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REGRESSION KINK EVIDENCE FROM CALIFORNIA ADMINISTRATIVE DATA

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ABSTRACT

Although the United States provides unpaid maternity and family leave to qualifying workers, it is the only OECD country without a national paid leave policy, making wage replacement a pivotal issue under debate. We use ten years of linked administrative data from California together with a regression kink (RK) design to estimate the causal impacts of benefits in the first state-level paid family leave program for women with earnings near the maximum benefit threshold. We find no evidence that a higher weekly benefit amount (WBA) increases leave duration or leads to adverse future labor market outcomes for mothers in this group. In contrast, we document consistent evidence that an increase in the WBA leads to a small increase in the share of quarters worked one to two years after the leave and a sizeable increase in the likelihood of making a future paid family leave claim across a variety of specifications.

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1 Introduction

A vast body of research has documented a persistent "motherhood wage penalty" that can last 10 to 20 years after childbirth. Mothers earn lower wages, work fewer hours, and are less likely to be employed than fathers or childless women and men (see, e.g.: Waldfogel, 1998; Lundberg and Rose, 2000; Blau and Kahn, 2000; Anderson *et al.*, 2002; Molina and Montuenga, 2009; Kleven *et al.*, 2018). Paid family leave (PFL)—a policy that allows working mothers to take time off work to recover from childbirth and care for their newborn (or newly adopted) children while receiving partial wage replacement—may be a tool for reducing this penalty if it facilitates career continuity and advancement for women. However, opponents of PFL caution that it could have the opposite effect: by allowing mothers to have paid time away from work, PFL may lower their future labor market attachment, while employers could face substantial costs that lead to increased discrimination against women.[1] These discussions are especially fervent in the United States, which is the only developed country without a national paid maternity or family leave policy.

A number of studies outside the U.S. have analyzed the impacts of extensions in existing PFL policies (or, less frequently, introductions of new programs) on maternal leave-taking and labor market outcomes, delivering mixed results (see Olivetti and Petrongolo, 2017 and Rossin-Slater, 2017 for recent overviews).[2] The substantial cross-country heterogeneity in major policy components—the benefit amount, statutory leave duration, and job protection—generates challenges for comparing policies and likely contributes to the lack of

[1]For more information on the arguments surrounding paid leave in the U.S., see, e.g.: `https://www.usnews.com/news/best-states/articles/2017-04-07/affordable-child-care-paid-family-leave-key-to-closing-gender-wage-gap` and `https://economix.blogs.nytimes.com/2014/01/27/the-business-of-paid-family-leave/?_r=0`.

[2]For example, some studies find either positive or zero effects on maternal employment in the years after childbirth (Baker and Milligan, 2008; Kluve *et al.*, 2013; Bergemann and Riphahn, 2015; Carneiro *et al.*, 2015; Dahl *et al.*, 2016; Stearns, 2016), while others document negative impacts, especially in the long-term (Lalive and Zweimüller, 2009; Lequien, 2012; Schönberg and Ludsteck, 2014; Bičáková and Kalíšková, 2016; Canaan, 2017). Cross-country comparisons suggest that provisions of leave up to one year in length typically increase the likelihood of employment shortly after childbirth, whereas longer leave entitlements can negatively affect women's long-term labor market outcomes (Ruhm, 1998; Blau and Kahn, 2013; Thévenon and Solaz, 2013; Olivetti and Petrongolo, 2017).

consistency in the literature.[3] In this paper, we study California, the first state to implement a PFL program, and focus on identifying the effects of a key policy parameter—*the benefit amount*. Specifically, we use ten years of administrative data to estimate the causal impacts of the wage replacement rate on maternal leave duration, labor market outcomes, and subsequent leave-taking with a regression kink (RK) design.

Californian mothers have been eligible for several weeks of paid maternity leave to prepare for and recover from childbirth through California's State Disability Insurance (CA-SDI) system since the passage of the 1978 Pregnancy Discrimination Act. In 2004, most working mothers also became eligible for 6 weeks of leave through California's Paid Family Leave program (CA-PFL), which they can take anytime during the child's first year of life.[4] In total, women with uncomplicated vaginal deliveries can get up to 16 weeks of paid maternity/family leave through SDI and PFL.[5] Paid leaves under SDI and PFL are not directly job protected, although job protection is available if the job absence simultaneously qualifies under the federal Family and Medical Leave Act (FMLA) or California's Family Rights Act (CFRA).[6]

Since the leave benefit amount is not randomly assigned, it is challenging to disentangle its causal impact from the possible influences of other unobservable differences between individuals. To circumvent this issue, we make use of a kink in the CA-PFL/SDI benefit schedule: participants get 55 percent of their prior earnings replaced, up to a maximum

[3]See Addati *et al.* (2014) and Olivetti and Petrongolo (2017) for more information on maternity and family leave policy details in countries around the world.

[4]To be eligible for CA-SDI and CA-PFL, an individual must have earned at least $300 in wages in a base period between 5 and 18 months before the PFL claim begins. Only wages subject to the SDI tax are considered in the $300 minimum. California's PFL and SDI programs are financed entirely through payroll taxes levied on employees.

[5]Women who have 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 through CA-SDI. 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.

[6]The FMLA was enacted in 1993 and provides 12 weeks of *unpaid* job protected family leave to qualifying workers. To be eligible for the FMLA, workers must have worked at least 1,250 hours in the preceding year for an employer with at least 50 employees (within a 75 mile radius of the employment location). The CFRA is nearly identical to the FMLA in its provisions and eligibility criteria. There are minor differences between the two laws: for example, women who have difficult pregnancies can use FMLA prior to giving birth, but CFRA leave can only be used after childbirth. See: `https://www.shrm.org/resourcesandtools/tools-and-samples/hr-qa/pages/californiadifferencecfrafmla.aspx`.

benefit amount.[7] Intuitively, we compare the outcomes of mothers with pre-leave earnings just below and just above the threshold at which the maximum benefit applies. These women have similar observable characteristics, but face dramatically different marginal wage replacement rates of 55 and 0 percent, respectively. The RK method identifies the causal effect of the benefit amount by testing for a change in the slope of the relationship between an outcome and pre-claim earnings at the same threshold (Card *et al.*, 2016).

While a key advantage of the RK method is that it can account for the endogeneity in the benefit amount, the primary limitation is that the RK sample is not representative of the population of leave-takers. The kink is located around the 92nd percentile of the California female earnings distribution, and women in the vicinity of the kink point are older and work in larger firms than the average female program participant. That being said, high-earning women's careers may be especially sensitive to employment interruptions—for example, Stearns (2016) shows that access to job protected paid maternity leave in Great Britain reduces the likelihood that high-skilled women are promoted or hold management positions five years after childbirth. Additionally, RK estimates provide important information about the implications of benefit changes around the maximum benefit threshold. These are highly policy relevant because all existing state PFL programs, as well as the current national PFL proposal (the Family and Medical Insurance Leave Act, or FAMILY Act), feature similar kinked benefit schedules, but have different kink point locations.[8]

More broadly, isolating the effect of the benefit amount is critical for informing debates

[7]The two programs have identical benefit schedules. More details on the CA-PFL/SDI benefits are in Section 2.

[8]The states with PFL policies are: California (since 2004), New Jersey (since 2008), Rhode Island (since 2014), New York (since 2018), Washington state (will go into effect in 2020), and Washington D.C. (will go into effect in 2020). In all states, benefits are paid as a percentage of prior earnings, up to a maximum benefit amount. The wage replacement rates are: 55 percent (California), 66 percent (New Jersey), 60 percent (Rhode Island), 67 percent (New York). D.C.'s marginal replacement rates vary with prior earnings. The maximum weekly benefit amounts as of 2017 are: \$1,173 (California), \$633 (New Jersey), \$817 (Rhode Island), and \$1,000 (DC). In New York, the maximum benefit amount is 67 percent of the average weekly wage in the state, which currently results in a maximum benefit of \$652. More information is available here: `http://www.nationalpartnership.org/research-library/work-family/paid-leave/state-paid-family-leave-laws.pdf`. For information on the FAMILY Act, see: `http://www.nationalpartnership.org/research-library/work-family/paid-leave/family-act-fact-sheet.pdf`.

about payment during leave. Since the vast majority of American workers already have access to unpaid leave through their employers and the FMLA, the wage replacement rate is arguably the most salient parameter under debate.[9] A long literature on other social insurance programs—including unemployment insurance (UI) (Baily, 1978; Chetty, 2008; Card *et al.*, 2012; Landais, 2015; Card *et al.*, 2015a,b, 2016; Schmieder and Von Wachter, 2016; Schmieder and von Wachter, 2017), Social Security Disability Insurance (SSDI) (Gelber *et al.*, 2016), and the Workers' Compensation program (Hansen *et al.*, 2017)—finds a positive relationship between the benefit amount and program participation duration, with elasticities ranging between 0.3 and 2 in the case of UI (Card *et al.*, 2015a).[10] As such, a higher PFL benefit may increase maternity leave duration, which could in turn affect women's subsequent labor market trajectories.

But different types of social insurance programs could lead to different responses. Childbirth is likely to be a more expected event than unemployment or a workplace injury. Maternity leaves may therefore be more planned and less responsive to benefit amounts than unemployment and injury leave spells. Consistent with this hypothesis, the only existing study (to the best of our knowledge) that isolates the effect of the maternity leave wage replacement rate while holding constant other policy parameters finds no impact on maternal job continuity or leave duration in Japan (Asai, 2015).[11] This evidence may not be readily applicable to the U.S. setting, however, since Japanese mothers are guaranteed one year of job protected paid maternity leave. By contrast, U.S. maternity leave durations are relatively short and often not job protected, and even among the highest-wage workers, less than

[9] Data from the 2016 National Compensation Survey show that 88 percent of civilian workers have access to unpaid leave through their employers (see: `https://www.bls.gov/ncs/ebs/benefits/2016/ownership/civilian/table32a.htm`. Additionally, according to most recent data from 2012, about 60 percent of American private sector workers are eligible for the FMLA (Klerman *et al.*, 2012).

[10] A recent paper on the elasticity of injury leave duration with respect to the benefit amount provided under Oregon's Workers' Compensation program finds an elasticity estimate in the range of 0.2 to 0.4 (Hansen *et al.*, 2017).

[11] We are also aware of two other studies that isolate the impacts of other PFL policy parameters in countries outside the U.S.: Lalive *et al.* (2014) separately estimate the labor market impacts of the duration of paid leave and job protection for Austrian mothers, while Stearns (2016) distinguishes between access to any paid leave and job protection in Great Britain.

a quarter have access to *any* employer-provided paid leave.[12] Moreover, as mentioned above, mothers in California are able to take leave intermittently until the child's first birthday, raising the possibility that they could be sensitive to the benefit amount when deciding how much time off to take.

If higher benefits increase maternity leave duration, the impacts on women's future labor market outcomes are theoretically ambiguous (Klerman and Leibowitz, 1994; Olivetti and Petrongolo, 2017). Increased time away from the job may be detrimental to future labor market success as a result of human capital depreciation or employer discrimination. Alternatively, if a higher benefit encourages a longer leave for a mother who would have otherwise quit her job, then there may be a positive effect on her future labor market outcomes through increased job continuity. Without changes to leave duration, PFL benefits could negatively impact future labor market outcomes through an income effect. Consistent with this hypothesis, Wingender and LaLumia (2017) find evidence that higher after-tax income during a child's first year of life reduces labor supply among new mothers. Or, similar in spirit to efficiency wage models (Akerlof, 1984; Stiglitz, 1986; Katz, 1986; Krueger and Summers, 1988), a higher wage replacement rate during leave may improve a worker's morale or promote firm loyalty (even if she recognizes that her employer is not paying her benefits directly), and increase the likelihood that a mother continues with her job or works more in the future overall.

