Unequal Use of Social Insurance Benefits: The Role of Employers

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February 11, 2022

Abstract

Disability Insurance (DI) and Paid Family Leave (PFL) programs are important sources of social insurance, but there is considerable inequality in benefit take-up, and little is known about the role of firms in determining benefit use. Using administrative data from California, we find that firms that pay higher earnings premiums also have substantially higher public DI and PFL take-up rates, and that this relationship is particularly strong among the lowest-earning workers within the firm. Our results suggest that changes in firm behavior may impact social insurance use, thus reducing an important dimension of inequality in America.

Keywords: Disability Insurance, Paid Family Leave, Social insurance, Firm premium
JEL: J31, J32, J38

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1 Introduction

A growing body of evidence demonstrates that access to temporary 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, has beneficial labor market and health effects on workers and their families (e.g., Rossin-Slater, 2018; Olivetti and Petrongolo, 2017; Stearns, 2015; Carneiro et al., 2015). These policies may also 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, 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 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., 2018). 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.

More broadly, not much is known about the attributes of firms that facilitate the use of public disability and family leave programs. In this paper, we draw on a well-established literature that demonstrates that observably similar firms pay observably similar workers different wages (i.e., employer-specific wage pre-

[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., Massachusetts, Oregon, and Connecticut 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`.

miums, 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) to 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.

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. 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. Consistent with the idea that high earnings premium firms are more likely to support the use of publicly provided leave, we also show that greater leave taking at high premium firms is combined with shorter leave durations and higher employee retention. However, an important limitation of this analysis is that we are unable to directly control for many worker characteristics. We interpret the individual fixed effects as a combination of skills and other factors that are rewarded equally across employers. We then interpret the firm effect as the earnings premium or discount paid to all employees. In addition to capturing reasons for firm-level earnings differences such as rent-sharing or efficiency wages, the firm effects could also reflect differences in experience profiles or reliance on part-time workers across firms. We discuss these issues further in Sections 4 and 5.3. But despite this limitation, we find no evidence that the observed pattern of leave is driven by the differential sorting of workers to high earnings premium firms in order to access publicly provided 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. (2020) show that a higher replacement rate does not increase PFL duration among high-earning mothers.

The evidence we report in this paper is consistent with a growing body of evidence on the connection between firm wage effects and non-wage job characteristics. Sorkin (2018) uses linked employer-employee data for the U.S. to estimate the extent to which higher AKM firm effects reflect rents and the extent to which they represent compensating differentials. Taber and Vejlin (2020) explore the relative roles of ability differences at labor market entry, human capital accumulation while in the labor market,

[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.

job search, and compensating differentials in wage determination in Denmark. While Sorkin (2018) attributes approximately 15 percent of the variance of earnings to compensating differentials, Taber and Vejlin (2020) find that the vast majority of the variance in earnings is attributable to differences in pre-market skills though the other factors play important roles in the observed distribution of earnings and job choices. In the Brazilian context, Lavetti and Schmutte (2018) estimate compensating wage differentials for occupational fatality risk. Finally, perhaps most similar to our study, Hotz et al. (2017) look at the role of family friendliness in wage determination in Sweden and find that mothers employed in more family friendly firms have higher earnings. Although the research described above comes at the problem in different ways, either through revealed preference or hedonic search frameworks, they all lean heavily on the pioneering AKM strategy to learn about the relationship between earnings and amenities.

Our paper also 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, less frequently, introductions of new programs) on parental leave-taking and labor market outcomes (see Rossin-Slater, 2018; 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

[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).

[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). There is also a recent literature on employer reponses to paid leave (Brenøe et al., 2020; Gallen, 2019; Ginja et al., 2020; Huebener et al., 2021; Bartel et al., 2021).

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 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 2020 SDI tax rate is 1 percent on the first $122,909 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

[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.

[7] The wage replacement rate increased to 60-70 percent as of January 1, 2018. The 2021 weekly maximum benefit is $1,357.

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

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 is designed to reduce 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 in PFL claims has narrowed over time.

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

[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.

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 low-cost 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.

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 birth mothers who file 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

[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.

unique employer identifier associated with those earnings, and the North American Industry Classification System (NAICS) industry code associated with the employer. As with most U.S. administrative earnings data sets, demographic characteristics of the workers and geographic information about the firms 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 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

[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.

[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. These individuals account for 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.

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: 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).

[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 A4.

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. We do not observe the gender of non-claimants in the data, so for descriptive purposes we adjust the total firm size by the percent male or female in the industry in each year using data from the American Community Survey (ACS). 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 the firm earnings premiums (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 lower-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 is 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.

Finally, Figure 1 shows the raw, unadjusted correlation between the firm earnings premium by quantile and the mean firm-level claim rate within that quantile. Male and female claims are combined in this figure. This relationship is quite strong and linear throughout most of the firm fixed effect distribution, although the very highest premium firms have lower DI and caring claim rates. This may in part be explained by the age composition of workers in the top firms, as earlier work has found that the mean firm premium associated with jobs held by workers over age 50 is slightly decreasing in age (Card et al., 2016, 2018). However, on the whole, the strong positive correlation is indicative of the regression results to come.

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, 2018). 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.

Because the EDD data only includes gross quarterly earnings, we cannot restrict the sample to full-time workers, narrow the age range, or subsample by gender of all workers. Following the AKM literature, we interpret the individual fixed effect as a combination of skills and other factors that are rewarded equally across employers. But unlike analyses using data that include interactions of gender and educational attainment with hours of work and experience, we are unable to separate these factors from the person effects. We then interpret the firm effect as the earnings premium or discount paid by a firm to all employees. As discussed in Card et al. (2013), this premium might reflect rent-sharing, an efficiency wage premium, or strategic wage posting in the style of Burdett and Mortensen (1998) and Moscarini and Postel-Vinay (2012). In our case, the firm effects may also reflect differences in reliance on part time workers and differential experience profiles across firms. We discuss these issues in Section 5.3.

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

[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 A5.

[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 A6.

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 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 2. 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 2 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. This test provides evidence that mobility is unrelated to unobserved

[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.

determinants of earnings changes among all workers, which is necessary for the estimation of unbiased firm fixed effects. Of course, one might also be concerned that people who expect to make social insurance claims differentially move to different types of firms. We address this issue in Section 5.4.

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.[21] 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.[22] 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.[23] 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. 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).[24]

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

[21]To help reader's intuition about the context, the Pseudo R-squared increases from 0.80 to 0.88 when firm fixed effects are added directly to a baseline model that includes all time varying controls, other than the AKM standardized firm fixed effects.

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

[23]Lachowska et al. (2019) estimate how firm fixed effects evolve over time and find that they are highly persistent, suggesting that there is no concern with assuming the firm earnings premium is constant over time.

[24]Bootstrapping in this setting is extremely computationally intensive, but we have estimated the main results using 400 bootstraps and standard errors are almost identical. Results are also similar using a negative binomial mode as well as a Poisson model that excludes firms that never have a claim, as shown in Appendix Table A3. Appendix Figure A1 shows the distribution of the firm premium for firms that ever have a claim over the sample period and firms that never have a claim over the sample period.

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 workers in the firm that would affect the number of claims. We provide supporting evidence of this assumption in Sections 5.3 and 5.4.

Specifically, 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 in Portugal (Card et al., 2016). However, there is limited evidence on this sorting behavior in other settings. If this relationship is true in our setting as well then, 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. But due to data limitations, we cannot say for sure that this type of sorting occurs among California women of child-bearing age or among workers most at risk of making a disability claim for non-birth reasons. As shown below, the consistency of our results across claimant demographic groups and types of firms suggests that other types of sorting are unlikely to drive the results. 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 additionally 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, which 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 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 A4-A6 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).

Figure 3 presents heterogeneous effects by claimant age, firm size, and industry. Although we only present estimates for any female and any male claim graphically, the patterns are similar for all claim types and the full results are shown in Appendix Tables A7 and A8. The first two rows in the figure show the effect of the firm premium on the number of claims among workers age 20-39 and age 40-59, respectively. The younger 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. 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.

The effects by firm size also suggest that the main results 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.[25] 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. It is also important to mention that the firm fixed effects are estimated with more noise for small firms. Therefore, an alternative interpretation of the heterogeneity by firm size is that the larger amount of measurement error for small firms causes greater attenuation bias in the estimated coefficients. If anything, results are somewhat stronger when excluding small firms, but different measures of the firm fixed effect are highly correlated across samples even for relatively small firms.[26]

There is more variation in the importance of the firm premium across industries. The bottom of Figure 3 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 percent fewer female claims overall, and the firm premium has no significant effect on the number of male overall or DI claims.[27] Overall, while there is variation in the effect sizes across industries,

[25] 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.

[26] To analyze the role of measurement error in the estimation of the firm fixed effects, we split the main sample used to estimate the fixed effects in equation (1) into two equal subsamples based on the employee identifier. We then re-estimated the model on each subsample, so the firm fixed effect is identified using only half the number of movers on average. The correlation of the firm fixed effects in the two samples is 0.63 for firms with less than 10 employees, 0.84 for firms with 10-24 employees, 0.94 for firms with 24-49 employees, 0.97 for firms with 50-99 employees, and above 0.99 for firms with at least 100 employees.

