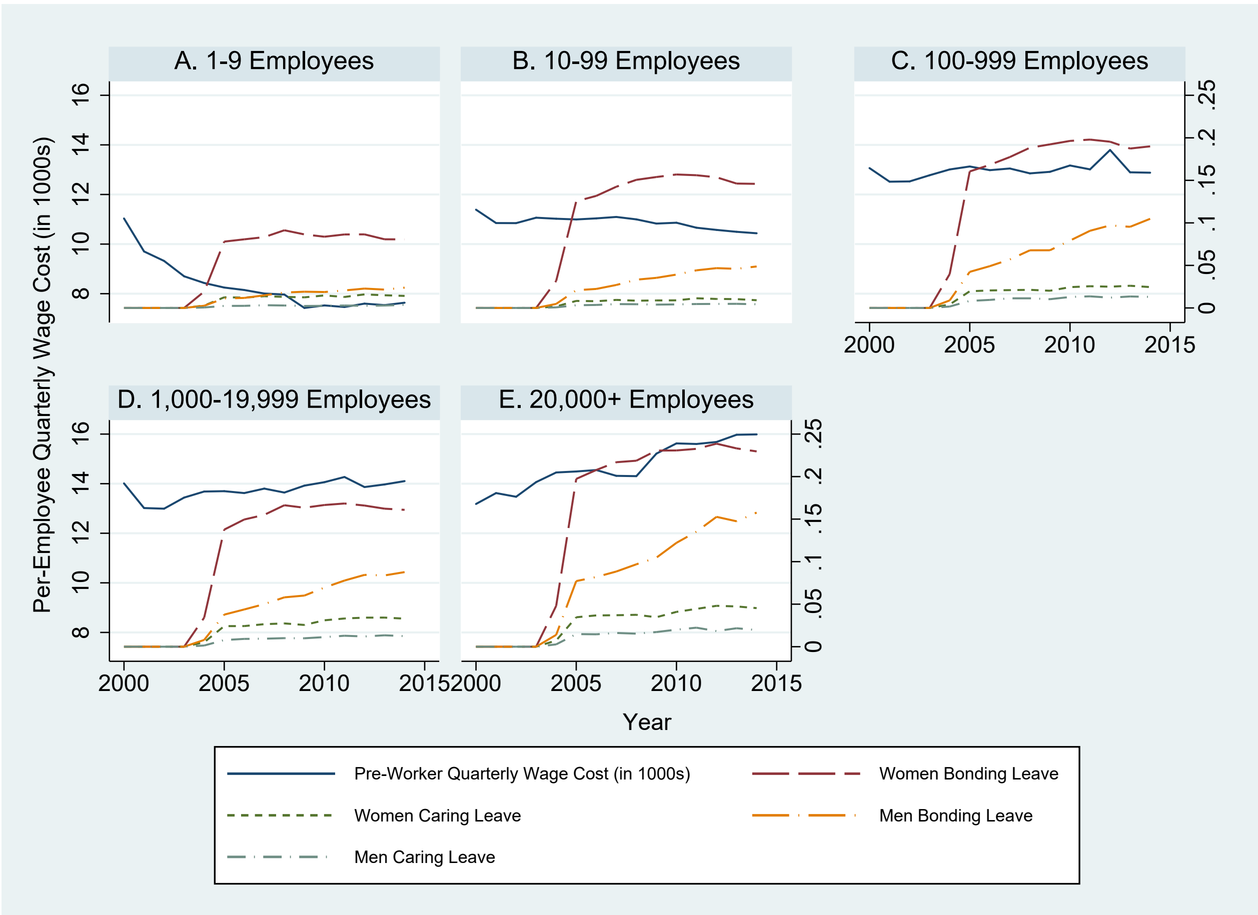
Notes: This figure shows the distribution of California firms by firm size category for selected years. Firm size categories are fewer than 10 employees, 10-99, 100-999, 1,000-19,9999, and 20,000+ employees. Firms are excluded in quarters in which they first appear in the data or in which they leave the data. They are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. Firms are included in a firm size category if their minimum and maximum size always fall within the category.

Figure 17: PFL and Turnover by Firm Size



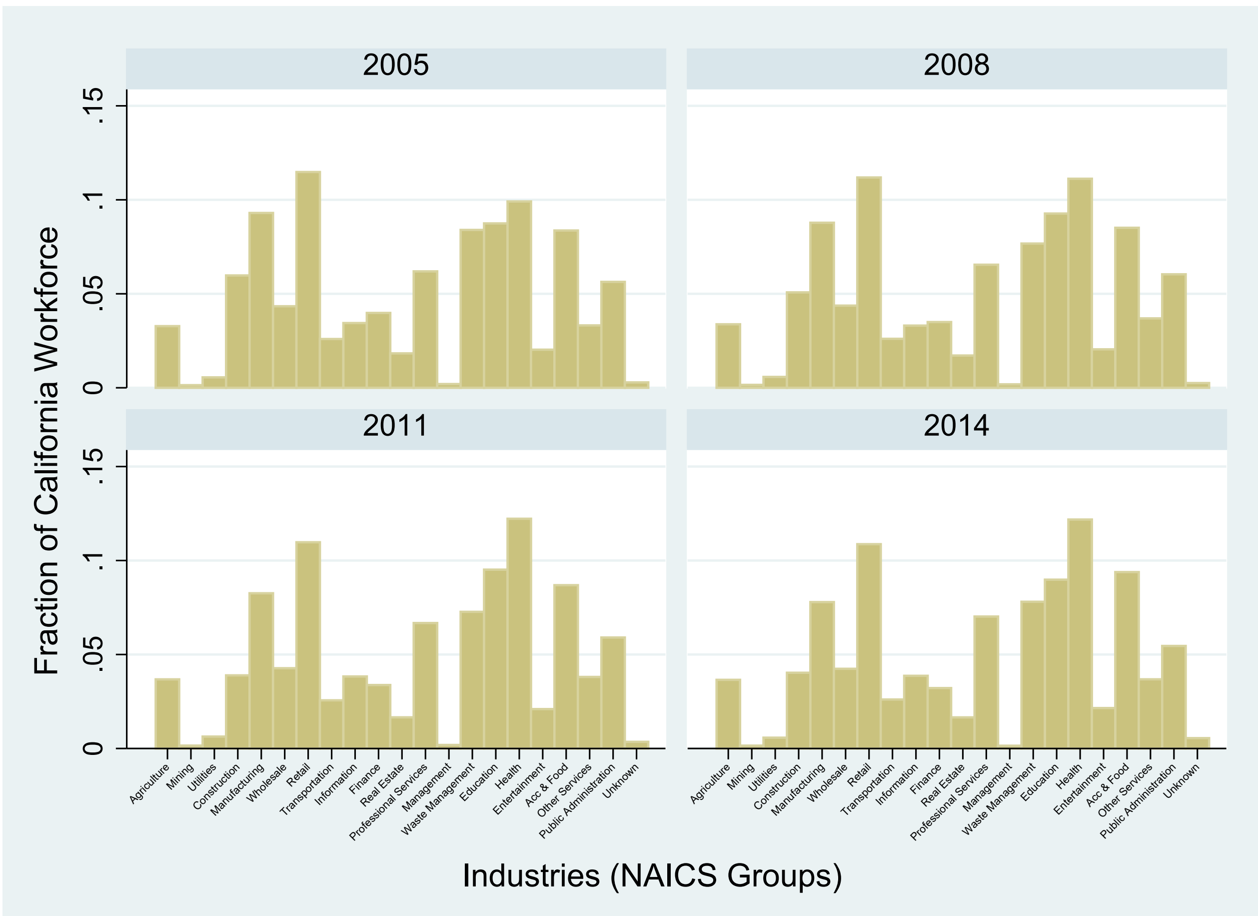
Notes: This figure shows average quarterly employee turnover for California firms and leave-taking of different types over time by firm size. All variables are quarterly values averaged at the annual level. Firm size categories are fewer than 10 employees, 10-99, 100-999, 1,000-19,9999, and 20,000+ employees. Firms are excluded in quarters in which they first appear in the data or in which they leave the data. They are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. Firms are included in a firm size category if their minimum and maximum size always fall within the category. Turnover is defined as the fraction of employees who exited the firm (had positive earnings at the firm last quarter but have no earnings this quarter). Turnover is the solid blue line. The leave types are shown separately by gender: women's bonding leave (red dashed line), men's bonding leave (orange dashed line), women's caring leave (green dotted line), and men's caring leave (teal dashed line).

