

The Impacts of Paid Family Leave Benefits: Regression Kink Evidence from California Administrative Data*

Sarah Bana[†]

Kelly Bedard[‡]

Maya Rossin-Slater[§]

June 13, 2017

Abstract

Although the United States provides unpaid 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 individuals with earnings near the maximum benefit threshold. We find no evidence that a higher weekly benefit amount (WBA) increases leave duration or leads to worse future labor market outcomes for this group. A 10 percent increase in the WBA leads to a 0.8 (0.3) percentage point increase in the share of quarters worked one to two years post-leave for mothers (fathers), and a 0.8 percentage point increase in the likelihood of return to the pre-leave employer for fathers. We also find that wage replacement is a tool for encouraging repeat program participation—a 10 percent increase in the WBA raises the likelihood of making a future paid leave claim by 1.6 (1.3) percentage points for mothers (fathers).

Keywords: paid family leave, regression kink design, fathers, program participation, temporary disability insurance

JEL: I18, J13, J16, J18

*We thank Clement de Chaisemartin, Yingying Dong, Peter Ganong, Simon Jaeger, Zhuan Pei, and Lesley Turner for valuable comments. All errors are our own.

[†]University of California at Santa Barbara, Department of Economics. E-mail: sarah.bana@gmail.com.

[‡]University of California at Santa Barbara, Department of Economics; IZA. E-mail: kelly.bedard@ucsb.edu.

[§]University of California at Santa Barbara, Department of Economics; NBER; IZA. E-mail: maya.rossin-slater@ucsb.edu.

1 Introduction

Nearly all developed countries have a paid family leave (PFL) program that allows working mothers and fathers to take time off work to care for their newborn or newly adopted children. These policies aim to help individuals balance competing job and family responsibilities, and advocates credit them with encouraging career continuity and advancement, especially for women. There is also growing interest in encouraging men to take leave, in an effort to promote gender equality both at home and in the labor market. However, opponents worry that paid time away from work may depress employees' future attachment to their jobs, lead to discrimination against women (who are more likely than men to take leave), and impose substantial costs on employers. These discussions are especially fervent in the United States, which is the only OECD country without a national PFL policy of any kind.¹

A number of studies outside the U.S. have examined the impacts of extensions in PFL policies on women's and (to a lesser extent) men's 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—such as the benefit amount, statutory leave duration, and job protection—likely contributes to the lack of consistency in the literature.³ In this paper, we study California's first-in-the-nation PFL program (CA-PFL) and focus on the role of a key policy parameter—the benefit amount. Specifically, we use ten years of administrative data to estimate the causal impacts of PFL wage replacement rates on maternal and paternal leave duration, labor market outcomes, and subsequent leave-taking with a regression kink (RK) design.

¹For more information on the politics surrounding paid leave in the U.S., see, e.g., this recent *New York Times* column: https://economix.blogs.nytimes.com/2014/01/27/the-business-of-paid-family-leave/?_r=0.

²For 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; Dahl *et al.*, Forthcoming; 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). See Section 2 for more details.

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

The CA-PFL program provides 6 weeks of paid leave to nearly all working new parents, with 55 percent of prior earnings replaced, up to a maximum benefit amount. Additionally, birth mothers can take several weeks of paid leave to prepare for and recover from childbirth through California’s State Disability Insurance (CA-SDI) system, which has an identical benefit schedule.⁴ Yet since benefits are not randomly assigned, it is challenging to disentangle their causal impacts from the possible influences of other (unobservable) differences between individuals. The RK design makes use of the kink in the benefit schedule that arises because of the cap on the benefit amount. In particular, we focus on women and men who make their first PFL claims to bond with a new child (hereafter, “bonding claim” or “bonding leave”), and compare the outcomes of individuals with pre-claim earnings just below and just above the threshold at which the maximum benefit applies. These individuals have similar pre-leave earnings (and, as we show, other pre-determined 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 address the concern of endogeneity in the benefit amount, an important drawback is that the RK sample is not representative of the entire population of PFL participants. Individuals in the vicinity of the kink point are older, work in larger firms, and have higher pre-claim earnings than the average claimant. However, estimates from the RK sample are well-suited for identifying the costs and benefits of marginal changes to benefits around the maximum benefit threshold, which are highly policy relevant: 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.⁵

⁴More details on the CA-PFL and CA-SDI programs are provided in Section 2.

⁵The states with PFL policies are: California (since 2004), New Jersey (since 2008), Rhode Island (since 2014), New York (will go into effect in 2018), 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 maxi-

Our results show that higher benefits do *not* increase leave duration among individuals with earnings near the maximum benefit threshold. For mothers, we can rule out that a 10 percent increase in the weekly benefit amount (WBA) would increase leave duration by more than 0.07 percent, while for fathers we can rule out that a 10 percent increase in the WBA would raise leave duration by more than 3 percent. Moreover, when we examine labor market outcomes measured one to two years after the initiation of bonding leave, we document small positive impacts on measures of employment continuity. For instance, we find that a 10 percent increase in the WBA leads to a 0.8 (0.3) percentage point increase in the share of quarters employed for mothers (fathers), as well as a 0.8 percentage point increase in the likelihood of returning to one’s pre-leave employer among fathers. These results assuage the concern that “too high” benefits may encourage individuals to spend a longer time on leave, with detrimental consequences for future labor market trajectories, especially for women. Our findings also imply that increases in PFL benefits may lead to reductions in employee turnover, potentially resulting in cost savings for employers (Boushey and Glynn, 2012).

Lastly, we provide novel evidence that wage replacement predicts repeat program participation. We find that an additional 10 percent in PFL benefits received during a parent’s first period of bonding leave is associated with a 1.6 (1.3) percentage point higher likelihood of having another paid leave claim in the following three years for mothers (fathers). For mothers, these impacts are driven by subsequent bonding leave, while for fathers, we find effects on subsequent take-up of caring and SDI leave. While our data do not allow us to observe the mechanisms underlying these effects, we note that a similar relationship between current benefits and future claims has been found in the context of the workers’

maximum benefit amount. The wage replacement rates are: 55% (California), 66% (New Jersey), 60% (Rhode Island), 67% (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% of the average weekly wage in the state. 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>.

compensation program in Oregon (Hansen *et al.*, 2017).

Our paper offers four primary contributions. First, unlike prior studies analyzing reforms that extend the statutory duration of leave or provide access to leave for a new group of workers, we are able to identify the effect of the PFL *benefit amount* while holding constant all other aspects of the policy. In other words, all individuals in our study are eligible for the same length of leave under CA-PFL (and, for birth mothers only, under CA-SDI); they only differ in the marginal wage replacement rates that they receive.⁶ Our estimates are particularly relevant for the U.S. context, where unpaid leave is already provided to many workers through the federal Family and Medical Leave Act (FMLA), making *payment* during leave the most salient issue under debate.⁷

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

Third, we bring the RK research design—which has been previously used to study the impacts of benefits provided through unemployment insurance (UI) (Card *et al.*, 2012; Landais, 2015; Card *et al.*, 2015a,b, 2016), Social Security Disability Insurance (SSDI) (Gelber *et al.*, 2016), and workers’ compensation (Hansen *et al.*, 2017)—to analyze PFL.⁸ Yet while there is some consensus that higher benefits lead to longer unemployment, disability, and injury leave durations, the question of the elasticity of family leave duration with respect to the benefit amount has not been explored. As these programs provide distinct types of social

⁶We are aware of one other study that is able to identify the impact of a particular PFL policy parameter: Stearns (2016) estimates the separate effect of job protection in the context of British maternity leave.

⁷According to most recent data from 2012, about 60 percent of American private sector workers are eligible for the FMLA (Klerman *et al.*, 2012).

⁸Less 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).

insurance and target different populations, it would be erroneous to apply the elasticities from the prior literature to the PFL context (Krueger and Meyer, 2002).

Fourth, we provide some of the first evidence on the impacts of CA-PFL benefits on *fathers'* labor market outcomes and subsequent leave-taking. While a few previous papers have estimated the impacts of CA-PFL implementation on maternal labor market outcomes using survey data (Rossin-Slater *et al.*, 2013; Baum and Ruhm, 2016), nearly all of the existing research on the impacts of PFL on fathers comes from countries outside the U.S., including Sweden (Duvander and Johansson, 2012; Ekberg *et al.*, 2013), Norway (Dahl *et al.*, 2014; Cools *et al.*, 2015), Germany (Schober, 2014), and Canada (Patnaik, 2016). These studies differ from ours as they all analyze reforms that earmark part of the general parental leave specifically for fathers (these are sometimes called “daddy quotas” or “daddy months”). Our work complements prior evidence from survey data by Bartel *et al.* (2015) and Baum and Ruhm (2016), who show that the implementation of CA-PFL led to a small increase in the rate of leave-taking among fathers.

The paper unfolds as follows. Section 2 provides more details on California’s PFL program and discusses the relevant literature. 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 Background

The FMLA is the only U.S. federal law regarding family leave. It was enacted in 1993 and provides 12 weeks of *unpaid* job protected family leave to qualifying workers.⁹

California was the first state to implement a *paid* family leave policy—financed through payroll taxes levied on employees—in July 2004. To be eligible for CA-PFL, an individual

⁹Prior to 1993, 25 states and the District of Columbia had some type of family leave provisions, which were mostly unpaid and did not offer job protection, and varied in length between six and sixteen weeks (Trzcinski and Alpert, 1994). To be eligible for the FMLA, workers have to 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).

must have earned at least \$300 in wages in a base period between 5 and 18 months before the PFL claim begins.¹⁰ Workers are entitled to six weeks of leave under CA-PFL. Additionally, the program is integrated with the CA-SDI system, which allows birth mothers (but not fathers or adoptive or foster parents) to take some paid leave around the period of childbirth. In total, most women who use both SDI and PFL can get up to 16 weeks of paid leave.¹¹ Paid leaves under PFL and SDI are not directly job protected, although job protection is available if the job absence simultaneously qualifies under the FMLA or California’s Family Rights Act (CFRA).¹²

The CA-PFL 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): Workers who make a PFL claim have 55 percent of their usual pay replaced, up to a maximum benefit amount.¹³ Figure 1 depicts the 2005, 2008, 2011, and 2014 benefit schedules, where both benefits and base period earnings are presented as quarterly nominal amounts. These graphs clearly show that there is a kink in the relationship between the quarterly benefit amount and the quarterly base period earnings—the slope of the benefit schedule changes from 0.55 to 0 at the earnings threshold at which the maximum benefit amount commences. The location of this kink varies over time (i.e., both the maximum benefit amount and the earnings threshold change). The earnings thresholds for 2005, 2008, 2011, and 2014 were \$19,830 (\$79,320), \$21,650 (\$86,600), \$23,305 (\$93,220), and \$25,385 (\$101,540) in nominal quarterly (annual) terms, respectively. 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 our analysis sample in more

¹⁰Only wages subject to the SDI tax are considered in the \$300 minimum.

¹¹Specifically, women who have a normal pregnancy with a vaginal delivery can get up to four weeks of leave before the expected delivery date and up to six weeks of leave after the actual delivery date. 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.

¹²Similar to the FMLA, CFRA provides unpaid job protected leave with continued employer-provided health insurance coverage to eligible workers. More information on CA-PFL and CA-SDI is available at http://www.edd.ca.gov/disability/FAQ_PFL_Benefits.htm.

¹³The CA-SDI benefit schedule is identical to the CA-PFL benefit schedule in every year.

detail in Section 3 below.

Appendix Figure A1 plots the maximum weekly benefit amount in nominal terms in each quarter during our sample time frame. The maximum weekly benefit has nominally increased from \$840 in 2005 to \$1,075 in 2014. In real 2014 dollars, this translates to an increase from \$1,018.22 to \$1,075 during this time period.

Hypotheses and related literature. Our analysis exploits variation generated by the kinked wage replacement schedule to deliver estimates of the impacts of CA-PFL benefits on leave duration, subsequent labor market outcomes, and future leave-taking for new mothers and fathers. To the best of our knowledge, we are the first to isolate the impacts of *benefit amounts* among individuals who have access to the same paid leave program. This question is important, as survey evidence suggests that “too little pay” serves as a barrier to taking family leave even among workers eligible for the program (Fass, 2009). Moreover, the UI literature finds a positive relationship between unemployment duration and the benefit amount, with elasticities ranging between 0.3 and 2 (Card *et al.*, 2015a).¹⁴ As such, in the PFL context, a higher benefit may also increase leave duration, which could in turn affect workers’ subsequent labor market outcomes such as employment, wages, and later leave-taking. Yet as highlighted by Krueger and Meyer (2002), we may expect diverse responses to different types of social insurance programs, making it difficult to apply the UI elasticities to the PFL setting.

Moreover, if higher benefits lead to increased leave duration, the impacts on future labor market outcomes are theoretically ambiguous (Klerman and Leibowitz, 1994; Olivetti and Petrongolo, 2017). On the one hand, increased time away from the job may be detrimental to future labor market success as a result of human capital depreciation. Additionally, employers who find long leaves costly may discriminate against groups most likely to take leave—mothers or female employees more broadly—by being less likely to hire them or by

¹⁴A 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).

offering them lower wages. Indeed, consistent with this idea, a large 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.*, 2016). On the other hand, if higher benefits encourage longer leaves among individuals who would have otherwise quit their jobs, then there may be a positive effect on 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. Alternatively, 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 worker morale or promote firm loyalty (even if workers realize that their firms are not directly paying their benefits) and thus increase the likelihood that a parent continues with his/her job or works more in the future.

The existing research on the labor market effects of PFL has mostly focused on mothers and examined extensions in the length of leave granted by existing policies. In a seminal study, Ruhm (1998) used variation in the length of paid leave across nine European countries over 1969-1993, finding 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 wages. More recent studies that cover more years and a wider set of countries largely confirm these results (Blau and Kahn, 2013; Thévenon and Solaz, 2013; Olivetti and Petrongolo, 2017). In other work, researchers have focused on one country at a time. For instance, Baker and Milligan (2008) show that extensions in paid maternity leave of up to one year in length in Canada raise the likelihood that women return to their pre-childbirth employers and have either positive or zero effects on overall employment. However, studies from Austria (Lalive and Zweimüller, 2009), Germany (Schönberg and Ludsteck, 2014), France (Lequien, 2012), and the Czech Republic (Bičáková and Kalíšková, 2016)

suggest that longer periods of leave can have adverse impacts on women’s wages in the short- and long-term. Recent work from Norway documents no significant impacts of a variety of extensions in paid maternity leave from four to eight months on either earnings or labor force participation among mothers (Dahl *et al.*, Forthcoming).

Fewer papers have studied the impacts of the introduction (rather than extension) of a paid leave policy. In Norway, the implementation of a 4-month paid maternity leave program had no effects on maternal employment or earnings up to five years after childbirth (Carneiro *et al.*, 2015). In Germany, the introduction of a one-year paid leave policy led to a 12 percent increase in mothers’ employment probability after the end of the benefit period (Kluve *et al.*, 2013), and positive impacts on employment three to five years after childbirth for women with relatively high levels of education (Bergemann and Riphahn, 2015). In Great Britain, Stearns (2016) shows that access to paid maternity leave increases the probability of returning to work in the short-run, but has no effect on long-run employment. She also finds that job protection during leave has distinct impacts on maternal labor market outcomes—there are large increases in maternal employment rates and job tenure five years after childbirth, but negative consequences on other measures of career success such as promotions to managerial positions.

In the U.S., we are aware of two papers on the labor market consequences of the introduction of CA-PFL for mothers. Rossin-Slater *et al.* (2013) show that CA-PFL implementation increased the weekly work hours of employed mothers of one to three year-old children by 10 to 17 percent. Baum and Ruhm (2016) find that CA-PFL raised employment probabilities of mothers by about 23 percent one year after childbirth, and increased hours and weeks of work during the child’s second year of life by 18 and 11 percent, respectively.¹⁵

The research on *paternal* labor market outcomes comes exclusively from studies on “daddy month” or “daddy quota” reforms. Cools *et al.* (2015) show that a Norwegian

¹⁵However, when studying all young women in California (and not just mothers), Das and Polachek (2015) find some evidence that CA-PFL led to higher labor force participation rates, unemployment rates, and unemployment duration in the years after implementation.

reform that reserved 4 weeks of paid leave exclusively for fathers had no impacts on their subsequent labor market outcomes. Similarly, Ekberg *et al.* (2013) find that introduction of a “daddy month” in Sweden had no effect on their long-term wages or employment. Patnaik (2016) also finds no impacts of a 5-week “daddy quota” in Canada on paternal involvement in the labor market.

Lastly, to the best of our knowledge, there are no existing studies on the determinants of *repeat* leave-taking. This question is especially important for fathers, as prior research has documented that the introduction of CA-PFL only increased leave-taking among fathers of first-born and not higher-order children (Bartel *et al.*, 2015). Moreover, the fact that fathers take much less leave than mothers overall is a central motivating factor for the adoption of “daddy month” and “daddy quota” reforms in other countries. While these types of policies have been effective in encouraging men to take paternity leave, we study whether the wage replacement rate can be another tool for promoting repeat leave-taking even within a gender-neutral PFL program.¹⁶

3 Data and Sample

We use three 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 over 2005-2014. For each claim, we have information on the claim effective date, claim filed date, the total benefit amount received, the authorized weekly benefit amount, the reason for the claim (bonding with a new child versus caring for an ill family member), the employee’s date of birth, the employee’s gender, and a unique employee identifier.¹⁷ Additionally, for women who make bonding claims, we have an indicator for whether there was an associated SDI transitional claim (i.e., an SDI

¹⁶Related, Dahl *et al.* (2014) use data from Norway to show that fathers whose co-workers or brothers take paternity leave are more likely to take leave themselves.