Our results show that higher benefits do *not* increase maternity leave duration among women with earnings near the maximum benefit threshold. Our estimates allow us to rule out that a 10 percent increase in the weekly benefit amount (WBA) would increase leave duration by more than 0.4 to 3.2 percent (i.e., we can reject elasticities higher than 0.04 to 0.32), depending on the specification. Our results underscore the notion that PFL provides a

[12] Data from the 2016 National Compensation Survey show that 14 percent of all civilian workers have access to PFL through their employers. Among those in occupations with wages in the highest decile, 23 percent have access to employer-provided PFL. With regard to leave duration, Rossin-Slater *et al.* (2013) estimate that California mothers took an average of about three weeks of maternity leave prior to the implementation of CA-PFL.

distinct type of social insurance and targets a unique population, making the (much larger) elasticities from the prior social insurance literature less relevant for PFL (Krueger and Meyer, 2002). We also find no evidence that PFL benefits have any adverse consequences on subsequent maternal labor market outcomes. If anything, our estimates indicate a small positive impact—a 10 percent increase in the WBA raises the share of quarters worked one to two years after the initiation of leave by 0.1 to 0.7 percentage points (a 0.1 to 0.9 percent increase), depending on the specification.

Lastly, we provide novel evidence that the benefit amount predicts repeat program participation. We find that an additional 10 percent in the benefit received during a mother's first period of leave is associated with a 1.2 to 2.0 percentage point higher likelihood of having another PFL claim within the following three years (a 5.8 to 9.0 percent increase), depending on the specification. This effect may in part operate through the positive impact on employment after the first period of leave, which makes it more likely that a mother becomes eligible for PFL for her next child. It is also possible that the increase in repeat leave-taking arises due to a change in fertility behavior, although past research offers mixed evidence on the relationship between PFL and fertility.[13] Alternatively, even if there were no changes in post-leave employment or fertility, women who get more wage replacement during leave may simply have a better experience and are therefore more likely to participate in the program again than those with lower benefits. Indeed, a similar relationship between current benefits and future claims has been found in the context of the Workers' Compensation program in Oregon (Hansen *et al.*, 2017).

Our study builds on several recent papers that use survey data to analyze the labor market effects of CA-PFL with difference-in-difference (DD) designs (Rossin-Slater *et al.*, 2013; Bartel *et al.*, 2018; Das and Polachek, 2015; Baum and Ruhm, 2016; Stanczyk, 2016;

[13]For example, Dahl *et al.* (2016) find no effects of Norwegian maternity leave extensions on mothers' completed fertility. By contrast, Lalive and Zweimüller (2009) find that an extension in parental leave in Austria increased subsequent fertility rates among mothers. In the case of CA-PFL, Lichtman-Sadot (2014) finds some evidence that disadvantaged women re-timed their pregnancies to become eligible for CA-PFL in the second half of 2004. However, we are not aware of any studies documenting effects of CA-PFL on subsequent fertility.

Byker, 2016). Our analysis of administrative data can overcome several limitations of these studies, which include small sample sizes, measurement error, non-response bias, lack of panel data, and missing information on key variables such as PFL take-up and leave duration.[14] Additionally, we bring the novel RK research design to analyze PFL for the first time.[15]

The paper unfolds as follows. Section 2 provides more details on the CA-PFL/SDI benefit schedule. Section 3 describes our data, while Section 4 explains our empirical methods. Section 5 presents our results and sensitivity analyses, while Section 6 offers some conclusions.

2 Benefit Schedule

The CA-PFL/SDI benefit schedule is a piece-wise linear function of base period earnings, which is defined as the maximum quarterly earnings in quarters 2 through 5 before the claim. Figures 1a and 1b plot the WBA as a function of quarterly based period earnings in nominal terms for the years 2005 and 2014, the first and last years in our data, respectively. These graphs clearly show that there is a kink in the relationship between the WBA and base period quarterly earnings—the slope of the benefit schedule changes from $\frac{0.55}{13} = 0.04$ to 0 at the maximum earnings threshold. Note that the replacement rate is divided by 13 to convert to a weekly amount since there are 13 weeks in a quarter. The location of this kink varies over time (i.e., both the maximum benefit amount and the earnings threshold change).[16] These graphs highlight that individuals with earnings near the kink point—who form the basis for our RK estimation—are relatively high earners. We describe the characteristics of

[14] Our paper is complementary to ongoing work that uses administrative data from Rhode Island to study the effects of paid maternity leave provided through Rhode Island's Temporary Disability Insurance system on maternal and child outcomes (Campbell *et al.*, 2017).

[15] Less relevant to the topic of this paper, the RK research design has also been used in studies of student financial aid and higher education (Nielsen *et al.*, 2010; Turner, 2014; Bulman and Hoxby, 2015), tax behavior (Engström *et al.*, 2015; Seim, Forthcoming), payday lending (Dobbie and Skiba, 2013), and local government expenditures (Garmann, 2014; Lundqvist *et al.*, 2014).

[16] The nominal quarterly earnings thresholds for 2005 and 2014 were \$19,830 and \$25,385, respectively. In \$2014 dollars, the 2005 threshold is \$23,461.09. Figure 1c plots the maximum WBA in nominal terms in each quarter during our sample time frame. The maximum WBA has nominally increased from \$840 in 2005 to \$1,075 in 2014. In \$2014 dollars, this translates to an increase from \$1,018.22 to \$1,075 during this time period.

our analysis sample in more detail in Section 3 below.

Finally, although the state pays PFL and SDI benefits according to the schedule just described, individual employers are able to supplement these benefits, making it possible for an employee to receive up to 100 percent of her base period earnings. To the extent that this phenomenon occurs, it diminishes the strength of the first stage relationship in our analysis, since some employees effectively do not face a kinked benefit schedule. While we could find no anecdotal evidence suggesting that this practice is common, we also have no data on such supplemental payments, and are therefore unable to precisely assess the magnitude of any attenuation. We can, however, focus on sub-samples of the data where this issue is least likely to be important: employees who made claims soon after the implementation of CA-PFL (2005-2010) and employees at firms with fewer than 1,000 workers. In both cases, the pattern of findings remains the same, although the estimates are less precise (see Section 5 for more details).

3 Data and Sample

We use two administrative data sets available to us through an agreement with the California Employment Development Department (EDD).

First, we have data on the universe of PFL claims from 2005 to 2014. For each claim, we have information on the reason for the claim (bonding with a new child or caring for an ill family member), claim effective date, claim filed date, the total benefit amount received, the authorized weekly benefit amount, the employee's date of birth, the employee's gender, and a unique employee identifier.[17] For women, we also have an indicator for whether there was an associated transitional SDI claim (i.e., an SDI claim for the purposes of preparation for and recovery from childbirth), along with the same information for SDI claims as we do for PFL claims.

[17] The employee identifiers in our data are scrambled. 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.

Second, we have quarterly earnings data over 2000-2014 for the universe of employees working for an employer that reports to the EDD tax branch.[18] For each employee, we have her unique identifier, her earnings in each quarter and in each job, a unique employer identifier associated with those earnings, and a North American Industry Classification System (NAICS) industry code associated with that employer.

Sample construction and key variables. For our main analysis sample, we begin with the universe of female PFL claims for the purpose of bonding with a new child (hereafter, "bonding claims" or "bonding leave") over 2005-2014.[19] We then merge the claims data to the quarterly earnings data using employee identifiers, and limit our sample to the *first* bonding claim observed for each woman.[20] Next, since the location of the kink changes over our sample time frame (recall Figure 1), we drop women who make their first bonding claim in quarters during which these changes happen.[21]

For each claim, we assign the relevant base period earnings by calculating the maximum quarterly earnings (summing over all earnings each quarter for workers holding multiple jobs) in quarters 2 through 5 before the claim effective date. We also obtain information on the size and industry code associated with the most recent employer prior to 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.

Next, in an effort to create a sample that is reasonably homogeneous and most likely

[18]Employers that employ one or more employees and pay wages in excess of $100 in a calendar quarter are required to report to the EDD according to California law. See `http://www.edd.ca.gov/pdf_pub_ctr/de44.pdf`.

[19]In previous versions of this paper, we had also reported results for male bonding claimants. However, since there are substantially fewer men than women in our claims data, the RK analysis yields imprecise results for fathers, and we have opted to focus our current analysis on mothers.

[20]Note that the first bonding claim may not necessarily be for the firstborn child. Some mothers may have chosen not to claim PFL for their firstborn child (but do claim for a later born). Additionally, many mothers had lower parity children before CA-PFL existed. Unfortunately, we cannot link our EDD data to information on births, and we therefore cannot focus on claims for firstborns only.

[21]We do so because we observe that in these quarters some individuals get assigned their WBA according to the old schedule, while others according to the new schedule. Women with first bonding claims in the following quarters are dropped: 2005q1, 2007q4, 2009q1, 2010q1, 2012q1, 2013q1, and 2014q1.

to be affected by the kink variation, we make the following sample restrictions: (1) We only include women who are aged 20-44 at the time of the first bonding claim; (2) We only keep female workers with base period quarterly earnings within a $\$10,000$ bandwidth of the kink point; (3) We drop women employed in industries in which employees are least likely to be subject to the SDI tax—private household workers, elementary and secondary school teachers, and public administration; (4) We drop women with total zero earnings in all of the base period quarters.

We then create a variable measuring the duration of leave in weeks by dividing the total benefit amount received by the authorized WBA. Since PFL does not need to be taken continuously, this duration measure accounts for possible gaps in between periods of leave. For women who make both bonding and transitional SDI claims, we add the two durations.[22] We analyze the natural log of leave duration in all of our specifications.

In addition to studying leave duration, we examine several post-leave labor market outcomes measured one to two years after leave initiation. We calculate the change between the log of total earnings (in $2014) in quarters 4 through 7 post-claim and quarters 2 through 5 pre-claim. We also study the share of quarters employed in quarters 4 through 7 after the claim. Further, we examine whether mothers return to their pre-leave employers—we create an indicator that is equal to 1 for a mother whose highest earnings in quarter 4 post-claim come from her pre-claim firm. Lastly, we create an indicator for any subsequent PFL bonding claim in the three years after the first bonding claim. To ensure that we observe outcomes in post-leave windows of the same length for all of the individuals in our data, we limit the analysis of labor market outcomes to years 2005-2012 and subsequent claims to years 2005-2011.

Summary statistics. Table 1 presents the means of key variables for women in the $10,000 bandwidth sample, as well as for women in narrower ($2,500, $5,000, and $7,500) bandwidths of base period quarterly earnings surrounding the kink point. As we zoom in closer to the

[22] We cap the maximum combined duration on SDI and PFL at 24 weeks (the 99th percentile).

threshold, women in our sample become slightly older, work in somewhat larger firms, and have higher base period earnings.

For descriptive ease, the following discussion focuses on the \$5,000 bandwidth sample. About 32 percent of the women are employed in the health industry before the claim, which is the top female industry in our data. The average weekly benefit received is \$921 (in \$2014), while average leave duration is slightly over 12 weeks, which is consistent with most women filing both transitional SDI and PFL bonding claims. When we consider subsequent labor market outcomes, we see that on average, women have substantially lower earnings post-claim than they did pre-claim. About 67 percent of women return to their pre-claim employers. Lastly, 22 percent of women make a subsequent bonding claim in the next three years.

4 Empirical Design

We are interested in identifying the causal impacts of PFL/SDI benefits on mothers' leave duration, labor market outcomes, and subsequent claiming. To make our research question more precise, consider the following stylized model:

$$Y_{iq} = \gamma_0 + \gamma_1 ln(b_{iq}) + u_{iq} \tag{1}$$

for each woman i who makes a benefit claim in quarter q. Y_{iq} is an outcome of interest, such as log leave duration or the change in log earnings before and after the claim. $ln(b_{iq})$ is the natural log of the WBA (in \$2014), while u_{iq} is a random vector of unobservable individual characteristics. We are interested in estimating γ_1, which measures the effect of a 100 percent increase in the WBA 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 our outcomes of interest, making it 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 kink in the CA-PFL/SDI benefit schedule. The benefit function can be described 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 proportion, $\tau = \frac{0.55}{13} = 0.04$, 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 0.04 to 0. The RK design, described in detail by Card *et al.* (2012), Card *et al.* (2015b) and Card *et al.* (2016), makes use of this change in the slope of the benefit function to estimate the causal effect of the benefit amount on the outcome of interest. Intuitively, the RK method tests for 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 base period earnings, evidence of a change in the slope would imply a causal effect of the benefit amount on the outcome. The RK design can be thought of as an extension of the widely used Regression Discontinuity (RD) method, and Card *et al.* (2016) provide a guide for practitioners on how local polynomial methods for estimation and inference (Porter, 2003; Imbens and Lemieux, 2008; Imbens and Kalyanaraman, 2012; Calonico *et al.*, 2014, 2016) can be applied to the RK setting.