Figure 18: PFL and Employee Wage Cost by Firm Size



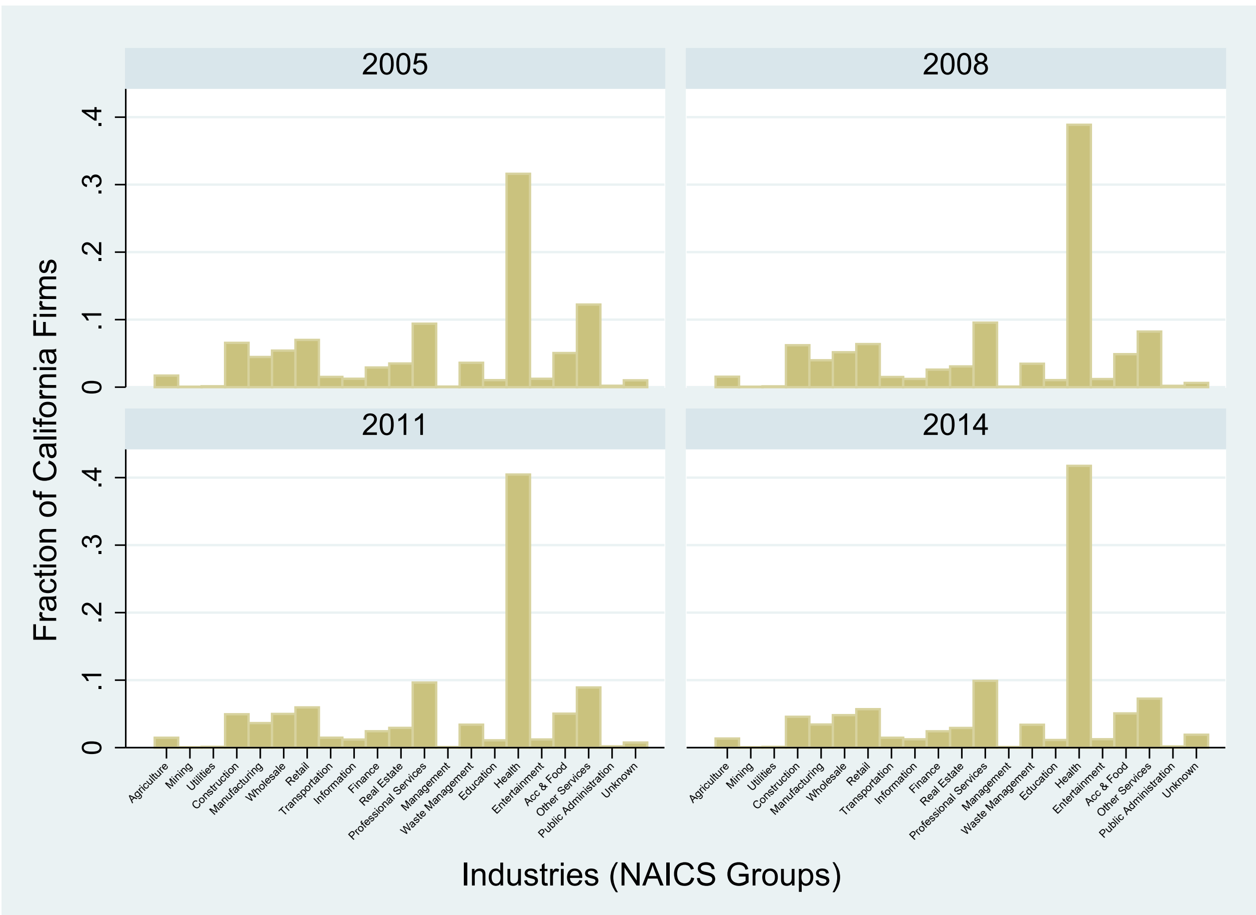
Notes: This figure shows average per employee quarterly wage cost for California firms and leave-taking of different types over time by firm size. All variables are quarterly values averaged at the annual level. Firm size categories are fewer than 10 employees, 10-99, 100-999, 1,000-19,9999, and 20,000+ employees. Firms are excluded in quarters in which they first appear in the data or in which they leave the data. They are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. Firms are included in a firm size category if their minimum and maximum size always fall within the category. Wage cost is in thousands of 2014 dollars, shown as a solid blue line. The leave types are shown separately by gender: women's bonding leave (red dashed line), men's bonding leave (orange dashed line), women's caring leave (green dotted line), and men's caring leave (teal dashed line).

Figure 19: Employees by Industry



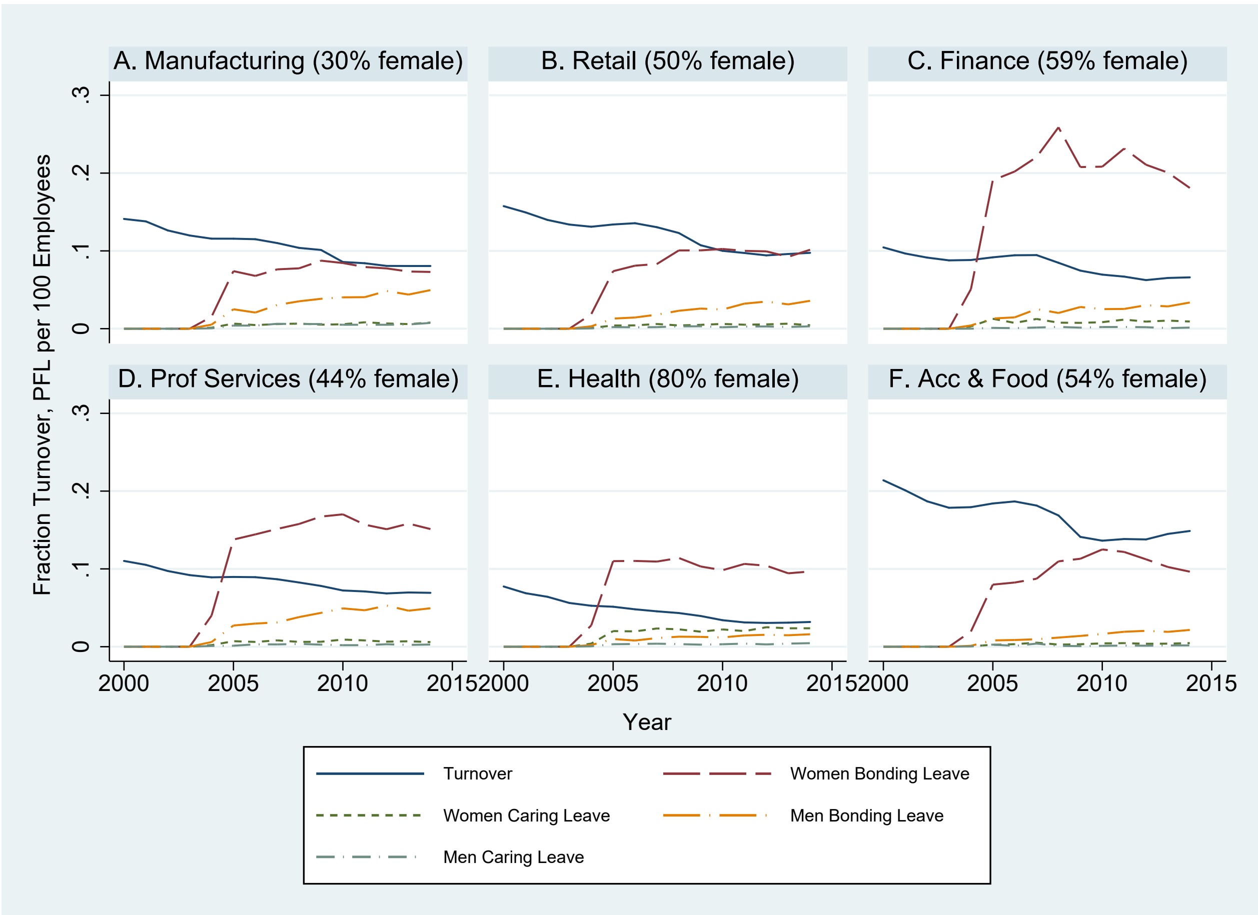
Notes: This figure shows the distribution of the California workforce by NAICS industry group for selected years. Firms are excluded in quarters with zero wage cost.

Figure 20: Firms by Industry



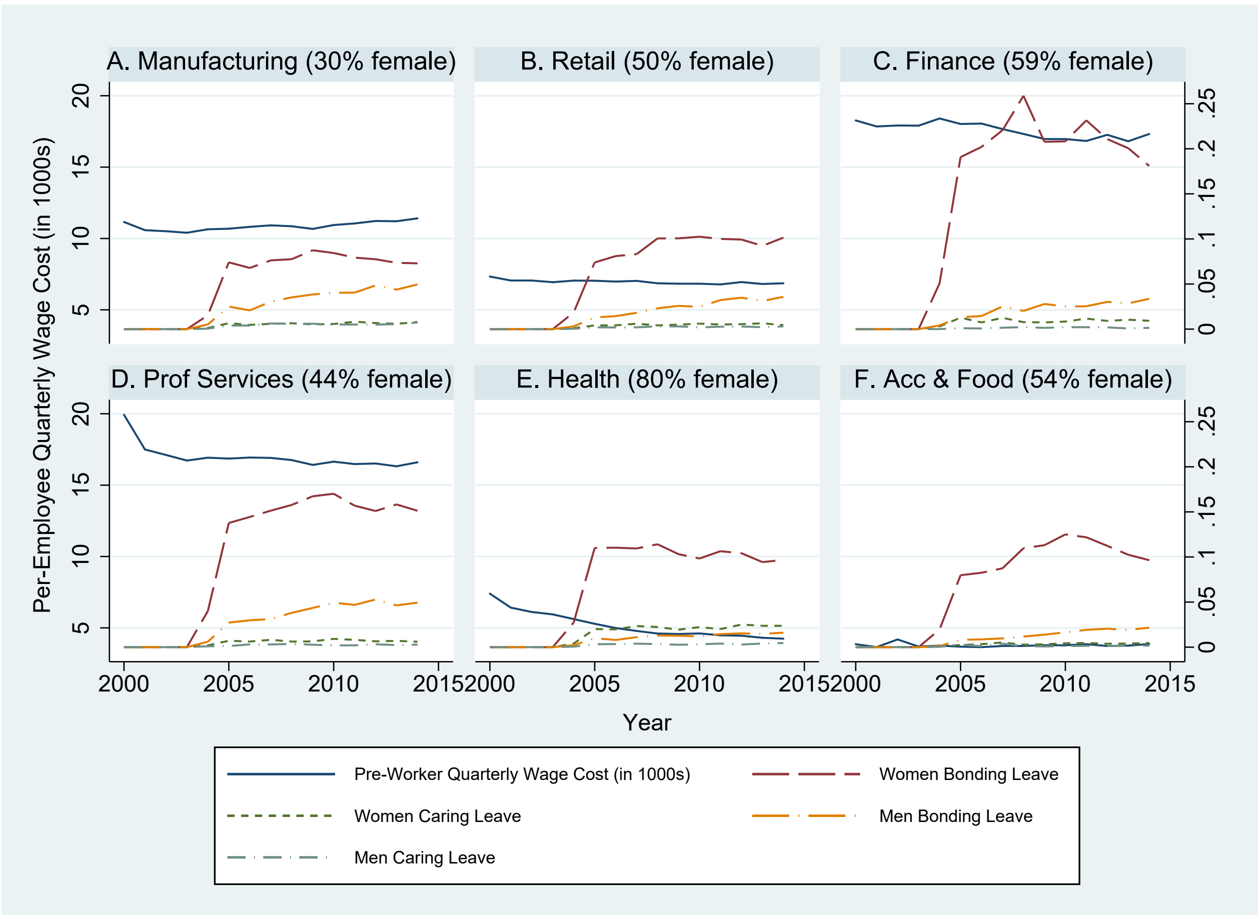
Notes: This figure shows the distribution of California firms by NAICS industry group for selected years. Firms are excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter.