¹⁷The 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.

claim for the purposes of preparation for and recovery from childbirth).¹⁸

Second, we have a similar data set on the universe of SDI claims over 2000-2014. This data set allows us to calculate total leave duration for women who make both bonding and transitional SDI claims. Additionally, we use these data to measure participation in the SDI program for reasons other than pregnancy/childbirth.

Third, we have quarterly earnings data over 2000-2014 for the universe of employees working for an employer that reports to the EDD tax branch.¹⁹ For each employee, we have his/her unique identifier, his/her earnings in each quarter and in each job, a unique employer identifier associated with those earnings, and a 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 PFL bonding claims. 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 individual. Next, since the location of the kink has changed over our sample time frame (recall Figure 1), we drop individuals who make their first bonding claims in quarters during which these changes happen.²⁰

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

¹⁸Less than 0.5 percent of the men in our data have an SDI transitional claim flag. Since men are ineligible for transitional SDI, we assume these are data errors and drop them.

¹⁹Employers 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.

²⁰We 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. Individuals with first bonding claims in the following quarters are dropped: 2005q1, 2007q4, 2009q1, 2010q1, 2012q1, 2013q1, and 2014q1.

quarter.

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.²¹ For women who make both bonding and transitional SDI claims, we add the two durations.²² We take the natural log of total leave duration in most of our specifications.

In addition to studying leave duration, we analyze several post-leave labor market outcomes measured one to two years after leave initiation. We calculate the log of average quarterly earnings (in real \$2014 terms) and the share of quarters employed in quarters 4 through 7 after the claim. We also examine whether workers return to their pre-leave employers—we create an indicator that is equal to 1 for workers whose highest earnings in quarter 4 after the claim come from their pre-claim firms.

Lastly, we create indicators for any subsequent bonding, caring, or non-transitional (i.e., non-pregnancy or childbirth-related) SDI claims in the three years after the first bonding claim.²³ 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 and men making their first bonding claims during 2005-2014. In the second and fourth columns, we limit the samples to individuals with base period earnings in the vicinity of the earnings threshold (i.e., our RK analysis sample), where the bandwidths are chosen with our preferred method described in the next section.²⁴

²¹PFL bonding leave can be taken at any time during the first year after the employee’s child’s birth, adoption, or foster care placement.

²²If the duration for a given claim is calculated to be longer than 6 weeks in the PFL data (0.6 percent of observations) or longer than 52 weeks in the SDI data (0.02 percent of observations), it is capped at those maximums.

²³We have also estimated models examining subsequent claims in the four years following the first bonding claim, finding similar results to those presented here.

²⁴In our RK analysis, a unique optimal bandwidth is chosen for each outcome that we consider. In Table 1, for simplicity, we report means for individuals in the “fuzzy IK” bandwidth that is selected when log total

When compared with the universe of PFL bonding claimants, individuals with earnings near the threshold are older (women are about 32 years old, while men are around age 34), work in somewhat larger firms, and have higher base period earnings, as expected. About a quarter of the women in the RK sample are employed in the health industry before the claim, which is the top female industry in our data. When we consider the top male industry, manufacturing, we find that about 15 percent of men in the RK sample are employed in it pre-claim. Average weekly benefits received are \$685 for women and \$911 for men (in \$2014) in the RK samples.

Overall, average leave duration for women is slightly over 12 weeks, which is consistent with most women filing both transitional SDI and PFL bonding claims. For men, average leave duration is just under 4 weeks. Interestingly, leave duration for both women and men is slightly shorter in the RK samples than in the entire population of bonding claimants. When we consider labor market outcomes in quarters 4 through 7 after the claim, we see that individuals in the RK samples have higher earnings and greater labor market attachment as measured by the share of quarters employed. About 63 percent of women and 73 percent of men in the RK samples return to their pre-claim employers. Lastly, subsequent bonding, caring, and non-transitional SDI claim rates are 19 (18), 0.7 (0.9), and 16 (11) percent for women (men) in the RK samples, respectively, and all higher than in the overall population.

The means in Table 1 make clear that our RK sample is not representative of the overall population of bonding claimants. But, we note that our preferred bandwidths retain approximately 40 and 25 percent of women and men from the underlying universe of claimants, respectively, implying that our analysis is based on a non-negligible fraction of PFL participants.

leave duration is the outcome (for women and men separately). More details on bandwidth selection are provided in the next section.

4 Empirical Design

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

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

for each individual i . Y_i is an outcome of interest, such as log leave duration or log average quarterly earnings in quarters 4-7 after the claim. b_i is the log WBA (in 2014 dollars), while u_i is a random vector of unobservable individual characteristics. We are interested in estimating γ , 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 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.²⁵

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

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.*

²⁵The replacement rate, 0.55, is divided by 13 to convert to a weekly amount since there are 13 weeks in a quarter.

(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:

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

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 (i.e., -0.04). 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 PFL benefits, but we cannot distinguish between earnings that are and are not subject to this tax in our data. As such, the empirical value of the slope change in the denominator in equation

(2) is not exactly -0.04 , and we must estimate it in a “fuzzy” RK design.²⁶

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).²⁷

There is an active literature in econometrics on optimal bandwidth choice in RD and RK settings. As in Card *et al.* (2015a)’s study of the impacts of UI benefits on unemployment duration, our preferred estimates use a version of the Imbens and Kalyanaraman (2012) bandwidth for the fuzzy RK design (hereafter, “fuzzy IK”).²⁸ We also show the sensitivity of our results to using bandwidth selection procedures with and without a “regularization” term developed by Calonico *et al.* (2014) (hereafter, “CCT”).²⁹ Similarly, following other RK studies, we try local linear and quadratic polynomials.

We estimate the following first stage regression (separately for females and males):

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

for each individual 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 . b_{iq} is the log WBA (in \$2014). The variable D is an indicator that is set equal to 1 when earnings are above E_q^0 and 0 otherwise: $D = \mathbf{1}_{[E_i - E_q^0 > 0]}$. As noted above, we control for normalized base period earnings

²⁶The “fuzzy” RK design is formally discussed in detail in Card *et al.* (2015b).

²⁷Card *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.

²⁸Specifically, 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).

²⁹Both IK and CCT procedures involve a regularization term, which reflects the variance in the bias estimation and guards against the selection of large bandwidths.

relative to the threshold ($E_i - E_q^0$) using local linear or quadratic polynomials (i.e., \bar{p} is either equal to 1 or 2). X_i is a vector of individual controls (employee age and age squared, as well as dummies for pre-claim employer industry and size). ω_q are quarter fixed effects, which control for time-varying factors such as inflation, changes in population demographics, and aggregate labor market conditions. e_i is the unobserved error term. The estimated change in the slope in the denominator of the ratio in equation (2) is given by θ_1 .

The second stage regression is:

$$Y_{iq} = \pi_0 + \pi_1 \widehat{b}_{iq} + \sum_{p=1}^{\bar{p}} \lambda_p (E_i - E_q^0)^p + \rho' X_i + \omega_q + e_i \quad \text{if } |E_i - E_q^0| \leq h \quad (4)$$

for each individual i with a first bonding claim in quarter q . Here, Y_{iq} is an outcome, and \widehat{b}_{iq} is instrumented with the interaction between D and the polynomial in normalized 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} 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).

We conduct standard tests of these assumptions. First, we show the frequency distribution of normalized base period earnings around the earnings threshold in Figure 2 separately for women (in panel a) and men (in panel b). The graphs use \$100 bins, with an average of 1,037 (494) observations per bin for women (men). The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The histograms look reasonably smooth, and we also

perform formal tests to support this assertion. Specifically, we conduct a standard 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 3rd order polynomial in normalized base period earnings, interacted with D , the indicator for being above the threshold. The coefficient on the interaction term for the first order polynomial, 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 frequency distribution or the slope change at the threshold.

Second, we check for any discontinuities in pre-determined covariates around the threshold. We construct a summary index of covariates by regressing log total leave duration on the variables in X_i and base period earnings (linear), and calculate *predicted* log duration. We then plot the mean predicted log duration in each bin surrounding the threshold, separately for females and males, in Appendix Figure A2. The indices evolve smoothly around the threshold, providing further reassurance for the validity of our identification strategy.

5 Results

Graphical evidence and estimation results. The graphs in Figure 3 plot the empirical relationship between the authorized WBA and the normalized base period earnings. Since the maximum benefit changes during our sample time frame (recall Appendix Figure A1), in these graphs we also normalize the WBA by dividing it by the relevant maximum in each quarter (i.e., individuals who are authorized to receive the maximum amount get a value of 1). For both women and men in Figure 3, there is clear evidence of a kink at the threshold at which the maximum benefit begins. These graphs suggest that there is a strong first stage for our fuzzy RK analysis.

Tables 2 and 3 present the fuzzy RK estimates for our primary outcomes of interest

for women and men, respectively, along with 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.³⁰ We also plot graphs with these outcome variables on the y -axes in Figures 4 through 11. The graphs all use \$100 bins in the assignment variable, plot mean outcome values in each bin, show predicted values from local linear regressions, and select the bandwidths with the fuzzy IK method.

We find no evidence that a higher WBA leads to longer bonding leave duration. For mothers, our precise estimates allow us to rule out that a 10 percent increase in the WBA would increase leave duration by more than 0.07 percent. For fathers, we can rule out that a 10 percent increase in the WBA would raise leave duration by more than 3 percent. The graphical evidence in Figure 4 is consistent with zero effects for both women and men. Importantly, these estimates are not explained by a highly skewed distribution of leave duration where individuals are already “maxing out” their leave. In Appendix Figure A3, we plot the distribution of total leave duration for women and men in the fuzzy IK sample. A large share of individuals take less than the maximum amount of leave (6 weeks for fathers and adoptive/foster parents and around 16 weeks for birth mothers who can take both SDI and PFL).

We next consider labor market outcomes measured one to two years after leave initiation in columns (2)-(4) of Tables 2 and 3. We find that a 10 percent increase in the WBA leads to 0.8 and 0.3 percentage point (0.1 and 0.4 percent) increases in the share of quarters employed for mothers and fathers, respectively. Additionally, we find that fathers are more likely to return to their pre-leave employers—an additional 10 percent in the WBA leads to a 0.8 percentage point (1 percent) increase in the likelihood of being employed by the pre-leave employer. Figures 5, 6, and 7 present the corresponding graphical evidence for

³⁰The first stage coefficients differ from 0.04 (i.e., the number discussed in Section 4 above) because we are using the natural log of the weekly benefit amount rather than the level as the endogenous variable. Our results are similar if we instead use the benefit in levels. We also report both the main bandwidth and the 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.

these outcomes.

In columns (5)-(8) of Tables 2 and 3, we examine subsequent leave-taking. For both women and men, we find statistically significant positive impacts on these outcomes. For women, we report that a 10 percent rise in the WBA leads to a 1.5 percentage point higher likelihood of having a future bonding claim, which represents a 7 percent increase when evaluated at the sample mean. Overall, we find a 1.6 percentage point (5 percent) increase in the likelihood of any future paid leave claim in the three years following the first bonding claim for women.

For men, we find that a 10 percent increase in the WBA is associated with 0.07 and 0.7 percentage point increases in the likelihoods of making future caring and SDI claims, respectively (8 and 6 percent increases at the sample means). In total, a 10 percent higher benefit raises the probability of any future claim by about 1 percentage point (5 percent) for men.

Consistent with the significant estimates of the effects of PFL benefits on future program participation, Figures 8, 9, 10, and 11 show clear evidence of kinks in the relationships between these outcomes and base period earnings. Our results suggest that the benefit amount authorized during one's first bonding leave is a strong predictor of future leave-taking.

Heterogeneity by firm size. A key difference between the CA-PFL policy and PFL policies in several other states, including Rhode Island and New York, is the lack of job protection. As noted above in Section 2, workers who take PFL in California are only eligible for job protection if they simultaneously qualify for the FMLA or the CFRA. Thus, individuals in firms with 50 or more employees are much more likely to have job protection than those in smaller firms. To shed light on the role of job protection, Appendix Tables A1 and A2 examine heterogeneous effects of benefits by firm size, for women and men, respectively.

We find that for women working in firms with less than 50 employees prior to taking leave, a higher WBA is associated with a lower likelihood of returning to the same employer following the leave. There are no effects on overall employment or earnings one to two years after leave for this group. By contrast, for women in larger firms, there is a positive relationship between the WBA and subsequent labor market outcomes—a 10 percent rise in the WBA is associated with a 1 percentage point (2 percent) higher rate of return to the pre-claim firm, as well as a 0.7 percentage point (0.8 percent) increase in the share of quarters worked and a 5 percent increase in earnings one to two years after the claim.

We do not see the same pattern for men. If anything, the effect of the WBA on returning to the pre-claim firm is somewhat higher for men in smaller firms than those in larger firms, although the difference is not statistically significant. Moreover, men in smaller firms experience a large positive effect on subsequent earnings, while men in larger firms do not.

When we consider subsequent leave-taking, we do not find much heterogeneity for women. For men, however, the positive effect on repeat participation is driven entirely by men in larger firms with 50 or more employees.

While we do not observe the mechanisms driving these differences, our results suggest that access to job protection may be an important determinant of job continuity for women, but not men. Additionally, the fact that the results on repeat program participation are present only for men in large firms may suggest that “snowball” peer effects play a role—men in larger firms may be exposed to more other men who take leave and therefore have more information on how their employers react to leave-taking than men in smaller firms (Dahl *et al.*, 2014).

Robustness. We next explore the robustness of our RK estimates to alternative methods for bandwidth selection, to using local quadratic polynomials, and to the omission of controls.³¹ Appendix Figures A4 through A11 present a series of coefficients and 95% confi-

³¹Our preferred estimates control for all available covariates to address the possibility of bias due to a confounding nonlinear relationship between the assignment variable and the outcome (Ando, 2013).

dence intervals for each of our main outcomes using the following specifications: (1) baseline: fuzzy IK bandwidth with local linear polynomials and individual controls (i.e., the specification used in Tables 2 and 3), (2) fuzzy IK bandwidth with local linear polynomials and no controls, (3) fuzzy IK bandwidth with local quadratic polynomials and controls, (4) CCT bandwidth with regularization, local linear polynomials and controls, (5) CCT bandwidth with regularization, local quadratic polynomials and controls, (6) CCT bandwidth without regularization, with local linear polynomials and controls, and (7) CCT bandwidth without regularization, with local quadratic polynomials and controls.

Overall, most of these alternative specifications yield estimates with overlapping confidence intervals. The CCT bandwidth with regularization and with local linear polynomials and controls produces the widest confidence intervals for many of our outcomes. As discussed by Card *et al.* (2015b) and Card *et al.* (2016), CCT's regularized bandwidth selector often generates very small bandwidths in the RK setting, implying imprecise estimates. However, when we examine the output on the whole, we note that our results are quite robust. For instance, we find statistically significant positive impacts on the share of quarters employed for women (in five models) and men (in six models), and on returning to the pre-claim firm for men (in five models). For women, the coefficients for subsequent bonding and SDI claims are statistically significant in all seven of the models we consider, while for men, the coefficients for these outcomes are significant in five and six models, respectively.

Finally, Appendix Figures A12 through A18 show the sensitivity of our estimates to all possible bandwidths in \$1,000 increments up to \$20,000. While bandwidths of less than \$5,000 in quarterly base period earnings typically yield very noisy estimates with large confidence intervals, the coefficients are reasonably stable and precise when we use slightly larger bandwidths. In sum, these graphs suggest that our results are not especially sensitive to the size of the bandwidth.

6 Conclusion

According to the most recent statistics, only 14 percent of American workers have access to paid family leave through their employers.³² The fact that the U.S. does not provide any PFL 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 mothers' and fathers' leave duration, labor market outcomes, and future leave-taking in California, the first state to implement a 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 workers with base period earnings below and above the maximum benefit threshold, we find that higher benefits have zero impacts on leave duration for both mothers and fathers. We do, however, find 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 0.8 (0.3) percentage points for mothers (fathers) and the likelihood of return to the pre-leave employer by 0.8 percentage points for fathers. We also find that benefits during one's first period of family leave determine future program participation for both women and men. An additional 10 percent in benefits is associated with a 1.6 (1.3) percentage point higher likelihood of having a subsequent PFL or SDI claim in the following three years for mothers (fathers).

Our results assuage concerns that wage replacement during family leave may have unintended negative consequences for workers' future labor market outcomes through an in-

³²See: <http://www.nationalpartnership.org/issues/work-family/paid-leave.html>.

crease in time away from work. 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. But, our estimates are arguably most relevant to current discussions in the U.S., where the longest PFL program enacted thus far (in New York) only guarantees 12 weeks of paid leave. Moreover, the fact that we see a small positive effect on the likelihood of returning to one’s pre-leave firm for men may imply that employers may benefit from a reduction in turnover rates, contrary to the widely propagated worry that businesses will be hurt by government-mandated paid leave.³³

Finally, we provide some of the first evidence that wage replacement during leave encourages repeat leave-taking, and may thus be used as a means for promoting program participation. Future research may explore the mechanisms underlying these effects, as well as the consequences of PFL benefits on measures of family and child well-being, as well as on gender division of time spent in childcare and in the labor market.

References

- ADDATI, L., CASSIRER, N. and GILCHRIST, K. (2014). *Maternity and paternity at work: Law and practice across the world*. International Labour Office.
- AKERLOF, G. A. (1984). Gift exchange and efficiency-wage theory: Four views. *The American Economic Review*, **74** (2), 79–83.
- ANDERSON, D. J., BINDER, M. and KRAUSE, K. (2002). The motherhood wage penalty: Which mothers pay it and why? *The American Economic Review*, **92** (2), 354–358.
- ANDO, M. (2013). How much should we trust regression-kink-design estimates? *Empirical Economics*, pp. 1–36.
- BAKER, M. and MILLIGAN, K. (2008). How Does Job-Protected Maternity Leave Affect Mothers’ Employment? *Journal of Labor Economics*, **26** (4), 655–691.
- BARTEL, A., ROSSIN-SLATER, M., RUHM, C., STEARNS, J. and WALDFOGEL, J. (2015). *Paid Family Leave, Fathers’ Leave-Taking, and Leave-Sharing in Dual-Earner Households*. Working Paper 21747, National Bureau of Economic Research.

