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ABSTRACT

California's Disability Insurance (DI) and Paid Family Leave (PFL) programs have become important sources of social insurance, with benefit payments now exceeding those of the state's Unemployment Insurance program. However, there is considerable inequality in program take-up. While existing research shows that firm-specific factors explain a significant part of the growing earnings inequality in the U.S., little is known about the role of firms in determining the use of public leave-taking benefits. Using administrative data from California, we find strong evidence that DI and PFL program take-up is substantially higher in firms with high earnings premiums. A one standard deviation increase in the firm premium is associated with a 57 percent higher claim rate incidence. Our results suggest that changes in firm behavior have the potential to impact social insurance use and thus reduce an important dimension of inequality in America.

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1 Introduction

The dramatic rise in U.S. inequality in recent decades has motivated a burgeoning literature on its causes and consequences along a number of dimensions, including wages (Acemoglu and Autor, 2011), income (Chetty et al., 2014), wealth (Saez and Zucman, 2016), health (Currie, 2011; Chetty et al., 2016), and family structure (Lundberg, 2015). When it comes to the growth in earnings inequality, recent research emphasizes the role of *employers*, finding that most of the increase is due to widening earnings dispersion between, rather than within, firms (Song et al., 2018). But less is known about the influence of employers on other aspects of inequality among Americans, or about *non-wage* differences between high-paying and low-paying firms. In this paper, we aim to understand how firms contribute to inequality in the use of public short-term leave-taking social insurance programs, which allow individuals to take partially paid leave for their own medical issues or to care for new children or ill family members.

A growing body of evidence demonstrates that access to temporary social insurance has beneficial labor market and health effects on workers and their families (e.g., Rossin-Slater, 2017; Olivetti and Petrongolo, 2017; Stearns, 2015; Carneiro et al., 2015), and can even generate positive externalities for the broader population (Stearns and White, 2018). However, the availability of short-term disability insurance (DI) and paid family leave (PFL) is highly limited in the United States. There is no federal legislation, and only five states have implemented public programs.[1] Most firms do not provide their own private benefits either, or if they do, they do not necessarily offer them to all of their employees. According to 2017 data, only about one third of all firms offer any paid maternity leave to workers, and only 17 percent offer paid paternity leave (Kurani et al., 2017). Overall, just 15 percent of workers have access to PFL and 39 percent have access to short-term DI.[2]

In addition to being limited, access to and the use of short-term social insurance in the U.S. is highly unequal. Only 6 and 19 percent of workers in the bottom quartile of the wage distribution have access to employer-provided PFL and short-term DI, respectively, compared to 25 and 54 percent of workers in the top quartile. Even in states with government programs, not all workers are equally able to take advantage

[1] California, New York, New Jersey, and Rhode Island have both short-term DI and PFL programs. Hawaii has a short-term DI program but no PFL. Washington state, Washington, D.C., and Massachusetts have enacted paid family and medical leave legislation set to go into effect in the coming years.

[2] Source: Bureau of Labor Statistics, National Compensation Survey, March 2017, https://www.bls.gov/ncs/ebs/benefits/2017/benefits_tab.htm.

of public benefits. For instance, despite the almost universal eligibility of workers in California, DI and PFL take-up rates are still substantially different across industries, firm sizes, and earnings quartiles for both men and women (Bana et al., 2018a). As most workers learn about public social insurance benefits through their employers, and polls document that lack of awareness about these programs is a major barrier to take-up (DiCamillo and Field, 2015), insights into the relationship between firm characteristics and program use are critical for understanding the drivers of these disparities.

This paper uses ten years of administrative data from California to provide the first evidence on the role of firms in explaining differences in short-term social insurance take-up. Drawing on a well-established literature that demonstrates that observably similar firms pay observably similar workers different wages (i.e., employer-specific wage premiums, or "firm fixed effects") (see, e.g.: Abowd et al., 1999; Card et al., 2013, 2016; Barth et al., 2016; Card et al., 2018; Sorkin, 2018; Song et al., 2018), we analyze the relationship between the employer earnings premium and the share of employees within a firm who take DI or PFL in any given year. Whether firms with higher earnings premiums are more or less conducive to benefit take-up is theoretically ambiguous. Workers at higher premium firms might face a higher opportunity cost of taking leave, or be more likely to have access to private DI or PFL benefits that could crowd-out the use of public programs. But employers that offer private benefits may have a particularly strong incentive to encourage public benefit take-up, as it can lower the cost to the firm. Higher earnings premium firms—which are likely to be more innovative and productive than their lower-premium counterparts (Van Reenen, 1996; Faggio et al., 2010; Barth et al., 2016)—may also view their wage setting policies as complements to creating a workplace culture conducive to leave-taking.

To answer this question, we combine two data sets from the California Employment Development Department (CA EDD): the universe of DI and PFL claims over fiscal years 2004-2013, and quarterly earnings data for nearly all California employees from 2000 to 2014. Our empirical strategy involves two main steps. First, we estimate employer earnings premiums using the seminal Abowd, Kramarz and Margolis (1999) (AKM) methodology that includes both worker and firm fixed effects to account for non-random sorting of workers across firms. Second, we aggregate the data to an employer level panel and estimate Poisson regressions of the number of social insurance claims within a firm in a given year on the firm earnings premium, controlling for firm size, industry and year fixed effects, and the percentage of female employees in each industry-year.

We find strong evidence that public temporary social insurance program take-up is higher in firms with relatively higher earnings premiums. A one standard deviation increase in the firm earnings premium is associated with a 57 percent increase in the incidence rate of claims. The effect of the firm premium is similar for claims made by men and women, and exists for both DI and PFL. We also show that the effect is largest for workers in the lower half of the employer-specific earnings distribution, suggesting that a firm's premium is particularly important in determining the non-wage benefit use of its lowest-earning employees. Although high-premium firms have higher claim rates relative to low-premium firms, they also have lower average leave durations and higher employee retention rates following periods of leave.

The results indicate that characteristics of firm culture that are reflected in the firm earnings premium may be key to increasing take-up rates of public social insurance in California. If all firms behaved as those in the top third of the firm premium distribution, a back-of-the-envelope calculation suggests that take-up rates for DI and PFL would increase by 25 and 29 percent, respectively.[3] By contrast, prior research demonstrates that specific policy levers—such as the wage replacement rate—have limited effects on take-up. Ziebarth (2013) shows that changes in wage replacement rates do not significantly affect take-up rates of a DI program that covers work absences longer than six weeks, while Ziebarth and Karlsson (2010) find that a large cut in the sick pay replacement rate in Germany had a relatively small impact on leave use, and only for a sub-group of workers with a limited history of work absences. In Japan, Asai (2015) finds that an increase in the maternity leave wage replacement rate has no effect on job continuity or leave duration among new mothers. Finally, in California, Bana et al. (2018b) show that a higher replacement rate does not increase PFL duration among high-earning mothers.

Our paper contributes to a growing literature on the determinants of public short-term leave take-up, which in the U.S. has mostly focused on the implementation of California's first-in-the-nation PFL program in 2004 (Rossin-Slater et al., 2013; Das and Polachek, 2015; Baum and Ruhm, 2016; Bartel et al., 2018).[4] Outside the U.S., many studies examine the effects of extensions in PFL policies (or,

[3]These calculations assume that claim rates are specific to three firms sizes (5-24, 25-99, and 100+ average employees), seventeen industries, and three terciles. The thought experiment reported here increases the claim rate in the first two terciles to the third tercile within specific firm size and industry categories. In other words, differential claim rates by firm size and industry are held constant.

[4]The small literature on state DI programs is largely focused on pregnacy-related coverage. Stearns (2015) exploits a law that required state DI programs to start covering pregnancy as a disability to look at the impact of benefits on infant health. Campbell et al. (2018) estimate the impact of pregnancy coverage under DI in Rhode Island on maternal labor supply and other outcomes. There is also a substantial literature on the effects of long-term disability (which covers permanent withdrawal from the labor market) on labor supply in the U.S. (e.g., Gruber, 2000; Autor and Duggan, 2003; Chen and van der Klaauw, 2008).

less frequently, introductions of new programs) on parental leave-taking and labor market outcomes (see Rossin-Slater, 2017; Olivetti and Petrongolo, 2017 for recent overviews), but less is known about the use of temporary DI programs. In general, the existing studies find that very short-term sick leave use is positively correlated with the generosity of the benefits, while the relationship with longer periods of leave is less clear (Pettersson-Lidbom and Thoursie, 2013; Henrekson and Persson, 2004; Johansson and Palme, 2005; Dale-Olsen, 2014; Ziebarth and Karlsson, 2010; Ziebarth, 2013).