Figure 21: PFL and Turnover for Selected Industries



Notes: This figure shows average quarterly employee turnover for California firms and leave-taking of different types over time by NAICS industry group. All variables are quarterly values averaged at the annual level. “Acc & Food” stands for accommodation and food services. Industry-level female employee percentages are calculated using 2006-2015 CPS data. Firms are excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. Turnover is defined as the fraction of employees who exited the firm (had positive earnings at the firm last quarter but have no earnings this quarter). Turnover is the solid blue line. The leave types are shown separately by gender: women’s bonding leave (red dashed line), men’s bonding leave (orange dashed line), women’s caring leave (green dotted line), and men’s caring leave (teal dashed line).

Figure 22: PFL and Employee Wage Costs for Selected Industries



Notes: This figure shows average per employee quarterly wage cost for California firms and leave-taking of different types over time by NAICS industry group. All variables are quarterly values averaged at the annual level. "Acc & Food" stands for accommodation and food services. Industry-level female employee percentages are calculated using 2006-2015 CPS data. Wage cost is in thousands of 2014 dollars, shown as a solid blue line. Firms are excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. The leave types are shown separately by gender: women's bonding leave (red dashed line), men's bonding leave (orange dashed line), women's caring leave (green dotted line), and men's caring leave (teal dashed line).

6 Tables

Table 1: Distribution of Paid Family Leave Claimants by Number of Claims, Type of Claim, and Gender

	Bonding Claims		Caring Claims	
	Women	Men	Women	Men
	(1)	(2)	(3)	(4)
One claim	80.42	83.14	91.66	92.83
Two claims	17.86	15.43	7.18	6.15
Three claims	1.62	1.33	0.89	0.76
Four claims	0.09	0.09	0.19	0.17
Five or more claims	0.01	0.01	0.08	0.09
Number of claimants	991,159	327,528	109,518	49,974

Notes: The sample includes PFL claims from July 2004 through December 2014.

Table 2: Bonding Claimant Summary Statistics by Number of Claims and Gender

	Women			Men		
	1 Claim (1)	2 Claims (2)	3+ Claims (3)	1 Claim (4)	2 Claims (5)	3+ Claims (6)
Age at first bonding claim	30.58	29.23	27.60	33.27	32.05	30.77
Pre-claim:						
Firm Size	5,685.12	6,195.36	6,980.23	6,330.22	7,570.18	9,369.19
Quarterly Wage	13,906.99	16,672.89	15,683.30	19,660.79	20,816.05	19,952.94
Pre-claim industry:						
Agriculture, Forestry, Fishing & Hunting	0.0136	0.0136	0.0192	0.0392	0.0297	0.0270
Mining, Quarrying, & Oil/Gas Extraction	0.0005	0.0005	0.0005	0.0050	0.0043	0.0060
Utilities	0.0025	0.0038	0.0046	0.0105	0.0151	0.0176
Construction	0.0141	0.0139	0.0130	0.0820	0.0750	0.0676
Manufacturing	0.0646	0.0639	0.0576	0.1397	0.1438	0.1456
Wholesale Trade	0.0399	0.0383	0.0331	0.0544	0.0462	0.0444
Retail Trade	0.1457	0.1339	0.1495	0.1520	0.1550	0.1906
Transportation & Warehousing	0.0156	0.0136	0.0155	0.0525	0.0589	0.0697
Information	0.0273	0.0282	0.0211	0.0516	0.0543	0.0440
Finance & Insurance	0.0793	0.0886	0.0849	0.0451	0.0458	0.0375
Real Estate & Rental and Leasing	0.0193	0.0182	0.0149	0.0131	0.0106	0.0086
Professional & Scientific/Technical Services	0.0927	0.1049	0.0808	0.0922	0.0908	0.0596
Management of Companies & Enterprises	0.0022	0.0026	0.0021	0.0016	0.0015	0.0009
Admin Support & Waste Management	0.0567	0.0471	0.0435	0.0504	0.0394	0.0380
Educational Services	0.0336	0.0247	0.0194	0.0139	0.0099	0.0103
Health Care & Social Assistance	0.2261	0.2596	0.2992	0.0927	0.1206	0.1445
Arts, Entertainment, & Recreation	0.0141	0.0123	0.0110	0.0154	0.0158	0.0137
Accommodation & Food Services	0.0872	0.0669	0.0662	0.0373	0.0256	0.0199
Other Services (except Public Admin)	0.0337	0.0290	0.0237	0.0220	0.0195	0.0124
Public Administration	0.0272	0.0321	0.0377	0.0263	0.0355	0.0397
Unknown	0.0040	0.0042	0.0024	0.0030	0.0027	0.0024
Number of claimants	797,118	176,973	17,068	272,299	50,526	4,703

Notes: The sample includes PFL bonding claims from July 2004 through December 2014. Pre-claim earnings are defined as the highest earnings in quarters 2 through 5 before the first bonding claim. Pre-claim firm size and industry are measured in the quarter before the first bonding claim. All dollar amounts are in 2014 dollars.

Table 3: Caring Claimant Summary Statistics by Number of Claims and Gender

	Women			Men		
	1 Claim (1)	2 Claims (2)	3+ Claims (3)	1 Claim (4)	2 Claims (5)	3+ Claims (6)
Age at first caring claim	45.78	46.36	46.16	44.42	44.86	45.60
Pre-claim:						
Firm Size	8331.47	9,541.57	10,753.81	7,023.85	8,528.90	10,436.43
Quarterly Wage	16,667.85	18,114.36	19,597.30	19,509.52	20,963.43	21,808.91
Pre-claim industry:						
Agriculture, Forestry, Fishing & Hunting	0.0145	0.0130	0.0079	0.0264	0.0161	0.0080
Mining, Quarrying, & Oil/Gas Extraction	0.0004	0.0009	0.0024	0.0067	0.0053	0.0020
Utilities	0.0040	0.0050	0.0055	0.0110	0.0145	0.0159
Construction	0.0080	0.0053	0.0055	0.0517	0.0421	0.0298
Manufacturing	0.0901	0.0960	0.0931	0.2018	0.2083	0.1909
Wholesale Trade	0.0281	0.0210	0.0205	0.0572	0.0480	0.0417
Retail Trade	0.1340	0.1301	0.1342	0.1422	0.1482	0.1650
Transportation & Warehousing	0.0227	0.0225	0.0276	0.0827	0.1104	0.1491
Information	0.0200	0.0175	0.0245	0.0367	0.0332	0.0258
Finance & Insurance	0.0661	0.0563	0.0426	0.0295	0.0164	0.0199
Real Estate & Rental and Leasing	0.0124	0.0074	0.0095	0.0143	0.0102	0.0139
Professional & Scientific/Technical Services	0.0540	0.0422	0.0434	0.0540	0.0460	0.0318
Management of Companies & Enterprises	0.0019	0.0010	0.0016	0.0011	0.0010	--
Admin Support & Waste Management	0.0357	0.0254	0.0237	0.0475	0.0398	0.0318
Educational Services	0.0214	0.0155	0.0103	0.0113	0.0089	0.0119
Health Care & Social Assistance	0.3513	0.3973	0.4104	0.1172	0.1476	0.1491
Arts, Entertainment, & Recreation	0.0130	0.0118	0.0126	0.0153	0.0154	0.0219
Accommodation & Food Services	0.0378	0.0321	0.0213	0.0308	0.0230	0.0179
Other Services (except Public Admin)	0.0240	0.0225	0.0284	0.0196	0.0151	0.0239
Public Administration	0.0591	0.0755	0.0742	0.0414	0.0496	0.0477
Unknown	0.0016	0.0018	0.0008	0.0014	0.0010	0.0020
Number of claimants	100,381	7,863	1,274	46,389	3,075	510

Notes: The sample includes PFL caring claims from July 2004 through December 2014. Pre-claim earnings are defined as the highest earnings in quarters 2 through 5 before the first bonding claim. Pre-claim firm size and industry are measured in the quarter before the first bonding claim. All dollar amounts are in 2014 dollars.