³³For more information on the argument against PFL from the business perspective, see, for example, the 2017 Labor Policy Recommendations put out by the U.S. Chamber of Commerce: https://www.uschamber.com/sites/default/files/documents/files/2017_labor_policy_recommendations.pdf.

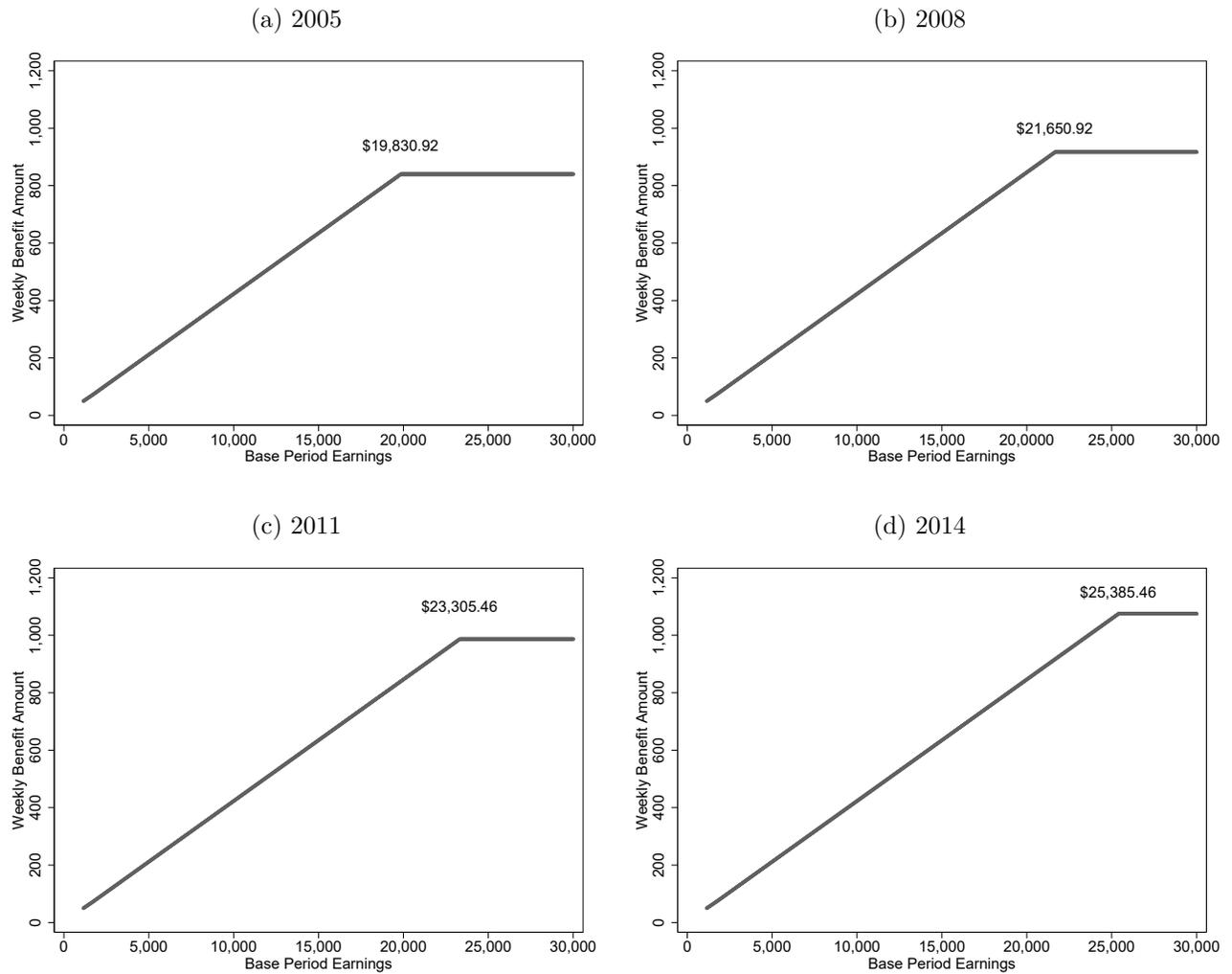
- BAUM, C. L. and RUHM, C. J. (2016). The effects of paid family leave in california on parental leave-taking and labor market outcomes. *Journal of Policy Analysis and Management*, **35** (2), 333–356.
- BERGEMANN, A. and RIPHAHN, R. T. (2015). Maternal Employment Effects of Paid Parental Leave (IZA DP No. 9073).
- BIČÁKOVÁ, A. and KALÍŠKOVÁ, K. (2016). *Career Breaks after Childbirth: The Impact of Family Leave Reforms in the Czech Republic*. Discussion Paper 10149, Institute for the Study of Labor (IZA).
- BLAU, F. and KAHN, L. (2000). Gender differences in pay. *Journal of Economic Perspectives*, **14** (4), 75–99.
- BLAU, F. D. and KAHN, L. M. (2013). Female labor supply: Why is the united states falling behind? *The American Economic Review*, **103** (3), 251–256.
- BOUSHEY, H. and GLYNN, S. J. (2012). *There are significant business costs to replacing employees*. Report 16, Center for American Progress.
- BULMAN, G. B. and HOXBY, C. M. (2015). The returns to the federal tax credits for higher education. *Tax Policy and Economy*, **29** (1), 13–88.
- CALONICO, S., CATTANEO, M. D. and FARRELL, M. H. (2016). Coverage error optimal confidence intervals for regression discontinuity designs, University of Michigan, unpublished manuscript.
- , — and TITIUNIK, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, **82** (6), 2295–2326.
- CARD, D., JOHNSTON, A., LEUNG, P., MAS, A. and PEI, Z. (2015a). The effect of unemployment benefits on the duration of unemployment insurance receipt: New evidence from a regression kink design in missouri, 2003–2013. *The American Economic Review*, **105** (5), 126–130.
- , LEE, D., PEI, Z. and WEBER, A. (2012). *Nonlinear policy rules and the identification and estimation of causal effects in a generalized regression kink design*. Working Paper 18564, National Bureau of Economic Research.
- , LEE, D. S., PEI, Z. and WEBER, A. (2015b). Inference on causal effects in a generalized regression kink design. *Econometrica*, **83** (6), 2453–2483.
- , —, — and — (2016). *Regression Kink Design: Theory and Practice*. Working Paper 22781, National Bureau of Economic Research.
- CARNEIRO, P., LOKEN, K. and SALVANES, K. (2015). A Flying Start: Maternity Leave Benefits and Long Run Outcomes of Children. *Journal of Political Economy*, **123** (2), 365–412.
- COOLS, S., FIVA, J. H. and KIRKEBØEN, L. J. (2015). Causal effects of paternity leave on children and parents. *The Scandinavian Journal of Economics*, **117** (3), 801–828.
- DAHL, G. B., LØKEN, K. V. and MOGSTAD, M. (2014). Peer effects in program participation. *The American Economic Review*, **104** (7), 2049–2074.

- , —, MOGSTAD, M. and SALVANES, K. V. (Forthcoming). What is the case for paid maternity leave? *Review of Economics and Statistics*.
- DAS, T. and POLACHEK, S. W. (2015). Unanticipated effects of california’s paid family leave program. *Contemporary Economic Policy*, **33** (4), 619–635.
- DOBBIE, W. and SKIBA, P. M. (2013). Information asymmetries in consumer credit markets: Evidence from payday lending. *American Economic Journal: Applied Economics*, **5** (4), 256–282.
- DUVANDER, A.-Z. and JOHANSSON, M. (2012). What are the effects of reforms promoting fathers’ parental leave use? *Journal of European Social Policy*, **22** (3), 319–330.
- EKBERG, J., ERIKSSON, R. and FRIEBEL, G. (2013). Parental leave—a policy evaluation of the swedish “daddy-month” reform. *Journal of Public Economics*, **97**, 131–143.
- ENGSTRÖM, P., NORDBLOM, K., OHLSSON, H. and PERSSON, A. (2015). Tax compliance and loss aversion. *American Economic Journal: Economic Policy*, **7** (4), 132–164.
- FASS, S. (2009). *Paid Leave in the States A Critical Support for Low-wage Workers and Their Families*. Tech. rep.
- GARMANN, S. (2014). The causal effect of coalition governments on fiscal policies: evidence from a regression kink design. *Applied Economics*, **46** (36), 4490–4507.
- GELBER, A., MOORE, T. and STRAND, A. (2016). *The Effect of Disability Insurance Payments on Beneficiaries’ Earnings*. Working Paper 21851, National Bureau of Economic Research.
- HANSEN, B., NGUYEN, T. and WADDELL, G. R. (2017). *Benefit Generosity and Injury Duration: Quasi-Experimental Evidence from Regression Kinks*. Discussion Paper 10621, IZA.
- IMBENS, G. and KALYANARAMAN, K. (2012). Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies*, p. rdr043.
- IMBENS, G. W. and LEMIEUX, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of econometrics*, **142** (2), 615–635.
- KATZ, L. F. (1986). Efficiency wage theories: A partial evaluation. *NBER macroeconomics annual*, **1**, 235–276.
- KLERMAN, J. A., DALEY, K. and POZNIAK, A. (2012). *Family and medical leave in 2012: Technical report*. Tech. rep., Abt Associates Inc, Prepared for the U.S. Department of Labor (Contract No. GS10FOO86K).
- and LEIBOWITZ, A. (1994). The Work-Employment Distinction Among New Mothers. *The Journal of Human Resources*, **29** (2), 277–303.
- KLEVEN, H. J., LANDAIS, C. and SØGAARD, J. E. (2016). Children and Gender Inequality: Evidence from Denmark, London School of Economics, unpublished manuscript.

- KLUGE, J., TAMM, M., KLUGE, J. and TAMM, M. (2013). Parental leave regulations, mothers' labor force attachment and fathers' childcare involvement: evidence from a natural experiment. *Journal of Population Economics*, **26** (3), 983–1005.
- KRUEGER, A. B. and MEYER, B. D. (2002). Labor supply effects of social insurance. In A. J. Auerbach and M. S. Feldstein (eds.), *Handbook of Public Economics*, vol. 4, New York: Elsevier, pp. 2327–2392.
- and SUMMERS, L. H. (1988). Efficiency wages and the inter-industry wage structure. *Econometrica*, pp. 259–293.
- LALIVE, R. and ZWEIMÜLLER, J. (2009). How Does Parental Leave Affect Fertility and Return to Work? Evidence from Two Natural Experiments. *The Quarterly Journal of Economics*, **124** (3), 1363–1402.
- LANDAIS, C. (2015). Assessing the welfare effects of unemployment benefits using the regression kink design. *American Economic Journal: Economic Policy*, **7** (4), 243–278.
- LEQUIEN, L. (2012). The Impact of Parental Leave Duration on Later Wages. *Annals of Economics and Statistics*, **107/108** (July/December), 267–285.
- LUNDBERG, S. and ROSE, E. (2000). Parenthood and the earnings of married men and women. *Labour Economics*, **7** (6), 689–710.
- LUNDQVIST, H., DAHLBERG, M. and MÖRK, E. (2014). Stimulating local public employment: Do general grants work? *American Economic Journal: Economic Policy*, **6** (1), 167–192.
- MCCRARY, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of econometrics*, **142** (2), 698–714.
- MOLINA, J. A. and MONTUENGA, V. M. (2009). The motherhood wage penalty in Spain. *Journal of Family and Economic Issues*, **30** (3), 237–251.
- NIELSEN, H. S., SØRENSEN, T. and TABER, C. (2010). Estimating the effect of student aid on college enrollment: Evidence from a government grant policy reform. *American Economic Journal: Economic Policy*, **2** (2), 185–215.
- OLIVETTI, C. and PETRONGOLO, B. (2017). The economic consequences of family policies: lessons from a century of legislation in high-income countries. *The Journal of Economic Perspectives*, **31** (1), 205–230.
- PATNAIK, A. (2016). Reserving time for daddy: The short and long-run consequences of fathers' quotas, Unpublished manuscript.
- PORTER, J. (2003). Estimation in the regression discontinuity model, University of Wisconsin at Madison, unpublished manuscript.
- ROSSIN-SLATER, M. (2017). *Maternity and Family Leave Policy*. Working Paper 23069, National Bureau of Economic Research.
- , RUHM, C. J. and WALDFOGEL, J. (2013). The effects of California's paid family leave program on mothers' leave-taking and subsequent labor market outcomes. *Journal of Policy Analysis and Management*, **32** (2), 224–245.

- RUHM, C. J. (1998). The economic consequences of parental leave mandates: Lessons from Europe. *Quarterly Journal of Economics*, **113** (1), 285–317.
- SCHOBER, P. S. (2014). Parental leave and domestic work of mothers and fathers: A longitudinal study of two reforms in west germany. *Journal of Social Policy*, **43** (02), 351–372.
- SCHÖNBERG, U. and LUDSTECK, J. (2014). Expansions in Maternity Leave Coverage and Mothers’ Labor Market Outcomes after Childbirth. *Journal of Labor Economics*, **32** (3), 469–505.
- SEIM, D. (Forthcoming). Behavioral responses to wealth taxes: Evidence from sweden. *American Economic Journal: Economic Policy*.
- STANCZYK, A. (2016). Does paid family leave improve household economic security following a birth? evidence from california, University of California at Berkeley, unpublished manuscript.
- STEARNS, J. (2016). Long-run effects of maternity leave: Evidence from britain, UC Santa Barbara, unpublished manuscript.
- STIGLITZ, J. E. (1986). Theories of wage rigidity. In e. a. J. Butkiewicz (ed.), *Keynes’ Economic Legacy: Contemporary Economic Theories*, New York: Praeger Publishers, pp. 153–206.
- THÉVENON, O. and SOLAZ, A. (2013). *Labour market effects of parental leave policies in OECD countries*. Working Paper 141, OECD Social, Employment, and Migration.
- TRZCINSKI, E. and ALPERT, W. T. (1994). Pregnancy and parental leave benefits in the united states and canada: Judicial decisions and legislation. *Journal of Human Resources*, pp. 535–554.
- TURNER, L. J. (2014). The road to pell is paved with good intentions: The economic incidence of federal student grant aid, University of Maryland, unpublished manuscript.
- WALDFOGEL, J. (1998). The family gap for young women in the united states and britain: Can maternity leave make a difference? *Journal of labor economics*, **16** (3), 505–545.

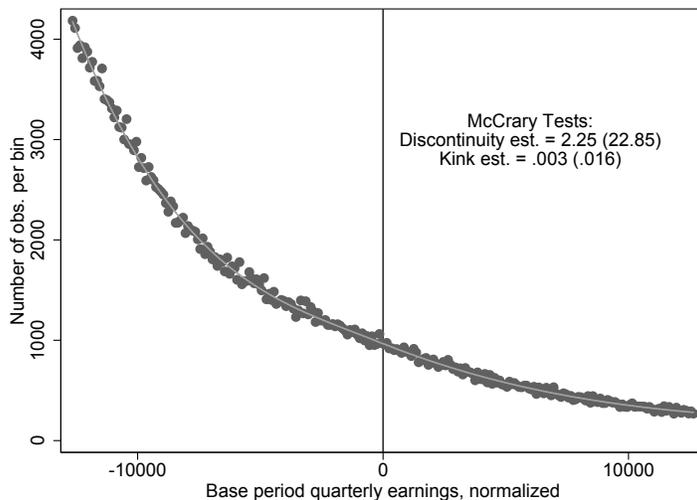
Figure 1: PFL Benefit Schedule in 2005, 2008, 2011, and 2014



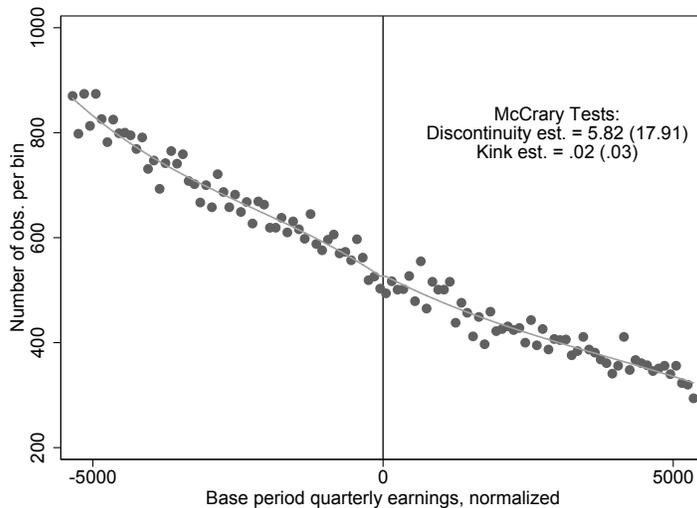
Notes: These figures plot nominal quarterly base period earnings on the x -axis and the nominal weekly benefit amount on the y -axis for 2005, 2008, 2011, and 2014. The earnings threshold at which the maximum benefit begins is labeled in each sub-figure.