Moreover, we know little about other *non-policy-driven* determinants of temporary social insurance take-up.[5] Research on the importance of workplace culture in promoting work-family balance often relies on case studies and small samples, and cannot shed light on the characteristics of firms that support benefit take-up on a broader scale (Clark, 2001; Kelly et al., 2011; Moen et al., 2016). More relevant to our work, Dahl et al. (2014) find large peer effects in the take-up of publicly provided paternity leave in Norway, arguing that increased knowledge about employer reactions to leave is a primary mechanism. A separate literature on firm-specific premiums has quantified their importance in driving wage inequality (Card et al., 2013, 2016; Song et al., 2018), but less is known about non-wage differences between high-premium and low-premium firms.[6] This paper bridges this gap by documenting a strong and robust association between employer earnings premiums and the use of temporary paid leave. Our findings suggest that firm-specific factors not only explain a substantial part of earnings dispersion, but also drive disparities in the use of public social insurance benefits.

2 Temporary Social Insurance in California

California's State Disability Insurance (SDI) is a partial wage-replacement insurance plan for workers in the state. Participation in the SDI program is mandatory for most private sector employees, and over 18 million workers are currently covered. The SDI program is funded entirely through employee payroll

[5] There is a small literature on the correlates with absenteeism, but these papers focus on very short-term absences (e.g., individual days) and are not necessarily relevant for studying PFL or DI. In these settings, absenteeism is often used as a proxy for effort. Dionne and Dostie (2007) find workplace conditions, including standard schedules, work at home options, and reduced workweeks are correlated with reduced absenteeism. Employment protection increases absenteeism as well (Riphahn, 2004; Ichino and Riphahn, 2005).

[6] Several recent papers examine the role of between- and within- firm factors on the gender wage gap. Hotz et al. (2017) show that exogenously moving mothers to more family-friendly firms would shrink the gender gap in wages and income. Coudin et al. (2018) show that sorting of workers inter firms explains more of the gender wage gap than bargaining in France, and Bruns (2018) shows high-wage firms disproportionately employ men in Germany.

tax deductions and currently consists of two types of benefits: Disability Insurance (DI) and Paid Family Leave (PFL). Work requirements for coverage are quite low. Eligible individuals must have earned at least $300 in taxable wages in a base period 5 to 18 months before the start of the claim, and eligibility is not employer-specific. The 2018 SDI tax rate is 1 percent on the first $114,967 earned, and is not experience rated. During a claim, workers receive 55 percent of their base period earnings, up to a maximum weekly benefit amount.[7]

The DI program was established in 1946 to provide short-term benefits to California workers who experience a loss of wages when they are unable to work due to a non-work-related illness or injury.[8] In 1978, the federal Pregnancy Discrimination Act required that states with DI programs start covering pregnancy as a disability. Birth mothers in California are eligible for four weeks of DI benefits in the period prior to their expected due date, and six weeks of benefits to recover from a vaginal, uncomplicated childbirth (benefits can be extended by two weeks if the delivery is by Cesarean section, or longer if there are other complications). The maximum length of a DI claim for any reason is 52 weeks, though the average claim duration is around 16 weeks. Pregnancy/childbirth-related claims account for approximately one quarter of all DI claims. There is a seven-day non-payable waiting period that must be served for all claims, which reduces the moral hazard problem associated with many sick leave programs. Claimants must also have a physician certify the disability. Workers are only eligible for benefits if they are losing income during their absence, but firms can "top off" DI benefits through employer-provided paid sick leave or other forms of paid time off up to the equivalent of the worker's full salary.

In July 2004, California introduced its PFL program for new parents and caregivers. Eligible workers can take up to six weeks of partially paid leave to bond with a newborn or newly adopted child or to care for a seriously ill family member. The PFL program is structured in the same way as DI, with identical earnings eligibility requirements and wage replacement rate schedules. Both men and women can use the six weeks of PFL, while birth mothers can separately claim both DI and PFL for a total of 16 to 18 weeks of partially paid maternity leave. Between 2004 and 2013, about 90 percent of PFL claims were for bonding with a new child; the remainder were for caregiving purposes. Roughly 74 percent of PFL claims were filed by women, although the gender gap has narrowed over time.

[7] As of January 1, 2018, the wage replacement rate has increased to 60-70 percent. The 2018 weekly maximum benefit is $1,216.

[8] Work-related injuries are covered under the Worker's Compensation Insurance program, which is separate from DI.

Paid leaves under DI and PFL are not directly job protected, although 12 weeks of job protection is available if the job absence simultaneously qualifies under the federal Family and Medical Leave Act (FMLA) or California's Family Rights Act (CFRA).[9] The lack of job protection may be a significant barrier to DI and PFL take-up for some workers. Other workers may choose not to use available benefits due to career concerns, or because they are unable to afford to take time off with only partial wage replacement.

The firm environment can also play a critical role in determining whether or not employees choose to take leave. Many workers—especially those who are low-income—only hear about government social insurance programs through their employers, if at all (Winston et al., 2017). A survey of a random sample of California registered voters shows that in 2014, a decade after PFL went into effect, only 36 percent of respondents were aware of the program (DiCamillo and Field, 2015). Thus, employers can potentially increase take-up through simply providing their workers with information on the government benefits available to them.

Whether or not California employers have an incentive to encourage eligible workers to use DI and PFL benefits is ambiguous. On one hand, the program provides partially paid leave to workers at no direct cost to firms. Employers do not have to pay workers during the absence, nor do they pay the taxes that finance the program. Thus, SDI allows firms to offer workers the opportunity to take partially paid leave for family or medical reasons in a relatively cheap way.

On the other hand, worker absences may be costly for firms in other ways. Even if firms do not pay workers for time spent absent from work, productivity may be lower when regular employees are gone, or employers may have to hire temporary replacements. If these costs are high enough, firms may actively discourage workers from utilizing the benefits to which they are entitled. While workers at large firms are legally protected under the FMLA and CFRA during absences of up to 12 weeks, employers may discourage take-up in other ways. For example, they may create a culture where leave-takers are passed over for future promotions, experience slower wage growth, or are assigned less desirable tasks upon their return to work.

[9]The FMLA was enacted in 1993 and provides 12 weeks of unpaid job protected family and medical leave to qualifying workers. To be eligible for the FMLA, workers must have worked at least 1,250 hours in the preceding year for an employer with at least 50 employees (within a 75 mile radius of the employment location). The CFRA is nearly identical to the FMLA in its provisions and eligibility criteria.

3 Data

We merge data from two administrative data sets available to us through an agreement with the California Employment Development Department (EDD). The first data set is the universe of DI and PFL claims from fiscal year 2004 to 2013. For each claim, we have information on the type of claim (DI, bonding with a new child, or caring for an ill family member), the claim filed and claim effective dates, the total benefit amount received, the authorized weekly benefit amount, the employee's date of birth and gender, and a unique employee identifier. For women with a PFL bonding claim, we also have an indicator for whether there is an associated DI claim for that birth.

The second data set consists of individual-level quarterly earnings data over 2000-2014 for the universe of employees working for an employer that reports to the EDD tax branch.[10] In addition to the employee identifier (which we use to link to the claims data), it includes earnings in each quarter and in each job, a unique employer identifier associated with those earnings, and the North American Industry Classification System (NAICS) industry code associated with the employer. As with most administrative earnings data sets, demographic characteristics about the workers are unavailable. We know worker age and gender only for those individuals who ever file a DI or PFL claim in this period.

3.1 Key variables

Because we are interested in the role of firms in social insurance benefit take-up, we collapse the individual-level data to an employer-level panel. For each employer, we calculate average employment and total earnings in each fiscal year (July-June).[11] We then use the claims data to measure the total number of claims taken within a firm in each year.[12] Since eligibility for DI and PFL benefits is determined using base period earnings and not current employment, we link each claim to the individual's employer in the quarter immediately preceding the start of the claim. Therefore, we are attributing the leave to the firm at

[10]Employers that employ one or more employees and pay wages in excess of $100 in a calendar quarter are required to report to the EDD according to California law.

[11]We conduct the analysis using fiscal years because PFL became available on July 1, 2004. Our analysis includes fiscal years 2004-2013 (and uses data on claims from July 1, 2004 to June 30, 2014). We have information on DI claims since 2000, and results including these earlier years are very similar. However, in order to be able to better compare the results across different types of claims, the main analysis is limited to the years in which both programs are available.

[12]As mentioned in Section 2, birth mothers are eligible to take both DI and PFL for a total of 16 weeks of leave, and this is recorded as two separate claims in the data. From the perspective of both the firm and the mother, this is often taken as a single, continuous period of leave. To avoid double counting leaves taken by these women, we treat associated DI and PFL claims as a single event in the total count of claims.

which the individual worked at the point when he or she most likely decided to make the claim.[13]

We also calculate the number of claims separately by type and gender. Our key dependent variables are: the total number of claims of any type by gender of the claimant, the number of DI claims by gender, the number of bonding claims by gender, and the number of caring claims by gender. If firms care only about the total number of worker absences and do not differentiate between leaves taken for different reasons, then counting the total number of claims within a firm is reasonable. But we also separate out claims by type because firms may have different attitudes toward leaves related to childcare, family member care, and own health issues, and the effect of the firm premium may differ as well.[14] We separate claims by gender because the overall take-up rates are quite different, and firms may treat male and female employees differently in terms of norms regarding work absences.