Table 4: Pre- and Post-Bonding Claim Labor Market Attachment by Gender, Age, and Earnings

	Pre-Claim		Post-Claim Labor Market Attachment				Post-Claim Employer Change			
	Not Attached (1)	Attached (2)	Never Employed (3)	Limited Employment (4)	Moderate Employment (5)	Always Employed (6)	Same Firm (7)	Different Firm (8)	Exit Market (9)	Sample Size (10)
Panel A: Women										
Lower Income (quarterly wages < $10,000):										
Age <25 at claim	0.418	0.582	0.129	0.349	0.313	0.208	0.317	0.274	0.409	15,537
Age 25-34 at claim	0.293	0.707	0.176	0.305	0.259	0.260	0.412	0.178	0.410	27,355
Age 35+ at claim	0.280	0.720	0.171	0.257	0.255	0.316	0.477	0.141	0.382	8,307
Higher Income (quarterly wages $10,000+):										
Age <25 at claim	0.135	0.865	0.090	0.232	0.301	0.377	0.471	0.285	0.244	1,996
Age 25-34 at claim	0.117	0.883	0.134	0.211	0.202	0.453	0.545	0.186	0.270	25,828
Age 35+ at claim	0.092	0.908	0.101	0.162	0.190	0.547	0.628	0.162	0.210	16,446
Panel B: Men										
Lower Income (quarterly wages < $15,000):										
Age <25 at claim	0.240	0.760	0.045	0.232	0.366	0.357	0.512	0.277	0.211	1,933
Age 25-34 at claim	0.175	0.825	0.068	0.218	0.294	0.420	0.580	0.221	0.199	7,152
Age 35+ at claim	0.186	0.814	0.071	0.223	0.253	0.454	0.633	0.166	0.201	3,657
Higher Income (quarterly wages $15,000+):										
Age <25 at claim	0.084	0.916	0.040	0.164	0.305	0.491	0.625	0.242	0.133	226
Age 25-34 at claim	0.090	0.910	0.046	0.135	0.213	0.606	0.667	0.221	0.113	6,680
Age 35+ at claim	0.070	0.930	0.037	0.121	0.203	0.639	0.703	0.198	0.099	7,660

Notes: The sample includes claimants making a single bonding claim between between July 2007 and September 2008. Pre-claim attached is defined as having 9 or more quarters of positive employment earnings during the window of 2-13 quarters before the claim and maximum pre-claim quarterly earnings of $2,500 or more. The remainder of claimants are classified as not attached. Post-claim labor market attachment measures are defined based on the number of quarters of employment in the window of 4-23 quarters after the claim. Never employed, limited employment, moderate employment, and always employed are defined as zero, 1 to 12, 12 to 19, and 20 quarters of employment, respectively, during this window. Post-claim employer change is defined as the same (different) employer if the claimant's primary employer is the same (different) four quarters after the claim as it was one quarter before the claim. Exit the market is similarly defined as positive earnings in the quarter before the claim, but no earnings four quarters after the claim. All dollar amounts are in 2014 dollars.

Table 5: Pre- and Post-Caring Claim Labor Market Attachment by Gender, Age, and Earnings

	Pre-Claim		Post-Claim Labor Market Attachment				Post-Claim Employer			
	Not Attached (1)	Attached (2)	Never Employed (3)	Limited Employment (4)	Moderate Employment (5)	Always Employed (6)	Return to Same Firm (7)	Change Firms (8)	Exit Market (9)	Sample Size (10)
Panel A: Women										
Lower Income:										
Age <25 at claim	0.304	0.696	0.009	0.215	0.486	0.290	0.443	0.343	0.214	687
Age 25-44 at claim	0.202	0.798	0.011	0.223	0.415	0.351	0.581	0.211	0.208	6,174
Age 45-64 at claim	0.138	0.862	0.016	0.306	0.360	0.318	0.622	0.143	0.235	5,829
Age 65+ at claim	0.106	0.894	0.022	0.519	0.294	0.164	0.536	0.081	0.382	489
Higher Income:										
Age <25 at claim	0.153	0.847	0.003	0.160	0.375	0.462	0.533	0.304	0.163	288
Age 25-44 at claim	0.065	0.935	0.004	0.144	0.311	0.541	0.682	0.192	0.127	10,507
Age 45-64 at claim	0.034	0.966	0.005	0.202	0.298	0.494	0.727	0.145	0.127	13,293
Age 65+ at claim	0.020	0.980	0.014	0.515	0.282	0.188	0.594	0.099	0.307	563
Panel B: Men										
Lower Income:										
Age <25 at claim	0.312	0.688	0.003	0.226	0.475	0.297	0.470	0.314	0.215	381
Age 25-44 at claim	0.140	0.860	0.010	0.189	0.380	0.421	0.626	0.204	0.169	3,990
Age 45-64 at claim	0.097	0.903	0.011	0.304	0.353	0.332	0.673	0.128	0.199	2,722
Age 65+ at claim	0.129	0.871	0.037	0.600	0.242	0.121	0.541	0.058	0.401	380
Higher Income:										
Age <25 at claim	0.118	0.882	--	0.147	0.485	0.368	0.485	0.279	0.235	68
Age 25-34 at claim	0.060	0.940	0.004	0.134	0.271	0.591	0.697	0.189	0.113	4,770
Age 25-34 at claim	0.033	0.967	0.004	0.226	0.326	0.444	0.717	0.139	0.144	4,448
Age 35+ at claim	0.039	0.961	0.012	0.523	0.287	0.178	0.592	0.098	0.310	258

Notes: The sample includes claimants making a single caring claim before September 2008. See notes to Table 4 for definitions of pre- and post-claim labor market attachment and employer change. All dollar amounts are in 2014 dollars.

Table 6: RK Results for the Benefit Amount; Using a $5,000 Bandwidth

	Bonding		Caring		SDI	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fem	Male	Fem	Male	Fem	Male
RK Denominator	-0.405***	-0.510***	-0.440***	-0.503***	-0.450***	-0.514***
	[0.00606]	[0.00550]	[0.0105]	[0.0128]	[0.00326]	[0.00285]
Dept. var mean	11.53	12.19	11.49	11.98	11.36	11.95
Obs.	123488	65451	16471	9992	321305	288077

Notes: Each column is from a separate regression. All quarterly earnings and quarterly benefit amounts are in thousands of 2014 dollars. The outcome is the quarterly benefit amount. The sample includes quarters in which the weekly benefit amount maximum is well-identified. Workers must have positive earnings in at least one of the two through five quarters prior to the quarter of the leave. The table presents results on the magnitude of β_2 in equation (3) in Appendix B, i.e., the denominator of the ratio in equation (2 in Appendix B). The sample is limited to observations within a $\$5,000$ bandwidth surrounding the earnings threshold ($h = 5,000$ in Appendix B). Results are presented for three types of claims—bonding (columns (1) and (2)), caring (columns (3) and (4)), and SDI (columns (5) and (6)). For each claim, we first present results for females and then for males. Standard errors are robust to heteroskedasticity. Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Table 7: RK Results for Total Leave Duration; Using a $5,000 Bandwidth

	Bonding		Caring		SDI	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fem	Male	Fem	Male	Fem	Male
RK Numerator	-0.00970	-0.00871	-0.0215	-0.00275	-0.0608***	-0.102***
	[0.0145]	[0.00988]	[0.0207]	[0.0270]	[0.0217]	[0.0262]
Dept. var mean	11.87	3.746	3.881	3.836	9.152	10.42
Obs.	123488	65451	16471	9992	321305	288077

Notes: Each column is from a separate regression. All quarterly earnings and quarterly benefit amounts are in thousands of 2014 dollars. The outcome is total leave duration in weeks under PFL and SDI programs (capped at 16 weeks). The sample includes quarters in which the weekly benefit amount maximum is well-identified. Workers must have positive earnings in at least one of the two through five quarters prior to the quarter of the leave. The table presents results on the magnitude of λ_2 in equation (4) in Appendix B, i.e., the numerator of the ratio in equation (2) in Appendix B. The sample is limited to observations within a $\$5,000$ bandwidth surrounding the earnings threshold ($h = 5,000$ in Appendix B). Results are presented for three types of claims—bonding (columns (1) and (2)), caring (columns (3) and (4)), and SDI (columns (5) and (6)). For each claim, we first present results for females and then for males. Standard errors are robust to heteroskedasticity. Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Table 8: RK Results for Employment Four Quarters After the Claim; Using a $5,000 Bandwidth

	Bonding		Caring		SDI	
	(1) Fem	(2) Male	(3) Fem	(4) Male	(5) Fem	(6) Male
RK Numerator	0.000239	0.000510	-0.000757	0.00770*	-0.000313	0.000175
	[0.00128]	[0.00128]	[0.00286]	[0.00410]	[0.000877]	[0.00105]
Dept. var mean	0.786	0.830	0.822	0.816	0.761	0.707
Obs.	123488	65451	16471	9992	321305	288077

Notes: Each column is from a separate regression. All quarterly earnings and quarterly benefit amounts are in thousands of 2014 dollars. The outcome is employment four quarters after the claim. The sample includes quarters in which the weekly benefit amount maximum is well-identified. Workers must have positive earnings in at least one of the two through five quarters prior to the quarter of the leave. Because employment outcomes are only known for the years 2000-2014, only claims filed in years 2004-2013 are included. The table presents results on the magnitude of λ_2 in equation (4) in Appendix B, i.e., the numerator of the ratio in equation (2) in Appendix B. The sample is limited to observations within a $\$5,000$ bandwidth surrounding the earnings threshold ($h = 5,000$ in Appendix B). Results are presented for three types of claims—bonding (columns (1) and (2)), caring (columns (3) and (4)), and SDI (columns (5) and (6)). For each claim, we first present results for females and then for males. Standard errors are robust to heteroskedasticity. Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Table 9: RK Results for Log Earnings Four Quarters After the Claim; Using a $5,000 Bandwidth