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

(a) Women

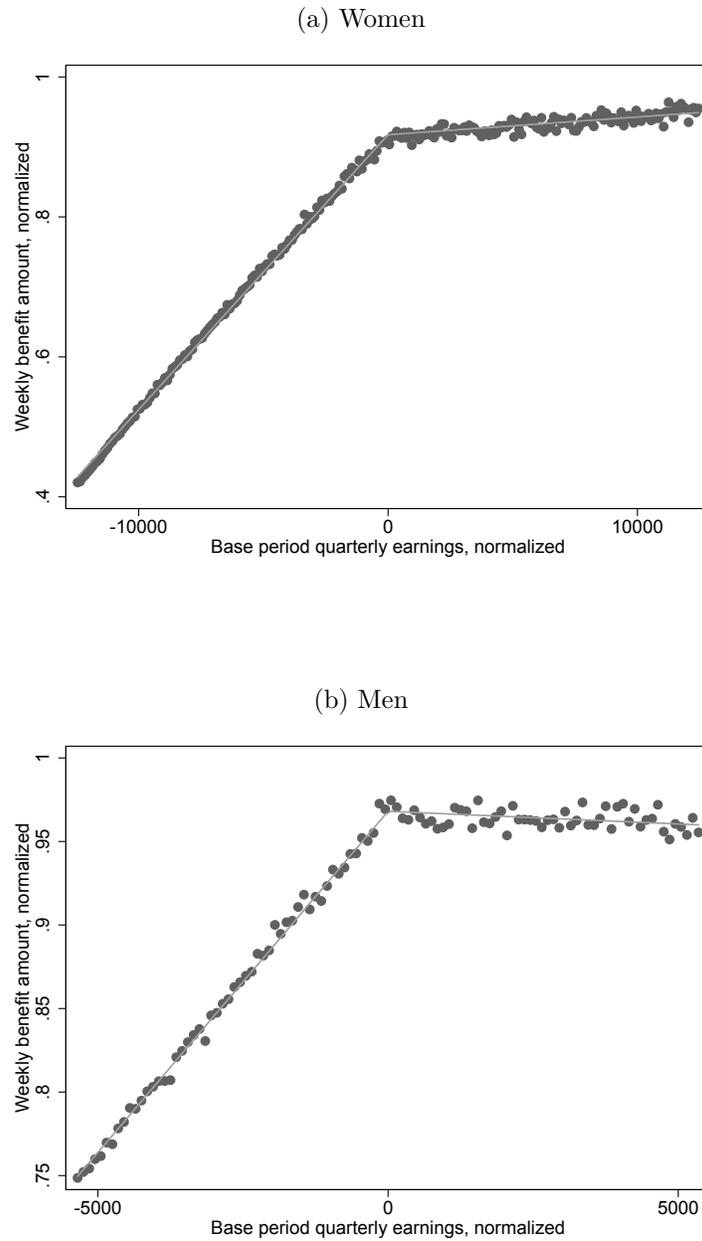


(b) Men



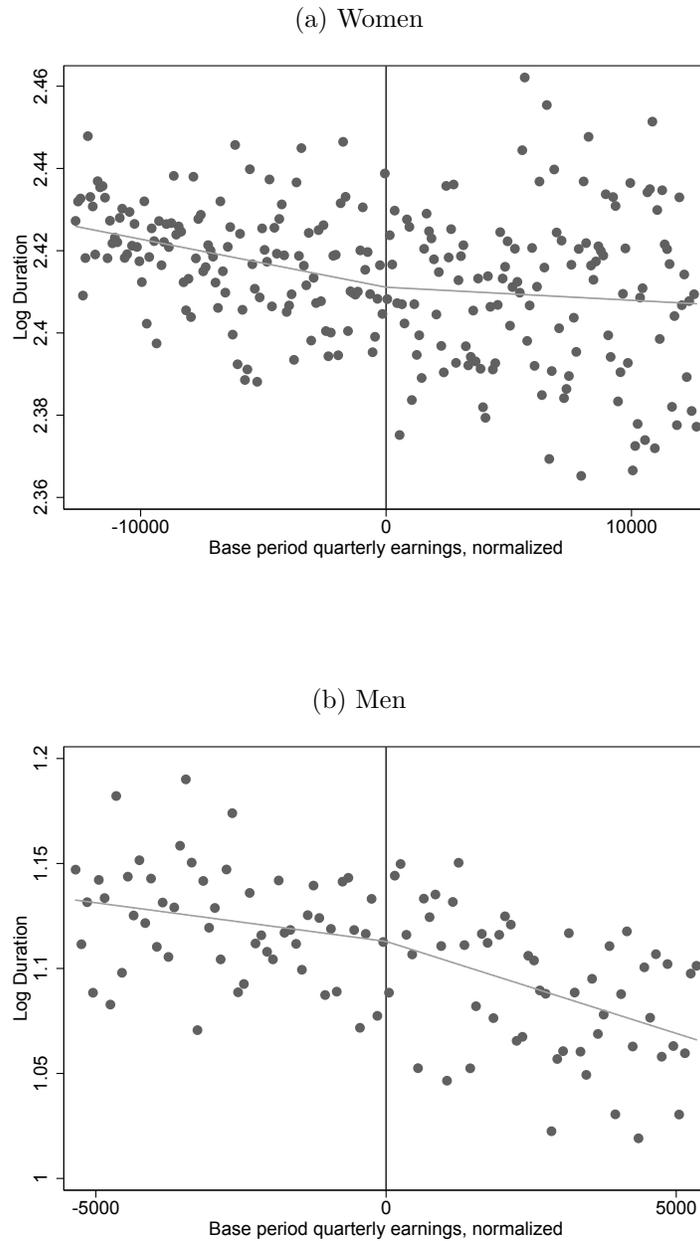
Notes: These figures show the estimated and predicted frequency distributions for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. Predicted frequencies are from a third-order polynomial model with unrestricted first and higher-order derivatives on each side of the threshold. 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.

Figure 3: RK First Stage, PFL Benefits and Base Period Earnings



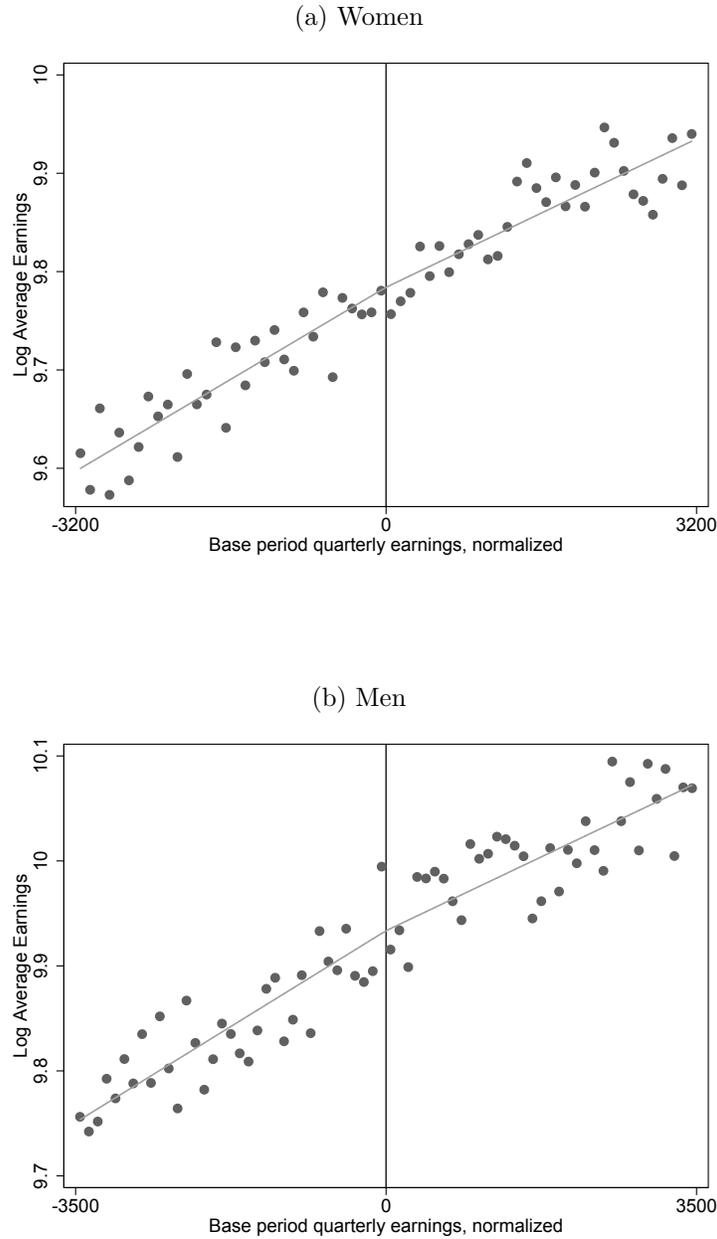
Notes: These figures show the empirical relationship between the normalized weekly benefit amount received and the normalized base period earnings for women (panel a) and men (panel b). The WBA is normalized by dividing the WBA by the maximum weekly benefit in that quarter (i.e., individuals who receive the maximum amount get the value of 1). The x -axis plots normalized base period quarterly earnings (in terms of distance to the earnings threshold) in bins, using \$100 bins. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 4: RK Evidence for Impacts on Log Leave Duration



Notes: These figures show the relationship between log leave duration and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

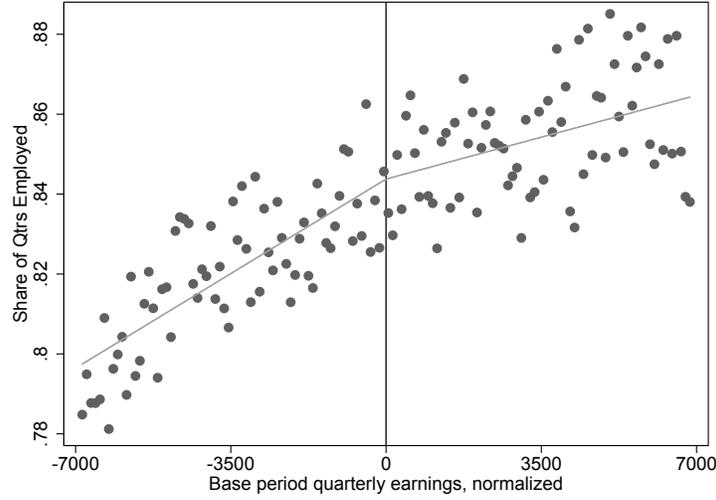
Figure 5: RK Evidence for Impacts on Log Average Earnings, Qtrs 4-7 Post-Claim



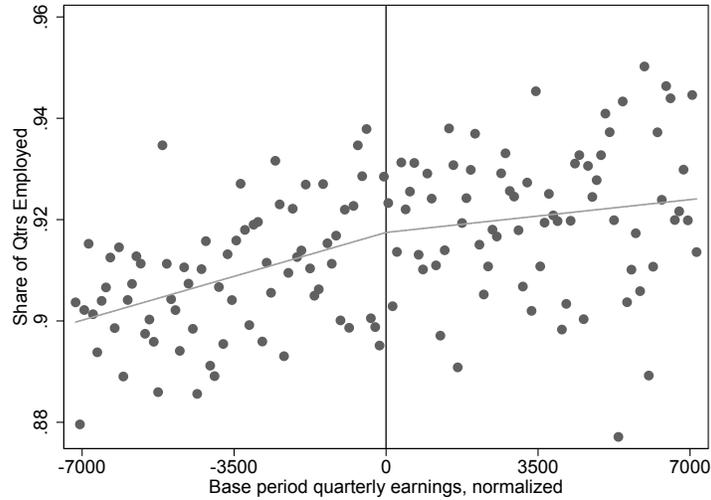
Notes: These figures show the relationship between log average quarterly earnings in quarters 4-7 after the claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 6: RK Evidence for Impacts on Share Quarters Employed, Qtrs 4-7 Post-Claim

(a) Women

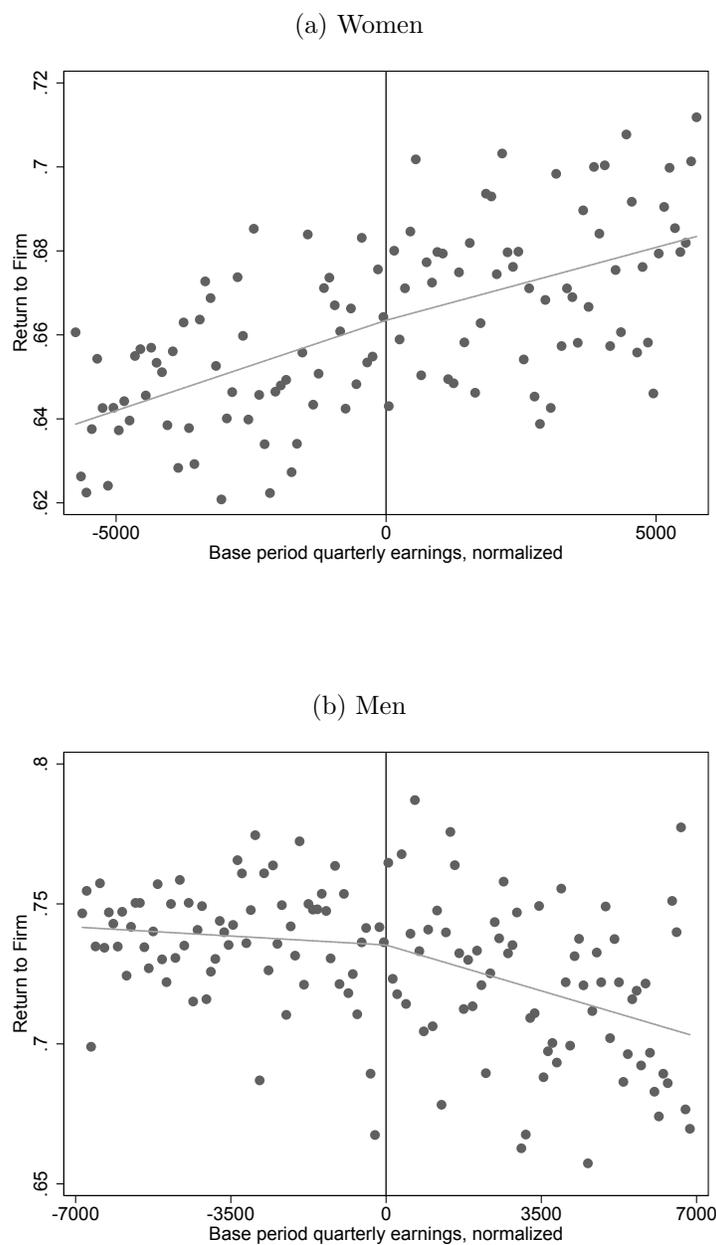


(b) Men



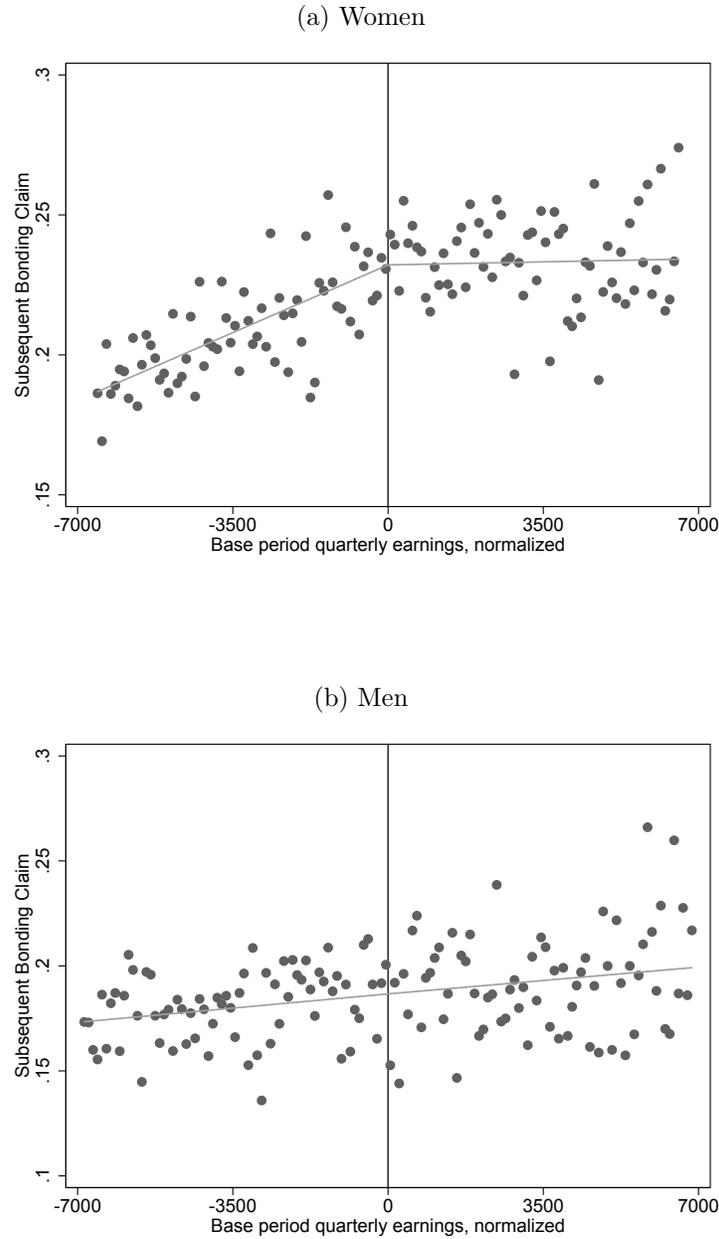
Notes: These figures show the relationship between the share of quarters employed in quarters 4-7 after the claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 7: RK Evidence for Impacts on Employment in Pre-Claim Firm, Qtr 4 Post-Claim