More formally, the RK estimator identifies:

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

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.

In theory, if benefit assignments followed the formula exactly and our data contained no measurement errors, then the denominator in the ratio in equation (2) would be a known constant. In practice, as in many other policy settings, there may be small deviations from the benefit formula due to non-compliance or measurement error. Additionally, in our setting, only base period earnings *subject to the SDI tax* are used to calculate SDI and PFL benefits, but we cannot distinguish between earnings that are and are not subject to this tax in our data. As such, we must estimate the slope change in the denominator of equation (2) in a "fuzzy" RK design.[23]

For estimation, we follow the methods outlined in Card *et al.* (2015b) and Card *et al.* (2016). In particular, the slope changes in the numerator and denominator in equation (2) are estimated with local polynomial regressions to the left and right of the kink point. Key to this estimation problem are choices about the kernel, the bandwidth, and the order of the polynomial. We follow the literature by using a uniform kernel, which allows us to apply a simple two-stage least squares (2SLS) method (i.e., the denominator is estimated with a first stage regression).[24]

There is an active econometrics literature on optimal bandwidth choice in RD and RK settings. For all of our outcomes, we first present estimates using all possible bandwidths in $500 increments from $2,500 to $10,000 of quarterly earnings. Additionally, we implement

[23]The "fuzzy" RK design is formally discussed in detail in Card *et al.* (2015b).

[24]Card *et al.* (2016) note that while a triangular kernel is boundary optimal, the efficiency losses from using a uniform kernel are small both in actual applications and in Monte Carlo simulations.

three different algorithms proposed in the literature: a version of the Imbens and Kalyanaraman (2012) bandwidth for the fuzzy RK design (hereafter, "fuzzy IK"),[25] as well as a bandwidth selection procedure developed by Calonico *et al.* (2014) (hereafter, "CCT") with and without a bias-correction ("regularization") term.[26] Moreover, following other RK studies, we try local linear and quadratic polynomials.

We estimate the following first stage regression:

$$ln(b_{iq}) = \beta_0 + \sum_{p=1}^{\overline{p}}[\psi_p(E_i - E_q^0)^p + \theta_p(E_i - E_q^0)^p \cdot D_i] + \rho' X_i + \omega_q + e_{iq} \quad \text{if} \quad |E_i - E_q^0| \leq h \quad (3)$$

for each woman i with a first bonding claim in quarter q and with base period earnings E_i in a narrow bandwidth h surrounding the threshold E_q^0. The variable D_i is an indicator that is set equal to 1 when earnings are above E_q^0 and 0 otherwise: $D_i = \mathbf{1}_{[\mathbf{E_i - E_q^0 > 0}]}$. As noted above, we control for normalized base period earnings relative to the threshold $(E_i - E_q^0)$ using local linear or quadratic polynomials (i.e., $\overline{p}$ is either equal to 1 or 2). e_{iq} is the unobserved error term. The estimated change in the slope in the denominator of the ratio in equation (2) is given by θ_1. We show results with and without individual controls, X_i, and quarter fixed effects, ω_q. X_i includes: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), and dummies for pre-claim employer industry (NAICS industry groups) and firm size (1-49, 50-99, 100-499, 500+).

The second stage regression is:

$$Y_{iq} = \pi_0 + \pi_1 \widehat{ln(b_{iq})} + \sum_{p=1}^{\overline{p}} \lambda_p (E_i - E_q^0)^p + \zeta' X_i + \delta_q + \varepsilon_{iq} \quad \text{if} \quad |E_i - E_q^0| \leq h \quad (4)$$

for each woman i with a first bonding claim in quarter q. Here, Y_{iq} is an outcome, and $\widehat{ln(b_{iq})}$ is instrumented with the interaction between D_i and the polynomial in normalized

[25] Specifically, Imbens and Kalyanaraman (2012) proposed an algorithm for computing the mean squared error (MSE) optimal RD bandwidth, while Card *et al.* (2015b) proposed its analog for the fuzzy RK setting, using asymptotic theory from Calonico *et al.* (2014).

[26] Both IK and CCT procedures involve a regularization term, which reflects the variance in the bias estimation and guards against the selection of large bandwidths.

base period earnings. The remainder of the variables are as defined before. The coefficient of interest, π_1, measures the effect of a 100 percent increase in the WBA on the outcome, and provides an estimate of γ_{RK} defined above.

Identifying assumptions. 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). Importantly, since we only use data on women who make a bonding claim, differential selection into program take-up across the threshold would violate our identifying assumptions.[27]

We conduct standard tests of these assumptions. First, we show the frequency distribution of normalized base period earnings around the earnings threshold in Figure 2a. This graph uses \$100 bins and a \$5,000 bandwidth.[28] The histogram looks reasonably smooth, and we also perform formal tests to support this assertion. Specifically, we conduct a McCrary test (McCrary, 2008) for a discontinuity in the assignment variable at the kink, reporting the change in height at the kink and the standard error. We also test for a discontinuity in the first derivative of the p.d.f. of the assignment variable, following Card *et al.* (2012), Landais (2015), and Card *et al.* (2015b): we regress the number of observations in each bin on a 10th order polynomial in normalized base period earnings, interacted with D, the indicator for being above the threshold. The coefficient on the interaction between D and the linear term, which tests for a change in the slope of the p.d.f., is reported in each panel, along with the standard error. We do not detect any statistically significant discontinuities in either the

[27]Our calculations suggest that between 40 and 47 percent of all employed new mothers used CA-PFL bonding leave during 2005-2014 (Bana *et al.*, 2018). See also Pihl and Basso (2016) for similar estimates on program take-up.

[28]The results presented in Figure 2a are similar under alternative bandwidths.

frequency distribution or the slope change at the threshold.[29]

Second, we check for any discontinuities or kinks in pre-determined covariates around the threshold. In Appendix Figure A1, we use $100 bins of normalized base period earnings and plot the mean age and firm size as well as the number of women in the health industry (the top industry in our data) in each bin. We also construct a summary index of covariates by regressing each of our main outcomes (log duration, change in log earnings, share of quarters employed, return to pre-claim firm, and any subsequent bonding claim) on firm fixed effects (for all firms with an average of 10,000 workers or more during our sample time frame; other firms are grouped into the residual category), as well as interactions of the following indicator variables: age categories (20-24, 25-29, 30-34, 35-39, 40-44), firm size categories (1-49, 50-99, 100-499, and 500+), industry codes, calendar year, and quarter. Appendix Figure A2 plots the mean predicted outcomes in each bin surrounding the threshold, and shows that the indices evolve smoothly around the threshold.[30]

These figures provide some support for the validity of the RK research design: We do not observe any evidence of sorting or underlying non-linearities around the kink point, which also argues against any differential selection into CA-PFL take-up across the earnings threshold.

5 Results

Figure 2b plots the empirical relationship between the natural log of the authorized WBA and normalized quarterly base period earnings. There is clear evidence of a kink at the threshold at which the maximum benefit begins, suggesting a strong first stage for our fuzzy RK analysis.

[29]We follow Card *et al.* (2015b) to choose the order of the polynomial. We fit a series of polynomial models of different orders that allow for a discontinuity at the threshold and also allow the first and higher-order derivatives to vary at the threshold, and then select the model with the smallest Akaike Information Criterion (AIC) value (10th order in our case).

[30]We have also tested for any changes in the slopes of the indices and covariates at the threshold. While a few of the estimates are statistically significant, they are very small in magnitude, and are unlikely to bias our results.

Figure 3 shows graphs using our main outcome variables on the $y-$axes; we use $100 bins in the assignment variable and plot the mean outcome values in each bin. We also present 2SLS estimates that use different bandwidths graphically: Figure 4 plots the coefficients (as dark gray triangles) and 95 percent confidence intervals (as light gray triangles) from specifications that use bandwidths in $500 increments of normalized quarterly base period earnings from $2,500 to $10,000, for each of our main outcomes. Additionally, Tables 2 through 6 present estimates from specifications that implement different optimal bandwidth selection algorithms, controlling for first or second order polynomials in the running variable. We show results from models without and with individual controls and quarter fixed effects (in the top and bottom panels, respectively). The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. The tables also report the first stage coefficients and standard errors (multiplied by 10^5 to reduce the number of leading zeros reported), the bandwidths, and the dependent variable means.[31] While Tables 2 through 6 report results from specifications that use the natural log of the benefit amount (as written in equation (4)), we show the corresponding estimates from models that use the benefit amount in levels in Appendix Tables A1 through A5.

We find no evidence that a higher WBA increases maternity leave duration among new mothers. The estimates in Table 2 allow us to rule out that a 10 percent increase in the WBA would increase leave duration by more than than 0.4 to 3.2 percent (or, elasticities from 0.04 to 0.32). Importantly, this finding is *not* explained by a highly skewed distribution of leave duration in which most women are "maxing out" their leave. In Figure 5, we plot the distribution of leave duration for women near the kink point ($5,000 bandwidth sample).

[31] We report the main and pilot bandwidth, as in Card *et al.* (2015b). The pilot bandwidth is used in the bias estimation part of the bandwidth selection procedure. See Card *et al.* (2015b) for more details.

We show the distribution of SDI leave, PFL leave, and combined SDI+PFL leave. About 16 percent of women take zero weeks of SDI leave (sub-figure a), which likely explains the mass at 6 weeks in the distribution of combined leave (sub-figure c). Conditional on taking PFL, about 80 percent of women use the entire 6 weeks (sub-figure b). But most women use both SDI and PFL to take less than the maximum amount of leave allowed on the two programs (16 weeks for women with uncomplicated vaginal deliveries).

It also does not appear that leave benefits have any adverse consequences for maternal labor market outcomes one to two years after the leave. The estimates for the change in log earnings in Table 3 are imprecise and only become positive at higher bandwidths (see Figure 4b).[32] The coefficient for share of quarters worked is more robust and consistently positive (and statistically significant in 6 out of the 12 models, see Table 4). The range of estimates suggests that a 10 percent increase in the WBA raises the share of quarters worked one to two years after the initiation of bonding leave by 0.1 to 0.7 percentage points (0.1 to 0.9 percent at the sample mean). This impact may operate through a higher likelihood of returning to the pre-claim firm, an outcome for which we a observe a positive coefficient in the majority of specifications (see Table 5). However, the estimates on returning to the pre-claim firm should be interpreted with caution, as we only see a statistically significant coefficient (at the 5 percent level) in one model. On the whole, the suggestive positive effects on labor market outcomes are inconsistent with an income effect channel (which would reduce maternal labor supply; see Wingender and LaLumia, 2017), and are instead more readily explained by a hypothesis that higher pay during leave improves morale and possibly promotes firm loyalty such that a mother is more likely to continue being employed after taking leave.

Additionally, we examine subsequent bonding claims. We find a robust positive effect in both Figure 4e and Table 6. Our estimates suggest that a 10 percent increase in the WBA raises the likelihood of a future bonding claim by 1.2 to 2.0 percentage points (5.8 to 9.0 percent at the sample mean). This effect may be partially explained by the increased

[32] Results using log earnings in quarters 4 through 7 after the claim (instead of the change in log earnings) are similar and available upon request.

employment post-leave, which enables mothers to be eligible for PFL for future births. Alternatively, the increase in repeat claiming could operate through an effect on subsequent fertility, which we do not observe in our data. However, past research from other countries offers mixed evidence on the relationship between PFL and maternal fertility (Dahl *et al.*, 2016; Lalive and Zweimüller, 2009), so we do not believe this to be the primary channel. A third possibility is that even in the absence of changes to employment or fertility, mothers with a higher benefit have a better experience during leave and are more likely to use the program again than those with lower payments.