To study leave duration and post-leave employment outcomes, we calculate the average leave duration within the firm (conditional on the firm having at least one claim), the share of the firm's claimants that return to work in the firm or in any job within five quarters following the start of the claim, and the average change in log real earnings of claimants between the quarter preceding the leave and the fifth quarter following the start of the claim.[15]

3.2 Sample restrictions

We make several restrictions on our analysis sample. First, we exclude firms whose average employment over 2004-2013 is less than 5 employees. We do so because self-employed workers (including independent contractors), individuals who are employers in sole proprietorships or partnerships, and individuals in family employment are not required to participate in the SDI program, and thus are not automatically eligible for benefits. Additionally, the probability of having a claim in any given year is close to zero for very small firms.[16] Second, because some public sector employees and domestic workers are not covered by SDI, we exclude firms in the three industries least likely to be subject to SDI coverage:

[13] Some individuals do not have reported earnings in the quarter preceding the claim. For these individuals, we use the employer from two quarters before the claim. This constitutes 3.3 percent of the sample.

[14] Although women who make associated DI and bonding claims are only counted once in the total claims measure, they are counted as having both a DI and a bonding claim in the counts by claim type. Therefore, the total number of claims is not equal to the sum of the other three measures.

[15] We use five quarters because the maximum length of a DI claim is 52 weeks. Doing so ensures that none of the firm's claimants are still on leave for the relevant claim.

[16] This restriction drops 68 percent of employer-year observations, but only 7.5 percent of workers. Results are qualitatively and quantitatively similar when only single-person firms are excluded, as shown in Appendix Table A3.

elementary and secondary schools, public administration, and private households.

Third, since our main variables of interest are constructed by summing counts over quarterly data, we exclude the 3.8 percent of firm-year observations where the firm is not observed in all four quarters of a given fiscal year. In practice, this restriction implies that we often exclude the year that a firm enters or exits the market. This exclusion is also important because former employees of firms that shut down may be more likely to make a DI or PFL claim as a way to effectively extend unemployment insurance benefits. As we seek to understand how the firm premium affects the likelihood that its current workers make claims, the behavior of workers following a firm closure is not of primary interest in this paper. Finally, as described below, the sample is limited to firms for which we can estimate a firm fixed effect. This restriction effectively excludes firms that are not connected by worker mobility in the sample period (see Section 4 for more detail).

3.3 Summary statistics

Our main analysis sample includes 2,709,253 firm-year observations. Table 1 shows summary statistics for our main variables of interest. The first row shows the average firm claim rate by claim type. Because overall take-up rates differ substantially by gender, the first four columns show female claims, and the next four columns show male claims. When calculating rates, the denominator is total firm size in the year, as we do not observe the gender of non-claimants in the data. The female overall and DI claim rates are significantly higher than the male claim rates. Even accounting for the fact that only women can file a DI pregnancy-related claim, women are still more likely than men to make a DI claim. This pattern is true for bonding and caring claims as well.

The remaining rows of Table 1 show the mean claim rate by firm size groups, select large industries, and terciles of the firm fixed effect distribution used to estimate firm quality (as described below). Larger and higher fixed effect firms both have higher claim rates, previewing the regression results to come. There is also substantial variation in the firm-level claim rates across industries. Firms in low-skill industries such as retail trade and accommodation and food services have relatively low claim rates. Firms in the healthcare and construction industries both have high female claim rates of about 6.2 percent (for any claim), despite a dramatic difference in the gender composition across the two industries. For context, only 9 percent of California construction workers between 2004 and 2013 were female, compared with

75 percent of workers in the healthcare industry. The age distribution of workers is less dispersed across industries. Between 40 and 56 percent of workers in each industry are of childbearing age (age 20-39), and 27-50 percent are age 40-59. Firms in accommodation and food services have the smallest share of workers above age 40, while health care and manufacturing firms have the largest share. The vast majority–92 percent–of bonding claims are made by workers age 20-39, while workers who make caring claims are somewhat older on average. Women of childbearing age are more likely to make a DI claim than older women, but the opposite is true for men. If 25 percent of all DI claims are for childbirth as estimated by Chang (2015), then the non-childbearing related DI claim rates are approximately 36 percent lower for younger compared to older women. This is very similar to the percentage difference in DI claim rates for older and younger men.

Although we do not observe the gender or age composition of employment at the firm level, we do know the demographic characteristics of California workers during this period at a more aggregate level. There are approximately 6.3 female claims per 100 female workers in California, compared to 2.7 male claims per 100 male workers. Female-specific claim rates are again higher than male claim rates for all types of claims. Gender-specific claim rates vary across industries, with health care having the highest any claim rate for both men and women. Importantly, while the levels differ, the pattern of the gender-specific claim rates across industries are similar for men and women. This suggests that the differences in firm-level claim rates in Table 1 are not driven by differences in worker composition across different types of firms. Appendix Table A1 shows these gender-specific claim rates for workers in California.

4 Empirical Strategy

Our empirical strategy is comprised of two main steps. First, we estimate firm-specific earnings premiums, following the methodology originally proposed by Abowd, Kramarz and Margolis (1999) and subsequently used by a growing literature on the role of firms in explaining earnings variance (Abowd et al., 2003; Card et al., 2013, 2016; Macis and Schivardi, 2016; Lavetti and Schmutte, 2016). The idea is to characterize the natural log of earnings as a function of additive worker and firm fixed effects. The model is identified by job switchers, and predicts that the average earnings change of individuals who move from a low to a high fixed effect firm will be opposite of the average earnings change of individuals who move from a high to a low fixed effect firm.

Specifically, we use our quarterly earnings data from 2000 to 2014 to estimate:

$$E_{ijq} = \alpha_i + \phi_{j(i,q)} + \gamma_q + \varepsilon_{ijq} \tag{1}$$

where E_{ijq} is the log quarterly earnings of worker i with primary employer j in quarter q.[17] The variable α_i is an individual fixed effect, which captures any time-invariant characteristics of the worker that are rewarded equally at all firms. The firm fixed effect, $\phi_{j(i,q)}$, represents the earnings premium that firm j pays to all workers relative to a randomly chosen reference firm.[18] We also flexibly control for aggregate time trends in earnings through quarter fixed effects, γ_q, and ε_{ijq} is an error term.

To reduce the computational burden, equation (1) is estimated using every third quarter of data from the first quarter of 2000 through the fourth quarter of 2014.[19] Because we are estimating both worker and firm fixed effects, $\phi_{j(i,q)}$ is identified only within a "connected set" of employers. A group of workers and employers is connected if the group includes all workers who ever worked for any employer in the group and all employers at which any worker in the group was ever employed. We restrict the analysis to the largest connected set, which includes 97.8 percent of firms and 99 percent of workers in the sample of movers (workers observed at more than one firm over time) in California during this period.[20]

A central identifying assumption for estimating unbiased firm fixed effects is that mobility across firms is unrelated to unobserved determinants of earnings changes among workers. This assumption would be violated if, for instance, workers who were becoming more productive were systematically moving to only certain types of firms. Additionally, model (1) assumes additive separability in the firm and worker fixed

[17]Because some individuals have earnings from multiple employers in the same quarter and we do not observe hours worked, we link workers to the firm at which they have the highest earnings in that quarter. The variable E therefore measures firm-specific earnings in an individual's highest earning job. Appendix Table A2 shows summary statistics for the AKM model.

[18]Ideally, we would control for total worker experience, but we do not observe employment history prior to 2000. We have also estimated a specification that controls for the worker's cumulative quarters of experience since the first quarter of 2000. The adjusted R^2 of equation (1) only increases by about 1 percentage point when this measure is included. Fixed effects generated with the inclusion of this experience measure produce results very similar to our main results, as shown in Appendix Table A4.

[19]The estimation approach mirrors the Card et al. (2013) algorithm by extracting the sample of workers who changed firms, finding the largest connected set and estimating the fixed effects using numerical methods. We modify Matlab code available on Patrick Kline's website: `http://eml.berkeley.edu//~pkline/papers/code_CHK.zip` (retrieved 12/27/2017). We use the full period of earnings data to estimate the fixed effects in order to maximize the number of observations per firm. We have also estimated fixed effects using only data from every quarter 2000-2004. Results are similar and are shown in Appendix Table A5.

[20]Although the connected set consists of almost all firms and workers within the sample of movers, not all workers change employers between 2000 and 2014. The connected set includes 90.4 percent of all firms and 60.6 percent of all workers in California during this period.

effects.

As evidence of the plausibility of these assumptions, we follow Card et al. (2013) and Card et al. (2018) and plot mean log earnings for workers in six and three quarters before, the quarter of, and three quarters after a job switch in Figure 1. We categorize workers into groups based on the mean earnings quartile of other workers in the old and new firms. Specifically, we classify the earnings quartile of the old job based on mean coworker earnings in the last year at that job, and the earnings quartile of the new job based on mean coworker earnings in the first year at the new job. Job changers are then assigned to one of 16 cells based on the quartiles of the old and new firms. For ease of exposition, Figure 1 only shows the earnings trajectories for workers in the eight cells that start at a firm either in the lowest or highest quartile.