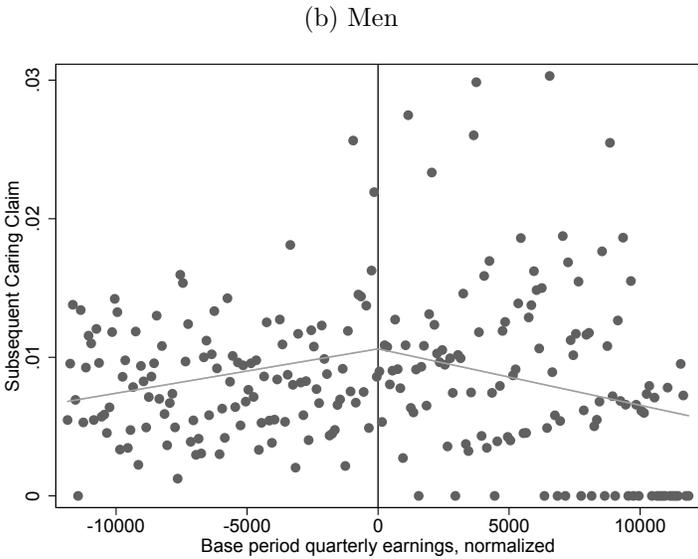
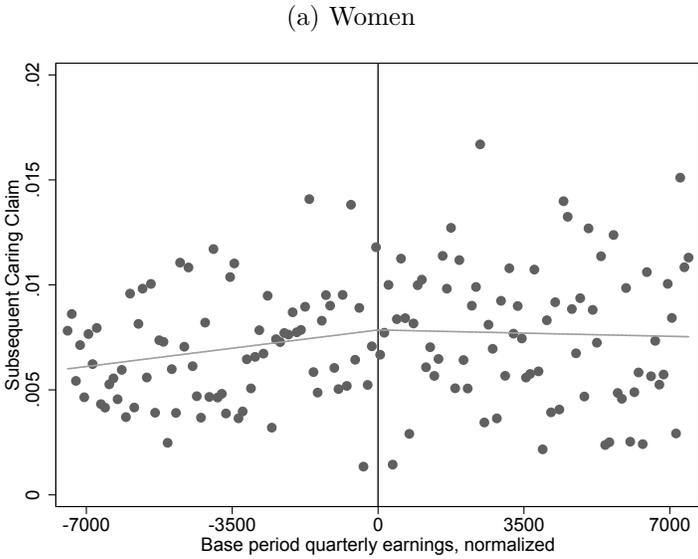
Notes: These figures show the relationship between an indicator for having positive earnings from one's pre-claim firm in the 4th quarter after the claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 8: RK Evidence for Impacts on Any Subsequent Bonding Claim



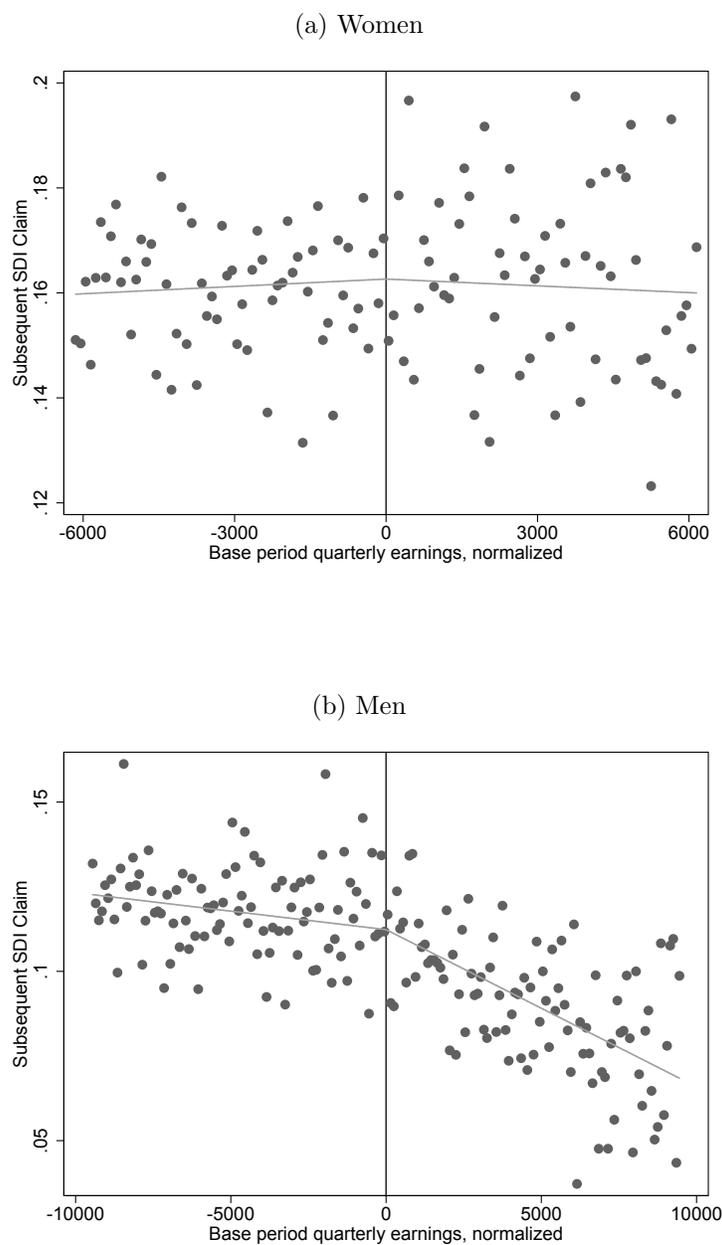
Notes: These figures show the relationship between an indicator for any subsequent bonding claim in the three years after the first bonding claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 9: RK Evidence for Impacts on Any Subsequent Caring Claim



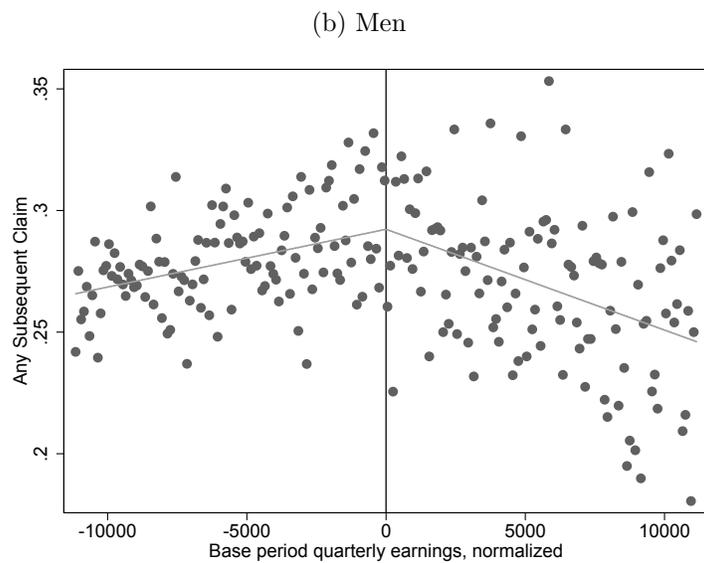
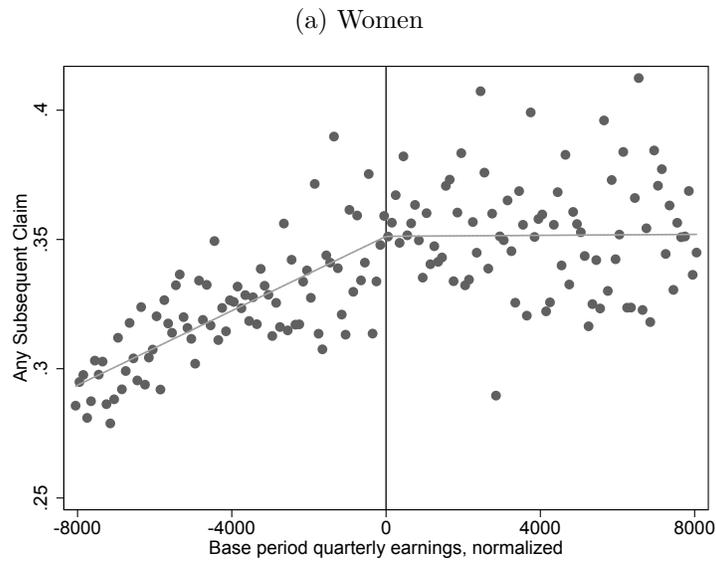
Notes: These figures show the relationship between an indicator for any subsequent caring claim in the three years after the first bonding claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 10: RK Evidence for Impacts on Any Subsequent SDI Claim



Notes: These figures show the relationship between an indicator for any subsequent non-transitional SDI claim in the three years after the first bonding claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Figure 11: RK Evidence for Impacts on Any Subsequent Bonding, Caring, or SDI Claim



Notes: These figures show the relationship between an indicator for any subsequent bonding, caring, or non-transitional SDI claim in the three years after the first bonding claim and normalized base period earnings for women (panel a) and men (panel b). The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method. The y -axis plots the mean of the outcome variable in each bin. The lines display predicted values from linear regressions that allow for different slopes on each side of the threshold.

Table 1: Descriptive Statistics

	Females		Males	
	All	RK	All	RK
Age	29.64	31.63	32.42	34.01
Firm Size 1-49	0.245	0.211	0.144	0.131
Firm Size 50-99	0.0807	0.0798	0.0763	0.0798
Firm Size 100-499	0.211	0.211	0.232	0.229
Firm Size 500+	0.463	0.498	0.548	0.560
Base Period Quarterly Earnings in \$2014	14090.3	18505.9	19612.8	23501.8
Health Ind. (Top Female)	0.225	0.256	0.0962	0.108
Manufacturing Ind. (Top Male)	0.0636	0.0654	0.139	0.147
Real Weekly Benefit Amount in \$2014	480.2	693.3	653.5	923.9
Total Leave Duration, Weeks	12.34	12.23	3.779	3.708
Avg Quarterly Earn, Qtrs 4-7 Post-Claim	9875.7	13511.3	16619.5	20692.8
Share Qtrs Employed, Qtrs 4-7 Post-Claim	0.732	0.803	0.879	0.914
Return to Pre-Claim Firm	0.529	0.625	0.687	0.733
Subsequent Bonding Claim	0.149	0.185	0.159	0.184
Subsequent Caring Claim	0.00544	0.00698	0.00744	0.00909
Subsequent SDI Claim	0.159	0.161	0.104	0.111
Observations	779338	327780	256432	59202

Notes: This table presents the means of some of the key variables for women and men making their first PFL bonding claims during 2005-2014. In the second and fourth columns, the samples are limited to individuals with base period earnings in the vicinity of the earnings threshold (i.e., our RK analysis sample), where the bandwidths are chosen with our preferred method (“fuzzy IK”) for log total leave duration as the outcome (for women and men separately).

Table 2: RK Estimates of the Effects of PFL Benefits, Females

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Dur	Log Avg Earn	Share Qtrs Emp	Return Firm	Future Bond	Future Care	Future SDI	Future Any
Log Weekly Benefit (\$2014)	-0.00967 (0.00875)	0.299 (0.238)	0.0758*** (0.0226)	0.000873 (0.0429)	0.149*** (0.0312)	0.00625 (0.00521)	0.00215 (0.0314)	0.156*** (0.0242)
Main Bandwidth	12729.4	3169.2	6926.9	5837.8	6606.3	7454.9	6185.4	8114.1
Pilot Bandwidth	15656.4	9692.9	15330.3	9062.4	16672.2	10264.1	9033.1	9805.8
First Stage Est x 10 ⁵	-6.037	-3.623	-4.396	-4.142	-4.337	-4.489	-4.235	-4.647
First Stage S.E. x 10 ⁵	0.0279	0.244	0.0735	0.0963	0.0791	0.0651	0.0878	0.0574
Dep. Var Mean	2.418	9.759	0.830	0.658	0.216	0.00707	0.161	0.328
N	327779	46765	120889	99855	104234	119864	96854	132973

Notes: Each coefficient is from a separate regression. The outcomes are: (1) log leave duration, (2) log of average quarterly earnings (in \$2014) in quarters 4-7 after the claim, (3) share of quarters employed in quarters 4-7 after the claim, (4) indicator for receiving positive earnings from pre-claim firm in quarter 4 after the claim, (5) indicator for any subsequent bonding claim in the three years after the claim, (6) indicator for any subsequent caring claim in the three years after the claim, (7) indicator for any subsequent (non-transitional) SDI claim in the three years after the claim, (8) indicator for any bonding, caring, or SDI claim in the three years after the claim. All regressions are estimated using the fuzzy IK bandwidth selector and local linear polynomials in normalized quarterly base period earnings (the assignment variable). We control for the following individual-level variables: age and age squared, dummies for firm size categories (1-49, 50-99, 100-499, 500+) of the pre-claim employer, and dummies for industry code of the pre-claim employer. 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

Table 3: RK Estimates of the Effects of PFL Benefits, Males

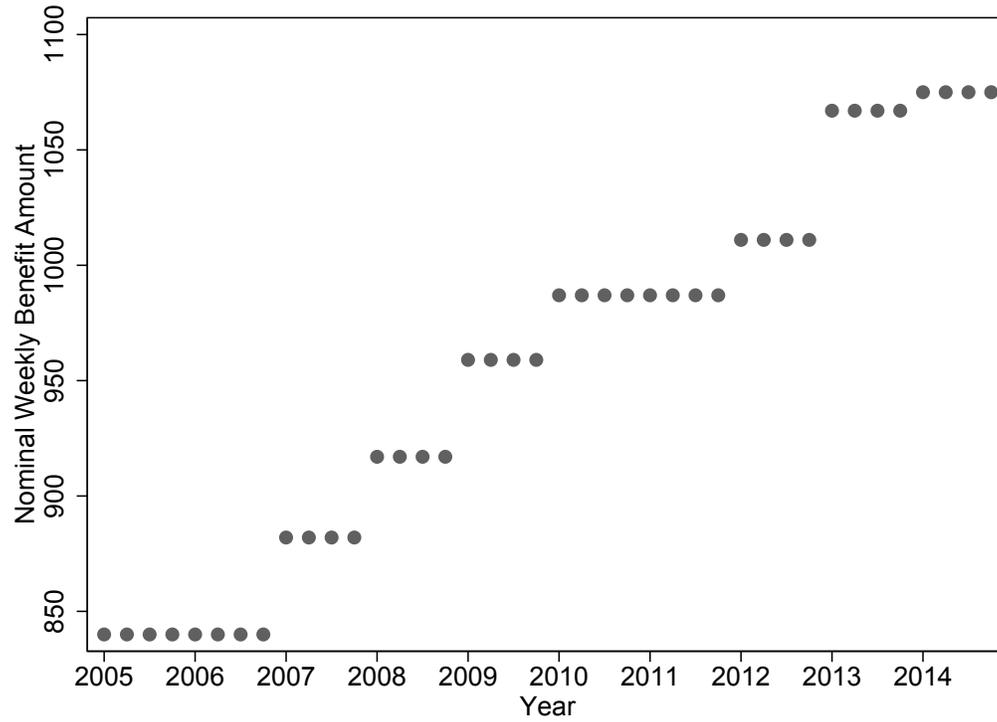
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Dur	Log Avg Earn	Share Qtrs Emp	Firm Return	Future Bond	Future Care	Future SDI	Future Any
Log Weekly Benefit (\$2014)	0.114 (0.0809)	0.222 (0.160)	0.0339* (0.0175)	0.0817** (0.0342)	0.0252 (0.0315)	0.00651** (0.00271)	0.0670*** (0.0140)	0.127*** (0.0151)
Main Bandwidth	5376.1	3510.8	7244.7	6929.1	6932.7	11871.2	9539.8	11231.0
Pilot Bandwidth	8593.0	7481.5	7696.7	7727.8	16542.3	18769.0	9579.1	8406.2
First Stage Est x 10 ⁵	-4.851	-4.531	-5.276	-5.170	-5.171	-6.287	-5.700	-6.109
First Stage S.E. x 10 ⁵	0.0929	0.183	0.0601	0.0640	0.0639	0.0273	0.0379	0.0297
Dep. Var Mean	1.112	9.905	0.912	0.733	0.184	0.00843	0.111	0.276
N	59199	29408	66927	63678	56153	105412	81527	98914

Notes: Each coefficient is from a separate regression. The outcomes are: (1) log leave duration, (2) log of average quarterly earnings (in \$2014) in quarters 4-7 after the claim, (3) share of quarters employed in quarters 4-7 after the claim, (4) indicator for receiving positive earnings from pre-claim firm in quarter 4 after the claim, (5) indicator for any subsequent bonding claim in the three years after the claim, (6) indicator for any subsequent caring claim in the three years after the claim, (7) indicator for any subsequent (non-transitional) SDI claim in the three years after the claim, (8) indicator for any bonding, caring, or SDI claim in the three years after the claim. All regressions are estimated using the fuzzy IK bandwidth selector and local linear polynomials in normalized quarterly base period earnings (the assignment variable). We control for the following individual-level variables: age and age squared, dummies for firm size categories (1-49, 50-99, 100-499, 500+) of the pre-claim employer, and dummies for industry code of the pre-claim employer. 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

A Appendix Figures and Tables

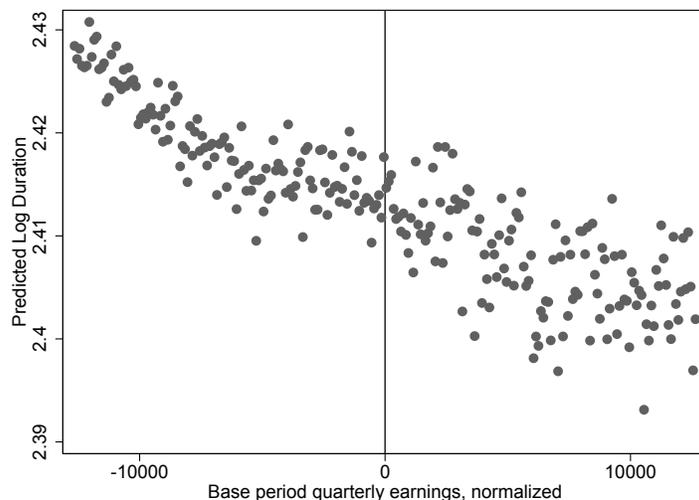
Appendix Figure A1: Maximum PFL Weekly Benefit Amount



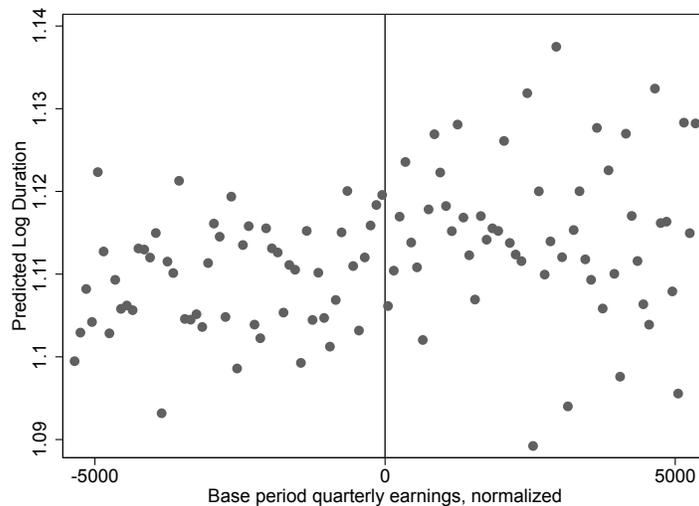
Notes: This figure plots the maximum weekly benefit amount by quarter in nominal dollars over the time period 2005 quarter 1 through 2014 quarter 4.