	Bonding		Caring		SDI	
	(1) Fem	(2) Male	(3) Fem	(4) Male	(5) Fem	(6) Male
RK Numerator	-0.00991***	-0.00981***	-0.0124*	-0.000494	-0.00218	-0.00635**
	[0.00283]	[0.00306]	[0.00735]	[0.00976]	[0.00245]	[0.00299]
Dept. var mean	2.963	3.041	2.996	2.960	2.849	2.757
Obs.	97106	54328	13536	8154	244573	203776

Notes: Each column is from a separate regression. All quarterly earnings and quarterly benefit amounts are in thousands of 2014 dollars. The outcome is log earnings four quarters after the claim. The sample includes quarters in which the weekly benefit amount maximum is well-identified. Workers must have positive earnings in at least one of the two through five quarters prior to the quarter of the leave. The table presents results on the magnitude of λ_2 in equation (4) in Appendix B, i.e., the numerator of the ratio in equation (2) in Appendix B. The sample is limited to observations within a $\$5,000$ bandwidth surrounding the earnings threshold ($h = 5,000$ in Appendix B). Results are presented for three types of claims—bonding (columns (1) and (2)), caring (columns (3) and (4)), and SDI (columns (5) and (6)). For each claim, we first present results for females and then for males. Standard errors are robust to heteroskedasticity. Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Table 10: Firm Summary Statistics

	Per Worker Wage			Turnover (Fraction Leaving Firms)			Turnover (Fraction Joining Firms)		
	Apr 2000 - June 2004	July 2004 - Sept 2010	Oct 2010 - Sept 2014	Apr 2000 - June 2004	July 2004 - Sept 2010	Oct 2010 - Sept 2014	Apr 2000 - June 2004	July 2004 - Sept 2010	Oct 2010 - Sept 2014
Panel A: All Firms									
All Firms	9741	8867	8492	0.109	0.088	0.067	0.107	0.085	0.067
Panel B: By Firm Size									
1-9 Employees	9205	7998	7630	0.075	0.059	0.043	0.071	0.056	0.043
10-99 Employees	10931	10988	10670	0.151	0.132	0.108	0.151	0.129	0.111
100-999 Employees	12697	12969	13176	0.137	0.119	0.100	0.139	0.118	0.103
1,000-19,999 Employees	13350	13683	14068	0.116	0.106	0.091	0.119	0.106	0.091
20,000+ Employees	13707	14538	15766	0.085	0.079	0.059	0.090	0.082	0.059
Panel C: By Industry									
Agriculture, Forestry, Fishing & Hunting	5355	5894	6232	0.240	0.212	0.187	0.232	0.207	0.182
Mining, Quarrying, & Oil/Gas Extraction	15162	17057	18041	0.125	0.113	0.089	0.122	0.115	0.091
Utilities	11645	12015	13202	0.092	0.086	0.071	0.093	0.088	0.072
Construction	9531	10199	9083	0.183	0.161	0.136	0.182	0.150	0.133
Manufacturing	10531	10777	11213	0.128	0.111	0.083	0.121	0.103	0.084
Wholesale Trade	14885	14768	15092	0.095	0.085	0.065	0.095	0.082	0.068
Retail Trade	7021	6967	6877	0.141	0.128	0.097	0.140	0.122	0.099
Transportation & Warehousing	9432	9261	9032	0.147	0.125	0.098	0.146	0.122	0.101
Information	32505	29088	27309	0.114	0.092	0.076	0.107	0.091	0.079
Finance & Insurance	17912	17670	17165	0.093	0.089	0.066	0.098	0.085	0.068
Real Estate & Rental and Leasing	10896	11113	10854	0.095	0.085	0.063	0.097	0.081	0.063
Professional & Scientific/Technical Services	17175	16760	16679	0.098	0.086	0.070	0.099	0.086	0.074
Management of Companies & Enterprises	34747	35956	31154	0.082	0.080	0.065	0.082	0.077	0.067
Admin Support & Waste Management	9258	9931	9820	0.161	0.139	0.110	0.158	0.134	0.111
Educational Services	8182	8129	7881	0.136	0.127	0.109	0.140	0.129	0.115
Health Care & Social Assistance	6102	4883	4455	0.062	0.046	0.032	0.063	0.046	0.032
Arts, Entertainment, & Recreation	41374	32973	33374	0.144	0.128	0.103	0.145	0.125	0.105
Accommodation & Food Services	3834	3713	3807	0.189	0.175	0.142	0.184	0.167	0.142
Other Services (except Public Admin)	5348	5604	6463	0.077	0.072	0.063	0.075	0.069	0.063
Public Administration	12658	13519	15471	0.092	0.084	0.075	0.096	0.089	0.073

Notes: The overall sample size is 39,942,254 for the per worker wage cost and 36,530,145 for turnover (fraction leaving and fraction joining). In all panels, firms are excluded in quarters in which they first appear in the data or in which they leave the data. Firms are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. In panel B, firms are included in a firm size category if their minimum and maximum size always fall within the category, other than when missing. The small number of firms with no designated industry are excluded from panel C. The per worker wage cost is the total wage bill divided by the number of employees in 2014 dollars. The fraction of employees exiting the firm is defined by the number of employees with positive earnings at the firm last quarter who have no earnings this quarter divided by the number of employees last quarter. The fraction of employees joining the firm is defined by the number of employees with no earnings at the firm last quarter who have positive earnings this quarter divided by the number of employees this quarter.

Table 11: Firm Turnover and Wage Costs

	Per Worker Wage	Turnover (Fraction Leaving Firms)	Turnover (Fraction Joining Firms)
Panel A: All Firms			
All Firms	-1674.25***	0.0130***	0.0600***
	(88.84)	(0.0009)	(0.0013)
Panel B: By Firm Size			
1-9 Employees	-1541.15***	0.0128***	0.0523***
	(95.04)	(0.0010)	(0.0012)
10-99 Employees	-3149.81***	0.0082	0.0720***
	(709.72)	(0.0057)	(0.0062)
100-999 Employees	2019.63	-0.2077***	0.0936***
	(8163.89)	(0.0262)	(0.0361)
1,000-19,999 Employees	24924.04	-1.5054***	-0.3337
	(23652.14)	(0.2835)	(0.3028)
20,000+ Employees	182590.60	-6.7539	-1.4590
	(112055.90)	(4.0822)	(3.0416)
Panel C: By Industry			
Agriculture, Forestry, Fishing & Hunting	-726.15***	-0.0663**	0.2477***
	(267.07)	(0.0247)	(0.0307)
Mining, Quarrying, & Oil/Gas Extraction	-9497.80*	0.1416	0.0297
	(5686.56)	(0.1219)	(0.1404)
Utilities	-4707.69*	-0.0639	0.0962
	(2693.82)	(0.0459)	(0.0637)
Construction	-1384.52***	0.0010	0.0886***
	(332.23)	(0.0078)	(0.0098)
Manufacturing	-2201.52***	0.0236**	0.0865***
	(426.50)	(0.0099)	(0.0121)
Wholesale Trade	-4918.38***	0.0177***	0.0860***
	(567.15)	(0.0060)	(0.0082)
Retail Trade	-1452.41***	0.0046	0.1107***
	(236.71)	(0.0061)	(0.0083)
Transportation & Warehousing	-2055.16***	0.0187	0.0646***
	(363.33)	(0.0164)	(0.0197)
Information	-6543.32**	0.0075	0.0690***
	(3276.68)	(0.0103)	(0.0145)
Finance & Insurance	-3833.09***	0.0116**	0.1032***
	(388.92)	(0.0057)	(0.0077)
Real Estate & Rental and Leasing	-2401.89***	0.0106	0.0961***
	(479.98)	(0.0066)	(0.0092)
Professional & Scientific/Technical Services	-3504.23***	0.0147***	0.0900***
	(260.12)	(0.0031)	(0.0043)
Management of Companies & Enterprises	-8822.58	0.0559	0.0516
	(6387.12)	(0.0547)	(0.0601)
Admin Support & Waste Management	-2384.48***	-0.0033	0.0884***
	(483.55)	(0.0080)	(0.0107)
Educational Services	-1595.38***	-0.0027	0.1044***
	(407.81)	(0.0143)	(0.0207)
Health Care & Social Assistance	-677.50***	0.01687***	0.0415***
	(44.06)	(0.0011)	(0.0015)
Arts, Entertainment, & Recreation	-2331.44	-0.0025	0.1003***
	(7309.80)	(0.0110)	(0.0171)
Accommodation & Food Services	-470.96***	-0.0063	0.1060***
	(112.41)	(0.0084)	(0.0114)
Other Services (except Public Admin)	-1407.60***	0.0132***	0.0636***
	(219.15)	(0.0039)	(0.0051)
Public Administration	-11527.15	0.0515	0.1004
	(9303.68)	(0.0542)	(0.0598)

Notes: The overall sample size is 39,942,254 for the per worker wage cost and 36,530,145 for turnover (fraction leaving and fraction joining). In all panels, firms are excluded in years in which they first appear in the data or in which they leave the data. Firms are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. In panel B, firms are included in a firm size category if their minimum and maximum size always fall within the category, other than when missing. The small number of firms with no designated industry are excluded from panel C. The per worker wage is the total wage bill divided by the number of employees in 2014 dollars. The fraction of employees exiting the firm is defined by the number of employees with positive earnings at the firm last quarter who have no earnings this quarter divided by the number of employees last quarter. The fraction of employees joining the firm is defined by the number of employees with no earnings at the firm last quarter who have positive earnings this quarter divided by the number of employees this quarter. Standard errors are reported in parentheses. The standard errors are clustered at the firm level. Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 12: Firm Turnover and Wage Costs by Types of Leave