The figure shows that, as expected, workers who start in the lowest and highest quartile firms have different initial earnings levels. However, among workers who start out in a firm in the bottom coworker earnings quartile, moving to a firm with higher coworker earnings raises own earnings. Analogously, among those who start in a firm in the top coworker earnings quartile, a move to a lower quartile firm leads to lower own earnings. Those who move to a firm in the same quartile experience very little change in earnings on average. There is no evidence of any transitory change in earnings in the year before or after a move, which, as Card et al. (2013) point out, suggests that the time-varying residual is uncorrelated with mobility. Further, the symmetry of the gains for those who move from the first quartile to a higher quartile and those who move down from the top quartile suggests that a simple additive model of worker and firm fixed effects is reasonable.

The estimated firm fixed effects, $\hat{\phi}_j$, can then be used to evaluate the relationship between the firm earnings premium and paid leave benefit take-up. We first standardize the firm fixed effects, and then estimate the effect of the firm's earnings premium on the number of DI or PFL claims in a firm-year using a Poisson model:

$$Claims_{jnt} = \beta\hat{\phi}_j + \delta ln(size)_{jt} + \psi PctFemale_{nt} + \theta_n + \eta_t + \epsilon_{jnt} \tag{2}$$

where $Claims_{jnt}$ is the number of claims in firm j in industry n and fiscal year t. The variable $ln(size)$ represents a firm's average quarterly employment over the fiscal year, $PctFemale$ is the percentage of female employees in the industry-year, and θ_n and η_t are industry and fiscal year fixed effects, respectively.[21] The coefficient of interest, β, captures the effect of a one standard deviation increase in the firm earnings premium on the annual number of claims within the firm. To account for both the over-dispersion in the data and the fact that $\hat{\phi}_j$ is a generated regressor, standard errors are bootstrapped 200 times.[22]

In order to interpret β as the causal effect of the firm earnings premium on the number of claims, the estimated firm fixed effect cannot be correlated with any other unobservable determinants of claims. One particular concern in this context is that we do not know what proportion of the firm's workforce is eligible to file a claim in any given year. While we assume that all of the firm's employees pay into the SDI system, not all workers will have a child and be eligible to make a bonding claim. Similarly, even if all workers are eligible to potentially receive DI benefits, they need to experience a non-work-related illness or injury in order to actually file a successful claim. We are therefore assuming that, conditional on firm size, industry, and year, the firm earnings premium is uncorrelated with other demographic characteristics of the firm that would affect the number of claims.

While this assumption is untestable in our data, we show that the effects of the firm premium are robust across type of claim and observable firm characteristics. Moreover, prior research suggests that the types of workers who are most likely to be eligible to take paid leave—e.g., women, who are more likely than men to need leave for childbirth, bonding with a new child, or elder care—are over-represented in low-premium rather than high-premium firms (Card et al., 2016). Thus, if anything, an unobserved correlation between firm demographics and the firm-specific premium would bias us toward finding a negative association between the firm premium and the leave-taking claim rate, which is the opposite of what we show below. To further address concerns about sorting, we also aggregate the data to the industry level and estimate regressions with and without industry-level controls in Section 5.3. This industry-level analysis suggests that our main results are unlikely to be driven by sorting of workers into firms.

Lastly, we test for effects on a large number of outcomes. This creates a multiple inference problem because the probability of making at least one Type I error due to sampling variability is increasing in the number of estimates. We use the Bonferroni method to adjust the p-values to account for the multiple

[21] Data on the percent of female employees in an industry-year in California comes from the 2004-2013 American Community Survey.

[22] If the left-hand side variable is over-dispersed, as is the case here, the Poisson model will still produce a consistent estimate of β. The variance matrix can be consistently estimated using robust standard errors, and bootstrapping produces standard errors that are asymptotically equivalent to the robust standard errors (Cameron and Trivedi, 2013). Bootstrapping in this setting is extremely computationally intensive, but we have estimated the main results using 400 bootstraps and standard errors are almost identical.

testing problem. This method controls the Family Wise Error Rate (FWER), which is the probability of rejecting at least one true null hypothesis. The Bonferroni correction multiplies each p-value by M, the total number of tests performed on a particular independent variable that are reported in all regular and appendix tables. This ensures that the overall Type I error rate is maintained when performing all M independent hypothesis tests. For example, for an estimated coefficient to be significant at the 1 percent level, we would need a p-value, p, such that $p * M \leq 0.01$. The downside of the method is that it suffers from poor power. As the number of hypotheses increases, the probability of Type II errors (failing to reject the null when there is an effect) also increases. However, because of the size of our data set, the estimated effects are quite precise and this loss of power is less of an issue than in other settings.

5 Results

5.1 Firm-specific premiums and leave-taking rates

Table 2 shows the effect of the firm earnings premium on the number of DI and PFL claims made by employees of the firm in a given fiscal year. The reported coefficients from the Poisson model are incidence rate ratios, obtained by calculating the exponential of the Poisson regression coefficients. Standard errors are similarly transformed. The first column shows that a one standard deviation increase in the firm premium is associated with a 56.9 percent increase in the firm's overall claim rate for any type of claim for both men and women. This effect is estimated with high precision, and the 95 percent confident interval allows us to rule out effects smaller than 54.2 percent.

The remaining columns of Table 2 show the effects on the number of claims by gender and claim type. The results present a remarkably consistent story. Higher premium firms have higher claim rates regardless of the type of claim or the gender of the claimant. The percentage effects are somewhat larger for male claims than female claims, and for PFL claims compared to DI claims. These results are not driven by sample restrictions or choices involving the estimation of the firm fixed effects. Appendix Tables A3-A5 show the results are robust to including very small firms with 2-4 employees, including observed worker experience in the estimation of the AKM fixed effects, and estimating the fixed effects using only data from 2000 to 2004 (prior to the start of the main estimation sample).[23]

[23]We have also estimated a specification that includes a measure of firm skill level as an additional control. We measure

Table 3 presents analogous results to Table 2, separated into claims made by younger and older workers. The first panel shows the effect of the firm premium on the number of claims among workers ages 20-39. These workers are of childbearing age, and make 92 percent of bonding claims in the estimation sample. About 50 percent of DI claims and 33 percent of caring claims are made by individuals in this age group as well. The second panel shows the effect on the number of claims to workers ages 40-59. These older workers make 40 percent of DI claims and 56 percent of caring claims, but only about 6 percent of bonding claims. While the underlying incidence rates of claims differ across these age groups, the estimated incidence rate ratios of the effect of working for a higher premium firm are similar to the overall results in Table 2 for both younger and older workers.

In order to explore if these effects are driven by certain firm characteristics, Table 4 shows the effects of the firm premium on the number of claims by firm size and industry. We present results for six firm size groups and the six largest industries, and estimate separate regressions for each group. The results suggest that the effects presented above are not driven by any one particular group. Although the effect of the firm premium is generally increasing in firm size, the effect sizes are economically and statistically significant for even the smallest firms. Interestingly, we do not find substantial differences in the effect of the firm premium on firms with just above versus just below 50 employees. This firm size cutoff is relevant because of eligibility for job protection under the FMLA and CFRA.[24] This pattern indicates that extending access to job protection may not be enough to reduce the gaps in leave take-up across different types of firms.

There is more variation in the importance of the firm premium across industries. Table 4 shows the effects on female claims are largest for firms in the construction sector, while the effects on male claims are largest in accommodation and food services. In general, the effects are consistently positive across industries. The one exception is that the effect of the firm premium on female claims is actually negative for manufacturing firms. Manufacturing firms with a one standard deviation higher fixed effect have 51

average skill by taking the average of the individual fixed effects (estimated in equation 1) of the firm's employees over the entire sample period. The estimated effects of the firm premium on the number of claims are very similar with this added control. This again suggests that the sorting of workers into firms is not driving the results. This measure of firm skill level is not included in our main specification because we can only estimate individual fixed effects for movers in the connected set, and so it does not capture the average skill of all workers in the firm. However, these results are available upon request.

[24]Our measure of firm size is averaged over time, and therefore not a perfect proxy for FMLA/CFRA eligibility. Additionally, FMLA/CFRA eligibility requires the employer to employ 50 or more employees within 75 miles of the work site, whereas we observe total firm size and not establishment size or location.

percent fewer female claims overall, and the firm premium has no significant effect on the number of male overall or DI claims.[25] There is also no significant effect of the firm premium on DI claims among male workers in the professional, scientific, and technical services industry, but the effects for male PFL claims and all types of female claims are positive and significant. Overall, while there is variation in the effect sizes across industries, there is no clear correlation between the firm premium and industry skill or other industry characteristics.

The results presented so far show that high premium firms have higher leave-taking rates, and these results are consistently significant across claim type, and the gender and age of claimant. The results are also not driven by any particular industry or firm size group. The robustness of the effects of the firm earnings premium on claim rates suggests that the relationship is unlikely to be solely driven by sorting into certain types of firms by workers who need leave. Instead, the similarity of our findings across worker and firm characteristics is more consistent with the interpretation that firm-specific culture—which is associated with the earnings premium—is an important predictor of paid leave use.