Appendix Figure A2: Predicted Log Leave Duration Around the Earnings Threshold

(a) Women

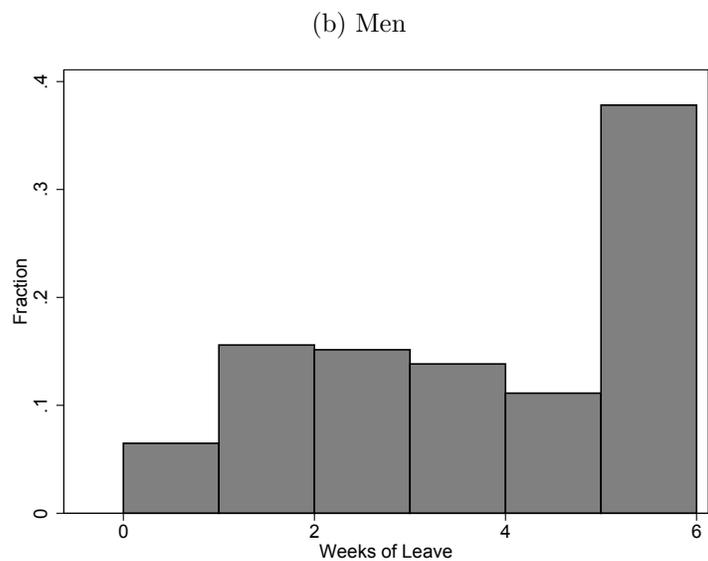
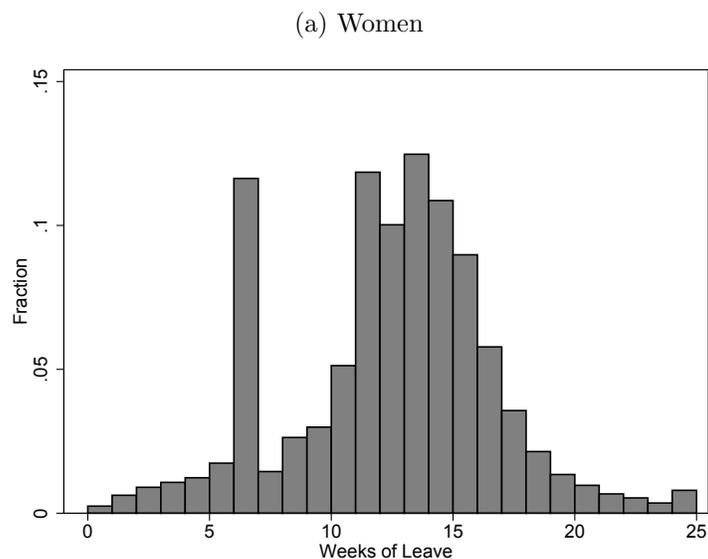


(b) Men



Notes: These figures show the relationship between *predicted* log leave duration and normalized base period earnings for women (panel a) and men (panel b). We predict duration using a regression of log total leave duration on the following control variables: age and age squared, dummies for firm size categories (1-49, 50-99, 100-499, and 500+), dummies for industry code, and base period quarterly earnings in real \$2014. The x -axis plots normalized base period quarterly earnings (relative to the earnings threshold in each year) in bins, using \$100 bins. The bandwidths displayed in these graphs are chosen with the fuzzy IK method.

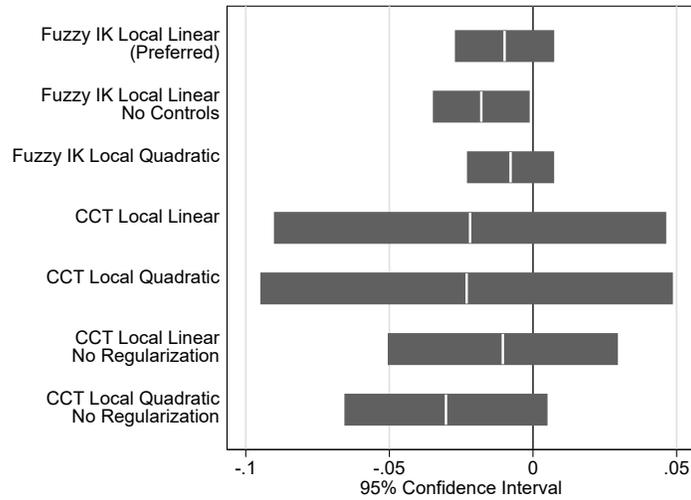
Appendix Figure A3: Distribution of Total Leave Duration for Individuals with Earnings Near the Threshold



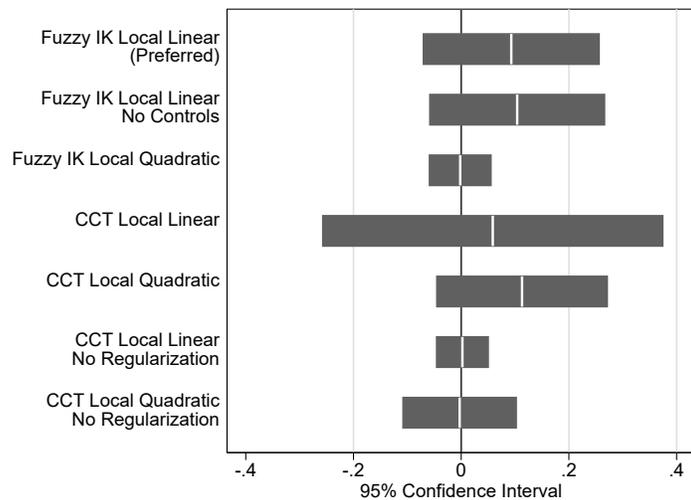
Notes: These figures plot the distributions of total leave duration for women and men, for individuals with pre-claim earnings within the fuzzy IK bandwidth surrounding the kink point.

Appendix Figure A4: RK Robustness for Log Leave Duration

(a) Women



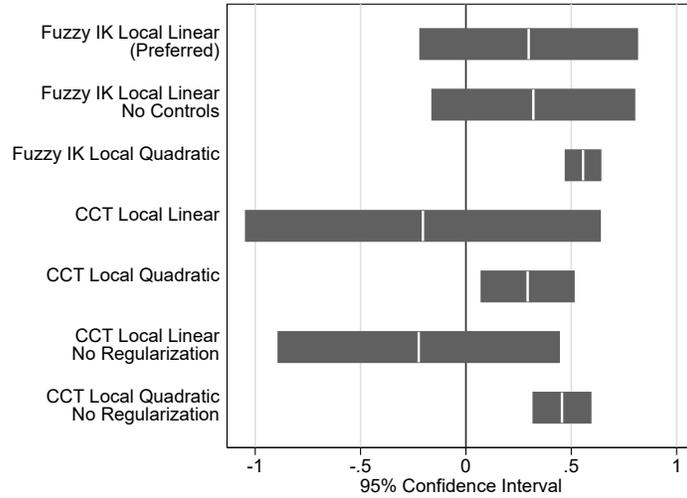
(b) Men



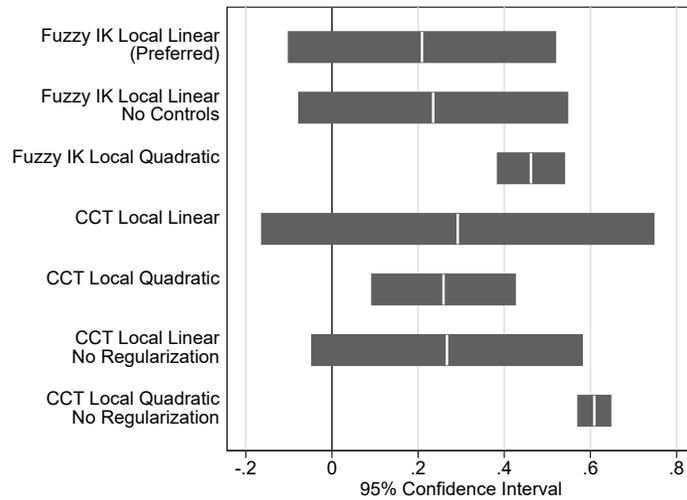
Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

Appendix Figure A5: RK Robustness for Log Average Earnings, Qtrs 4-7 Post-Claim

(a) Women



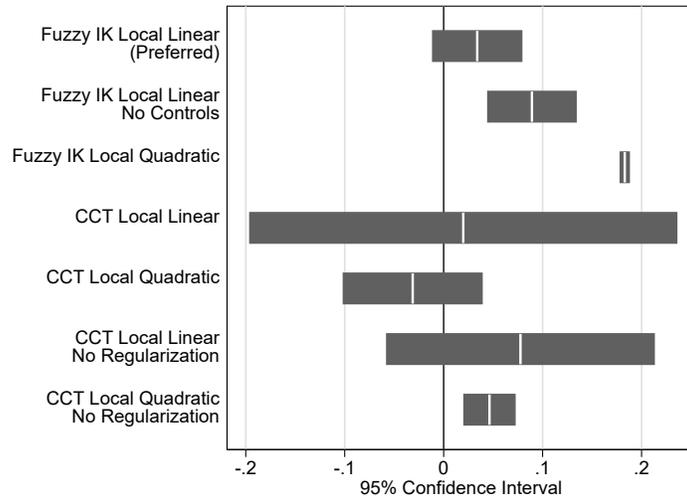
(b) Men



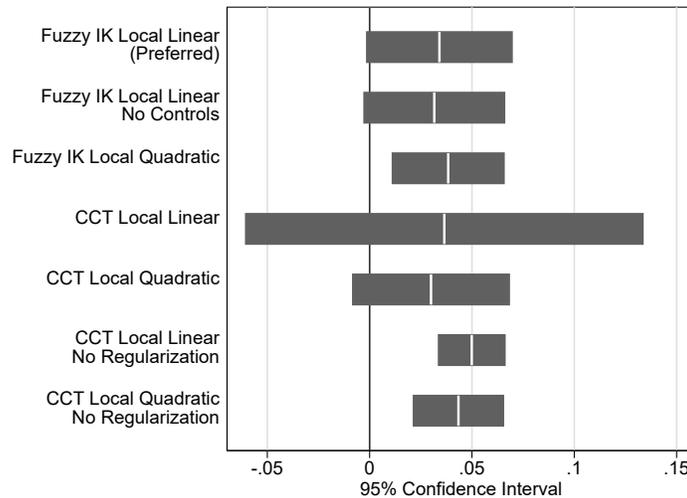
Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

Appendix Figure A6: RK Robustness for Share Quarters Employed, Qtrs 4-7 Post-Claim

(a) Women

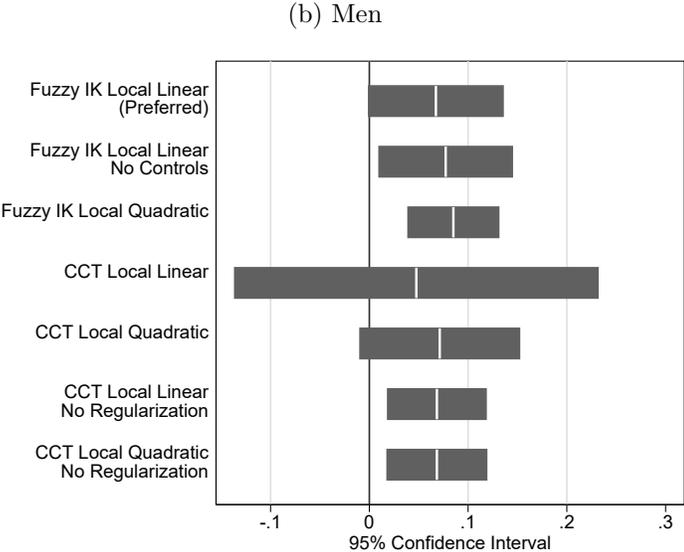
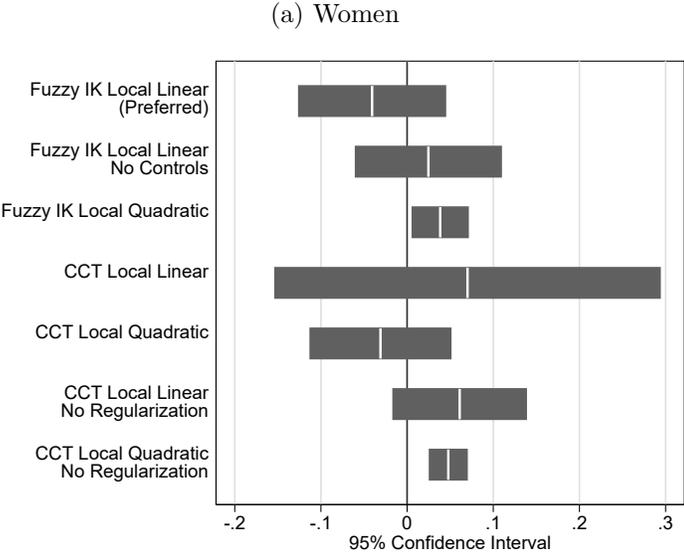


(b) Men



Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

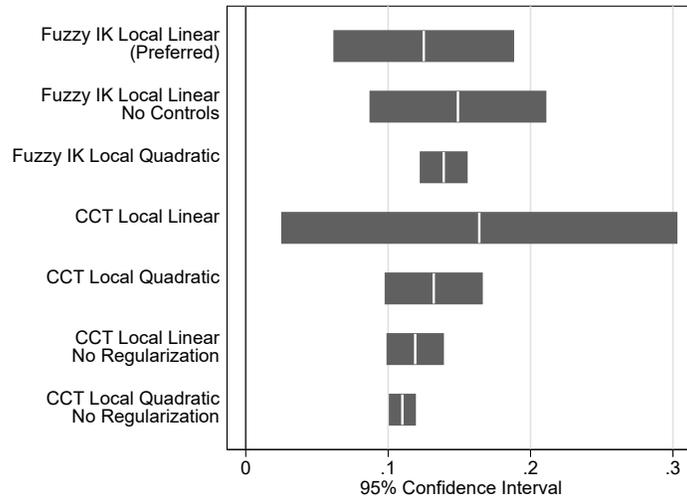
Appendix Figure A7: RK Robustness for Employment in Pre-Claim Firm, Qtr 4 Post-Claim



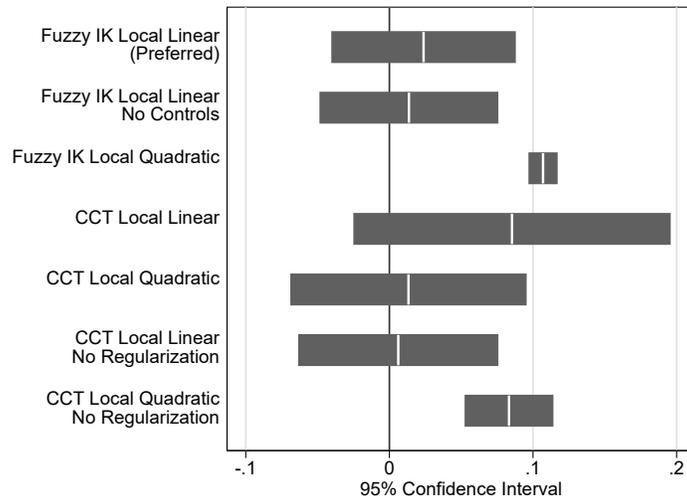
Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