We have also analyzed heterogeneity in the effects of benefits across employee and employer characteristics (age, firm size, and industry groups), finding no consistent patterns. The lack of significant heterogeneity across women in firms that have 50 or more employees and their counterparts in smaller firms is notable in light of the fact that workers in the former group are more likely to be eligible for job protection through the FMLA or the CFRA. Our results suggest that eligibility for government-mandated job protection does not contribute to differences in the impacts of PFL benefits, at least in our RK sample.

Lastly, as discussed in Section 2, one might be concerned that some employers are undoing the CA-PFL benefit cap—and thereby weakening our RK design—by supplementing PFL benefits so that employees on leave receive 100 percent of their salary (or at least more than 55 percent of their salary). Unfortunately, our data do not report such payments, nor could we locate any external evidence that such practices are common. Instead, to assess whether this issue may be impacting our main results, we examine subsamples where it is least likely to be important. First, employees who made claims soon after the implementation of CA-PFL (in 2005-2010) are less likely to have received such payments as it takes time for new programs to be incorporated in firm benefit plans, and media coverage of existing employer-provided paid leave policies (mostly at tech companies in California) suggests that such policies were rare prior to 2010.[33] Second, workers in smaller firms (with fewer than

[33]See, for example: `https://tcf.org/content/report/tech-companies-paid-leave/`.

1,000 workers) are less likely to have access to such generous supplemental funds, as these employers tend to have more modest human resource infrastructures. We therefore replicate Figure 4 for these two subsamples. The results are reported in Appendix Figures A3 and A4. In all cases, the pattern of findings for these subsamples are similar to those for the entire sample, although the estimates are less precise. Put differently, we find no suggestion that supplemental payments that remove the kink are driving the main results.

Permutation tests. An important concern for the RK design is the possibility of spurious effects resulting from non-linearities in the underlying relationship between the outcome and the assignment variable. To address this concern, we perform a series of permutation tests, as proposed in recent work by Ganong and Jäger (2017). The idea is to estimate RK models using placebo kinks at various points in the distribution of base period earnings. Importantly, as detailed in Card *et al.* (2016), this permutation test may not work if one does not properly account for the role of curvature heterogeneity in the conditional expectation function of the outcome variable (see also: Ando, 2017).[34] Therefore, we follow Card *et al.* (2016) in using outcome residuals from regressions on pre-determined covariates in implementing the permutation tests. Specifically, we start with a sample of women making their first bonding claims with base period quarterly earnings within a $40,000 window of the true kink point, and regress each outcome on firm fixed effects (for all firms with an average of 10,000 workers or more during our sample time frame; other firms are grouped into the residual category), as well as interactions of age categories, $10,000 earnings bins (based on total real earnings in quarters 2 through 5 before the claim), firm size categories, industry groups, calendar year, and quarter. We compute the residuals, and then estimate 150 placebo reduced form RK models with the residual as the outcome, using a $4,000 bandwidth surrounding each placebo kink point. Figure 6 presents the results, where the placebo kink points are denoted on the $x-$axis normalized relative to the true kink point (i.e., the true kink point is at 0).

[34]Card *et al.* (2016) write: "...if researchers wish to conduct the permutation test, it will be important to control for confounding nonlinearities by taking the distribution of observables into account" (page 18 of the NBER working paper version).

We do not find any statistically significant estimates using any of the placebo kinks that we consider, suggesting that non-linearities in the outcome functions are not driving our results. Note that the permutation tests are estimated as reduced form models. As such, the placebo kink coefficients are of the opposite sign from those in our main IV models (which are scaled by negative first stage coefficients).

6 Conclusion

According to the most recent statistics, only 14 percent of American workers have access to paid family leave through their employers.[35] The fact that the U.S. does not provide any paid maternity or family leave at the national level—and, in doing so, is an outlier when compared to other developed countries—has received substantial attention from politicians, policy advocates, and the press. There exists, however, some access to government-provided unpaid family leave through the FMLA, implying that understanding the specific consequences of *monetary benefits* during leave is of first-order importance to both researchers and policy-makers. In this paper, we attempt to make progress on this question by estimating the causal effects of PFL wage replacement rates on maternal leave duration, labor market outcomes, and future leave-taking in California, the first state to implement its own PFL program.

We leverage detailed administrative data on the universe of PFL claims linked to quarterly earnings records together with an RK research design. Comparing outcomes of mothers with base period earnings below and above the maximum benefit threshold, we find that higher benefits have zero impacts on leave duration, a result that contrasts sharply with prior evidence from other social insurance programs. We also find some evidence of small positive impacts on measures of employment continuity one to two years after leave initiation: a 10 percent increase in the WBA raises the share of quarters employed by 0.1 to 0.9 percent. Further, benefits during the first period of paid family leave predict future program participation. An additional 10 percent in benefits is associated with a 5.8 to 9.0 percent increase

[35]See: `http://www.nationalpartnership.org/issues/work-family/paid-leave.html`.

in the probability of having a subsequent PFL claim in the following three years.

The results reported in this paper serve as an important step toward understanding the influence of benefit levels on leave duration, subsequent labor market outcomes, and future leave-taking for women in the United States. Our results assuage concerns that wage replacement during family leave may have unintended negative consequences for mothers' future labor market outcomes through an increase in time away from work, at least among high-earning women. Of course, it is important to recognize that these findings may be specific to the relatively short statutory leave duration permitted under CA-PFL; benefits provided in the context of much longer leaves—such as those in many European countries—may have different effects. Our RK estimates also generate insights on the implications of benefit changes around the maximum benefit threshold. This evidence is valuable because all existing state PFL programs, as well as the national FAMILY Act proposal, feature similar kinked benefit schedules. As other jurisdictions have opted for different replacement rates and benefit caps than California, future research on these other policies will further contribute to our understanding about the relationships between PFL benefits and outcomes across the earnings distribution.

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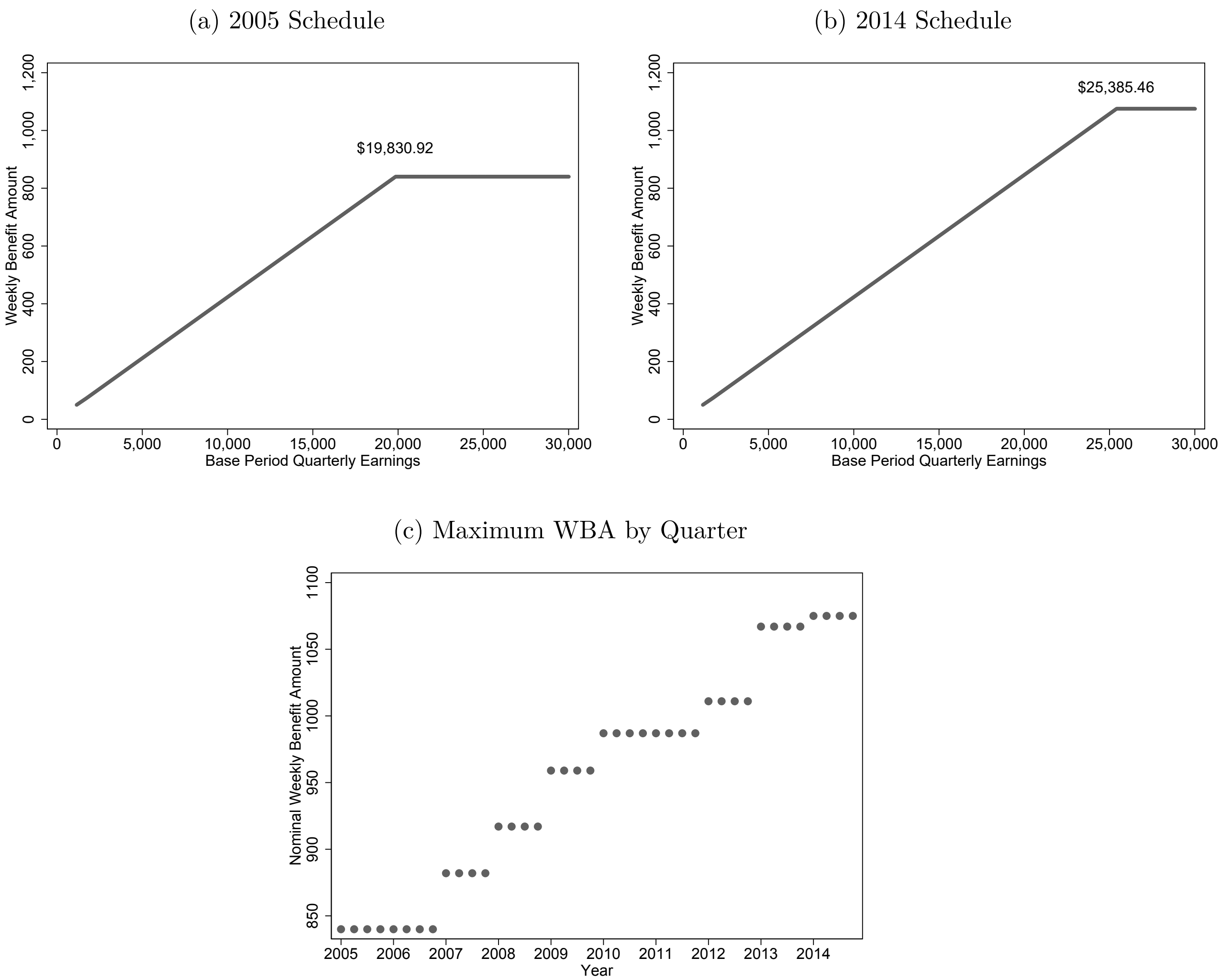
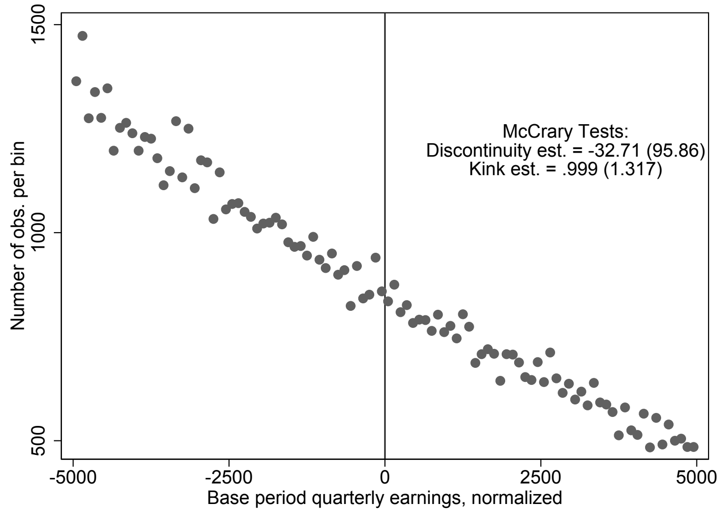
Figure 1: PFL/SDI Benefit Schedule in 2005 and 2014 and the Maximum Weekly Benefit Amount Over Time



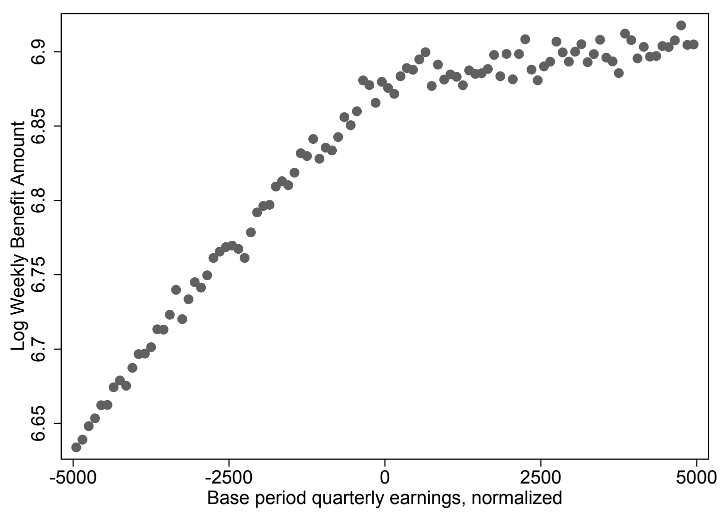
Notes: Sub-figures (a) and (b) plot nominal quarterly base period earnings on the $x-$axis and the nominal weekly benefit amount on the $y-$axis for 2005 and 2014, respectively, with the earnings threshold at which the maximum benefit begins labeled in each sub-figure. Sub-figure (c) plots the maximum weekly benefit amount by quarter in nominal dollars over the time period 2005 quarter 1 through 2014 quarter 4.