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

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 the 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 are most likely to need access to 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 earning 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 3. 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. These results might further lead one to wonder whether the results are driven by part-time workers. While we cannot identify part-time status directly because we do not observe hours of work, Appendix Table A9 excludes workers with less than $1200 in average quarterly earnings from the sample and finds point estimates very similar to those reported in Table 2.

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 3 imply that high-premium employers are relatively more supportive of their low-earnings workers taking paid leave through public DI and PFL programs 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 individuals with higher and lower worker fixed effects.

One potential concern with these results is that the estimates of the firm premium might be affected by limited mobility bias. Because the estimated coefficients from the two-way fixed effects model contain sampling errors, they will likely result in upward bias in the variances of the firm and person fixed effects, and downward bias in the covariance between the firm and person fixed effects (Andrews et al., 2008; Kline et al., 2020; Gerard et al., 2021). To explore the importance of this issue, we use a split-sample approach where we estimate the firm fixed effects using only half of the sample of workers, then estimate the effect of the firm earnings premium on claims using the other half of the sample of workers. This approach ensures that individuals who potentially make claims do not contribute to the estimation of the firm fixed effects. These results are shown in Appendix Table A10 and are qualitatively similar to the main results. Because the firm fixed effects are estimated using only half of the individuals from the full sample, there are substantially fewer movers to identify the firm earnings premiums. We therefore limit the sample in this analysis to firms with at least 10 employees on average in the full sample and note that the results should be somewhat attenuated due to increased measurement error in the estimated firm fixed effects. Overall, we interpret these results as supporting the idea that limited mobility bias is not driving the effects.

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.[28] Table 4 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

[28] In this subsection, we restrict the analysis to firm-years with at least one claim to examine effects on leave duration and other post-leave outcomes. The distribution of estimated firm fixed effects for firms with at least one claim has a lower variance than the distribution for firms without a claim, with fewer extreme values in both tails. However, this does not affect the interpretation of the effect of the firm premium on the number of leave-taking claims.

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 several 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 high-premium firms may be more likely to offer more flexible work arrangements, making it easier for workers to return to work while still managing health or family obligations. Finally, 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; Tô, 2018). While it is not possible to distinguish between these explanations completely, the latter two suggest 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 5 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 5 shows the effect on the number of claims where the worker returns to the same firm within five quarters. These results strongly suggest that higher premium 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 6 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.[29] These

[29]Table 5 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

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 2), 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.

In sum, conditional on making a claim, workers in higher earnings premium firms make shorter claims and are more likely to return to the same firm following a claim. While this is consistent with the interpretation that the high premium firms are better quality firms, we cannot directly observe what these firms are doing that makes them appear to be more desirable. We can, however, show that the firm earnings premium remains large even once we control for available measures of firm attributes.

5.3 Additional Controls and Alternative Measures

While the results reported in Section 5.1 show that firms with higher earnings premiums have higher leave-taking claims across firm size and industries, in this sub-section we present results from specifications that include controls for an expanded set of firm characteristics to alleviate lingering concerns about the interpretation of leave-taking behavior. Given the robustness of the results across worker characteristics observable in our data, it is unlikely that the results are driven by worker sorting on these demographics. However, the correlation between the firm premium and leave-taking could stem from unobserved firm-level behavior such as leadership support for leave use or a work culture conducive to leave-taking, a mechanical relationship between wages and leave-taking rates, worker sorting on other dimensions, or from other firm or industry-level characteristics that make leave-taking easier to accommodate for some firms.[30] For example, large firms may simply have more flexibility to substitute labor to cover for absent

never returned to the pre-claim employer. These results are shown in Appendix Table A11.

[30]Controlling for finer-level industry fixed effects in Equation (2) leaves the effects of the firm premium essentially unchanged. We interpret this as evidence that these effects are driven by firm-level characteristics rather than industry-specific characteristics.

workers due to reasons unrelated to why they pay higher earnings premiums. Stated somewhat differently, the interpretation of the firm earnings premium effect changes if higher premium firms employ higher fixed effect workers who are also more likely to take leave, or if earnings premiums are proxying for other firm characteristics that attract workers who are more likely to take leave. Although the firm fixed effects are identified from within-person earnings changes across firms which should already account for these sources of endogeneity, Table 7 expands the set of controls included in the analysis to alleviate such concerns. As many of the variables defined below measure within-firm worker characteristics, this analysis is restricted to firms with at least 10 employees.

The specification reported in Table 7 expands the set of controls included in Table 2 to further include within-firm average annual earnings growth, average employee fixed effects, the dispersion in worker fixed effects within firms measured by the 75-25 worker fixed effect differential, the firm's growth rate as defined in Davis et al. (1998) (henceforth referred to as the DHS growth rate), and firm desirability measured by employee turnover and a poaching index. Average annualized earnings growth of employees within the firm is the average earnings change from one year to the next of all employees who remain employed with the same firm. If average earnings growth is correlated with the firm premium, then the effect of the firm premium on claims may be driven by the type of workers in the firm rather than by characteristics of the firm itself. The average individual fixed effect (estimated in equation (1)) is the average for the firm's employees over the sample period.[31] If high premium firms have high claim rates only because they employ workers with higher individual fixed effects, controlling for the average worker fixed effect of the firm should attenuate the effect of the firm premium. We further include the average 75-25 differential in worker fixed effects for the firm to control for within firm skill composition. Firms with more similarly skilled workers may be more able to substitute tasks across employees. The DHS growth rate captures any aspects of the firm that are correlated with whether it is growing or shrinking over time. The firm retention rate is the average share of employees who remain employed by the firm from one quarter to the next. If firms that pay relatively well are compensating for providing less desirable working conditions on other margins, this should be captured by the retention rate. Finally, other work has argued that employee transitions between firms can be used as alternate, revealed preference, measures of firm

These results are shown in Appendix Table A12.

[31] Equation (1) is estimated only using movers in the connected set for computational reasons. To obtain individual fixed effects for non-movers, we compute their average residual using the coefficients from this regression.

desirability or quality (Sorkin, 2018; Bagger and Lentz, 2018). The poaching index measures 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.

Table 7 reports estimates from the baseline model and the model with the expanded controls for the sample of firms with an average of 10 or more employees over the sample period. As one might expect, the coefficient on the firm earnings premium is attenuated by including these other firm characteristics, most of which are positively correlated with the firm earnings premium. But notably, the firm premium still has a large and statistically significant effect on the number of social insurance claims even controlling for all of these other measures. This indicates that the firm earnings premium is capturing some other unobserved aspects of firm behavior that cannot be explained fully by the potential mechanisms above. It seems likely that the remaining explanation has to do with firm culture and management, although more research is needed to pin down these mechanisms directly.

An alternate way to explore on potential mechanisms is to disaggregate the data to explore sub-samples and interactions. Another explanation for the strong relationship between the firm premium and claim rates could be that growing firms pay higher wages to attract workers. If workers who take leave at growing firms have relatively more job security compared to those at stagnant or shrinking firms, then observed higher leave-taking rates at these firms could be a result of worker decisions based on increased job security rather than firm behavior. To explore this possibility, Figure 4 shows the effect of the firm earnings premium on total claims for women and men separately for shrinking firms with a growth rate in the lowest 25 percent of the distribution (a growth rate of less than -6.6 percent), stagnant firms in the middle 50 percent of the distribution (-6.6 to 8 percent), and for growing firms in the top quartile (greater than 8 percent). The effects of the firm premium are quite similar across sub-samples, suggesting that the effect of the firm premium is not capturing differences in job security or other aspects of worker behavior at growing versus shrinking firms. Full results for all types of claims are shown in Appendix Table A13. For this analysis, the firm's growth rate is computed using all years in the data, and is constant within a firm over time.

Figure 4 next shows the any claim results subsampled by quartiles of the firm's average person fixed effect (skill), with full results shown in Appendix Table A14. Similar to the results in Table 3 showing that the firm earnings premium plays a bigger role in leave-taking for relatively lower earning workers within firms, the results reported in Appendix Table A14 suggest that firms also have more influence over leave-taking for lower fixed effect workers. It is important to highlight that skill quartiles are defined based on the average skill level of the entire workforce, while the earnings results in Table 3 are within-firm relative earnings. Together these results suggest that high-premium employers facilitate access to leave particularly for lower fixed effect workers. This is consistent with the idea that lower fixed effect and lower-earning workers are less likely to have access to firm-provided paid leave benefits, and therefore are more likely to take public leave benefits if they work for firms that are more supportive of workers taking leave that is unpaid by the firm. Figure 4 and Appendix Table A14 also show results subsampled by quartiles of the firm 75-25 worker fixed effect differential, while also controlling for the average level of worker fixed effects. These results suggest that, at least among men, leave-taking may be easier in firms where workers are more similar. This is consistent with other literature on the effects of worker substitutability on leave take-up (Hotz et al., 2017). However, there is no clear pattern in the effects of the firm premium on female claims by the firm's 75-25 skill differential. Appendix Figure A2 confirms these results, showing that the firm earnings premium is most important for workers outside the top quartile of the skill distribution. This figure plots the overall probability of making a claim as a function of the firm's earnings premium quartile and the individual's person fixed effect quartile. For workers outside the top skill quartile, the effect of the firm premium is stronger across person fixed effect quartiles than within-firm earnings quartiles. This suggests that sorting of different ability workers into different types of firms is not driving the results.