Appendix Figure A8: RK Robustness for Any Subsequent Bonding Claim

(a) Women

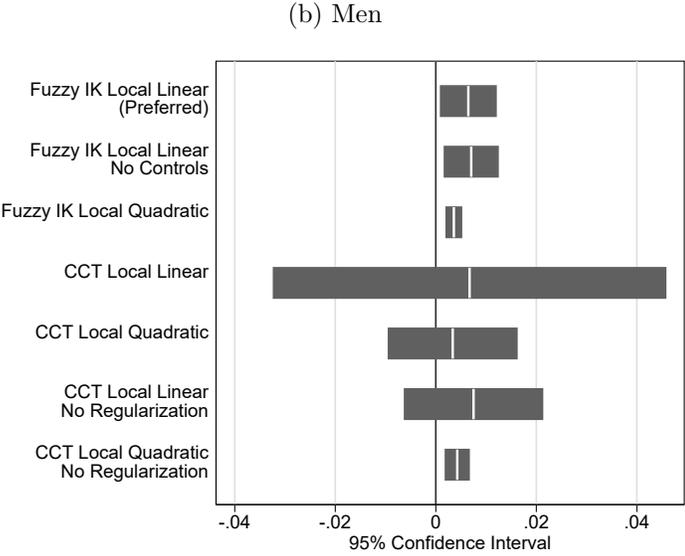
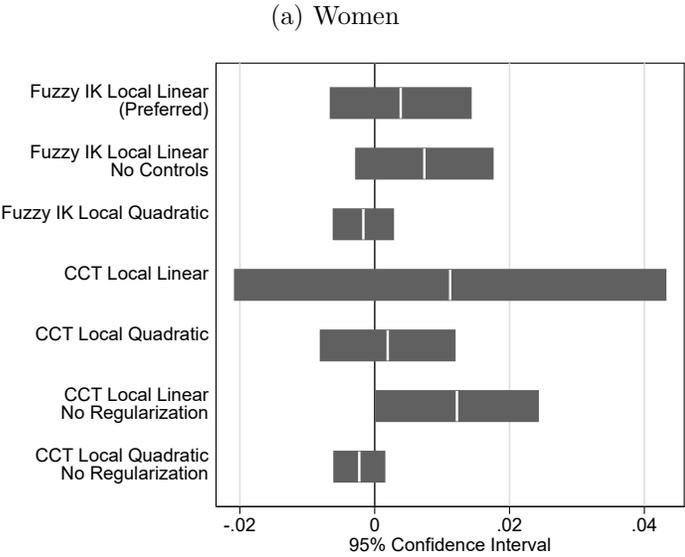


(b) Men



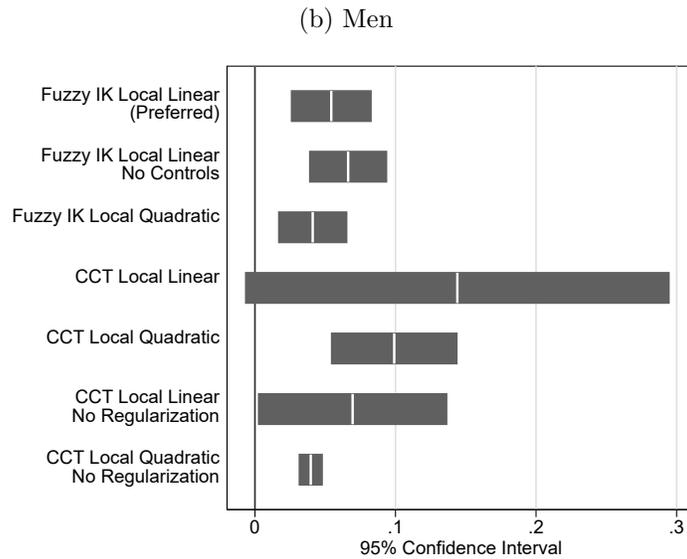
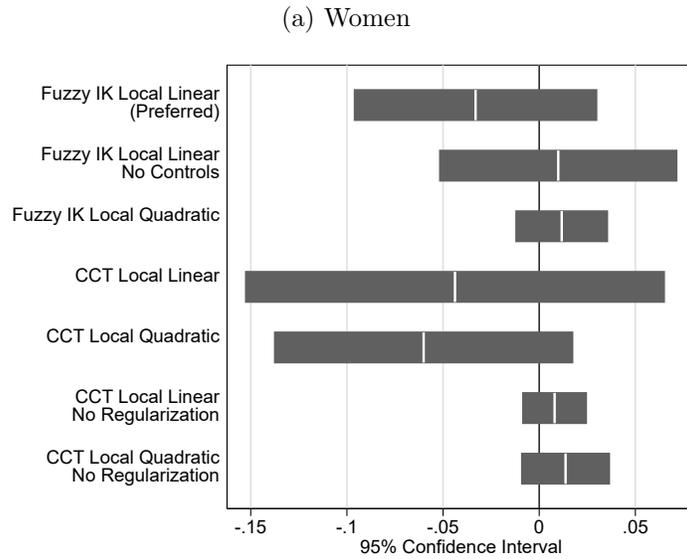
Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

Appendix Figure A9: RK Robustness for Any Subsequent Caring Claim



Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

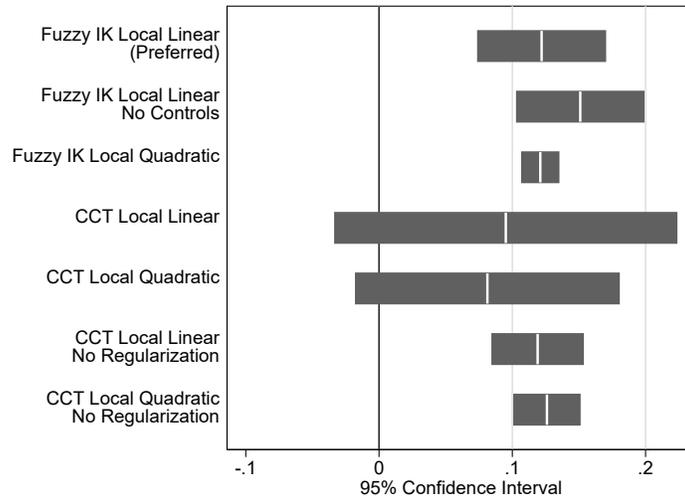
Appendix Figure A10: RK Robustness for Any Subsequent SDI Claim



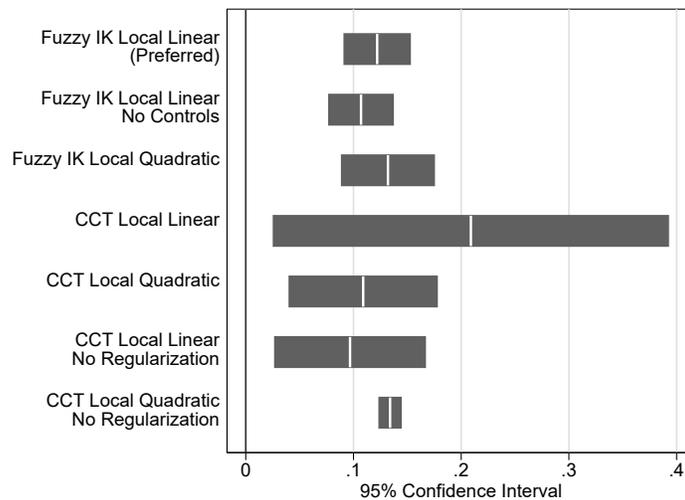
Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

Appendix Figure A11: RK Robustness for Any Subsequent Bonding, Caring, or SDI Claim

(a) Women



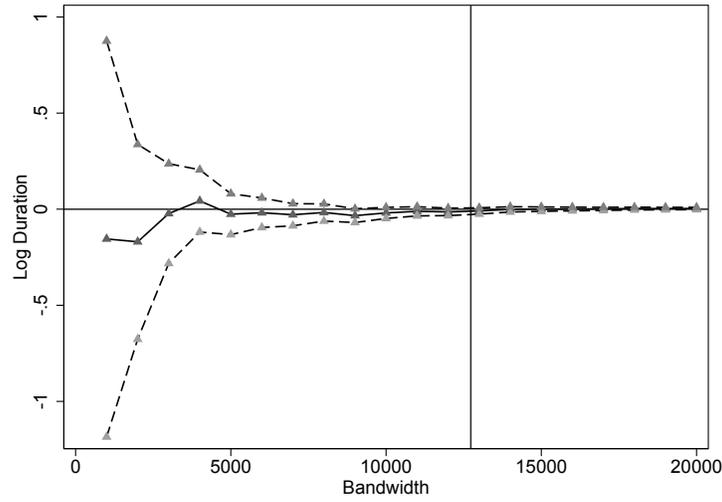
(b) Men



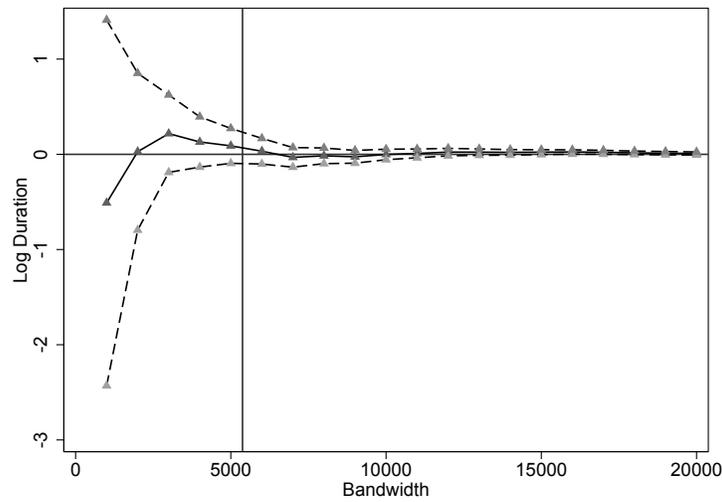
Notes: These figures show the coefficients (as white stripes) and 95% confidence intervals (as gray horizontal bars) from 7 different RK specifications: fuzzy IK bandwidth with local linear polynomials (our preferred model), fuzzy IK bandwidth with local linear polynomials and no individual controls, fuzzy IK bandwidth with local quadratic polynomials, CCT bandwidth with local linear polynomials and regularization, CCT bandwidth with local quadratic polynomials and regularization, CCT bandwidth with local linear polynomials and no regularization, and CCT bandwidth with local quadratic polynomials and no regularization. All of the models except for the second one include individual controls.

Appendix Figure A12: RK Estimates Using Different Bandwidths for Log Leave Duration

(a) Women



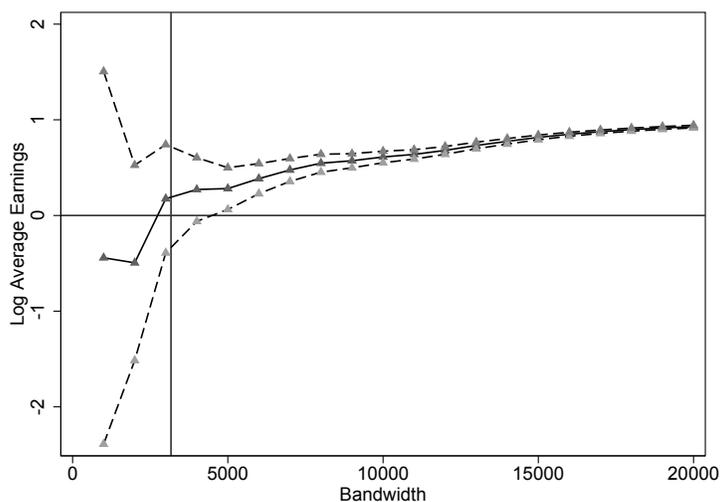
(b) Men



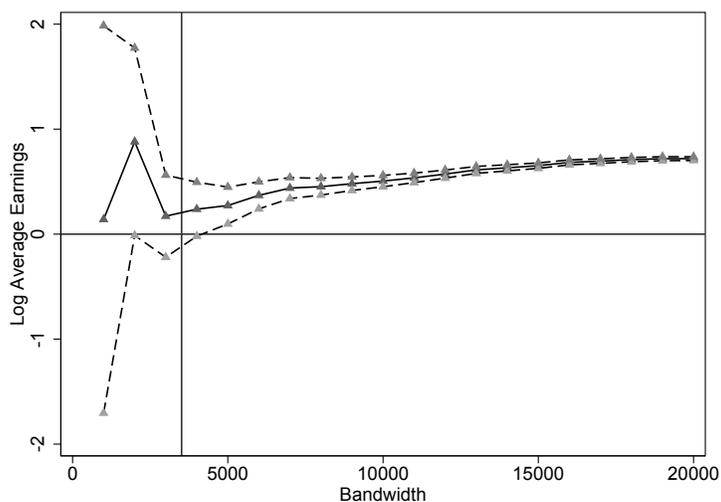
Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Figure A13: RK Estimates Using Different Bandwidths for Log Average Earnings, Qtrs 4-7 Post-Claim

(a) Women

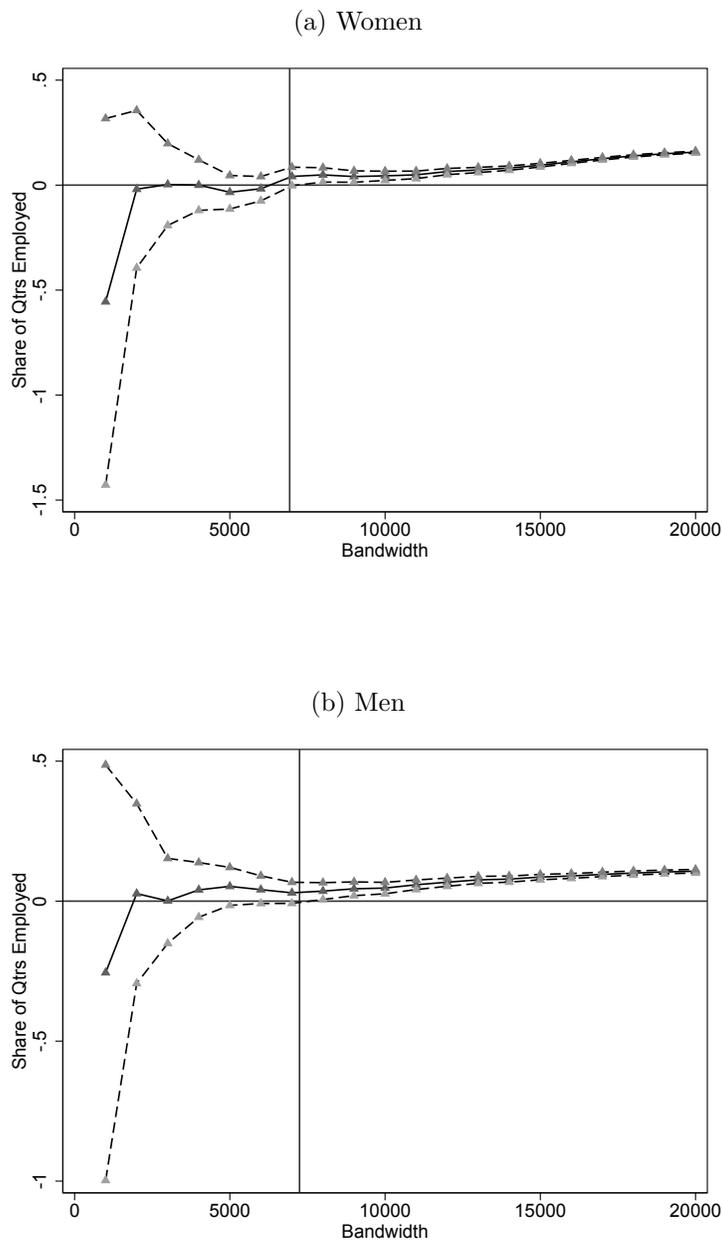


(b) Men



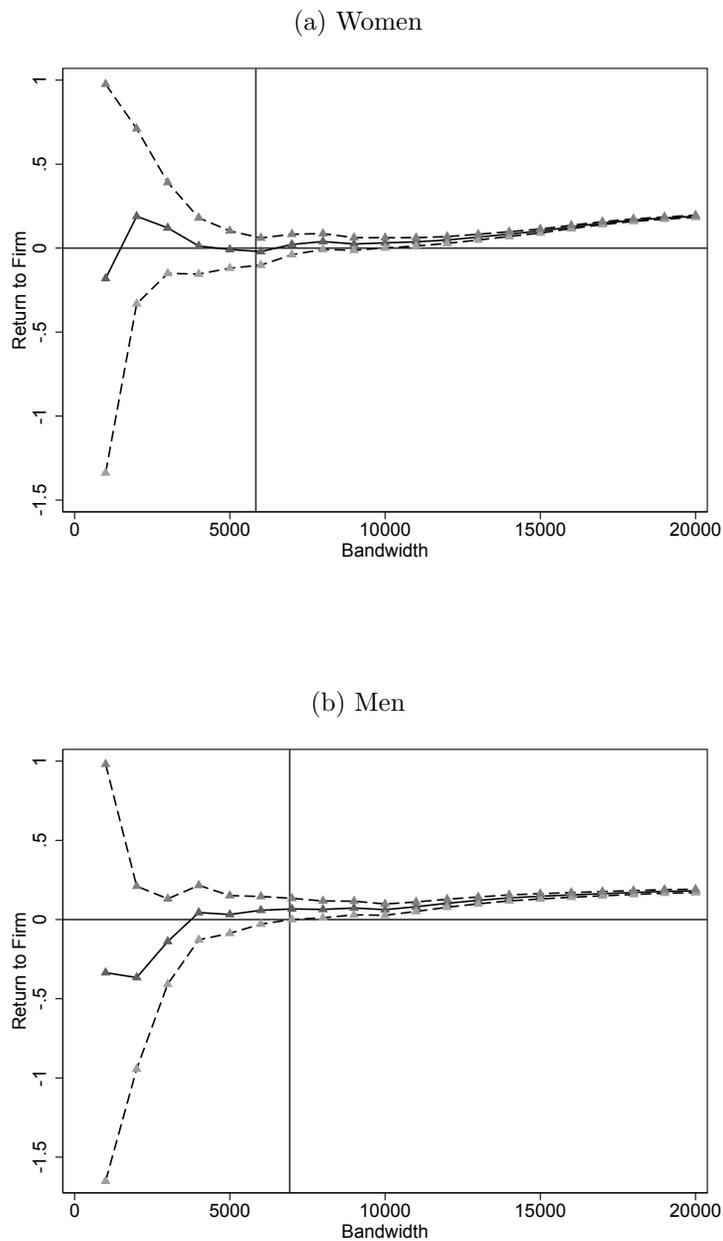
Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Figure A14: RK Estimates Using Different Bandwidths for Share Quarters Employed, Qtrs 4-7 Post-Claim