Figure 2: Frequency Distribution of Base Period Earnings Around the Earnings Threshold and First Stage

(a) Frequency Distribution



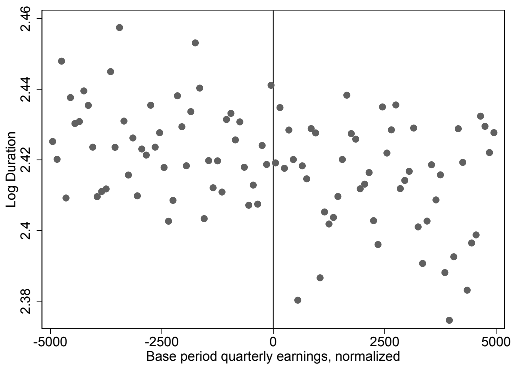
(b) First Stage



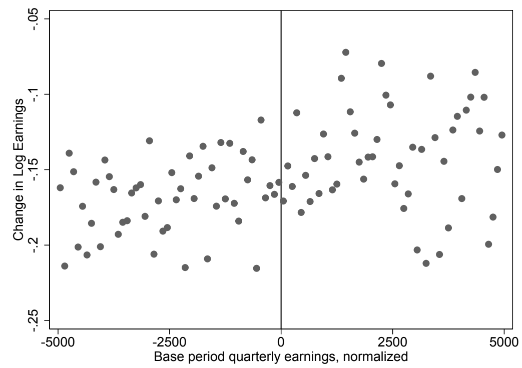
Notes: Sub-figure (a) shows the frequency distribution for women. The $x-$axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins, and with a \$5,000 bandwidth. We display two tests of the identifying assumptions of the RK design. The first is a standard McCrary test of the discontinuity of the p.d.f. of the assignment variable ("Discontinuity est."). The second is a test for discontinuity in the first derivative of the p.d.f. ("Kink est."). For both, we report the estimate and the standard error in parentheses. We follow Card *et al.* (2015b) to choose the order of the polynomial in these tests. We fit a series of polynomial models of different orders that impose continuity but allow the first and higher-order derivatives to vary at the threshold, and then select the model with the smallest Akaike Information Criterion (AIC) value (10th order in our case). Sub-figure (b) shows the empirical relationship between the log weekly benefit amount received and normalized base period earnings for women. The $x-$axis plots normalized base period quarterly earnings (in terms of distance to the earnings threshold) in bins, using \$100 bins.

Figure 3: RK Figures for Main Outcomes

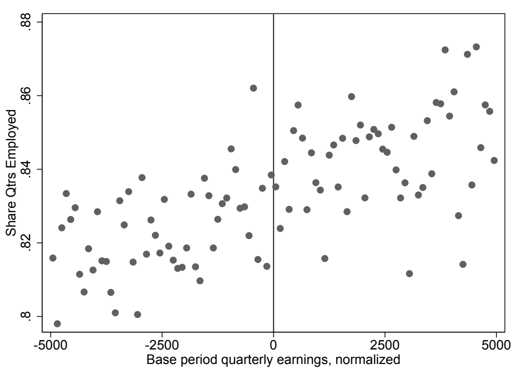
(a) Log Leave Duration



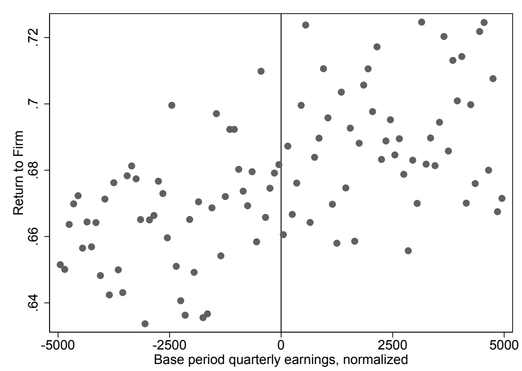
(b) Change in Log Earnings



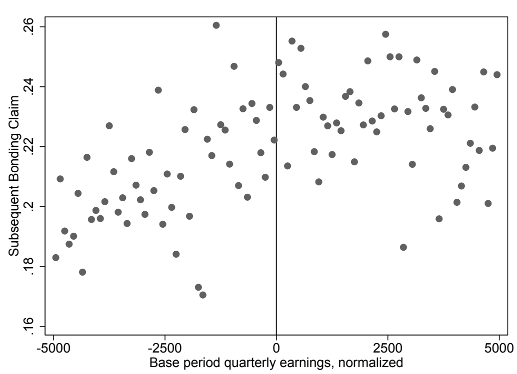
(c) Share Quarters Employed



(d) Return to Pre-Claim Firm



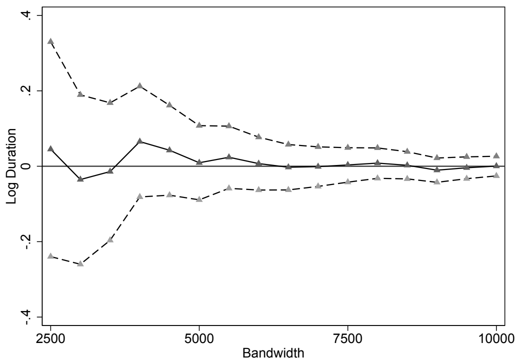
(e) Any Subsequent Claim



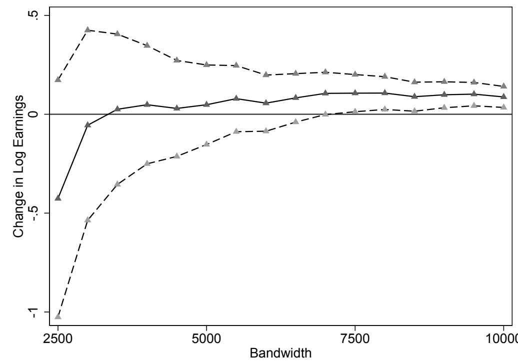
Notes: The $x-$axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The $y-$axis plots the mean of the outcome in each bin.

Figure 4: RK Estimates for Main Outcomes Using Different Bandwidths

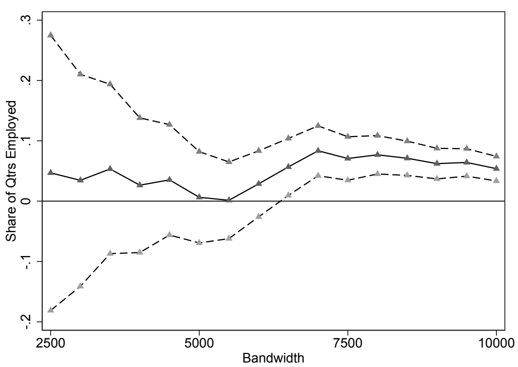
(a) Log Leave Duration



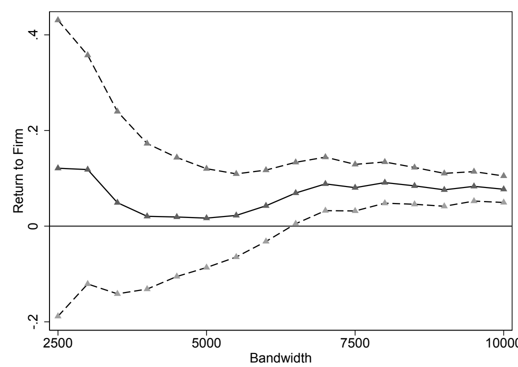
(b) Change in Log Earnings



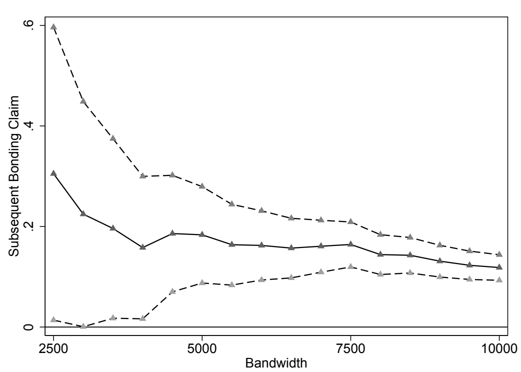
(c) Share Quarters Employed



(d) Return to Pre-Claim Firm



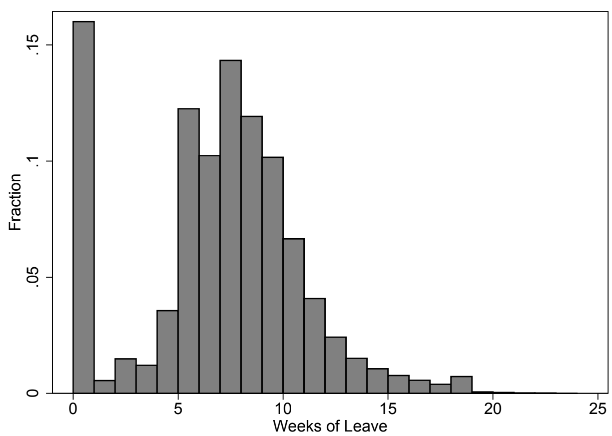
(e) Any Subsequent Claim



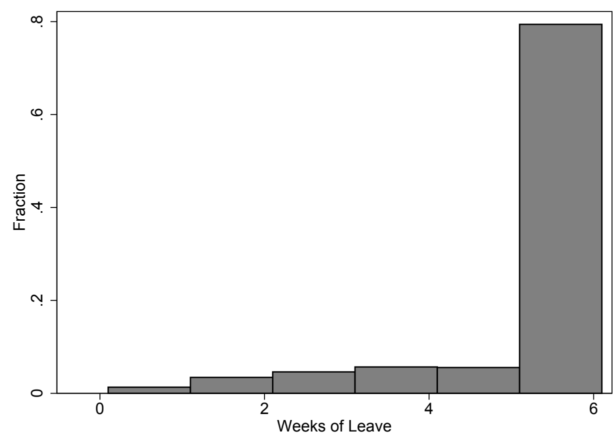
Notes: These figures show the coefficients (as dark gray triangles) and 95 percent confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$500 of normalized quarterly base period earnings (denoted on the $x-$axis).

Figure 5: Distribution of Leave Duration for Women with Earnings Near the Threshold

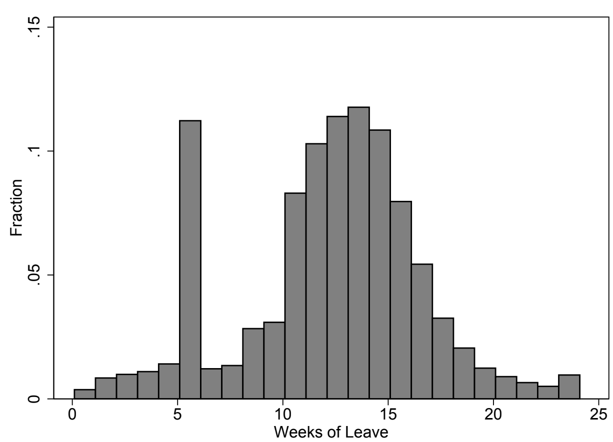
(a) SDI Only



(b) PFL Only



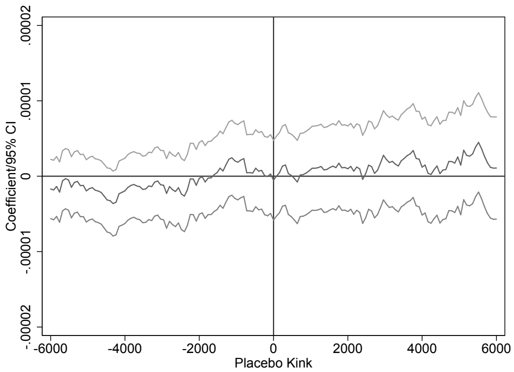
(c) Total (SDI+PFL)



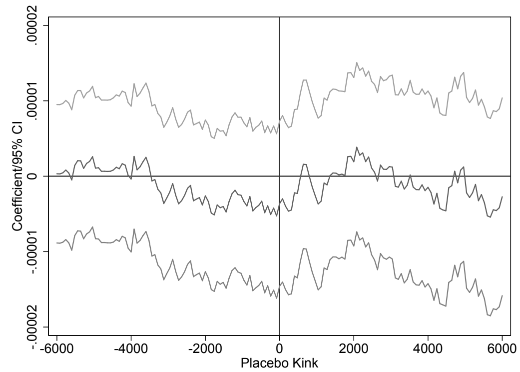
Notes: These figures plot the distributions of leave duration for women with pre-claim earnings within a $5,000 bandwidth surrounding the kink point.