Another potential mechanism that could explain the relationship between the firm earnings premium and claim rates is peer effects. If peer-to-peer information is the primary channel by which takeup rates increase in high premium firms, then claim rates should be higher in firms that have recently hired more workers from other high premium firms. To test this mechanism, we calculate the number of movers in each year that move to the firm from a firm in the top quartile of the firm earnings premium distribution, as well as the number of movers from other firms. We then include the log number of movers from high and lower earnings premium firms as additional controls in the analysis. Figure 4 next shows that the results are very similar to the main results when these additional controls are included (full results are shown in Appendix Table A15). Additionally, the incidence rate ratios capturing the relationship between the number of movers from high premium firms and the number of claims are generally close to one. This implies that, conditional on the current firm earnings premium, the recent employment experiences of coworkers have little influence on own claim decisions. However, this analysis does not completely allow us to rule out the possibility of peer effects as a mechanism. Importantly, we cannot measure relationships or closeness between coworkers. Other work on peer effects suggests that peer effects are strongest when individuals are more closely connected, so an average measure may be too noisy to detect these effects at the firm level (Dahl et al., 2014).

The last set of estimates in Figure 4 show effects estimated accounting for heterogeneity in the degree of drift in the estimated firm fixed effects over time. For this analysis, we estimate the firm fixed effects using data only from the first half of the sample period (2000-2006) and again using data only from the second half (2007-2013). Using the sample of firms which appear in both periods, we calculate the change in the estimated fixed effect across periods. The figure shows effects for firms in the bottom 25% of the distribution of the change in the estimated fixed effect, firms in the 25-75th percentiles, and firms in the top 25% of the distribution. Results across these categories are quite similar, suggesting that the importance of firm earnings premium on claims is not a function of the drift in the firm effects over time. Full results are shown in Appendix Figure A16.

As discussed in Section 4, the earnings data used in this analysis does not include age, gender, educational attainment, or hours of work. This means that the firm fixed effects we estimate to examine the impact of the firm premium on leave take-up reflect firm-level differences in reliance on part-time workers and differential experience profiles across firms, or other differences in worker characteristics that are unobservable in our data. One might be concerned that these characteristics are direct contributors to the probability of needing or making a social insurance claim. Although we cannot directly control for these characteristics or restrict the sample to specific types of workers based on qualities unavailable in the data, we have shown that the results persist across industries, firms of different sizes, firms with different skill compositions, and firms with different growth rates. We have also shown that the results persist across most of the relative earnings distribution and for firms with different average worker fixed effect levels. Together these results suggest that experience and hours composition differences across firms are not driving the observed leave-taking patterns. They also suggest that measures of firm growth, earnings growth, skill levels, and peer effects are unlikely mechanisms to explain the majority of the relationship between the firm premium and leave take-up.

Finally, another potential 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 8. 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.[32] 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 8 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 the firm wage premium 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, 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, 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.

5.4 Selective Mobility

The above analysis suggests that unobservable sorting on time-invariant characteristics—such as worker quality—is unlikely to explain our results. It is still possible, however, that there are dynamic forms of selection driving our estimates. For instance, we might worry that individuals who expect to take leave in the future systematically try to move to firms that are more amenable to leave-taking in advance of making their claim. While we can't observe why workers move, and one might also think that workers might prefer to work for firms with higher earnings premiums for many reasons, we can examine the patterns of leave taking for those who make specific sorts of job changes before they take a leave. More specifically, we examine whether workers who make different types of moves subsequently have different claim rates. Figure 5 estimates an individual worker's probability of filing a DI or PFL claim as a function of their

[32] 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.

current firm's earnings premium quartile and their last firm's quartile.[33] Confirming the firm-level results, the figure shows that the probability of making a claim is higher for workers currently in higher premium firms. However, workers who move from lower premium firms to higher premium firms are no more likely to make claims than those who previously worked in a higher premium firm. Taken as a whole, we don't find any systematic evidence that moving is correlated with leave taking.

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 are unlikely to 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,

[33]The worker's previous firm is defined as the worker's last firm within a three year window. Workers who have two or more quarters of non-employment separating a move are defined as moving from non-employment. Workers who work for the same firm for the entire window are defined as staying in the same quartile. Results are not sensitive to using a longer or shorter window.

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.

7 Acknowledgments

We thank Kent Strauss for valuable research assistance and Jennifer Mehl for assistance with the Secure Compute Research Environment. We thank Isaac Sorkin, as well as seminar participants at MIT, the University of British Columbia, the University of California, Bekeley, the University of Chicago, the

University of Toronto, the All-California Labor Economics conference, the AEA meetings, the Canadian Labour Economics Forum, and the Models of Linked Employer-Employee Data Conference for helpful comments. Rossin-Slater is grateful for support from the National Science Foundation (NSF) CAREER Award No. 1752203. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation. All errors are our own. The California Employment Development Department (EDD) had the right to comment on the results of the paper, per the data use agreement between the authors and the EDD.

References

Abowd, John, Paul A. Lengermann, and Kevin McKinney. 2003. "The Measurement of Human Capital in the U.S. Economy." longitudinal employer-household dynamics technical papers, Center for Economic Studies, U.S. Census Bureau.

Abowd, John M, Francis Kramarz, and David N Margolis. 1999. "High wage workers and high wage firms." *Econometrica*, 67(2): 251–333.

Andrews, M. J., L. Gill, T. Schank, and R. Upward. 2008. "High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias?" *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 171(3): 673–697, URL: `http://www.jstor.org/stable/30135090`.

Asai, Yukiko. 2015. "Parental Leave Reforms and the Employment of New Mothers: Quasi-Experimental Evidence from Japan." *Labour Economics*, 36 72–83, URL: `http://www.sciencedirect.com/science/article/pii/S0927537115000226`, DOI: `http://dx.doi.org/https://doi.org/10.1016/j.labeco.2015.02.007`.

Autor, David H, and Mark G Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *The Quarterly Journal of Economics*, 118(1): 157–206.

Bagger, Jesper, and Rasmus Lentz. 2018. "An Empirical Model of Wage Dispersion with Sorting." *The Review of Economic Studies*, 86(1): 153–190, URL: `https://doi.org/10.1093/restud/rdy022`, DOI: `http://dx.doi.org/10.1093/restud/rdy022`.

Bana, Sarah, Kelly Bedard, and Maya Rossin-Slater. 2018. "Trends and Disparities in Leave Use under California's Paid Family Leave Program: New Evidence from Administrative Data." *AEA Papers and Proceedings*, 108 388–391, URL: `http://www.aeaweb.org/articles?id=10.1257/pandp.20181113`, DOI: `http://dx.doi.org/10.1257/pandp.20181113`.

Bana, Sarah H., Kelly Bedard, and Maya Rossin-Slater. 2020. "The Impacts of Paid Family Leave Benefits: Regression Kink Evidence from California Administrative Data." *Journal of Policy Analysis and Management*, 39(4): 888–929, URL: `https://onlinelibrary.wiley.com/doi/abs/10.1002/pam.22242`, DOI: `http://dx.doi.org/https://doi.org/10.1002/pam.22242`.

Bartel, Ann P, Maya Rossin-Slater, Christopher J Ruhm, Meredith Slopen, and Jane Waldfogel. 2021. "The Impact of Paid Family Leave on Employers: Evidence from New York." Working Paper 28672, National Bureau of Economic Research.

Bartel, Ann P, Maya Rossin-Slater, Christopher J Ruhm, Jenna Stearns, and Jane Waldfogel. 2018. "Paid Family Leave, Fathers' Leave-Taking, and Leave-Sharing in Dual-Earner Households." *Journal of Policy Analysis and Management*, 37(1): 10–37.

Barth, Erling, Alex Bryson, James C. Davis, and Richard Freeman. 2016. "It's Where You Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States." *Journal of Labor Economics*, 34(S2): S67–S97, URL: `https://doi.org/10.1086/684045`, DOI: `http://dx.doi.org/10.1086/684045`.

Baum, Charles L, and Christopher J Ruhm. 2016. "The Effects of Paid Family Leave in California on Labor Market Outcomes." *Journal of Policy Analysis and Management*, 35(2): 333–356.

Brenøe, Anne A, Serena P Canaan, Nikolaj A Harmon, and Heather N Royer. 2020. "Is Parental Leave Costly for Firms and Coworkers?" Working Paper 26622, National Bureau of Economic Research.

Bruns, Benjamin. 2018. "Changes in Workplace Heterogeneity and How They Widen the Gender Wage Gap." *American Economic Journal: Applied Economics*, Forthcoming.

Burdett, Kenneth, and Dale Mortensen. 1998. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review*, 39(2): 257–73, URL: `https://EconPapers.repec.org/RePEc:ier:iecrev:v:39:y:1998:i:2:p:257-73`.

Cameron, A. Colin, and Pravin K Trivedi. 2013. *Regression Analysis of Count Data*.: Cambridge University Press.