	Per Worker Wage	Turnover (Fraction Leaving Firms)	Turnover (Fraction Joining Firms)
Female Bonding Leaves / Total Employees	-2205.21***	0.0191***	0.0727***
	110.9	(0.0013)	(0.0017)
Male Bonding Leaves / Total Employees	-1498.46***	0.0079***	0.0208***
	186.37	(0.0023)	(0.0029)
Female Caring Leaves / Total Employees	-370.77***	0.0130***	0.0217***
	52.95	(0.0020)	(0.0026)
Male Caring Leaves / Total Employees	-560.55*	0.0106**	0.0151**
	309.92	(0.0045)	(0.0060)

Notes: The overall sample size is 39,942,254 for the per worker wage cost and 36,530,145 for turnover (fraction leaving and fraction joining). In all panels, firms are excluded in quarters in which they first appear in the data or in which they leave the data. Firms are also excluded in quarters with zero wage cost or the firm grows or shrinks by a factor of ten or more in a single quarter. The per worker wage is the total wage bill divided by the number of employees in 2014 dollars. The fraction of employees exiting the firm is defined by the number of employees with positive earnings at the firm last quarter who have no earnings this quarter divided by the number of employees last quarter. The fraction of employees joining the firm is defined by the number of employees with no earnings at the firm last quarter who have positive earnings this quarter divided by the number of employees this quarter. Standard errors are reported in parentheses. The standard errors are clustered at the firm level. Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

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A Data and Sample Construction

We obtained several administrative data sets from the California EDD that are merged together. First, we have the universe of PFL claims over July 2004 - December 2014. For each claim over this time period, we have information on the date, duration, the weekly benefit amount, reason for the claim (bonding with a newborn or newly adopted child vs. caring for a sick family member), the employee's date of birth, the employee's gender, and a unique employee identifier.[17] Finally, for women who make bonding claims, we also have an indicator for whether there was an associated SDI transitional bonding claim (i.e., an SDI claim for the purposes of preparation for and recovery from childbirth).

Second, we have the universe of SDI claims over 2000-2014. Similar to the PFL data, for each SDI claim, we have information on the date, duration, the weekly benefit amount, the employee's birth date, the employee's gender, and a unique employee identifier.

Third, we have quarterly earnings data over 2000-2014 from the EDD tax branch. For each employee, we have his/her unique identifier, his/her earnings in each quarter and in each job, a unique employer identifier associated with those earnings, and a NAICS industry code associated with that employer.

Fourth, we collect publicly-available data from the Bureau of Labor Statistics (BLS) on the unemployment rate, use 2006-2014 American Community Survey (ACS) data to calculate earnings quantiles, and 2006-2015 Current Population Survey (CPS) data to estimate the percentage of the workforce who are female by industry. We also obtain data on the total number of births in California in every year from the National Center for Health Statistics (NCHS) Vital Statistics database.

Employee-level sample construction. The first part of our analysis considers employee-level outcomes. To construct our employee-level sample, we first take the universe of PFL and SDI claims, and drop all duplicate claims.[18] We separate the claims by type (bonding,

[17] The employee identifiers in our data are scrambled social security numbers. Thus, we cannot actually identify any individual in our data set, but we can link information across data sets for each employee using the unique identifiers.

[18] If there are two claims of the same type with the same claim effective date, but different claim filed dates, the latter claim's information is used. If there are two claims with the same claim filed date, the one with the greater weekly benefit amount authorized is used.

caring, or SDI) and gender in most of our analysis.

For each claim, we create a variable measuring the duration of leave in weeks by dividing the total benefit amount received by the weekly benefit amount authorized. Since PFL does not need to be taken continuously, this duration measure accounts for possible gaps in between periods of leave. We study the duration of PFL leave and the duration of SDI leave separately. Additionally, for women who take bonding claims, we create an alternative "total duration" variable that adds the length of the transitional SDI bonding claim to the PFL bonding claim duration. If the duration for a given claim is calculated to be longer than 6 weeks in the PFL data or longer than 52 weeks in the SDI data, it is capped at those maximums.[19]

We merge the claims data to the quarterly earnings data using employee identifiers. For each claim, we calculate the pre-claim "base period" earnings in quarters two through five prior to the claim. Note that the maximum quarterly earnings during this time period determines the benefit amount. We sum all earnings each quarter for workers holding multiple jobs.

Finally, for each claim, we obtain information on the size and industry code associated with the employer in the quarter before the claim. For workers who have multiple jobs, we use the employer associated with the highest earnings. Employer size is calculated by adding up all of the employees working at that firm in that quarter.

Employer-level sample construction. The second part of our analysis considers the effect of employee leave-taking on employer outcomes. Using the unique employer identifiers available in our data, we aggregate our sample to an employer×quarter panel over 2000-2014. We allow employers to enter and exit our data during this time frame, but we exclude employers in quarters in which they first appear in the data or in which they leave the data (firm "births" and "deaths") because many measures are inaccurate in these quarters.

We then create the following turnover outcomes: (i) leave share = the percentage of employees who were at the firm last quarter but with no earnings from the firm this quarter, and (ii) join share = the percentage of employees who were not at the firm last quarter but

[19]There were a small number of cases in which a PFL claim was authorized but no leave was taken. These claims are not included in our analysis.

who do have positive earnings from the firm this quarter.[20] We also study the average wage per worker (i.e., the total wage bill divided by the number of employees). Finally, we use the total number of leave-takers in each employer×quarter to create a ratio of leave-takers of each type to the total number of employees that quarter.

To study heterogeneity by firm size, we create firm size categories based on the average number of employees in the firm over the whole time period. We also look across NAICS industry groups.

B Details on the Regression Kink Method

In addition to the descriptive analysis, we are also interested in studying the *causal* impacts of PFL and SDI benefits on workers' leave-taking and labor market outcomes. To make our question of interest more precise, consider the following model:

$$Y_i = \gamma b_i + u_i \tag{1}$$

for each individual i. Y_i is an outcome of interest, such as leave duration in weeks or labor market attachment one year after the quarter of the claim. b_i is the benefit amount in thousands of dollars, while u_i is a random vector of unobservable individual characteristics. We are interested in estimating γ, which measures the effect of a one thousand dollar increase in the benefit amount on the outcome of interest.

The challenge with estimating equation (1) using an ordinary least squares (OLS) regression is that there are unobserved variables that are correlated with the benefit amount that may also affect the outcome of interest. For instance, individuals with higher education levels or longer labor market experience are likely to have higher PFL and SDI benefits and may also have better post-PFL/post-SDI labor market outcomes relative to those with lower education levels or shorter labor market experience. As such, it is difficult to separate out the causal effect of the benefit from the influences of these other factors.

To overcome this challenge, we leverage quasi-experimental variation stemming from a non-linearity in the PFL and SDI benefit schedule. Specifically, as described in Section 2,

[20]We exclude the turnover outcomes for firms in the quarter that they enter or exit or if they have more than ten times the number of employees they had last quarter or less than one-tenth of the employees they had last quarter because our focus is employee turnover and not firm turnover.

the benefit is a direct function of an employee's baseline earnings, which are calculated over a 12-month base period, and include all earnings subject to the SDI tax paid 5 to 18 months before the date of claim initiation. The benefit amounts to approximately 55 percent of an employee's base period earnings, up to a maximum benefit amount, which is updated on a regular basis.

Mathematically, we can describe the benefit function as follows: For each individual i who files a claim in quarter q, $b_{iq}(E_i, b_q^{max}, E_q^0)$ is a fixed fraction, $\tau = 0.55$, of an individual's base period earnings, E_i, up to the maximum benefit in quarter q, b_q^{max}, where E_q^0 denotes the earnings threshold that corresponds to the amount of base period earnings above which all employees receive the maximum benefit amount:

$$b_{iq}(E_i, b_q^{max}, E_q^0) = \begin{cases} \tau \cdot E_i & \\ b_q^{max} & \text{if} \quad E_i \geq E_q^0 \end{cases}$$

Put differently, there is a negative change in the slope of $b_{iq}(\cdot)$ at the earnings threshold, E_q^0, from about 0.55 to 0. The RK design, described in detail by Card *et al.* (2012), makes use of this change in the slope of the benefit function to estimate the causal effect of an additional \$1000 in benefits on the outcome of interest.[21] Intuitively, the RK method tests for whether there is a change in the slope of the relationship between the outcome and base period earnings at the earnings threshold. Assuming that—in the absence of the kink in the benefit function—there would be a smooth (i.e., non-kinked) relationship between the outcome and earnings, evidence of a change in the slope would imply a causal effect of the benefit amount on the outcome.

More formally, the RK estimator identifies:

$$\gamma_{RK} = \frac{lim_{\epsilon \uparrow 0}\left[\frac{\partial Y|E=E_q^0+\epsilon}{\partial E}\right] - lim_{\epsilon \downarrow 0}\left[\frac{\partial Y|E=E_q^0+\epsilon}{\partial E}\right]}{lim_{\epsilon \uparrow 0}\left[\frac{\partial b|E=E_q^0+\epsilon}{\partial E}\right] - lim_{\epsilon \downarrow 0}\left[\frac{\partial b|E=E_q^0+\epsilon}{\partial E}\right]} \tag{2}$$

[21] Other recent applications of the RK method include: Landais (2015) on the effects of unemployment benefits and Turner (2014) on the incidence of federal student grant aid.