Figure 6: Permutation Tests

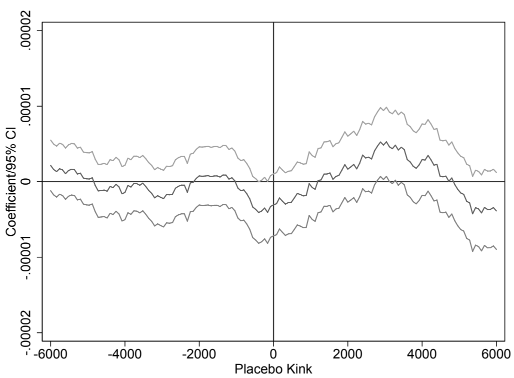
(a) Log Leave Duration



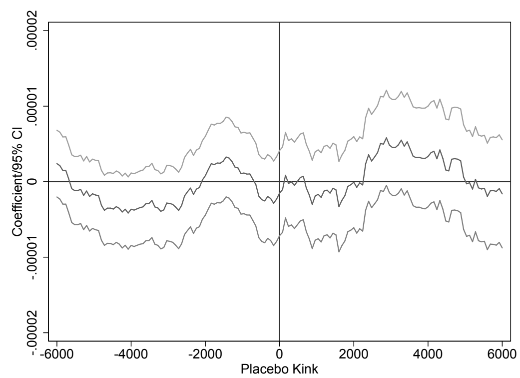
(b) Change in Log Earnings



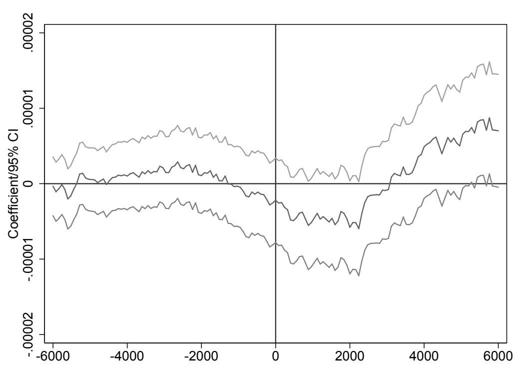
(c) Share Quarters Employed



(d) Return to Pre-Claim Firm



(e) Any Subsequent Claim



Notes: These figures show the coefficients (as dark gray lines) and 95 percent confidence intervals (as light gray lines) from placebo RK specifications with a placebo kink specified in terms of distance from the true kink point (i.e., the true kink point is at 0 on the $x-$axis). To estimate the placebo RK specifications, we first use a sample of women making their first bonding claims with base period earnings within a $40,000 window of the true kink point and regress the outcome on firm fixed effects (for all firms with an average of 10,000 workers or more during our sample time frame; other firms are grouped into the residual category), as well as interactions of the following indicator variables: age categories (20-24, 25-29, 30-34, 35-39, 40-44), $10,000 earnings bins (based on the sum of all earnings in quarters 2 through 5 before the claim), firm size categories (1-49, 50-99, 100-499, and 500+), industry codes, calendar year, and quarter. We compute the residual, and then estimate placebo RK models with the residual as the outcome, using a $4,000 bandwidth surrounding each placebo kink point.

Table 1: Descriptive Statistics

	Bandwidths			
	2,500	**5,000**	**7,500**	**10,000**
Age	32.73	32.62	32.47	32.14
	(4.11)	(4.14)	(4.22)	(4.36)
Firm Size 1-49	0.19	0.19	0.20	0.21
	(0.39)	(0.40)	(0.40)	(0.41)
Firm Size 50-99	0.07	0.08	0.08	0.08
	(0.26)	(0.27)	(0.27)	(0.27)
Firm Size 100-499	0.20	0.21	0.21	0.21
	(0.40)	(0.40)	(0.41)	(0.41)
Firm Size 500+	0.53	0.52	0.51	0.50
	(0.50)	(0.50)	(0.50)	(0.50)
Weekly Benefit Amount ($2014)	959.61	920.58	867.87	798.95
	(128.87)	(141.53)	(165.73)	(196.18)
Base Period Qtrly Earnings ($2014)	24,102	23,411	22,268	20,582
	(1785)	(3219)	(4623)	(5918)
Health Ind.	0.33	0.32	0.30	0.28
	(0.47)	(0.47)	(0.46)	(0.45)
Total Leave Duration (Wks)	12.23	12.24	12.24	12.25
	(4.24)	(4.24)	(4.23)	(4.24)
Δ Log Earnings	-0.15	-0.16	-0.17	-0.18
	(0.82)	(0.85)	(0.87)	(0.90)
Share Qtrs Employed	0.83	0.83	0.82	0.81
	(0.34)	(0.35)	(0.35)	(0.36)
Return to Pre-Claim Firm	0.68	0.67	0.66	0.65
	(0.47)	(0.47)	(0.47)	(0.48)
Subsequent Bonding Claim	0.22	0.22	0.21	0.19
	(0.42)	(0.41)	(0.40)	(0.40)
Observations	42,727	87,366	137,982	202,159

Notes: This table presents the means and standard deviations (in parentheses) of some of the key variables for women making their first PFL bonding claims during 2005-2014 with base period earnings within the bandwidths listed at the top of each column. We make the following sample restrictions: (1) We only include women who are aged 20-44 at the time of the first bonding claim; (2) We drop women employed in industries in which employees are least likely to be subject to the SDI tax—private household workers, elementary and secondary school teachers, and public administration; (3) We drop women with zero total earnings in the base period quarters.

Table 2: RK Estimates of the Effects of PFL Benefits on Log Leave Duration

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
Log WBA ($2014)	0.00737	0.0121	0.0331	0.00120	0.000440	0.00630
	(0.0192)	(0.0198)	(0.144)	(0.0960)	(0.0133)	(0.0308)
First Stage Est x 10^5	-5.452	-3.126	-4.297	-4.103	-6.009	-3.256
First Stage S.E. x 10^5	0.0454	0.187	0.275	0.686	0.0336	0.263
B. With Controls						
Log WBA ($2014)	-0.00648	-0.00358	0.0299	0.00252	-0.00741	-0.0186
	(0.0199)	(0.0204)	(0.143)	(0.0954)	(0.0138)	(0.0316)
First Stage Est x 10^5	-5.213	-3.209	-4.241	-4.238	-5.706	-3.410
First Stage S.E. x 10^5	0.0431	0.176	0.257	0.644	0.0322	0.246
Main Bandwidth	8290.6	8116.4	2519.9	3426.5	10363.3	6447.0
Pilot Bandwidth	7360.5	11183.6	5144.3	5427.4	7831.7	8195.4
Dep. Var Mean	2.421	2.421	2.420	2.420	2.422	2.421
N	156344	152137	43011	59244	202159	115681

Notes: Each coefficient in each panel and column is from a separate regression, using log total leave duration as the outcome. The WBA is expressed as the natural log of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Table 3: RK Estimates of the Effects of PFL Benefits on Change in Log Earnings (Qtrs 4-7 Post-Claim vs. Qtrs 2-5 Pre-Claim)

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
Log WBA ($2014)	0.103***	0.0415	-0.463	-0.182	0.0525	0.0555
	(0.0304)	(0.0943)	(0.317)	(0.274)	(0.154)	(0.131)
First Stage Est x 10^5	-5.945	-3.265	-4.117	-3.851	-4.242	-3.461
First Stage S.E. x 10^5	0.0427	0.421	0.325	1.147	0.158	0.555
B. With Controls						
Log WBA ($2014)	0.0317	-0.0156	-0.519	-0.264	0.0118	0.00237
	(0.0320)	(0.0968)	(0.319)	(0.284)	(0.157)	(0.135)
First Stage Est x 10^5	-5.661	-3.301	-4.047	-4.747	-4.145	-3.548
First Stage S.E. x 10^5	0.0411	0.394	0.302	1.079	0.148	0.518
Main Bandwidth	9458.9	5223.4	2466.3	2701.4	3990.4	4347.4
Pilot Bandwidth	4730.1	8989.3	5089.5	4575.5	6669.1	5498.5
Dep. Var Mean	-0.179	-0.159	-0.151	-0.153	-0.157	-0.158
N	139621	68816	31791	34902	51930	56667

Notes: Each coefficient in each panel and column is from a separate regression, using the difference between log total earnings in quarters 4-7 after the claim and log total earnings in quarters 2-5 before the claim as the outcome. The WBA is expressed as the natural log of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 4: RK Estimates of the Effects of PFL Benefits on Share of Quarters Employed (Qtrs 4-7 Post-Claim)

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
Log WBA ($2014)	0.0718***	0.0624	0.0637	0.0629	0.0539***	0.0684***
	(0.0146)	(0.0614)	(0.212)	(0.0640)	(0.0104)	(0.0137)
First Stage Est x 10^5	-5.637	-3.626	-4.030	-3.765	-6.144	-3.417
First Stage S.E. x 10^5	0.0473	0.638	0.507	0.656	0.0359	0.176
B. With Controls						
Log WBA ($2014)	0.0364**	0.0177	0.0308	0.0144	0.0332***	0.0365**
	(0.0151)	(0.0625)	(0.199)	(0.0649)	(0.0108)	(0.0142)
First Stage Est x 10^5	-5.398	-3.877	-4.220	-4.007	-5.864	-3.407
First Stage S.E. x 10^5	0.0453	0.600	0.483	0.618	0.0347	0.167
Main Bandwidth	8446.8	3803.8	1751.5	3723.2	12857.2	8731.3
Pilot Bandwidth	3446.9	6437.0	3501.3	5829.4	3833.9	8039.8
Dep. Var Mean	0.818	0.831	0.834	0.831	0.812	0.817
N	137636	56272	25613	55107	174748	143920

Notes: Each coefficient in each panel and column is from a separate regression, using the share of quarters employed in quarters 4-7 after the claim as the outcome. The WBA is expressed as the natural log of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 5: RK Estimates of the Effects of PFL Benefits on Employment in Pre-Claim Firm (Qtr 4 Post-Claim)

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
Log WBA ($2014)	0.0198	0.00121	0.141	0.0218	0.0254	0.0911***
	(0.0739)	(0.0689)	(0.143)	(0.0865)	(0.0643)	(0.0196)
First Stage Est x 10^5	-4.378	-3.576	-4.274	-3.747	-4.491	-3.343
First Stage S.E. x 10^5	0.138	0.532	0.264	0.654	0.124	0.186
B. With Controls						
Log WBA ($2014)	-0.0377	-0.0596	0.0797	-0.0408	-0.0311	0.0354*
	(0.0744)	(0.0695)	(0.145)	(0.0872)	(0.0649)	(0.0201)
First Stage Est x 10^5	-4.249	-3.678	-4.123	-3.979	-4.353	-3.361
First Stage S.E. x 10^5	0.130	0.500	0.247	0.616	0.117	0.176
Main Bandwidth	4124.1	4268.0	2677.4	3731.4	4459.4	8469.2
Pilot Bandwidth	3860.4	9602.5	5357.1	5846.9	8209.4	8382.3
Dep. Var Mean	0.675	0.675	0.677	0.676	0.675	0.660
N	61131	63334	39274	55209	66243	138098