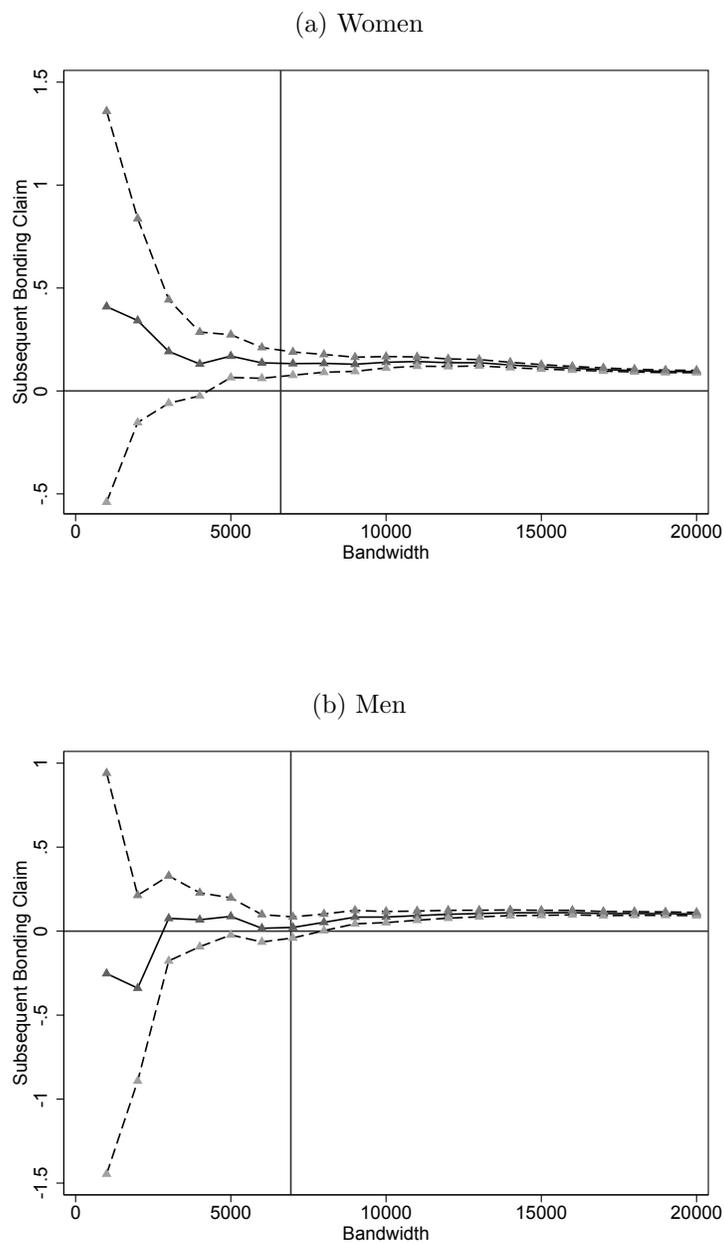
Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Figure A15: RK Estimates Using Different Bandwidths for Employment in Pre-Claim Firm, Qtr 4 Post-Claim



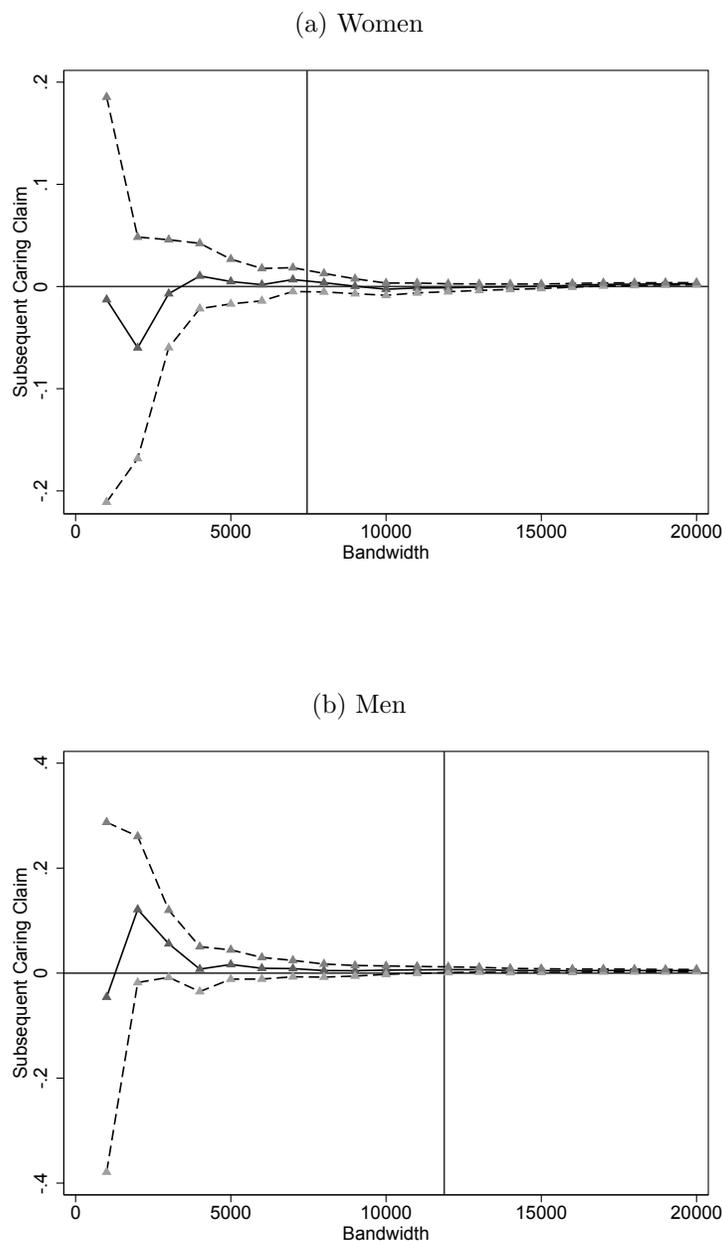
Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Figure A16: RK Estimates Using Different Bandwidths for Any Subsequent Bonding Claim



Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

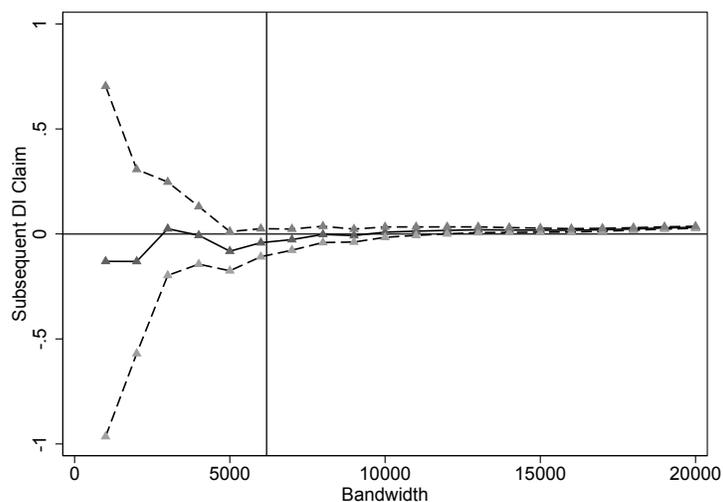
Appendix Figure A17: RK Estimates Using Different Bandwidths for Any Subsequent Caring Claim



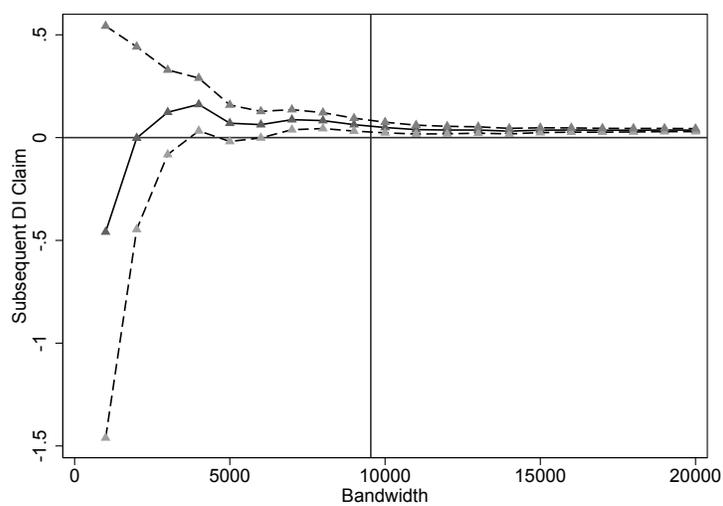
Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Figure A18: RK Estimates Using Different Bandwidths for Any Subsequent SDI Claim

(a) Women



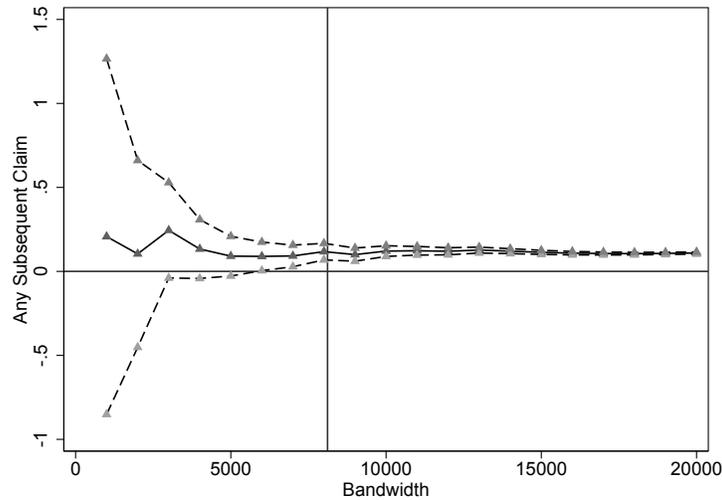
(b) Men



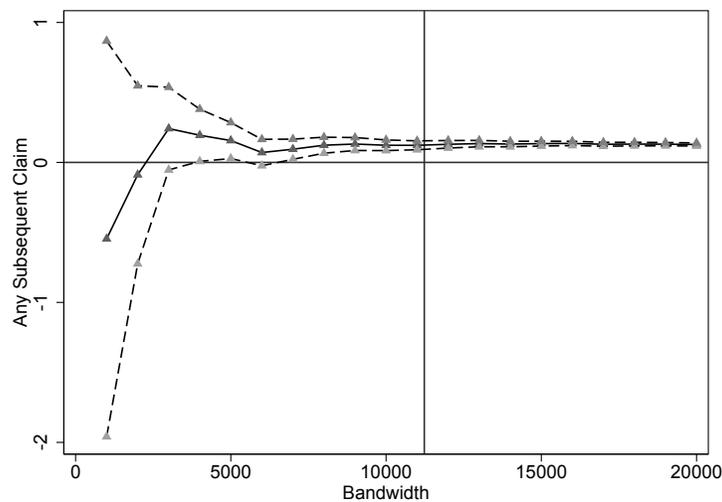
Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Figure A19: RK Estimates Using Different Bandwidths for Any Subsequent Bonding, Caring, or SDI Claim

(a) Women



(b) Men



Notes: These figures show the coefficients (as dark gray triangles) and 95% confidence intervals (as light gray triangles) from RK specifications that use different bandwidths in increments of \$1,000 of normalized quarterly base period earnings (denoted on the x -axis). The location of the fuzzy IK bandwidth is marked with the vertical line.

Appendix Table A1: RK Estimates of the Effects of PFL Benefits, Females, By Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Dur	Log Avg Earn	Share Qtrs Emp	Return Firm	Future Bond	Future Care	Future SDI	Future Any
A. Pre-Claim Employment in Firms with <50 Employees								
Log Weekly Benefit (\$2014)	0.000296 (0.0208)	-0.0753 (0.328)	0.0584 (0.0618)	-0.282** (0.135)	0.199*** (0.0499)	-0.00195 (0.00374)	0.0141 (0.0243)	0.148*** (0.0423)
Main Bandwidth	11554.5	4070.7	6348.4	4754.6	7544.0	10578.7	9900.7	8807.4
Pilot Bandwidth	13849.2	11242.4	11322.6	15097.4	14741.3	10423.1	11293.5	16039.2
First Stage Est x 10 ⁵	-6.470	-4.428	-4.904	-4.543	-5.253	-6.099	-5.874	-5.568
First Stage S.E. x 10 ⁵	0.0739	0.341	0.179	0.270	0.141	0.0826	0.0914	0.109
Dep. Var Mean	2.412	9.619	0.772	0.590	0.210	0.00317	0.127	0.297
N	56983	10045	19880	14135	22656	38485	34239	28343

B. Pre-Claim Employment in Firms with 50+ Employees

Log Weekly Benefit (\$2014)	-0.0120 (0.00985)	0.482* (0.249)	0.0708*** (0.0163)	0.100*** (0.00645)	0.171*** (0.0448)	0.00344*** (0.000827)	0.0179 (0.0261)	0.141** (0.0566)
Main Bandwidth	12919.5	3434.3	8785.4	15254.8	5833.9	17485.1	7448.3	5431.9
Pilot Bandwidth	10720.8	8646.5	9650.0	11442.0	14639.4	10211.9	10479.2	10478.7
First Stage Est x 10 ⁵	-5.893	-3.355	-4.555	-7.255	-4.015	-8.768	-4.337	-4.066
First Stage S.E. x 10 ⁵	0.0306	0.246	0.0561	0.0249	0.109	0.0222	0.0736	0.123
Dep. Var Mean	2.419	9.779	0.837	0.623	0.218	0.00687	0.168	0.344
N	264893	42363	130851	310755	74400	361505	97469	68962

Notes: Each coefficient in each panel is from a separate regression. The outcomes are: (1) log leave duration, (2) log of average quarterly earnings (in \$2014) in quarters 4-7 after the claim, (3) share of quarters employed in quarters 4-7 after the claim, (4) indicator for receiving positive earnings from pre-claim firm in quarter 4 after the claim, (5) indicator for any subsequent bonding claim in the three years after the claim, (6) indicator for any subsequent caring claim in the three years after the claim, (7) indicator for any subsequent (non-transitional) SDI claim in the three years after the claim, (8) indicator for any bonding, caring, or SDI claim in the three years after the claim. All regressions are estimated using the fuzzy IK bandwidth selector and local linear polynomials in normalized quarterly base period earnings (the assignment variable). We control for the following individual-level variables: age and age squared, dummies for firm size categories (1-49, 50-99, 100-499, 500+) of the pre-claim employer, and dummies for industry code of the pre-claim employer. 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, Males, By Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Dur Log Avg Earn Share Qtrs Emp Return Firm Future Bond Future Care Future SDI Future Any							
A. Pre-Claim Employment in Firms with <50 Employees								
Log Weekly Benefit (\$2014)	0.129 (0.0936)	0.710*** (0.0234)	0.0363 (0.0594)	0.0918** (0.0367)	-0.153 (0.171)	0.00214 (0.00442)	-0.0336 (0.0366)	-0.186 (0.164)
Main Bandwidth	9438.6	25013.0	7465.3	12289.2	4720.3	11758.6	9148.3	5179.6
Pilot Bandwidth	13898.5	11690.7	10260.2	36700.6	7756.3	10715.9	15229.1	13121.7
First Stage Est x 10 ⁵	-5.714	-10.10	-5.298	-6.629	-4.361	-6.415	-5.626	-4.532
First Stage S.E. x 10 ⁵	0.103	0.0560	0.156	0.0707	0.317	0.0721	0.109	0.269
Dep. Var Mean	1.083	9.246	0.844	0.596	0.162	0.00304	0.0765	0.227
N	14843	24078	9227	17010	4847	14150	10251	5431
B. Pre-Claim Employment in Firms with 50+ Employees								
Log Weekly Benefit (\$2014)	0.0652 (0.0728)	0.236 (0.170)	0.0698 (0.0480)	0.0695 (0.0499)	0.101*** (0.00688)	0.00709*** (0.00238)	0.0499*** (0.00448)	0.148*** (0.0271)
Main Bandwidth	5900.7	3357.6	4171.8	5711.5	16356.3	13368.3	18327.9	8543.7
Pilot Bandwidth	8428.4	11024.5	8263.0	8245.3	10961.5	13667.4	8783.8	7929.4
First Stage Est x 10 ⁵	-4.984	-4.646	-4.593	-4.952	-7.638	-6.711	-8.222	-5.473
First Stage S.E. x 10 ⁵	0.0882	0.209	0.144	0.0918	0.0204	0.0253	0.0190	0.0486
Dep. Var Mean	1.116	9.920	0.925	0.753	0.166	0.00905	0.113	0.288
N	56779	24571	32139	44730	123816	103554	132161	61975

Notes: Each coefficient in each panel is from a separate regression. The outcomes are: (1) log leave duration, (2) log of average quarterly earnings (in \$2014) in quarters 4-7 after the claim, (3) share of quarters employed in quarters 4-7 after the claim, (4) indicator for receiving positive earnings from pre-claim firm in quarter 4 after the claim, (5) indicator for any subsequent bonding claim in the three years after the claim, (6) indicator for any subsequent caring claim in the three years after the claim, (7) indicator for any subsequent (non-transitional) SDI claim in the three years after the claim, (8) indicator for any bonding, caring, or SDI claim in the three years after the claim. All regressions are estimated using the fuzzy IK bandwidth selector and local linear polynomials in normalized quarterly base period earnings (the assignment variable). We control for the following individual-level variables: age and age squared, dummies for firm size categories (1-49, 50-99, 100-499, 500+) of the pre-claim employer, and dummies for industry code of the pre-claim employer. 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