However, one may still be concerned that the results are driven by only the highest skilled workers within the firm. If high-premium firms are more supportive of only their top workers taking leave, but are less inclined to support the low-earning workers, then the role of firms in reducing inequality in leave take-up may be less important than it appears. To examine this possibility, we estimate the effect of the firm premium on claims in each quartile of the *firm-specific* earnings distribution in Table 5. We find that the firm premium has the strongest effects on the number of claims made by workers in the lower half of the within-firm earnings distribution. In fact, the effects are monotonically *decreasing* in the within-firm earnings quartile. A one standard deviation increase in the firm premium leads to more than a 100 percent increase in the claim rate for all types of claims among workers in the bottom quartile. But the effects of the firm premium on the number of claims in the top quartile are much smaller. For female overall and DI claims, the estimates are actually significantly negative, although relatively small.

As high-ranking employees are the most likely to have access to employer-provided leave benefits and/or flexible schedules, firms appear to play a bigger role in determining public social insurance take-up among workers toward the bottom of the earnings distribution. The results in Table 5 imply that high-premium employers are relatively more supportive of their low-earnings workers taking paid leave through

[25]Incidence rate ratios below 1 indicate a relatively lower likelihood of an event.

DI or PFL compared to lower-premium employers, but the role of the firm premium is less important for relatively high-earning workers within a firm. Therefore, high-premium employers may contribute to reducing disparities in leave use across high- and low-skill individuals.

5.2 Firm-specific premiums, leave duration, and post-leave outcomes

The results so far present clear evidence that higher-premium firms have higher paid leave claim rates. However, conditional on having at least one employee who files a claim, firms with higher earnings premiums have shorter average claim durations. Table 6 shows that a one standard deviation increase in the firm premium is associated with female claimants taking 1.02 fewer weeks of leave on average. Because average duration is not a count variable, the regression results in this table are estimated using OLS, so the coefficient can be interpreted as the effect of a one standard deviation change in the firm fixed effect on average leave duration in weeks. The effect on DI claim duration is similar for men and women, but the effect on bonding claim duration is more than twice as large for women than for men. This is largely driven by gender differences in mean leave duration. Because birth mothers can also take DI, the firm-level mean bonding leave duration is 14 weeks compared to 3.8 weeks for men. In percentage terms, the effect is about twice as large for male bonding claims. The effect on the duration of caring claims is very similar across claimant gender, and the mean claim lengths are similar as well at 4.3 and 4.0 weeks for women and men, respectively.

There are at least two reasons why higher premium firms may have shorter average leave durations. First, the results on the number of claims suggest that high-premium firms may nudge marginal employees into taking leave, and these marginal claimants may need such leave for shorter amounts of time. Second, these effects are also consistent with the idea that workers may limit the amount of leave they take in order to reduce the risk of separating from a job with a high earnings premium. Not all workers have access to job protection, and even if they do, they may be concerned about the negative career consequences of spending time away from work (Stearns, 2018; Thomas, 2016). While it is not possible to distinguish between these explanations completely, the latter suggests that high fixed effect firms should not only have higher claim rates, but also a higher rate of return to the same firm following a period of leave. While marginal claimants may be more likely to return to work than other claimants, there is less reason to think that, conditional on making a claim, they would be more likely to return to the same firm.

The first row in Table 7 shows the effect of the firm earnings premium on the number of claims where the worker returns to employment at any firm within five quarters, with employment defined as having strictly positive earnings in a quarter. These regressions are again estimated with a Poisson model, and we additionally control for the log of the total number of claims within the firm, regardless of whether the claimants return to work. The first column shows that a one standard deviation increase in the firm earnings premium increases the likelihood that a worker who makes a claim returns to employment within five quarters. The effects are similar for female DI and bonding claims as well as male DI claims, but much smaller for male PFL claims. This pattern makes sense, as the firm-level average rate of return to work following a male PFL claim is 96 percent. The average rates of return to employment following a DI or female bonding claim are lower, at around 84 percent for women and 78 percent for male DI claimants.

To evaluate whether high-premium firms have higher employee retention following periods of leave, the second row of Table 7 shows the effect on the number of claims where the worker returns to the same firm within five quarters. These results strongly suggest that better firms have much higher retention rates among social insurance claimants. Conditional on the number of claims, a one standard deviation increase in the firm premium increases the probability that female claimants return to the firm by 21 percent and the probability that male claimants return by 24 percent. Though the magnitudes are larger, the pattern across columns is very similar to the effects on returning to any employment, with similar point estimates for male and female DI claims and female bonding claims, but smaller percentage effects for caring and male bonding claims. This is consistent with the idea that workers at high-premium firms want to protect their jobs. It is also consistent, however, with high-premium firms offering more supportive work environments that promote employee retention.

How do these effects of the firm earnings premium on the return to work translate into effects on future earnings? Table 8 shows the effects of the firm premium on the average change in log earnings of leave claimants between the quarter prior to the start of the claim and five quarters after the claim, separately by whether the claimants are employed at the same firm or a different firm. This sample is limited to firms that experience at least one claim where the worker is employed at the same firm or a different firm, respectively, in the fifth quarter following the claim. The regressions control for the total number of claims within the firm, regardless of whether or not the workers return to work. The results in the top panel show that for claimants who return to work at the same firm, the firm premium is associated with slightly higher earnings growth. This is consistent with the idea that firms that encourage leave-taking are also less likely to penalize workers who take extended absences. It also may be the case that firms with higher earnings premiums have higher earnings growth in general. On the other hand, workers who file claims in firms with higher premiums and then change employers experience substantially lower subsequent earnings growth compared to those who start out at lower fixed effect firms. These effects are large. A one standard deviation increase in the firm premium is associated with a 32-35 percent drop in earnings for movers who make DI claims and a 19-28 percent drop in earnings for those who make bonding claims.[26] These effects are likely driven by several factors. First, because movers who start at a high premium firm are mechanically more likely to move to a firm with a lower premium than are movers who start at a low premium firm (consistent with Figure 1), we should expect a negative relationship if the firm premium is a significant determinant of earnings. Second, there might be a direct effect of the employment gap on future earnings that differs among individuals who start at higher versus lower premium firms. Finally, it is important to note that we do not observe work hours and cannot distinguish between changes in wages and changes in employment on the intensive margin. It is possible that workers at high-premium firms leave if these employers are less willing to accommodate part-time work or more flexible schedules. But this explanation seems unlikely given that workers at high-premium firms are actually more likely to return to the firm following a claim.

5.3 Alternative Measures

Although the results presented above consistently show that use of public social insurance is positively correlated with the firm earnings premium, it is not possible to identify what characteristics of high premium firms encourage public leave take-up. In particular, one concern is that firms that pay relatively well are compensating for providing less desirable working conditions on other margins. Other work has argued that employee transitions between firms can be used as alternate, revealed preference, measures of firm desirability or quality (Sorkin, 2018; Bagger and Lentz, 2018). In Table 9, we show the effect of two additional measures of firm desirability on the number of social insurance claims made within the firm.

[26]Table 7 shows there is selection into returning to the firm as a function of the firm premium. We have therefore estimated the overall effect of the change in earnings for all claimants who are employed five quarters following the claim and find negative effects. We have also estimated effects for those who return to the same firm but move by the fifth quarter and for those who never returned to the pre-claim employer. These results are available upon request.

Panel A shows the effect of a one standard deviation increase in the firm retention rate, measured as the average share of employees who remain employed by the firm from one quarter to the next. These results are qualitatively similar to the effects of the firm earnings premium: both higher premium firms and those with a higher retention rate are more likely to have workers who file claims. Panel B shows the effect of a one standard deviation increase in the poaching index, which is the average share of workers hired in a given quarter who are "poached" from another firm as opposed to coming from non-employment. Bagger and Lentz (2018) argue that the poaching index is an unbiased estimate of the firm's rank in the distribution of firm productivity. Again, firms with a higher poaching index have higher claim rates, although the relationship is generally weaker than it is for the firm premium or firm retention rate. Finally, Panel C shows the effect of the firm earnings premium on the number of claims, controlling for the standardized retention rate and poaching index. Even controlling for these alternate measures of firm quality, the firm premium still has a large and statistically significant effect on the number of social insurance claims.

Finally, one alternate explanation for these results is that the type of people who work at high premium firms are different in ways that are also correlated with program take-up. To address concerns about unobservable sorting of workers into firms, we redo the main analysis at the industry level in Table 10. To do this, we calculate the average firm premium in four-digit industries that can be identified in both the EDD data and the ACS.[27] We then regress the number of claims on the industry-aggregated firm premium. There is less concern with worker sorting as a function of desired social insurance use at the industry level, and Sorkin (2018) shows that about 55 percent of the variance in the firm pay premium is between four-digit industries. The first panel of Table 10 shows that the results are qualitatively similar when using this industry-level measure of the firm premium. This industry analysis additionally allows us to test for the importance of selection on observables by controlling for other industry-level observable characteristics that may be correlated with firm quality and the likelihood of leave take-up. In the second panel, we add controls for observable gender-specific industry-level characteristics including the share of workers who have employer-provided health insurance, are foreign-born, are above age 40, are an under-represented minority, and have a four-year college degree, the usual hours worked per week, and the average transportation time to work. The results are very similar when these controls are included,

[27]We use the INDNAICS Specific Variable Codes in the ACS to define industries. While most industries are aggregated at the four digit level, some large industries can be identified at the five or six digit level, and some small industries are aggregated to the two or three digit level. We exclude industries with fewer than 500 ACS observations from 2004-2013.

corroborating the idea that selection on observables is relatively unimportant in this setting and that the results are unlikely to be entirely driven by sorting of workers into firms.