Notes: Each coefficient in each panel and column is from a separate regression, using employment in the pre-claim firm in quarter 4 post-claim as the outcome. The WBA is expressed as the natural log of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Table 6: RK Estimates of the Effects of PFL Benefits on Any Subsequent Bonding Claim

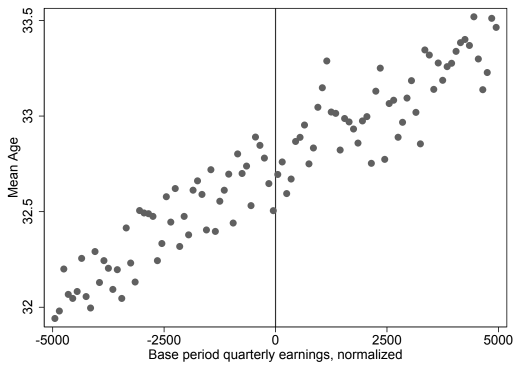
	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
Log WBA ($2014)	0.182***	0.152***	0.188	0.200	0.162***	0.196***
	(0.0490)	(0.0290)	(0.127)	(0.129)	(0.0417)	(0.0547)
First Stage Est x 10^5	-4.645	-3.494	-4.163	-4.112	-4.791	-3.553
First Stage S.E. x 10^5	0.110	0.284	0.253	1.063	0.0958	0.489
B. With Controls						
Log WBA ($2014)	0.153***	0.123***	0.164	0.181	0.131***	0.169***
	(0.0497)	(0.0299)	(0.131)	(0.132)	(0.0427)	(0.0557)
First Stage Est x 10^5	-4.508	-3.583	-3.977	-4.831	-4.607	-3.526
First Stage S.E. x 10^5	0.104	0.267	0.237	1.009	0.0909	0.459
Main Bandwidth	4995.4	6614.1	2841.7	2781.8	5447.7	4663.1
Pilot Bandwidth	5969.6	7559.8	5768.9	4506.8	19538.9	5379.7
Dep. Var Mean	0.216	0.211	0.223	0.223	0.215	0.217
N	67859	92677	37901	37102	74618	63048

Notes: Each coefficient in each panel and column is from a separate regression, using an indicator for any subsequent bonding claim in the 3 years following the first claim as the outcome. The WBA is expressed as the natural log of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * p<0.1 ** p<0.05 *** p<0.01

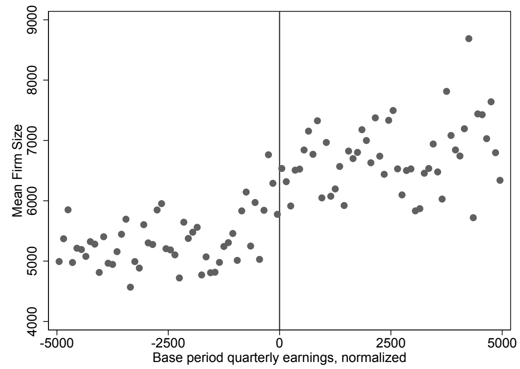
A Appendix Figures and Tables

Appendix Figure A1: Covariates Around the Earnings Threshold

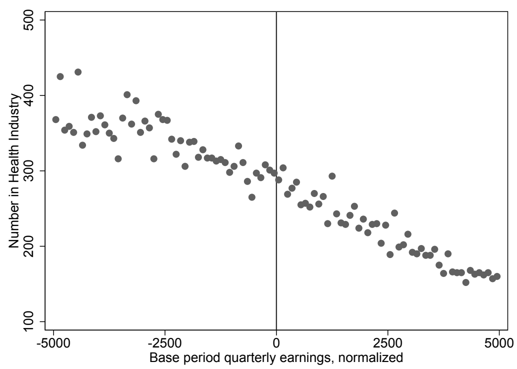
(a) Age



(b) Firm Size



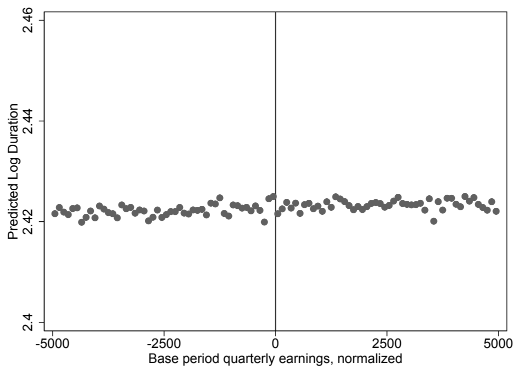
(c) Health Industry



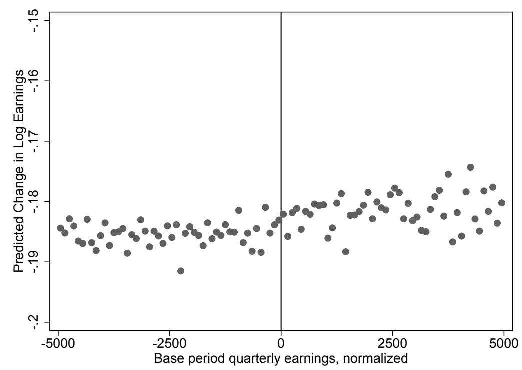
Notes: The $x-$axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using $100 bins. In sub-figures (a) and (b), the $y-$axis plots the mean of the covariate in each bin. In sub-figure (c), the $y-$axis plots the count of women in the health industry in each bin.

Appendix Figure A2: Predicted Outcomes Around the Earnings Threshold

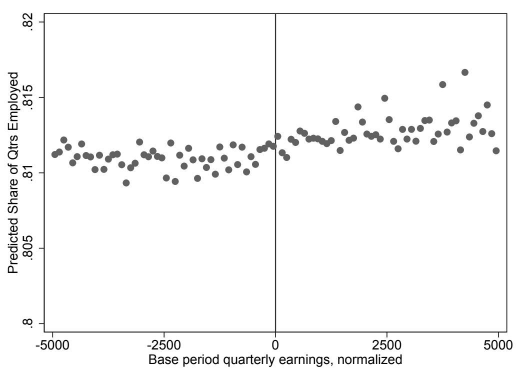
(a) Log Leave Duration



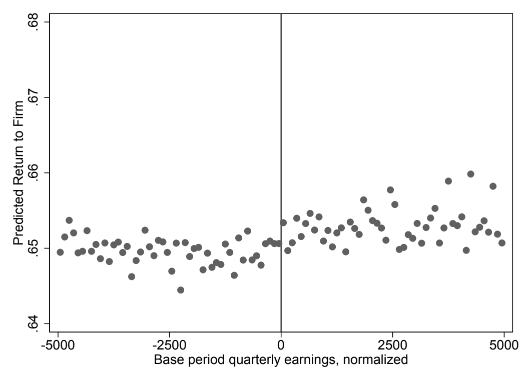
(b) Change in Log Earnings



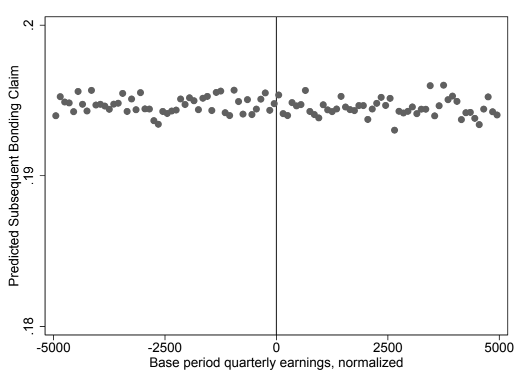
(c) Share Quarters Employed



(d) Return to Pre-Claim Firm



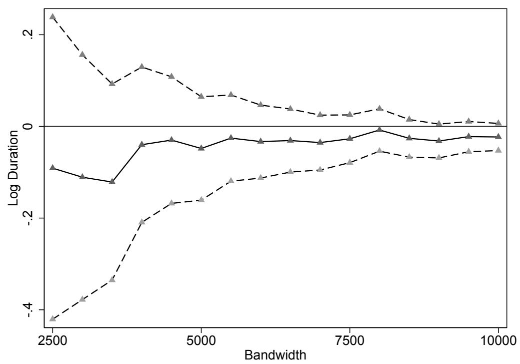
(e) Any Subsequent Claim



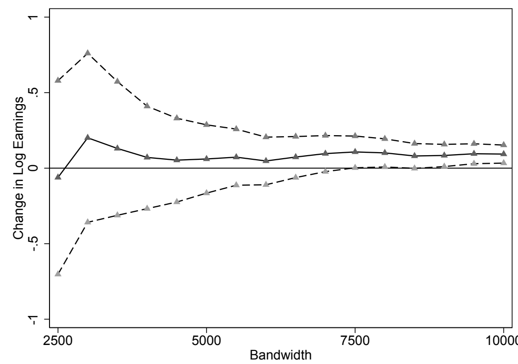
Notes: These figures show the relationship between the *predicted* outcome and normalized base period earnings. We predict each outcome using a regression of the outcome on firm fixed effects (for all firms with an average of 10,000 workers or more during our sample time frame; other firms are grouped into the residual category), as well as interactions of the following indicator variables: age categories (20-24, 25-29, 30-34, 35-39, 40-44), firm size categories (1-49, 50-99, 100-499, and 500+), industry codes, calendar year, and quarter.

Appendix Figure A3: RK Estimates for Main Outcomes Using Different Bandwidths: 2005-2010 Only

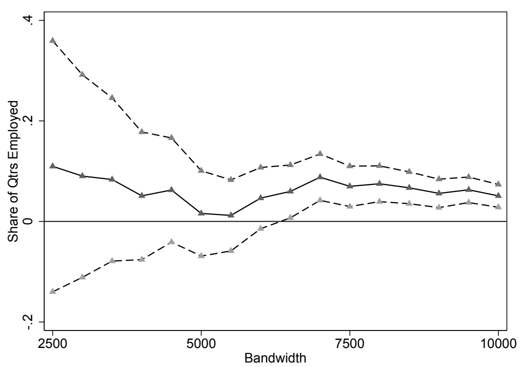
(a) Log Leave Duration



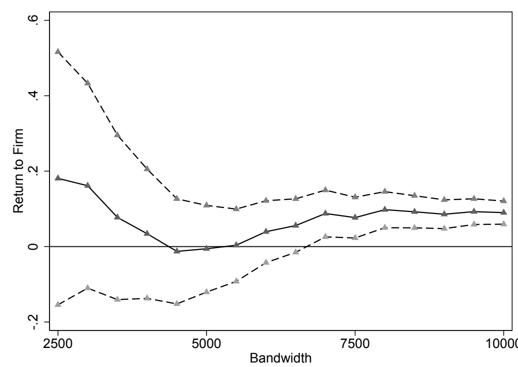
(b) Change in Log Earnings



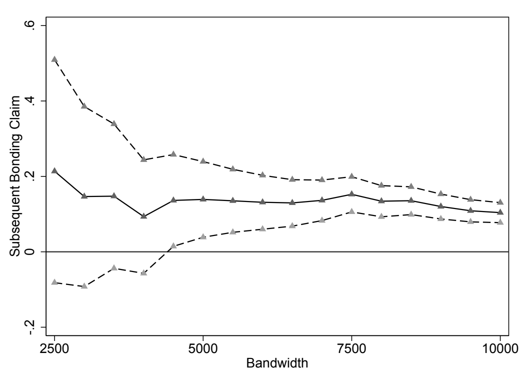
(c) Share Quarters Employed



(d) Return to Pre-Claim Firm



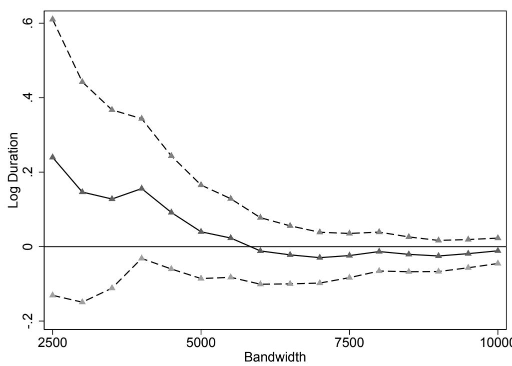
(e) Any Subsequent Claim



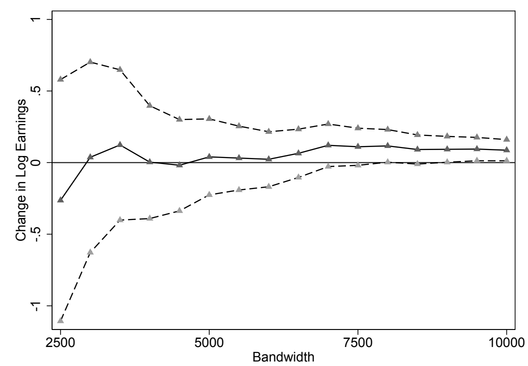
Notes: These figures show the coefficients (as dark gray triangles) and 95 percent confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$500 of normalized quarterly base period earnings (denoted on the $x-$axis). The sample is limited to claims made in 2005-2010 only.