Campbell, Zakary, Eric Chyn, and Justine Hastings. 2018. "The Impact of Paid Maternity Leave: Evidence from a Temporary Disability Insurance Program."Technical report.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline. 2018. "Firms and Labor Market Inequality: Evidence and Some Theory." *Journal of Labor Economics*, 36(S1): S13–S70, URL: `https://doi.org/10.1086/694153`, DOI: `http://dx.doi.org/10.1086/694153`.

Card, David, Ana Rute Cardoso, and Patrick Kline. 2016. "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women." *The Quarterly Journal of Economics*, 131(2): 633–686, URL: http://dx.doi.org/10.1093/qje/qjv038, DOI: http://dx.doi.org/10.1093/qje/qjv038.

Card, David, Jörg Heining, and Patrick Kline. 2013. "Workplace Heterogeneity and the Rise of West German Wage Inequality." *The Quarterly journal of economics*, 128(3): 967–1015.

Carneiro, Pedro, Katrine V. Lken, and Kjell G. Salvanes. 2015. "A Flying Start? Maternity Leave Benefits and Long-Run Outcomes of Children." *Journal of Political Economy*, 123(2): 365–412, URL: https://doi.org/10.1086/679627, DOI: http://dx.doi.org/10.1086/679627.

Chang, Andrew & Company. 2015. "Paid Family Leave Market Research."Technical report, California Employment Development Department, Sacramento, CA.

Chen, Susan, and Wilbert van der Klaauw. 2008. "The Work Disincentive Effects of the Disability Insurance Program in the 1990s." *Journal of Econometrics*, 142(2): 757 – 784, URL: http://www.sciencedirect.com/science/article/pii/S0304407607001169, DOI: http://dx.doi.org/https://doi.org/10.1016/j.jeconom.2007.05.016, The regression discontinuity design: Theory and applications.

Clark, Sue Campbell. 2001. "Work Cultures and Work/Family Balance." *Journal of Vocational Behavior*, 58(3): 348–365.

Coudin, Elise, Sophie Maillard, and Maxime To. 2018. "Family, Firms and the Gender Wage Gap in France." IFS Working Papers W18/01, Institute for Fiscal Studies.

Dahl, Gordon B., Katrine V. Løken, and Magne Mogstad. 2014. "Peer Effects in Program Participation." *American Economic Review*, 104(7): 2049–2074, URL: https://www.aeaweb.org/articles?id=10.1257/aer.104.7.2049, DOI: http://dx.doi.org/10.1257/aer.104.7.2049.

Dale-Olsen, Harald. 2014. "Sickness Absence, Sick Leave Pay, and Pay Schemes." *Labour*, 28(1): 40–

63, URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/labr.12022, DOI: http://dx.doi.org/10.1111/labr.12022.

Das, Tirthatanmoy, and Solomon W Polachek. 2015. "Unanticipated Effects of California's Paid Family Leave Program." *Contemporary Economic Policy*, 33(4): 619–635.

Davis, Steven J., John C. Haltiwanger, and Scott Schuh. 1998. *Job Creation and Destruction*. 1 of MIT Press Books: The MIT Press, , URL: https://ideas.repec.org/b/mtp/titles/0262540932.html.

DiCamillo, Mark, and Mervin Field. 2015. "Just 36% of Voters Aware of State's Paid Family Leave Program."Technical report, Field Research Corporation.

Dionne, Georges, and Benoit Dostie. 2007. "New Evidence on the Determinants of Absenteeism Using Linked Employer-Employee Data." *ILR Review*, 61(1): 108–120, URL: https://doi.org/10.1177/001979390706100106, DOI: http://dx.doi.org/10.1177/001979390706100106.

Faggio, Giulia, Kjell G Salvanes, and John Van Reenen. 2010. "The Evolution of Inequality in Productivity and Wages: Panel Data Evidence." *Industrial and Corporate Change*, 19(6): 1919–1951.

Gallen, Yana. 2019. "The Effect of Parental Leave Extensions on Firms and Coworkers."

Gerard, Franois, Lorenzo Lagos, Edson Severnini, and David Card. 2021. "Assortative Matching or Exclusionary Hiring? The Impact of Employment and Pay Policies on Racial Wage Differences in Brazil." *American Economic Review*, 111(10): 3418–57, URL: https://www.aeaweb.org/articles?id=10.1257/aer.20181596, DOI: http://dx.doi.org/10.1257/aer.20181596.

Ginja, Rita, Arizo Karimi, and Pengpeng Xiao. 2020. "Employer Responses to Family Leave Programs." IZA Discussion Papers 13833.

Gruber, Jonathan. 2000. "Disability Insurance Benefits and Labor Supply." *Journal of Political Economy*, 108(6): 1162–1183, URL: https://doi.org/10.1086/317682, DOI: http://dx.doi.org/10.1086/317682.

Henrekson, Magnus, and Mats Persson. 2004. "The Effects on Sick Leave of Changes in the Sickness Insurance System." *Journal of Labor Economics*, 22(1): 87–113, URL: `https://doi.org/10.1086/380404`, DOI: `http://dx.doi.org/10.1086/380404`.

Hotz, V. Joseph, Per Johansson, and Arizo Karimi. 2017. "Parenthood, Family Friendly Workplaces, and the Gender Gaps in Early Work Careers." Working Paper 24173, National Bureau of Economic Research.

Huebener, Mathias, Jonas Jessen, Daniel Khnle, and Michael Oberfichtner. 2021. "A Firm-Side Perspective on Parental Leave." IZA Discussion Papers 14478, Institute of Labor Economics (IZA).

Ichino, Andrea, and Regina T. Riphahn. 2005. "The Effect of Employment Protection on Worker Effort: Absenteeism during and after Probation." *Journal of the European Economic Association*, 3(1): 120–143, URL: `http://dx.doi.org/10.1162/1542476053295296`, DOI: `http://dx.doi.org/10.1162/1542476053295296`.

Johansson, Per, and Mårten Palme. 2005. "Moral Hazard and Sickness Insurance." *Journal of Public Economics*, 89(9): 1879–1890, URL: `http://www.sciencedirect.com/science/article/pii/S0047272705000290`, DOI: `http://dx.doi.org/https://doi.org/10.1016/j.jpubeco.2004.11.007`.

Kelly, Erin L, Phyllis Moen, and Eric Tranby. 2011. "Changing Workplaces to Reduce Work-Family Conflict: Schedule Control in a White-Collar Organization." *American Sociological Review*, 76(2): 265–290.

Kline, Patrick, Raffaele Saggio, and Mikkel Slvsten. 2020. "Leave-Out Estimation of Variance Components." *Econometrica*, 88(5): 1859–1898, URL: `https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA16410`, DOI: `http://dx.doi.org/https://doi.org/10.3982/ECTA16410`.

Kurani, Nisha, U Ranji, A Salganicoff, and M Rae. 2017. "Paid Family Leave and Sick Days in the US: Findings from the 2016 Kaiser/HRET Employer Health Benefits Survey."Technical report, Kaiser Family Foundation, Washington, D.C.

Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A Woodbury. 2019. “Do Firm Effects Drift? Evidence from Washington Administrative Data.”Technical report.

Lavetti, Kurt, and Ian M. Schmutte. 2018. “Estimating Compensating Wage Differentials with Endogenous Job Mobility.” Working Paper 29, Labor Dynamics Institute, Cornell University.

Macis, Mario, and Fabiano Schivardi. 2016. “Exports and Wages: Rent Sharing, Workforce Composition, or Returns to Skills?” *Journal of Labor Economics*, 34(4): 945–978, URL: `https://doi.org/10.1086/686275`, DOI: `http://dx.doi.org/10.1086/686275`.

Moen, Phyllis, Erin L Kelly, Wen Fan, Shi-Rong Lee, David Almeida, Ellen Ernst Kossek, and Orfeu M Buxton. 2016. “Does a Flexibility/Support Organizational Initiative Improve High-Tech Employees’ Well-Being? Evidence from the Work, Family, and Health Network.” *American Sociological Review*, 81(1): 134–164.

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2012. “The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment.” *American Economic Review*, 102(6): 2509–39, URL: `https://www.aeaweb.org/articles?id=10.1257/aer.102.6.2509`, DOI: `http://dx.doi.org/10.1257/aer.102.6.2509`.

Olivetti, Claudia, and Barbara Petrongolo. 2017. “The Economic Consequences of Family Policies: Lessons from a Century of Legislation in High-Income Countries.” *Journal of Economic Perspectives*, 31(1): 205–30, URL: `http://www.aeaweb.org/articles?id=10.1257/jep.31.1.205`, DOI: `http://dx.doi.org/10.1257/jep.31.1.205`.

Pettersson-Lidbom, Per, and Peter Skogman Thoursie. 2013. “Temporary Disability Insurance and Labor Supply: Evidence from a Natural Experiment.” *The Scandinavian Journal of Economics*, 115(2): 485–507, URL: `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9442.2012.01746.x`, DOI: `http://dx.doi.org/10.1111/j.1467-9442.2012.01746.x`.