6 Conclusion

The firm-specific earnings premium is an important predictor of both current and future earnings, and also plays a meaningful role in determining social insurance benefit take-up. In this paper, we first estimate the firm earnings premium using administrative earnings data from California, and then show that higher firm premiums are associated with substantially higher DI and PFL claim rates. This finding is robust across the type of claim, gender and age of the claimant, and other firm characteristics, suggesting that the results cannot be driven by the sorting of workers into firms.

Our findings are important for several reasons. First, the results suggest that firm-specific factors drive disparities in the use of public social insurance. Firms appear to influence inequality in leave-taking, even when benefits are—at least on paper—universally available to workers. As leave-taking is positively correlated with health, employment, and cognitive outcomes of both workers and their families, our findings suggest that firms may contribute not only to wage dispersion, but also to health- and family-related dimensions of inequality in America.

Second, firm-specific attributes appear to be more important in determining social insurance take-up than are changes to specific policy levers. A back of the envelope calculation suggests that DI and PFL take-up would be substantially higher if all employers cultivated a leave-taking culture more similar to that of firms at the top of the firm premium distribution. In contrast, prior work shows that changes to the wage replacement rate or benefit duration have much smaller effects on leave take-up.

Third, short-term leave benefits constitute an increasingly important part of the U.S. social safety net. In 2017, California's DI and PFL programs were the largest source of earnings replacement in the state, paying out a total of over $5.6 billion in benefits. This amount exceeded the $5.3 billion in Unemployment Insurance payments, indicating the extent to which workers value access to short-term paid leave. Our results highlight the important role that firms can play in determining the scale of these programs, which are currently particularly policy relevant as proposals for paid family and medical leave gain substantial momentum at both the state and federal levels.

Although the firm earnings premium is strongly associated with leave-taking claims, we cannot infer the specific aspects of firm behavior or culture that encourage program take-up. Prior work suggests that employers are an important source of information about the existence of these policies and that peer effects within firms play a significant role in determining use (Dahl et al., 2014). It seems likely that these mechanisms are both at play in the California setting as well. Higher premium firms may promote leave-taking for own illness or family care as part of attempts to create a positive and productive workplace culture. If workers can take leave without facing negative career consequences, their peers may be more likely to choose to do so as well. We find that claimants experience earnings losses on average following a period of leave even if they return to the same job, but this is not the case for workers who return to high premium firms. This finding is consistent with the idea that high premium firms are more supportive of their workers taking leave.

One important caveat to these results is that it is not possible to definitively determine whether an increase in DI or PFL take-up is socially optimal. Although these programs serve as an important form of social insurance, they are subject to moral hazard problems. While more research is needed to estimate the welfare gains associated with increased take-up, the consistency of our results across types of claims and types of workers suggests that take-up in lower-premium firms is below the individually-optimal level. In this case, understanding which characteristics of firms promote social insurance take-up is key to extending this form of the social safety net.

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Figure 1: Mean Earnings of Job Changers Classified by Quartile of Mean Earnings of Coworkers at Origin and Destination Firm

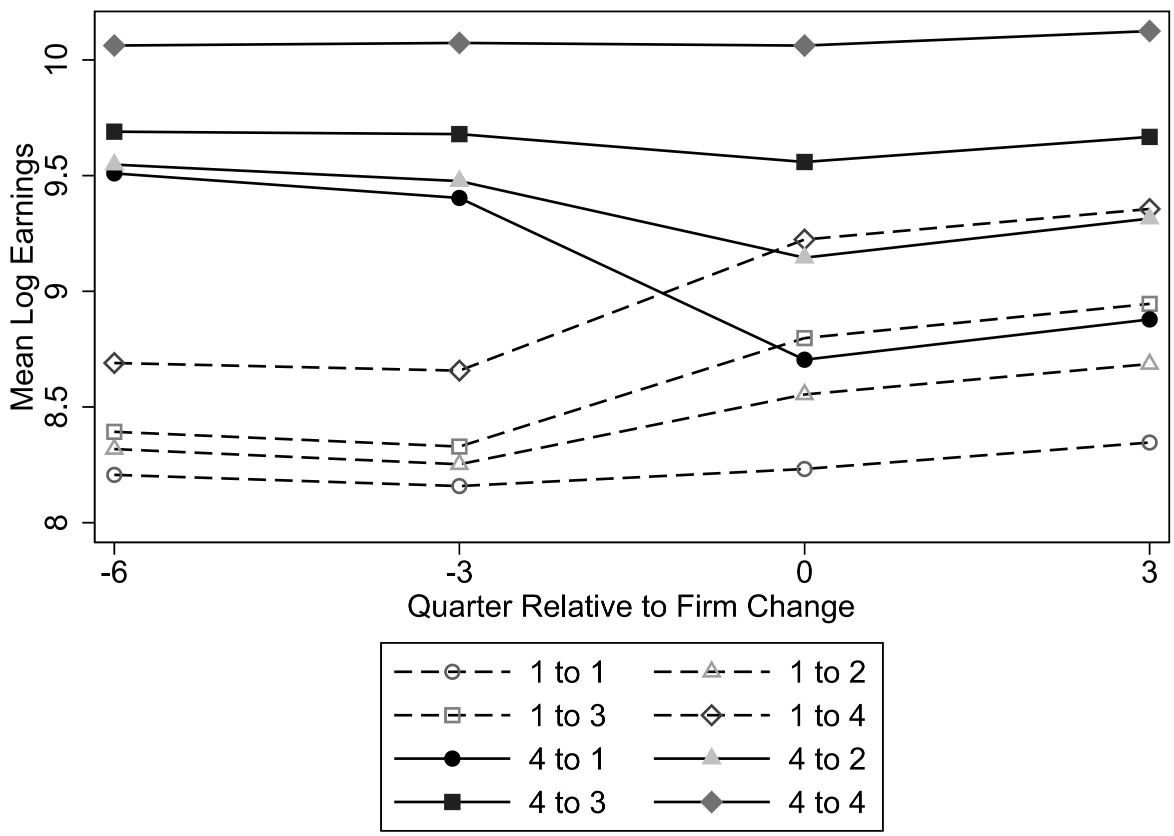

Figure shows mean log earnings of job changers, classified by quartile of coworker earnings at the origin and destination firm. For ease of interpretation, only workers who start in the top or bottom quartile of the coworker earnings distribution are shown.

Table 1: Claim Rates by Firm Characteristics

	Female Claims				Male Claims				Observations
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring	
Mean Claim Rate	0.045	0.044	0.014	0.001	0.018	0.016	0.002	0.000	2,709,253
Mean Claim Rate by:									
<u>Firm Size</u>									
Small	0.042	0.041	0.013	0.001	0.016	0.014	0.002	0.000	2,005,409
Medium	0.050	0.048	0.015	0.001	0.023	0.020	0.003	0.000	529,236
Large	0.065	0.062	0.019	0.002	0.029	0.024	0.005	0.001	174,608
<u>Industry</u>									
Construction	0.062	0.060	0.018	0.001	0.027	0.024	0.003	0.000	264,072
Manufacturing	0.046	0.045	0.011	0.001	0.025	0.023	0.002	0.000	238,861
Retail Trade	0.034	0.033	0.010	0.000	0.021	0.019	0.002	0.000	270,993
Professional Services	0.052	0.050	0.020	0.001	0.012	0.009	0.003	0.000	290,219
Health Care	0.062	0.061	0.019	0.001	0.015	0.012	0.003	0.000	335,933
Accommodation	0.030	0.030	0.009	0.000	0.010	0.009	0.001	0.000	314,595
<u>Firm Fixed Effect Terciles</u>									
Low	0.034	0.034	0.010	0.000	0.012	0.011	0.001	0.000	903,081
Middle	0.048	0.046	0.014	0.001	0.021	0.018	0.002	0.000	903,082
High	0.053	0.051	0.018	0.001	0.022	0.018	0.003	0.000	903,090

Notes: Table shows mean claim rates at the firm-year level from fiscal year 2004-2013. The measure of firm size used in calculating rates is time-varying. Small firms have 5-24 workers, medium firms have 25-99 workers, and large firms have more than 100 workers. For this classification, firm size is averaged over all years the firm appears in the sample and is constant over time. Industries shown are the six largest industries in California. Professional Services is Professional, Scientific, and Technical Services, and Accommodation is Accommodation and Food Services. Firm fixed effects are estimated using the AKM methodology as explained in Section 4 and divided into terciles.