Appendix Figure A4: RK Estimates for Main Outcomes Using Different Bandwidths: Firms with <1,000 Employees Only

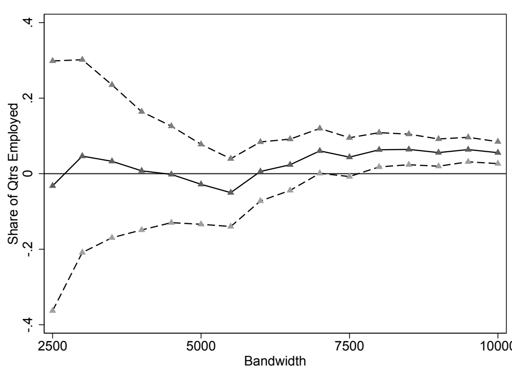
(a) Log Leave Duration



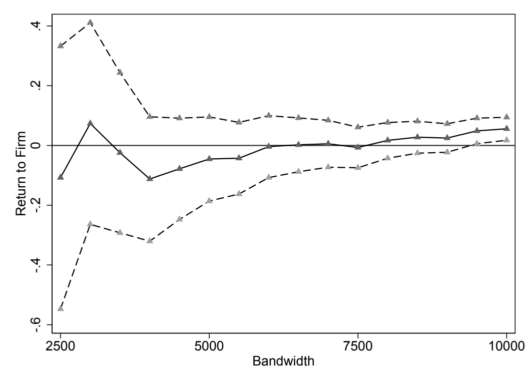
(b) Change in Log Earnings



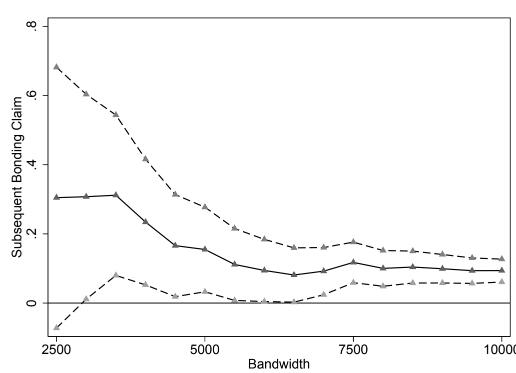
(c) Share Quarters Employed



(d) Return to Pre-Claim Firm



(e) Any Subsequent Claim



Notes: These figures show the coefficients (as dark gray triangles) and 95 percent confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of $500 of normalized quarterly base period earnings (denoted on the $x-$axis). The sample is limited to claims made by women in firms with fewer than 1,000 employees only.

Appendix Table A1: RK Estimates of the Effects of PFL Benefits (in Levels) on Log Leave Duration

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
WBA in $100	0.0000621	0.000926	0.00361	0.000152	0.0000621	0.000208
	(0.00187)	(0.00267)	(0.0157)	(0.0105)	(0.00187)	(0.00376)
First Stage Est x 10^5	-42.60	-35.29	-39.44	-38.92	-42.60	-34.74
First Stage S.E. x 10^5	0.191	1.119	1.641	4.082	0.191	1.542
B. With Controls						
WBA in $100	-0.00103	-0.00128	0.00324	0.000379	-0.00103	-0.00274
	(0.00193)	(0.00271)	(0.0155)	(0.0104)	(0.00193)	(0.00381)
First Stage Est x 10^5	-40.92	-35.94	-39.18	-40.14	-40.92	-35.83
First Stage S.E. x 10^5	0.177	1.021	1.498	3.737	0.177	1.404
Main Bandwidth	11977.8	7970.3	2519.9	3426.5	10363.3	6447.0
Pilot Bandwidth	7203.2	11868.9	5144.3	5427.4	7831.7	8195.4
Dep. Var Mean	2.422	2.422	2.420	2.420	2.422	2.421
N	202159	148797	43011	59244	202159	115681

Notes: Each coefficient in each panel and column is from a separate regression, using log total leave duration as the outcome. The WBA is in 100s of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure.

Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Appendix Table A2: RK Estimates of the Effects of PFL Benefits (in Levels) on Change in Log Earnings (Qtrs 4-7 Post-Claim vs. Qtrs 2-5 Pre-Claim)

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
WBA in $100	0.0121*	0.00540	-0.0505	-0.0188	0.00585	0.00664
	(0.00712)	(0.0111)	(0.0344)	(0.0296)	(0.0172)	(0.0148)
First Stage Est x 10^5	-41.27	-33.89	-37.76	-31.61	-38.05	-34.00
First Stage S.E. x 10^5	0.401	2.458	1.921	6.778	0.919	3.255
B. With Controls						
WBA in $100	0.00340	-0.00124	-0.0559	-0.0268	0.00130	0.000643
	(0.00735)	(0.0113)	(0.0342)	(0.0301)	(0.0173)	(0.0150)
First Stage Est x 10^5	-39.88	-34.35	-37.59	-37.98	-37.53	-34.62
First Stage S.E. x 10^5	0.373	2.253	1.760	6.271	0.846	2.990
Main Bandwidth	6818.2	5205.4	2466.3	2701.4	3990.4	4347.4
Pilot Bandwidth	4707.2	8969.2	5089.5	4575.5	6669.1	5498.5
Dep. Var Mean	-0.166	-0.159	-0.151	-0.153	-0.157	-0.158
N	92223	68585	31791	34902	51930	56667

Notes: Each coefficient in each panel and column is from a separate regression, using the difference between log total earnings in quarters 4-7 after the claim and log total earnings in quarters 2-5 before the claim as the outcome. The WBA is in 100s of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.

Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Appendix Table A3: RK Estimates of the Effects of PFL Benefits (in Levels) on Share of Quarters Employed (Qtrs 4-7 Post-Claim)

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
WBA in $100	0.00771***	0.00724	0.00698	0.00722	0.00771***	0.00910***
	(0.00149)	(0.00689)	(0.0232)	(0.00715)	(0.00149)	(0.00185)
First Stage Est x 10^5	-42.94	-35.49	-36.79	-36.20	-42.94	-37.54
First Stage S.E. x 10^5	0.201	3.749	3.019	3.855	0.201	1.015
B. With Controls						
WBA in $100	0.00469***	0.00223	0.00341	0.00182	0.00469***	0.00446**
	(0.00153)	(0.00693)	(0.0219)	(0.00719)	(0.00153)	(0.00189)
First Stage Est x 10^5	-41.44	-37.28	-38.21	-38.11	-41.44	-37.34
First Stage S.E. x 10^5	0.190	3.464	2.820	3.563	0.190	0.938
Main Bandwidth	11465.4	3804.6	1751.5	3723.2	12857.2	8731.3
Pilot Bandwidth	3445.5	6478.3	3501.3	5829.4	3833.9	8039.8
Dep. Var Mean	0.812	0.831	0.834	0.831	0.812	0.817
N	174748	56284	25613	55107	174748	143920

Notes: Each coefficient in each panel and column is from a separate regression, using the share of quarters employed in quarters 4-7 after the claim as the outcome. The WBA is in 100s of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Appendix Table A4: RK Estimates of the Effects of PFL Benefits (in Levels) on Employment in Pre-Claim Firm (Qtr 4 Post-Claim)

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
WBA in \$100	0.00477	0.00351	0.0154	0.00304	0.00289	0.0117***
	(0.00932)	(0.00793)	(0.0156)	(0.00967)	(0.00733)	(0.00263)
First Stage Est x 10^5	-38.88	-35.35	-39.24	-36.04	-39.38	-36.99
First Stage S.E. x 10^5	0.913	3.146	1.564	3.842	0.720	1.070
B. With Controls						
WBA in \$100	-0.00213	-0.00354	0.00854	-0.00385	-0.00352	0.00406
	(0.00932)	(0.00793)	(0.0155)	(0.00966)	(0.00732)	(0.00267)
First Stage Est x 10^5	-37.99	-36.23	-38.45	-37.89	-38.55	-36.95
First Stage S.E. x 10^5	0.844	2.906	1.444	3.552	0.664	0.989
Main Bandwidth	3818.1	4233.7	2677.4	3731.4	4459.4	8469.2
Pilot Bandwidth	3846.7	9405.2	5357.1	5846.9	8209.4	8382.3
Dep. Var Mean	0.676	0.675	0.677	0.676	0.675	0.660
N	56473	62818	39274	55209	66243	138098

Notes: Each coefficient in each panel and column is from a separate regression, using employment in the pre-claim firm in quarter 4 post-claim as the outcome. The WBA is in 100s of \$2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses.
Significance levels: * p<0.1 ** p<0.05 *** p<0.01

Appendix Table A5: RK Estimates of the Effects of PFL Benefits (in Levels) on Any Subsequent Bonding Claim

	(1) Fuzzy IK LL	(2) Fuzzy IK LQ	(3) CCT LL	(4) CCT LQ	(5) CCT LL, No Reg	(6) CCT LQ, No Reg
A. No Controls						
WBA in $100	0.0195***	0.0194***	0.0204	0.0216	0.0192***	0.0229***
	(0.00391)	(0.00380)	(0.0138)	(0.0140)	(0.00493)	(0.00629)
First Stage Est x 10^5	-41.03	-36.19	-38.44	-36.33	-40.53	-35.50
First Stage S.E. x 10^5	0.433	1.722	1.484	6.268	0.553	2.840
B. With Controls						
WBA in $100	0.0157***	0.0156***	0.0175	0.0190	0.0154***	0.0195***
	(0.00399)	(0.00387)	(0.0140)	(0.0142)	(0.00499)	(0.00635)
First Stage Est x 10^5	-39.67	-36.64	-37.24	-41.83	-39.37	-35.39
First Stage S.E. x 10^5	0.404	1.589	1.368	5.829	0.512	2.616
Main Bandwidth	6302.1	6392.8	2841.7	2781.8	5447.7	4663.1
Pilot Bandwidth	5832.2	7632.3	5768.9	4506.8	19538.9	5379.7
Dep. Var Mean	0.212	0.212	0.223	0.223	0.215	0.217
N	87669	89176	37901	37102	74618	63048

Notes: Each coefficient in each panel and column is from a separate regression, using an indicator for any subsequent bonding claim in the 3 years following the first claim as the outcome. The WBA is in 100s of $2014 dollars. The top panel does not include individual controls, while the bottom panel includes the following controls: indicators for employee age categories (20-24, 25-29, 30-34, 35-39, 40-44), dummies for pre-claim employer industry (NAICS industry groups), dummies for employer size (1-49, 50-99, 100-499, 500+), and quarter fixed effects. The specifications are: (1) fuzzy IK bandwidth with local linear polynomials, (2) fuzzy IK bandwidth with local quadratic polynomials, (3) CCT bandwidth with regularization and local linear polynomials, (4) CCT bandwidth with regularization and local quadratic polynomials, (5) CCT bandwidth without regularization and with local linear polynomials, and (6) CCT bandwidth without regularization and with local quadratic polynomials. We also report the first stage coefficients and standard errors, the dependent variable means, and the main and pilot bandwidths. The pilot bandwidth is used in the bias estimation part of the main bandwidth selection procedure. Robust standard errors are in parentheses. Significance levels: * p<0.1 ** p<0.05 *** p<0.01