In words, the RK estimator is a ratio of two terms. The numerator is the change in the slope of the outcome as a function of base period earnings at the earnings threshold. The denominator is the change in the slope of the benefit function at the earnings threshold.

While the denominator in the ratio in equation (2) can be gauged from the benefit schedule and should equal approximately -0.55, we obtain an empirical estimate of its magnitude using our data on actual benefits received by claimants. The reason that the empirical relationship between earnings and the benefit amount in our data may differ from the benefit schedule is because only earnings subject to the SDI tax are used to calculate benefit amounts. However, not all earnings are subject to the SDI tax, and we cannot distinguish between eligible and ineligible earnings. As such, the empirical magnitude of the denominator in the ratio of equation (2) is likely to not be exactly -0.55.

We run regression models that test for a change in the slope of the quarterly benefit amount as a function of quarterly base period earnings at the earnings threshold, while controlling for base period earnings (in 2014 dollars) and other covariates. Our baseline models are local linear regressions that limit the sample to observations in narrow bandwidths surrounding the earnings threshold:

$$b^g_{iq} = \beta_0 + \beta_1 E_i + \beta_2 (E_i - E^0_q) \cdot D + \rho' X_i + \omega_q + e_i \quad \text{if} \quad |E_i - E^0_q| \leq h \tag{3}$$

for each individual i, with a claim in quarter q, of gender g. b^g_{iq} is the quarterly benefit amount. The variable D is an indicator that is set equal to 1 when earnings are above the threshold E^0_q and 0 otherwise (i.e., $D = 1[E_i > E^0_q]$). We control for base period earnings E_i. All earnings and benefit amounts are quarterly and in real 2014 dollars unless otherwise stated. X_i is a vector of individual controls (employee age and age squared, as well as dummies for employer industry and employer size). ω_q are quarter fixed effects, which control for time-varying factors such as inflation, changes in population demographics, and aggregate labor market conditions. e_i is the unobserved error term. The change in the slope in the denominator of the ratio in equation (2) is given by β_2. As noted above, we limit our sample to observations with base period earnings in narrow bandwidths surrounding E^0_q, as denoted by h. We also test the robustness of our estimates to using different bandwidths, h.

We proceed similarly to estimate the numerator of the ratio in equation (2):

$$Y_{iq}^{g} = \lambda_0 + \lambda_1 E_i + \lambda_2 (E_i - E_q^0) \cdot D + \theta' X_i + \omega_q + e_i \quad \text{if} \quad |E_i - E_q^0| \leq h \tag{4}$$

for each individual i, with a claim in quarter q, of gender g. Here, Y_{iq}^{g} is an outcome such as leave duration or employment four quarters after the claim. The remainder of the variables is as defined above. The change in the slope in the numerator of the ratio in equation (2) is given by λ_2.

Thus, to obtain an estimate of our key parameter of interest, γ, which measures the effect of a one thousand dollar increase in the benefit amount on the outcome of interest, we can simply divide λ_2 by β_2. Mathematically, $\gamma_{RK} = \frac{\lambda_2}{\beta_2}$.

The identifying assumptions for inference using the RK design are: (1) in the vicinity of the earnings threshold, there is no change in the slope of the underlying direct relationship between base period earnings and the outcome of interest, and (2) the conditional density of base period earnings is continuously differentiable at the earnings threshold. These assumptions imply that individuals cannot perfectly sort at the earnings threshold (i.e., they cannot manipulate their earnings to end up on one or the other side of the threshold). We conduct some indirect tests of these assumptions below.

C Details on the Employer-Level Analysis

To study the effects of PFL on employer-level outcomes, we aggregate our data to an employer by quarter panel, as described above. We study within-employer changes in outcomes as a function of changes in employee leave-taking rates using models with employer fixed effects. Specifically, we estimate versions of the following equation:

$$Y_{kt} = \pi_0 + \pi_1 L_{kt} + \delta' X_{kt} + \omega_q + \psi_k + \varepsilon_{kt} \tag{5}$$

for each employer k in quarter t. Y_{kt} is an outcome of interest such as the turnover rate or average wage cost. L_{kt} is the share of employees who are on leave either on PFL or transitional bonding through SDI. X_{kt} is a vector of time-varying controls such as employer size. ψ_k is an employer fixed effect, ω_q is a quarter fixed effect, and ε_{kt} is an unobserved error term, which we cluster at the employer level. The coefficient π_1 measures the effect of a one percentage point change in the share of employees who are on leave on the outcome of interest.

D Additional Results

Trends in leave duration. In Appendix Figure 1 (page 67), we document trends in the average duration of leave under the PFL and SDI programs. In the top left panel, we show the average length of PFL bonding leave for women (in the solid blue line) and for men (in the dashed green line). We also show the average length of total leave for women who use SDI and PFL consecutively (in the dashed red line). All three of these averages have been very stable since the implementation of the CA-PFL program. Women have consistently taken an average of a little less than 6 weeks of PFL bonding leave, and an average of about 12 weeks of total leave when combining both PFL and SDI. Men have taken about 4 weeks of PFL bonding leave during our sample time frame.

The top right panel of Appendix Figure 1 shows that the average duration of caring leave has also been stable over time. For women, caring leave duration is somewhat lower than bonding leave duration—just above 4 weeks on average. Men's caring leave duration has been just under 4 weeks through most of this time period.

The bottom left panel of Appendix Figure 1 depicts trends in average SDI leave duration by gender. Unlike PFL leave duration, average SDI leave duration has increased over our sample time frame, especially for men. The timing of the increase coincides with the rise in the unemployment rate (see Figure 1 for the trend in the unemployment rate plotted on the right $y-$axis), suggesting that there may have been an impact of the Great Recession on SDI leave duration for men (but seemingly no impact on SDI take-up, as shown in Figure 1). Men were taking an average of about 11 weeks of SDI leave over 2001-2007, and this average increased to about 12 weeks by 2009. Women were taking a little less than 10 weeks of SDI leave over 2001-2011, and a bit more than 10 weeks over 2012-2014.

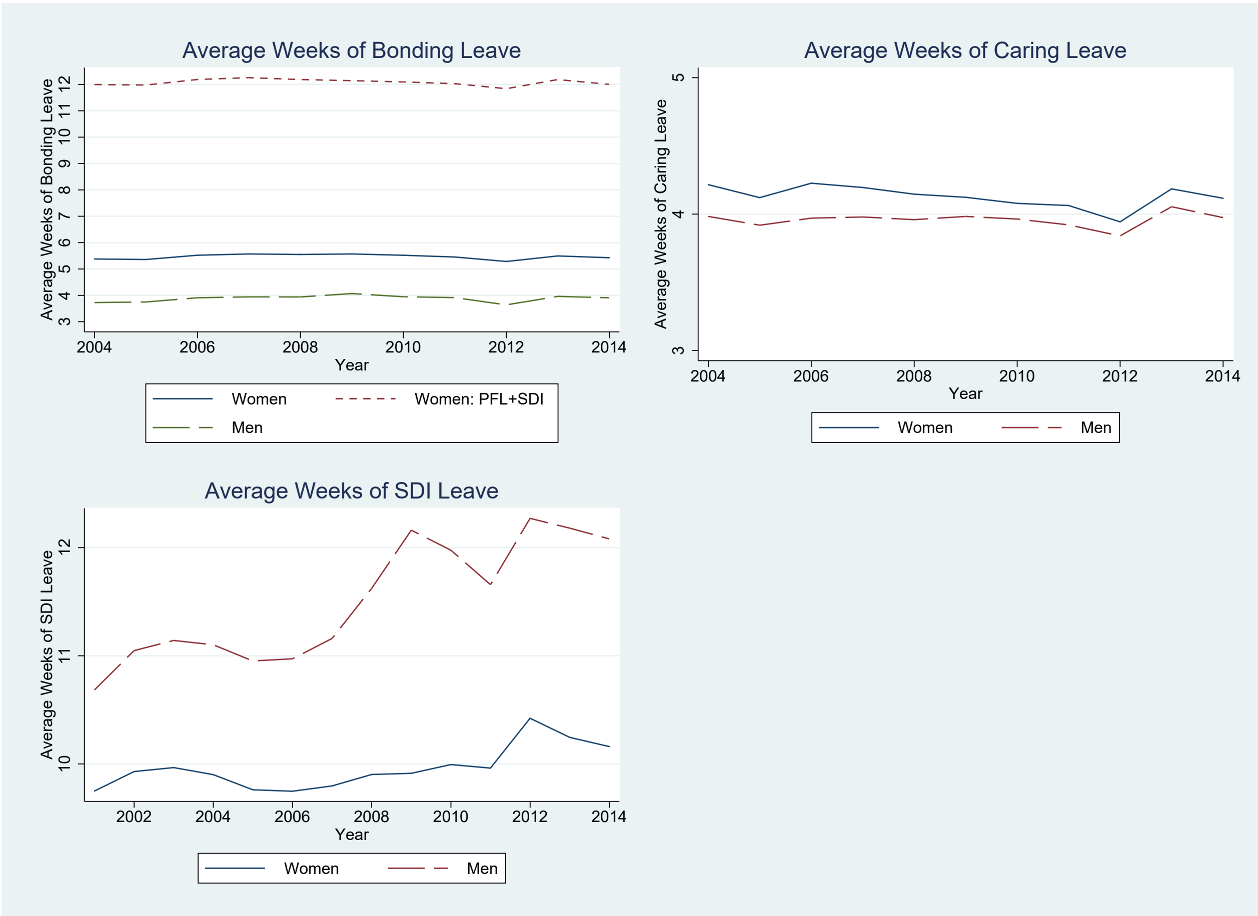
Robustness of the RK method. We have tested the sensitivity of our RK estimates to different bandwidths surrounding the earnings threshold. Appendix Tables 1 and 2 (page 68) present results for female bonding claimants for the benefit amount and log earnings four quarters after the claim, respectively (results for all other outcomes and types of claimants are available upon request). In both tables, we show results from specifications that use bandwidths of size $3,000, $5,000, $7,000, and $9,000 in columns (1) through (4). Appendix Table 1 demonstrates that the RK denominator is consistently negative and statistically significant. It is not particularly sensitive to the size of the bandwidth. Appendix Table 2 shows that when log earnings four quarters after the claim is the outcome, the RK numerator is negative and statistically significant for three out of the four bandwidth sizes. It is not statistically significant when using a very narrow bandwidth of $3,000, perhaps due to power issues.