Table 2: Effect of Firm Premium on Number of Leave-Taking Claims

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.569*	1.447*	1.427*	1.512*	2.076*	1.797*	1.660*	2.628*	2.589*
	(0.014)	(0.013)	(0.013)	(0.013)	(0.041)	(0.026)	(0.021)	(0.051)	(0.058)
Mean Number of Claims	2.218	1.407	1.352	0.369	0.037	0.811	0.671	0.123	0.017

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year. All columns include 2,709,253 observations. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * p<0.01.

Table 3: Effect of Firm Premium on Number of Leave-Taking Claims by Age of Claimant

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Claims at Age 20-39								
Firm Premium	1.427*	1.410*	1.526*	2.127*	1.868*	1.585*	2.633*	2.524*
	(0.012)	(0.012)	(0.013)	(0.048)	(0.030)	(0.025)	(0.052)	(0.070)
Mean Number of Claims	0.804	0.778	0.345	0.012	0.348	0.235	0.106	0.007
Claims at Age 40-59								
Firm Premium	1.586*	1.561*	2.078*	2.132*	1.809*	1.757*	2.660*	2.700*
	(0.022)	(0.022)	(0.031)	(0.047)	(0.027)	(0.026)	(0.065)	(0.077)
Mean Number of Claims	0.484	0.459	0.016	0.022	0.367	0.342	0.016	0.009

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims by age of the claimant within the firm in a given year. All regressions include 2,709,253 observations. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table 4: Effect of Firm Premium on Number of Leave-Taking Claims by Firm Size and Industry

	Female Claims				**Male Claims**				**Observations**
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring	
Firm Premium									
Firm Size 5-9	1.172*	1.165*	1.410*	1.178	1.363*	1.302*	2.004*	1.655*	1,115,617
	(0.006)	(0.006)	(0.012)	(0.048)	(0.011)	(0.011)	(0.045)	(0.136)	
Firm Size 10-24	1.217*	1.208*	1.486*	1.305*	1.597*	1.504*	2.650*	2.166*	889,792
	(0.005)	(0.005)	(0.012)	(0.046)	(0.010)	(0.009)	(0.054)	(0.125)	
Firm Size 25-49	1.292*	1.276*	1.581*	1.699*	1.793*	1.648*	3.515*	2.574*	347,930
	(0.008)	(0.007)	(0.015)	(0.064)	(0.014)	(0.013)	(0.071)	(0.148)	
Firm Size 50-99	1.328*	1.309*	1.591*	1.804*	2.076*	1.888*	3.869*	3.373*	181,306
	(0.008)	(0.008)	(0.016)	(0.061)	(0.017)	(0.016)	(0.082)	(0.178)	
Firm Size 100-499	1.413*	1.385*	1.600*	2.181*	2.145*	1.925*	3.709*	3.516*	143,719
	(0.009)	(0.009)	(0.014)	(0.049)	(0.018)	(0.018)	(0.051)	(0.107)	
Firm Size 500+	1.566*	1.547*	1.545*	2.233*	1.701*	1.578*	2.346*	2.353*	30,889
	(0.022)	(0.022)	(0.023)	(0.061)	(0.043)	(0.041)	(0.072)	(0.086)	
Construction	2.302*	2.255*	2.831*	3.377*	2.737*	2.560*	4.804*	4.022*	264,072
	(0.068)	(0.067)	(0.114)	(0.438)	(0.039)	(0.037)	(0.128)	(0.260)	
Manufacturing	0.485*	0.476*	0.754*	0.672*	1.066	0.973	1.951*	1.427*	238,861
	(0.018)	(0.018)	(0.022)	(0.044)	(0.033)	(0.030)	(0.089)	(0.089)	
Retail Trade	1.443*	1.430*	1.203*	2.086*	2.933*	2.812*	3.513*	3.622*	270,993
	(0.034)	(0.033)	(0.038)	(0.101)	(0.084)	(0.081)	(0.187)	(0.156)	
Professional Services	1.246*	1.222*	1.644*	1.624*	1.284*	1.071	2.316*	2.002*	290,219
	(0.026)	(0.025)	(0.028)	(0.064)	(0.025)	(0.022)	(0.059)	(0.078)	
Health Care	1.753*	1.730*	1.906*	2.466*	2.032*	1.776*	3.256*	3.198*	335,933
	(0.020)	(0.019)	(0.022)	(0.080)	(0.040)	(0.035)	(0.091)	(0.188)	
Accommodation	1.400*	1.371*	1.057	8.242*	3.648*	3.291*	7.222*	17.105*	314,595
	(0.026)	(0.025)	(0.016)	(0.619)	(0.089)	(0.079)	(0.320)	(1.536)	

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year, subsampled by firm size and industry groups. Firm size categories are based on employment averaged over all years in the data, and are constant over time. Professional Services is Professional, Scientific, and Technical Services, and Accommodation is Accommodation and Food Services. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table 5: Effect of Firm Premium on Number of Leave-Taking Claims by Within-Firm Earnings Quartile of Claimant

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Quartile 1								
Firm Premium	2.454*	2.420*	2.470*	4.049*	2.631*	2.427*	4.892*	4.800*
	(0.048)	(0.046)	(0.030)	(0.209)	(0.037)	(0.033)	(0.131)	(0.189)
Mean Number of Claims	0.284	0.274	0.069	0.006	0.137	0.120	0.014	0.002
Quartile 2								
Firm Premium	1.751*	1.722*	1.795*	2.908*	2.358*	2.136*	3.890*	4.052*
	(0.019)	(0.019)	(0.018)	(0.080)	(0.032)	(0.027)	(0.091)	(0.121)
Mean Number of Claims	0.411	0.396	0.105	0.011	0.207	0.172	0.030	0.004
Quartile 3								
Firm Premium	1.278*	1.259*	1.445*	1.778*	1.876*	1.695*	2.954*	2.783*
	(0.013)	(0.012)	(0.016)	(0.034)	(0.029)	(0.026)	(0.071)	(0.080)
Mean Number of Claims	0.398	0.383	0.107	0.011	0.238	0.193	0.039	0.005
Quartile 4								
Firm Premium	0.938*	0.923*	1.005	1.226*	1.236*	1.152*	1.654*	1.581*
	(0.009)	(0.009)	(0.011)	(0.029)	(0.018)	(0.017)	(0.031)	(0.041)
Mean Number of Claims	0.314	0.300	0.087	0.009	0.230	0.185	0.039	0.005

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year, subsampled by the within-firm earnings quartile of claimants. Quartile 1 is the lowest 25 percent of earners within the firm and quartile 4 is the highest. The effect in each quartile is estimated from a separate regression. All regressions include 2,709,253 observations. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table 6: Effect of Firm Premium on Mean Claim Duration (Weeks)

	Female Claims				Male Claims			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	-1.016*	-1.255*	-0.983*	-0.382*	-2.048*	-1.410*	-0.475*	-0.313*
	(0.023)	(0.024)	(0.020)	(0.021)	(0.036)	(0.035)	(0.013)	(0.031)
Observations	717,453	705,925	337,788	42,980	524,970	481,444	117,671	25,490
Mean Claim Duration	11.643	10.181	13.991	4.258	11.383	12.514	3.769	4.007

Notes: Table shows the effect of the firm premium on the mean claim duration (measured in weeks) within a firm-year, conditional on having at least one claim. The effects are estimated using an OLS regression. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table 7: Effect of Firm Premium on Number of Leave-Taking Claimants Who Return to Work

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Return to Employment								
Firm Premium	1.089*	1.089*	1.096*	1.044*	1.092*	1.096*	1.020*	1.031*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)
Mean Number of Claims Returning to Employment	4.794	4.675	2.674	2.273	3.659	3.222	2.754	1.795
Return to Firm								
Firm Premium	1.213*	1.216*	1.255*	1.101*	1.239*	1.254*	1.107*	1.090*
	(0.005)	(0.005)	(0.004)	(0.005)	(0.008)	(0.008)	(0.005)	(0.007)
Mean Number of Claims Returning to Firm	4.249	4.135	2.370	2.137	3.123	2.705	2.499	1.682
Observations (all rows)	717,453	705,925	337,788	42,980	524,970	481,444	117,671	25,490

Notes: Table shows the effect of the firm premium on the number of claims made by workers who return to employment at any firm within five quarters of the start of the claim (first row) and the effect of the firm premium on the number of claims made by workers who return to work at the same firm within five quarters of the start of the claim (second row). The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Regressions control for the log number of claims made within the firm-year, unconditional on returning to work. Additional controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table 8: Effect of Firm Premium on the Average Change in Earnings of Claimants

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Employed At Same Firm								
Firm Premium	0.054*	0.052*	0.083*	0.017	0.051*	0.038*	0.058*	0.031*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)	(0.007)
Observations	406,298	400,631	187,464	36,686	264,654	241,810	71,420	21,358
Mean Change in Log Earnings	-0.070	-0.069	-0.071	-0.016	-0.066	-0.073	0.009	-0.014
Employed At Different Firm								
Firm Premium	-0.331*	-0.323*	-0.275*	-0.031*	-0.352*	-0.346*	-0.185*	-0.013
	(0.006)	(0.006)	(0.010)	(0.007)	(0.007)	(0.007)	(0.017)	(0.014)
Observations	246,327	244,117	100,685	27,803	176,361	165,063	38,880	16,227
Mean Change in Log Earnings	-0.223	-0.218	-0.186	-0.054	-0.209	-0.205	-0.095	-0.042

Notes: Table shows the effect of the firm premium on the mean change in log real earnings of claimants between the quarter prior to the start of the claim and five quarters after the claim, conditional on the firm having at least one claimant who returns to employment. The top panel shows the effect for those who are employed at the same firm in the fifth quarter after the claim, and the second panel shows the effect for those who are employed at a different firm in the fifth quarter after the claim. The effects are estimated using an OLS regression. Sample includes fiscal years 2004-2013. Regressions control for the log number of claims made within the firm-year, unconditional on returning to work. Additional controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * p<0.01.