Riphahn, Regina T. 2004. “Employment Protection and Effort among German Employees.” *Economics Letters*, 85(3): 353–357, URL: `http://www.sciencedirect.com/science/article/pii/`

S0165176504002034, DOI: http://dx.doi.org/https://doi.org/10.1016/j.econlet.2004.03.035.

Rossin-Slater, Maya. 2018. "Maternity and Family Leave Policy." In *Oxford Handbook of Women and the Economy*. eds. by Susan L. Averett, Laura M. Argys, and Saul D. Hoffman, New York: Oxford University Press, , URL: http://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780190628963.001.0001/oxfordhb-9780190628963-e-23.

Rossin-Slater, Maya, Christopher J Ruhm, and Jane Waldfogel. 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.

Song, Jae, David J Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter. 2018. "Firming Up Inequality." Working Paper 21199, National Bureau of Economic Research.

Sorkin, Isaac. 2018. "Ranking Firms Using Revealed Preference." *The Quarterly Journal of Economics*, 133(3): 1331–1393, URL: http://dx.doi.org/10.1093/qje/qjy001, DOI: http://dx.doi.org/10.1093/qje/qjy001.

Stearns, Jenna. 2015. "The Effects of Paid Maternity Leave: Evidence from Temporary Disability Insurance." *Journal of Health Economics*, 43 85–102, URL: http://www.sciencedirect.com/science/article/pii/S0167629615000533, DOI: http://dx.doi.org/https://doi.org/10.1016/j.jhealeco.2015.04.005.

Stearns, Jenna. 2018. "The Long-Run Effects of Wage Replacement and Job Protection: Evidence from Two Maternity Leave Reforms in Great Britain."Technical Report 3030808, SSRN.

Stearns, Jenna, and Corey White. 2018. "Can Paid Sick Leave Mandates Reduce Leave-Taking?" *Labour Economics*, 51 227–246, URL: http://www.sciencedirect.com/science/article/pii/S0927537118300034, DOI: http://dx.doi.org/https://doi.org/10.1016/j.labeco.2018.01.002.

Taber, Christopher, and Rune Vejlin. 2020. "Estimation of a Roy/Search/Compensating Differential Model of the Labor Market." *Econometrica*, 88(3): 1031–1069, URL: https://onlinelibrary.

wiley.com/doi/abs/10.3982/ECTA14441, DOI: http://dx.doi.org/https://doi.org/10.3982/ECTA14441.

Thomas, Mallika. 2016. "The Impact of Mandated Maternity Benefits on the Gender Differential in Promotions: Examining the Role of Adverse Selection." URL: http://digitalcommons.ilr.cornell.edu/ics/16.

Tô, Linh T. 2018. "The Signaling Role of Parental Leave." URL: https://scholar.harvard.edu/files/linhto/files/signaling.pdf.

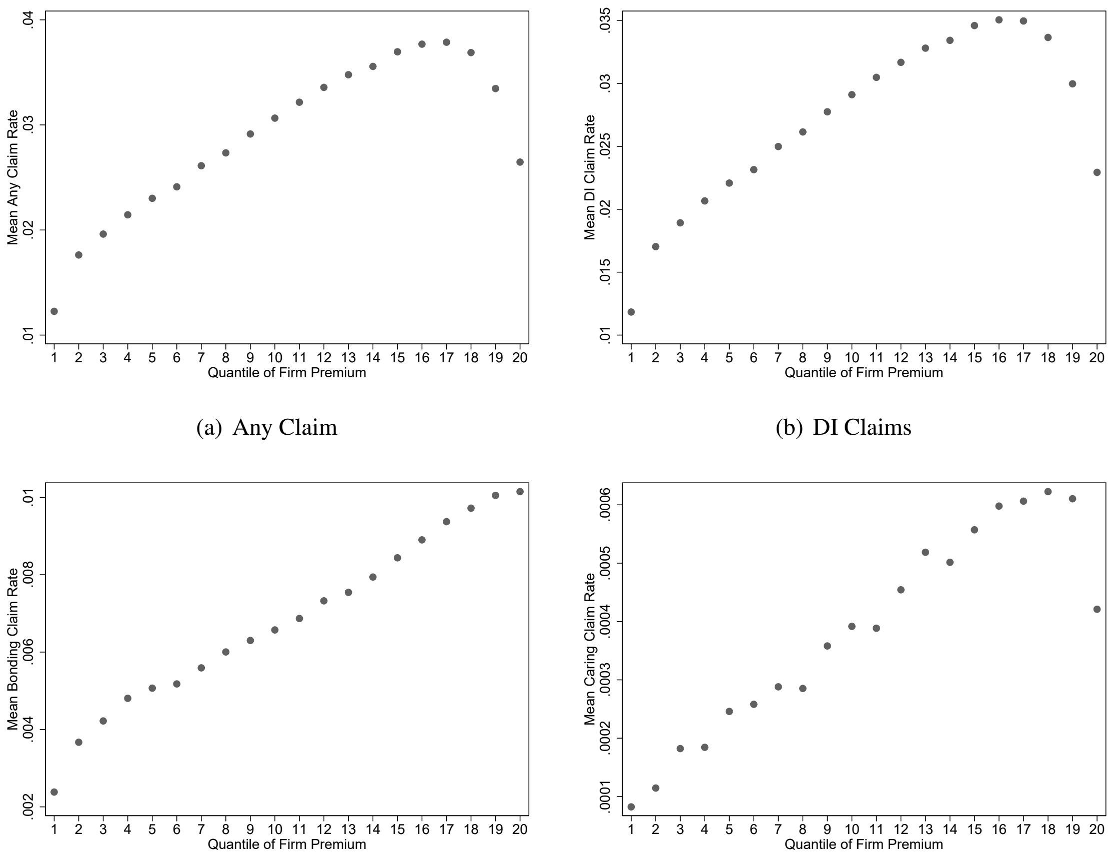
Van Reenen, John. 1996. "The Creation and Capture of Rents: Wages and Innovation in a Panel of UK Companies." *The Quarterly Journal of Economics*, 111(1): 195–226.

Winston, Pamela, Ariel Pihl, Lincoln Groves, Colin Campbell, Elizabeth Coombs, and Sharon Wolf. 2017. "Exploring the Relationship Between Paid Family Leave and the Well-being of Low-Income Families: Lessons from California." research report, U.S. Department of Health and Human Services.

Ziebarth, Nicolas R. 2013. "Long-Term Absenteeism and Moral Hazard—Evidence from a Natural Experiment." *Labour Economics*, 24 277–292, URL: http://www.sciencedirect.com/science/article/pii/S0927537113001036, DOI: http://dx.doi.org/https://doi.org/10.1016/j.labeco.2013.09.004.

Ziebarth, Nicolas R., and Martin Karlsson. 2010. "A Natural Experiment on Sick Pay Cuts, Ssickness Absence, and Labor Costs." *Journal of Public Economics*, 94(11): 1108–1122, URL: http://www.sciencedirect.com/science/article/pii/S0047272710001180, DOI: http://dx.doi.org/https://doi.org/10.1016/j.jpubeco.2010.09.001.

Figure 1: Mean Claim Rate by Firm Earnings Premium Quantile



(a) Any Claim

(b) DI Claims

(c) Bonding Claims

(d) Caring Claims

Figure shows the mean undadjusted firm claim rate of firms in each quantile of the firm earnings premium distribution.

Figure 2: Mean Earnings of Job Changers Classified by Quartile of Mean Earnings of Coworkers at Origin and Destination Firm