Indirect tests of identifying assumptions in the RK method. Finally, we conduct some graphical tests of the identifying assumptions in the RK methodology. Appendix Figure 2 (page 69) considers the density of base period earnings around the earnings threshold. Specifically, we plot the total number of claimants by 0.01 bins of normalized earnings, by type of claim and gender of claimant. Across the two genders and three types of claims, there is no visible evidence of any discontinuities or kinks in these distributions around the threshold. These graphs suggest that individuals are not strategically sorting to be on either side of the kink.

Appendix Figures 3 and 4 (pages 70 and 71) consider the distributions of workers' ages and pre-claim firm sizes, respectively. These are pre-determined characteristics that should not be affected by the benefit amount. As such, these variables should not exhibit any kinks when plotted as a function of normalized earnings. Evidence to the contrary would suggest a possible failure of the first assumption of the RK design discussed above. Appendix Figure 3 confirms that there is no noticeable change in the slope of average worker age at the earnings threshold for all claim types and genders. Appendixx Figure 4, however, suggests that there may be a change in the slope of average firm size at the earnings threshold for female caring claimants. As such, the RK results for female caring claimants should be interpreted with some caution. We plan to explore the reason for this non-linearity in firm size in subsequent work. We will also conduct more formal tests of the RK identifying assumptions.

E Appendix Figures and Tables

Appendix Figure 1: Paid Family Leave and State Disability Insurance Duration Trends



Notes: These sub-figures plot trends in the average duration of bonding leave (top left), caring leave (top right), and SDI leave (bottom left) for women and men.

Appendix Table 1: RK Results for the Benefit Amount; Female Bonding Claimants; Robustness to Different Bandwidths

	(1) $h = 3,000$	(2) $h = 5,000$	(3) $h = 7,000$	(4) $h = 9,000$
RK Denominator	-0.380***	-0.405***	-0.417***	-0.427***
	[0.0134]	[0.00606]	[0.00361]	[0.00245]
Dept. var mean	11.86	11.53	11.14	10.67
Obs.	73047	123488	177045	236134

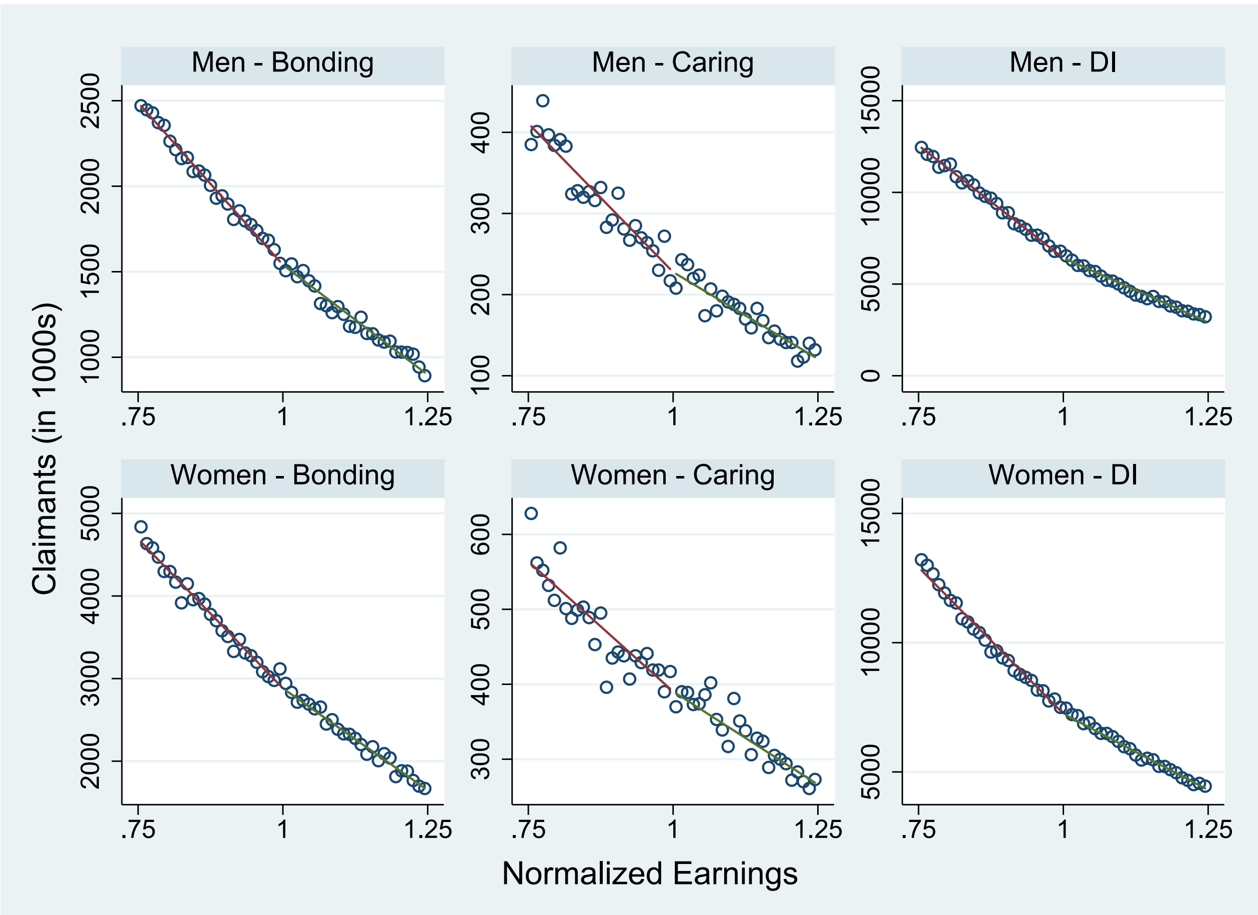
Notes: Each column is from a separate regression. All quarterly earnings and quarterly benefit amounts are in thousands of 2014 dollars. The outcome is the quarterly benefit amount for female bonding claimants. The sample includes quarters in which the weekly benefit amount maximum is well-identified. Workers must have positive earnings in at least one of the two through five quarters prior to the quarter of the leave. The table presents results on the magnitude of β_2 in equation (3), i.e., the denominator of the ratio in equation (2). The sample is limited to observations within $\$3,000$, $\$5,000$, $\$7,000$, and $\$9,000$ bandwidths, respectively, surrounding the earnings threshold. Standard errors are robust to heteroskedasticity. Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Appendix Table 2: RK Results for Log Earnings Four Quarters After the Claim; Female Bonding Claimants; Robustness to Different Bandwidths

	(1) $h = 3,000$	(2) $h = 5,000$	(3) $h = 7,000$	(4) $h = 9,000$
RK Numerator	0.00349	-0.00991***	-0.0167***	-0.0206***
	[0.00610]	[0.00283]	[0.00175]	[0.00119]
Dept. var mean	2.988	2.963	2.924	2.874
Obs.	57662	97106	138523	183605

Notes: Each column is from a separate regression. All quarterly earnings and quarterly benefit amounts are in thousands of 2014 dollars. The outcome is the log earnings four quarters after the claim for female bonding claimants. The sample includes quarters in which the weekly benefit amount maximum is well-identified. Workers must have positive earnings in at least one of the two through five quarters prior to the quarter of the leave. Because employment outcomes are only known for the years 2000-2014, only claims filed in years 2004-2013 are included. The table presents results on the magnitude of λ_2 in equation (4), i.e., the numerator of the ratio in equation (2). The sample is limited to observations within $\$3,000$, $\$5,000$, $\$7,000$, and $\$9,000$ bandwidths, respectively, surrounding the earnings threshold. Standard errors are robust to heteroskedasticity. Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Appendix Figure 2: Density Around Earnings Threshold



Notes: These sub-figures show the density of PFL and SDI claimants by 0.01 bins of normalized earnings, by type of claim and gender of claimant. The $y-$axis plots the number of claimants in each bin in 1000s. Normalized quarterly earnings is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.

Appendix Figure 3: Distribution of Employee Age Around Earnings Threshold

Notes: These sub-figures show the average age of claimants by 0.01 bins of normalized earnings, by type of claim and gender of claimant. Normalized quarterly earnings is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.

Appendix Figure 4: Distribution of Employee's Firm Size Around Earnings Threshold

Notes: These sub-figures show the average firm size of claimants by 0.01 bins of normalized earnings, by type of claim and gender of claimant. Normalized quarterly earnings is equal to the base period earnings divided by the earnings required to obtain the maximum benefit amount. The red and green lines are from linear regressions fitted to the data on the two sides of the threshold.