Table 9: Effect of Alternate Firm Quality Measures on Number of Leave-Taking Claims

	Female Claims				Male Claims			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Panel A								
Retention Rate	1.899*	1.854*	1.616*	5.945*	2.021*	1.812*	3.594*	6.370*
	(0.021)	(0.020)	(0.015)	(0.182)	(0.031)	(0.028)	(0.082)	(0.229)
Panel B								
Poaching Index	1.062*	1.054*	1.150*	1.434*	1.403*	1.330*	1.890*	1.609*
	(0.011)	(0.011)	(0.010)	(0.030)	(0.016)	(0.015)	(0.032)	(0.041)
Panel C								
Firm Premium	1.218*	1.207*	1.413*	1.189*	1.564*	1.475*	2.076*	1.616*
	(0.015)	(0.014)	(0.014)	(0.027)	(0.027)	(0.026)	(0.048)	(0.043)
Retention Rate	1.550*	1.528*	1.157*	4.663*	1.334*	1.273*	1.682*	3.580*
	(0.022)	(0.022)	(0.013)	(0.160)	(0.024)	(0.023)	(0.042)	(0.142)
Poaching Index	1.018	1.012	1.078*	1.348*	1.312*	1.245*	1.85*	1.543*
	(0.010)	(0.010)	(0.009)	(0.028)	(0.017)	(0.016)	(0.036)	(0.041)
Mean Number of Claims	1.407	1.353	0.369	0.037	0.811	0.671	0.123	0.017

Notes: Table shows the effect of measures of firm quality on the number of DI or PFL claims within the firm in a given year. Panel A shows the effect of the firm's standardized average quarterly retention rate, and all columns include include 2,709,253 observations. Panel B shows the effect of the firm's standardized average quarterly poaching index, and all columns include 2,709,155 observations. Panel C includes the standardized firm earnings premium, retention rate, and poaching index, and all columns include 2,709,155 observations. The correlation between the firm premium and the retention rate is 0.47, the correlation between the firm premium and the poaching index is 0.21, and the correlation between the retention rate and poaching index is 0.01. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table 10: Effect of Industry Average Firm Premium on Number of Leave-Taking Claims

	Female Claims				Male Claims			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
No Industry-Level Controls								
Average Industry Premium	1.973*	1.931*	1.701*	4.308*	1.482*	1.353*	2.235*	2.411*
	(0.097)	(0.093)	(0.050)	(0.451)	(0.072)	(0.067)	(0.143)	(0.228)
With Industry-Level Controls								
Average Industry Premium	1.880*	1.868*	1.990*	2.378*	1.484*	1.402*	1.793*	1.538*
	(0.106)	(0.104)	(0.096)	(0.222)	(0.089)	(0.085)	(0.124)	(0.145)
Mean Number of Claims	1935.832	1861.357	510.254	51.242	1093.192	904.659	165.147	23.385

Notes: Table shows the effect of the industry average firm premium on the number of DI or PFL claims within the industry in a given year. All columns include 1,920 observations from 192 industries. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. All regressions include industry size and year fixed effects as well as the percentage of the industry that is female. The bottom panel additionally includes gender-specific industry-level controls for the share of workers who have employer-provided health insurance, are foreign-born, are above age 40, are an under-represented minority, and have a four-year college degree, the usual hours worked per week, and the average transportation time to work. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Appendix A Additional Tables

Table A1: Claim Rates by Worker Characteristics

	Female Claims				Male Claims			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Number of Claims	4,032,876	3,879,858	1,061,309	104,248	2,307,892	1,914,805	344,613	48,474
Claim Rate	0.063	0.061	0.017	0.002	0.027	0.023	0.004	0.001
Claim Rate by Age:								
20-39	0.080	0.077	0.034	0.001	0.025	0.017	0.008	0.000
40-59	0.051	0.049	0.002	0.002	0.030	0.028	0.001	0.001
Claim Rate by Industry:								
Construction	0.051	0.049	0.015	0.001	0.026	0.023	0.003	0.000
Manufacturing	0.062	0.059	0.013	0.002	0.033	0.028	0.004	0.001
Retail Trade	0.074	0.071	0.018	0.002	0.036	0.030	0.006	0.001
Professional Services	0.050	0.048	0.019	0.001	0.016	0.011	0.005	0.000
Health Care	0.079	0.076	0.018	0.003	0.037	0.029	0.008	0.001
Accommodation	0.055	0.054	0.016	0.001	0.019	0.016	0.002	0.000

Notes: Table shows mean gender-specific claim rates at the worker-year level from fiscal year 2004-2013. Claims data is merged with data from the American Community Survey 2004-2013 to create gender-specific employment counts by year. Industries shown are the six largest industries in California. Professional Services is Professional, Scientific, and Technical Services, and Accommodation is Accommodation and Food Services. Note that this table is representative of workers, whereas Table 1 is representative of firms. This table also includes workers at very small firms of 1-4 workers, which are excluded from our main analysis, because firm size is not available. Workers at firms of 1-4 workers only make up 7.8 percent of the California workforce and 3.6 percent of claims.

Table A2: AKM Model Summary Statistics

	Full Sample	Movers	Largest Connected Set
Sample Size			
Person-Quarters	300,424,074	227,840,807	227,614,272
Individuals	34,166,334	20,740,162	20,716,651
Firms			2,203,086
Summary Statistics			
Mean Log Earnings	8.868	8.792	8.793
Standard Deviation of Log Earnings	1.278	1.265	1.265
Summary of Parameter Estimates			
Standard Deviation of Firm Effects			0.591
Standard Deviation of Person Effects			0.751
Correlation of Person/Firm Effects			0.226
RMSE of AKM Residual			0.739
Adjusted R^2			0.659
Comparison Match Model			
RMSE of AKM Residual			0.534
Adjusted R^2			0.822
Model Including Potential Experience			
RMSE of AKM Residual			0.731
Adjusted R^2			0.666

Notes: Sample includes every third quarter from the first quarter of 2000 through 2014. There is one observation per person-quarter. If an individual held multiple jobs, the observation is the job from which they had the highest earnings. The comparison match model includes interactions between employers and individuals. The model including potential experience includes the number of past quarters the person is observed in the data.

Table A3: Effect of Firm Premium on Number of Leave-Taking Claims, Including 2-4 Person Firms

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.545*	1.429*	1.410*	1.495*	2.001*	1.760*	1.633*	2.381*	2.368*
	(0.01)	(0.012)	(0.012)	(0.011)	(0.031)	(0.023)	(0.022)	(0.042)	(0.046)
Mean Number of Claims	1.366	0.868	0.835	0.229	0.023	0.498	0.412	0.075	0.011

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year. All columns include 4,498,541 observations. Sample includes all firms with an average of two or more employees. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table A4: Effect of Firm Premium on Number of Leave-Taking Claims, Firm Fixed Effects Estimated Controlling for Experience

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.594*	1.472*	1.451*	1.534*	2.125*	1.822*	1.681*	2.666*	2.654*
	(0.01)	(0.014)	(0.014)	(0.014)	(0.044)	(0.024)	(0.022)	(0.053)	(0.063)
Mean Number of Claims	2.218	1.407	1.352	0.369	0.037	0.811	0.671	0.123	0.017

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year. All columns include 2,709,253 observations. The firm premium fixed effects are estimated while additionally controlling for the worker's experience, measured as the number of past quarters they are observed in the data. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.

Table A5: Effect of Firm Premium on Number of Leave-Taking Claims, Firm Fixed Effects Estimated Using 2000-2004 Data

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.454*	1.356*	1.340*	1.389*	1.718*	1.606*	1.530*	1.883*	1.909*
	(0.02)	(0.014)	(0.014)	(0.014)	(0.037)	(0.026)	(0.022)	(0.046)	(0.050)
Mean Number of Claims	2.556	1.620	1.557	0.417	0.044	0.935	0.774	0.140	0.021

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year. All columns include 2,137,839 observations. The firm premium fixed effects are estimated using earnings data from every quarter of 2000-2004. The effects are estimated using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. Sample includes fiscal years 2004-2013. Controls include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. Standard errors (in parentheses) are bootstrapped 200 times. To account for multiple hypothesis testing, p-values have been corrected using the Bonferroni correction. * $p<0.01$.