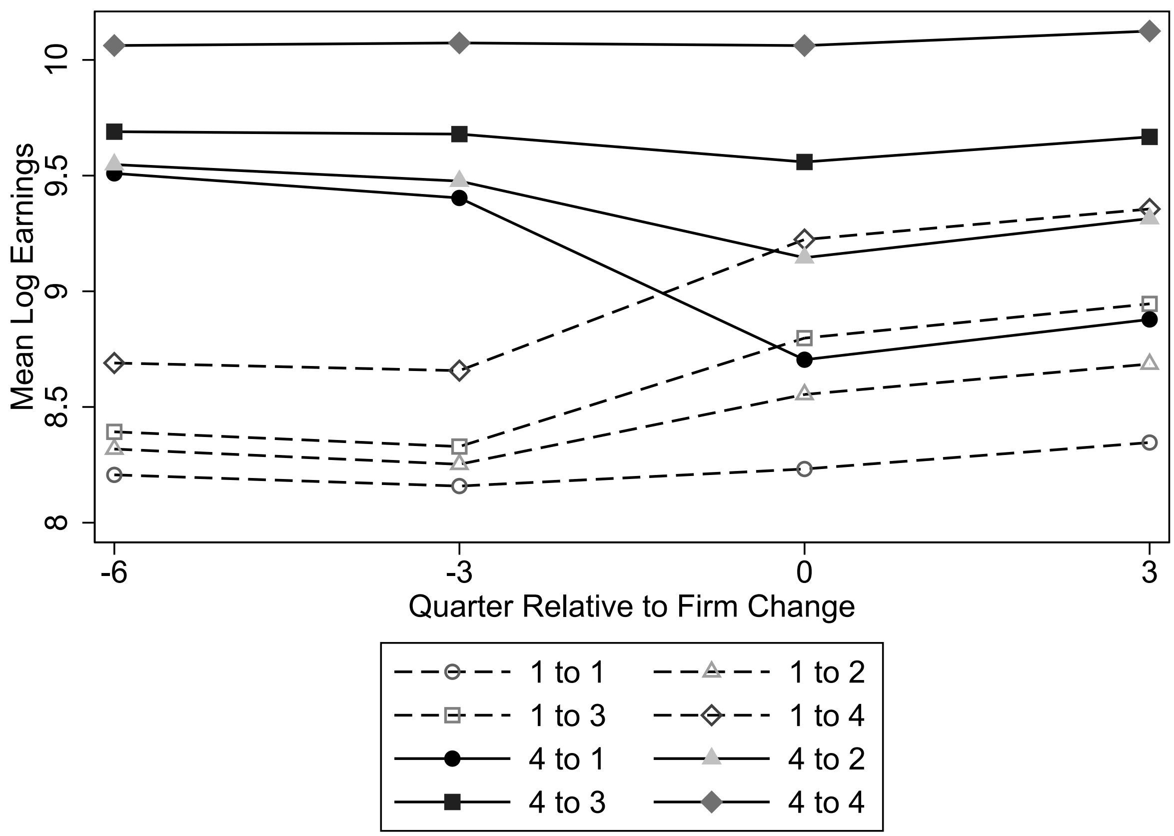


Figure shows mean log earnings of job changers, classified by quartile of coworker earnings at the origin and destination firm. For ease of interpretation, only workers who start in the top or bottom quartile of the coworker earnings distribution are shown.

Figure 3: Effect of Firm Premium on Number of Leave-Taking Claims by Age of Claimant, Firm Size, and Industry

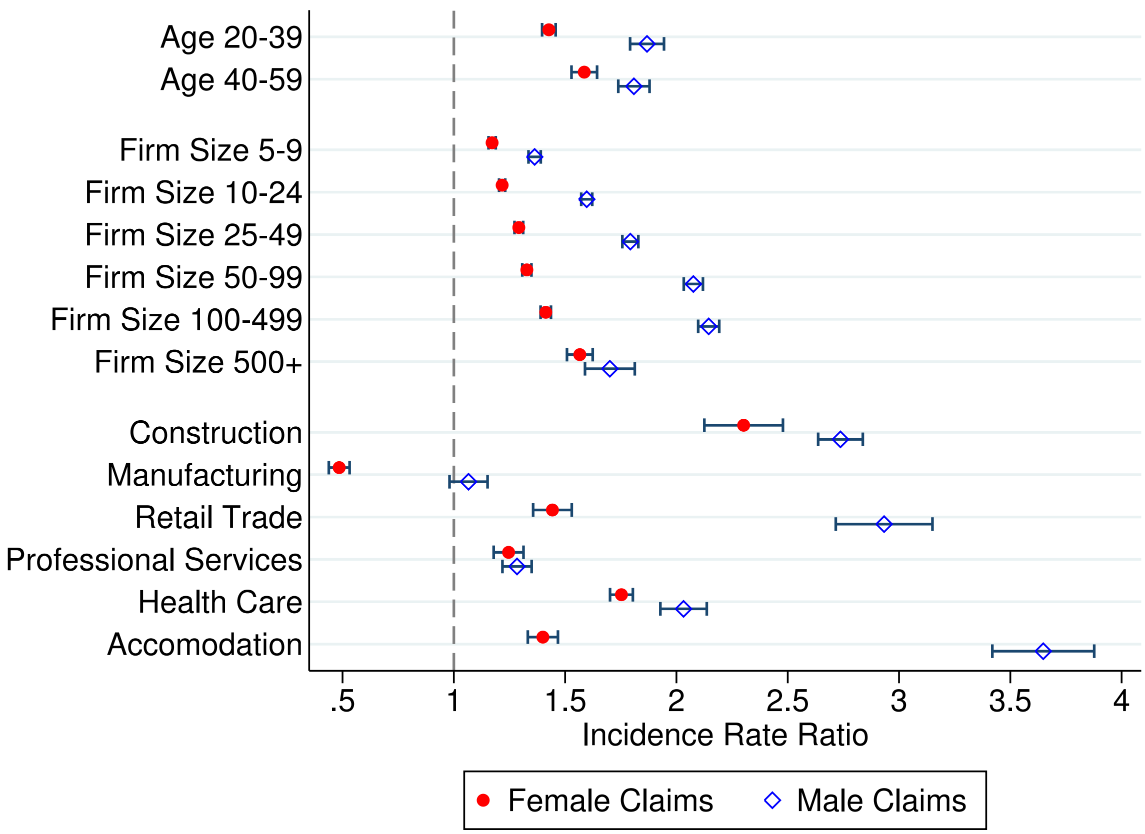


Figure shows the effect of the firm premium on the number of DI and PFL claims within the firm in a given year. Estimates correspond to the "Any Claim" coefficients for female and male claims in Table 2. All regressions include 2,709,253 observations. The effects are estimated using a Poisson regression 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. Error bars indicate 99% confidence intervals.

Figure 4: Effect of Firm Premium on Number of Leave-Taking Claims by Firm Heterogeneity

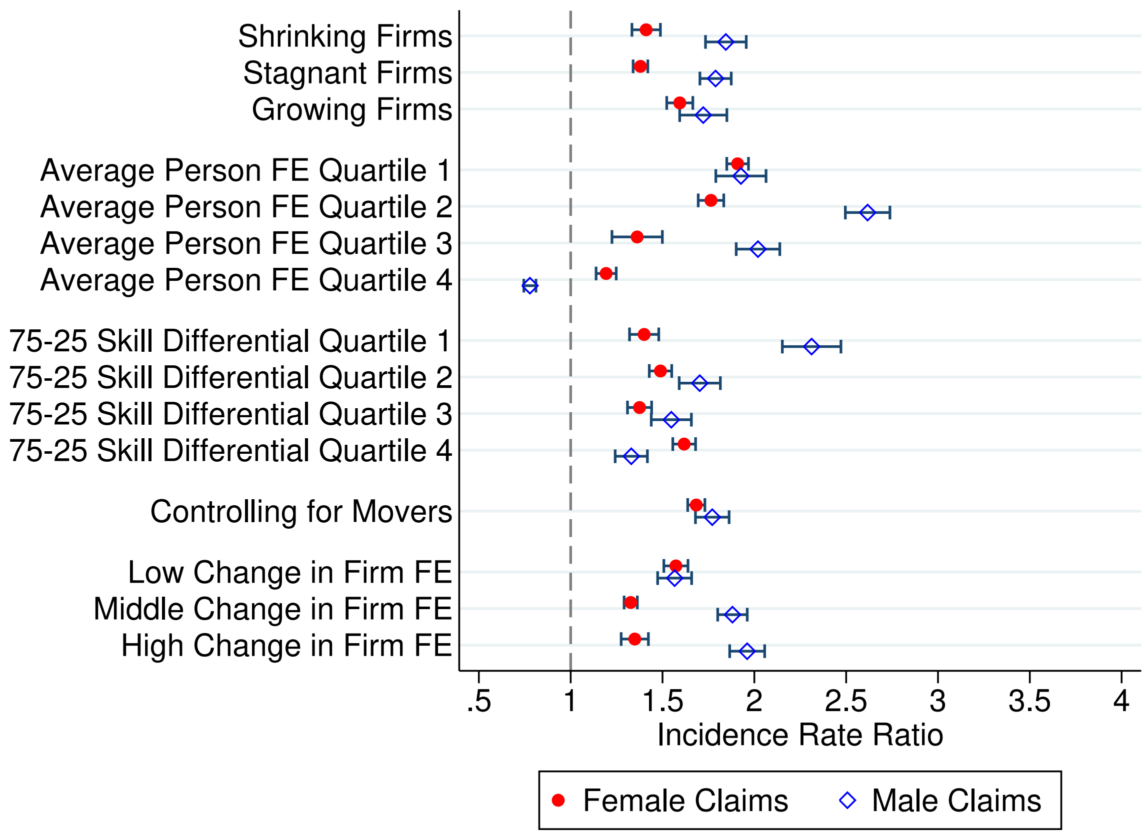


Figure shows the effect of the firm premium on the number of DI and PFL claims within the firm in a given year. Estimates correspond to the "Any Claim" coefficients for female and male claims in Appendix Tables A14-A16. The effects are estimated using a Poisson regression and the estimates and standard 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. Error bars indicate 99% confidence intervals.

Figure 5: Probability of Making Any Claim by Current and Previous Firm Premium Quartile

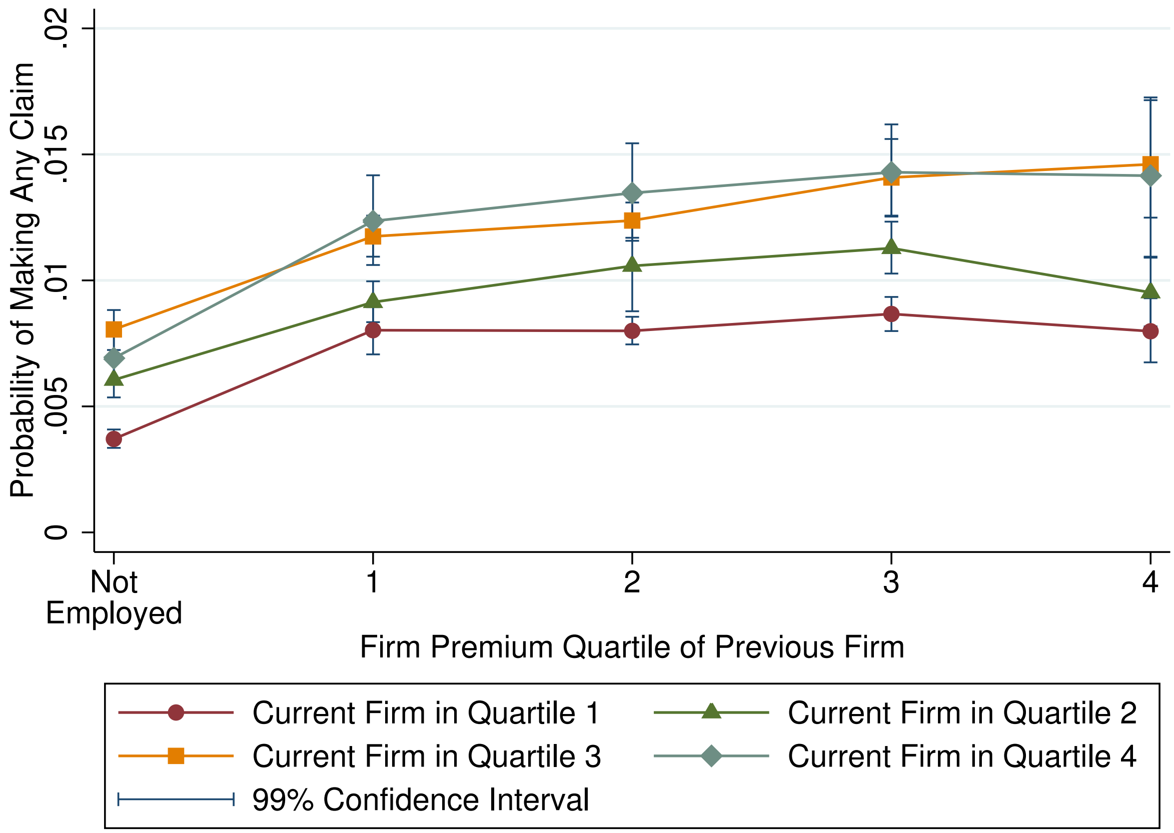


Figure shows the probability that an individual makes any PFL or DI claim by the firm premium quartiles of their current and previous firm. Coefficients are estimated from an individual level regression. Previous firm is the last firm the individual worked for within a 3 year window. Individuals who did not change firms within this window are coded as staying in the same quartile. Those with two or more consecutive quarters of non-employment (zero earnings) between the current job and any prior job are considered as previously not employed. Coefficients are calculated using a linear probability model with interacted current and previous firm premium quartile indicators. Confidence intervals are bootstrapped.

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 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 4: 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 5: 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 6: 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 7: Effect of Firm Premium on Number of Leave-Taking Claims with Additional Controls

	Female Claims				Male Claims			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Baseline Firm Size 10+								
Firm Premium	1.463*	1.442*	1.522*	2.111*	1.806*	1.666*	2.647*	2.604*
	(0.013)	(0.012)	(0.012)	(0.040)	(0.028)	(0.025)	(0.056)	(0.067)
With Additional Controls								
Firm Premium	1.266*	1.256*	1.519*	1.196*	1.332*	1.235*	1.936*	1.331*
	(0.018)	(0.018)	(0.019)	(0.030)	(0.028)	(0.026)	(0.063)	(0.047)
Mean Number of Claims	2.297	2.208	0.596	0.062	1.333	1.099	0.204	0.029

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 1,593,635 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 firms with an average of at least 10 employees in fiscal years 2004-2013. Controls in the baseline specification include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. The second panel additionally controls for within-firm average annual earnings growth, average employee skill level, the dispersion in skill within firms measured by the 75-25 skill differential, the firm's DHS growth rate, and firm desirability measured by employee turnover and a poaching index. 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 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 Figures and Tables

Figure A1: Distribution of Firm Earnings Premiums

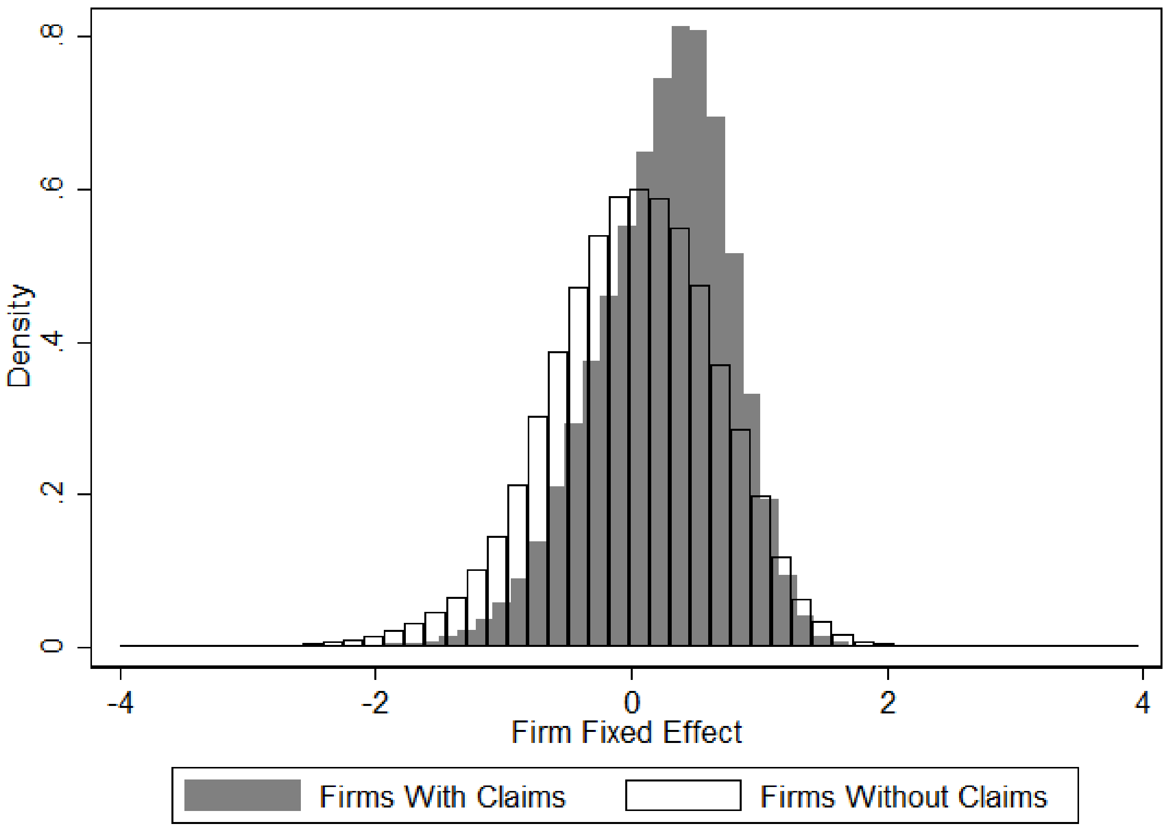


Figure shows the distribution of firm premiums for firms that ever have at least one claim over the sample period and for firms that never have a claim. The data in this figure is collapsed to include a single observation per firm so as to not overweight longer-surviving firms.

Figure A2: Probability of Making Any Claim by Firm Premium Quartile and Worker Fixed Effect Quartile

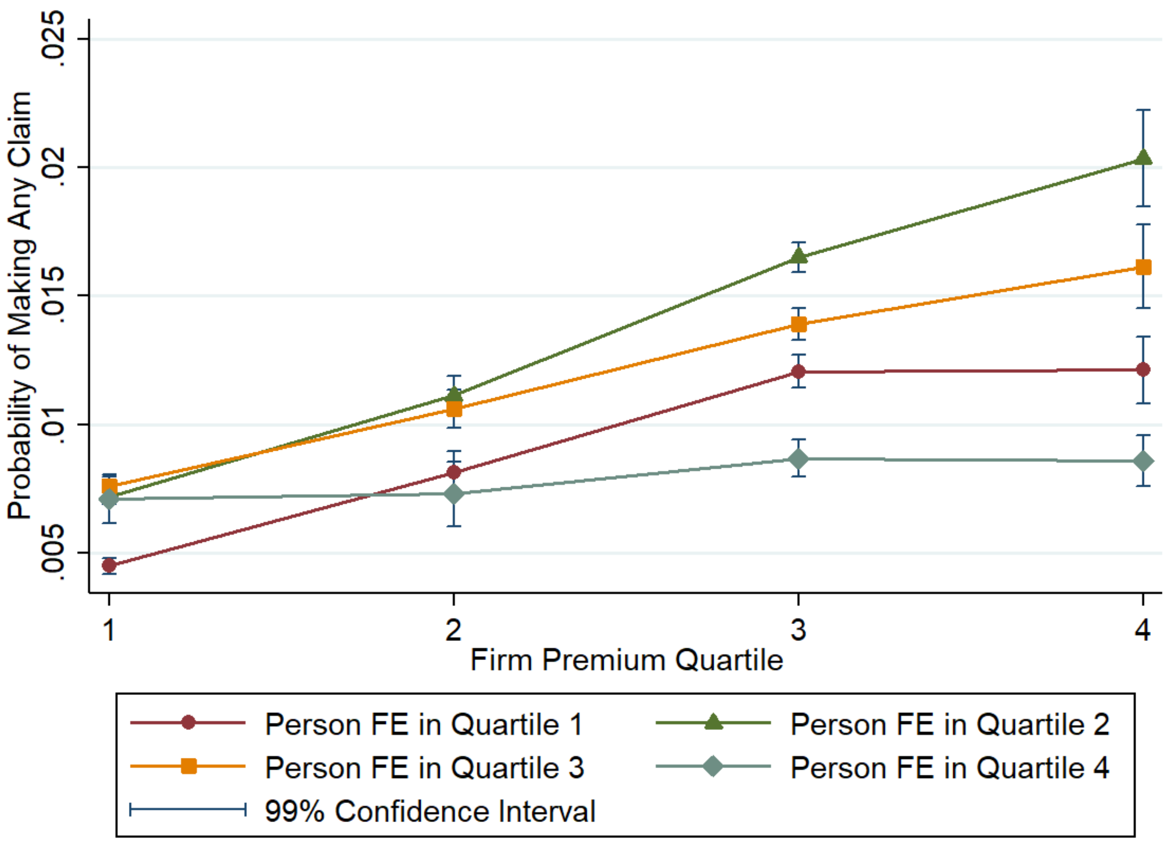


Figure shows the probability that an individual makes any PFL or DI claim by the firm premium quartile and the worker's fixed effect quartile. Coefficients are estimated from an individual level regression. Coefficients are calculated using a linear probability model with interacted firm premium quartile and worker fixed effect quartile indicators. Confidence intervals are bootstrapped.

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, Alternate Specifications

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Negative Binomial Model									
Firm Premium	1.489*	1.296*	1.279*	1.540*	2.175*	1.864*	1.705*	3.587*	3.543*
	(0.003)	(0.012)	(0.003)	(0.006)	(0.025)	(0.007)	(0.007)	(0.024)	(0.058)
Observations	2,709,253	2,709,253	2,709,253	2,709,253	2,709,253	2,709,253	2,709,253	2,709,253	2,709,253
Mean Number of Claims	2.218	1.407	1.352	0.369	0.037	0.811	0.671	0.123	0.017
Excluding Firms That Never Have a Claim									
Firm Premium	1.549*	1.437*	1.416*	1.446*	2.034*	1.719*	1.589*	2.166*	1.934*
	(0.012)	(0.012)	(0.012)	(0.011)	(0.045)	(0.026)	(0.023)	(0.043)	(0.065)
Observations	2,163,728	1,742,846	1,729,365	1,100,146	191,686	1,418,881	1,341,500	440,188	120,795
Mean Number of Claims	2.777	2.187	2.119	0.908	0.528	1.549	1.355	0.755	0.392

Notes: Table shows the effect of the firm premium on the number of DI or PFL claims within the firm in a given year. The effects in the first panel are estimated using a negative binomial regression. The second panel shows estimates from a Poisson regression and exludes firms that never have a claim of that type over the full sample period. 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, 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 A5: 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 A6: 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. * $p<0.01$.

Table A7: 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 A8: 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 A9: Effect of Firm Premium on Number of Leave-Taking Claims, Excluding Low Earners

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.513*	1.392*	1.372*	1.455*	1.986*	1.739*	1.608*	2.526*	2.492*
	(0.013)	(0.012)	(0.012)	(0.012)	(0.036)	(0.024)	(0.022)	(0.048)	(0.059)
Mean Number of Claims	2.211	1.402	1.347	0.367	0.037	0.809	0.669	0.123	0.018

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 2,702,594 observations. Sample is restricted to include only workers who earn at least $1200 per quarter on average in real terms. 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 A10: Effect of Firm Premium on Number of Leave-Taking Claims, Split Sample Approach

	All	**Female Claims**				**Male Claims**			
	Any Claim	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.304*	1.203*	1.185*	1.248*	1.802*	1.487*	1.367*	2.182*	2.266*
	(0.01)	(0.012)	(0.011)	(0.010)	(0.036)	(0.026)	(0.024)	(0.053)	(0.067)
Mean Number of Claims	3.564	2.256	2.166	0.578	0.063	1.309	1.073	0.206	0.030

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 758,162 observations. The firm premium fixed effects are estimated using earnings data from half of the sample of individuals. The effects on claims are estimated using the other half of individuals in the data using a Poisson regression and the estimates and standard errors have been exponentiated such that the coefficients shown here are incidence rate ratios. The analysis is limited to firms that have an average of at least 10 workers in the full sample. 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 A11: Effect of Firm Premium on the Average Change in Earnings of Claimants, Additional Subsamples

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Employed At Any Firm								
Firm Premium	-0.078*	-0.078*	-0.030*	-0.004	-0.116*	-0.127*	-0.035*	0.014
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.004)	(0.008)	(0.012)
Observations	536,599	528,788	249,410	40,002	365,370	332,490	95,765	23,570
Mean Change in Log Earnings	-0.110	-0.109	-0.102	-0.034	-0.103	-0.109	-0.017	-0.028
Returned to Same Firm and Moved								
Firm Premium	-0.215*	-0.205*	-0.158*	-0.017*	-0.201*	-0.186*	-0.077*	0.004
	(0.007)	(0.007)	(0.011)	(0.007)	(0.010)	(0.009)	(0.021)	(0.017)
Observations	148,034	146,881	61,152	23,239	95,947	89,353	26,042	13,280
Mean Change in Log Earnings	-0.319	-0.311	-0.278	-0.053	-0.324	-0.303	-0.179	-0.051
Never Returned to Same Firm								
Firm Premium	-0.396*	-0.389*	-0.344*	-0.017	-0.421*	-0.415*	-0.251*	-0.009
	(0.008)	(0.008)	(0.015)	(0.008)	(0.010)	(0.010)	(0.025)	(0.013)
Observations	147,503	146,442	52,263	19,549	112,587	107,660	17,176	11,176
Mean Change in Log Earnings	-0.123	-0.121	-0.065	-0.030	-0.124	-0.132	0.036	-0.013

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 any firm in the fifth quarter after the claim, the second panel shows the effect for those who initially returned to the same firm but are employed at a different firm in the fifth quarter after the claim, and the third panel shows the effect for those who are employed in the fifth quarter after the claim but never returned to the same firm. 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 A12: Effect of Firm Premium on Number of Leave-Taking Claims, Finer Industry Controls

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Firm Premium	1.480*	1.457*	1.617*	2.187*	1.834*	1.662*	2.984*	2.954*
	(0.011)	(0.011)	(0.010)	(0.032)	(0.022)	(0.020)	(0.049)	(0.064)
Mean Number of Claims	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. This table includes industry fixed effects at the three-digit level (industries with fewer than 5,000 observations are combined with the smallest industry with at least 5,000 observations within their two digit category), whereas the main specification includes industry fixed effects at the two-digit level. 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 A13: Effect of Firm Premium on Number of Leave-Taking Claims by Firm Growth Rate

	Female Claims				**Male Claims**				**Observations**
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring	
Shrinking Firms									
Firm Premium	1.411*	1.390*	1.509*	2.139*	1.845*	1.714*	3.147*	3.254*	677,314
	(0.030)	(0.029)	(0.030)	(0.078)	(0.043)	(0.041)	(0.096)	(0.138)	
Mean Number of Claims	0.997	0.963	0.255	0.022	0.661	0.577	0.072	0.012	
Stagnant Firms									
Firm Premium	1.380*	1.359*	1.427*	1.954*	1.789*	1.666*	2.484*	2.406*	1,354,627
	(0.015)	(0.015)	(0.015)	(0.044)	(0.033)	(0.031)	(0.058)	(0.068)	
Mean Number of Claims	1.905	1.828	0.480	0.056	1.067	0.873	0.169	0.025	
Growing Firms									
Firm Premium	1.594*	1.576*	1.748*	2.315*	1.722*	1.523*	2.861*	2.647*	677,312
	(0.028)	(0.027)	(0.028)	(0.090)	(0.050)	(0.040)	(0.119)	(0.157)	
Mean Number of Claims	0.819	0.792	0.260	0.016	0.449	0.360	0.081	0.008	

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 firm's growth rate. Shrinking firms are firms in the lowest quartile of the firm DHS growth rate distribution, stagnant firms are those in the 25-75th percentiles, and growing firms are firms in the top quartile of the growth rate distribution. The firm's DHS growth rate is computed using all years in the data, and is constant over time. 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 A14: Effect of Firm Premium on Number of Leave-Taking Claims by Measures of Firm Skill Composition

	Female Claims				**Male Claims**				**Observations**
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring	
By Person Fixed Effect Quartiles									
Quartile 1 Firm Premium	1.909*	1.898*	2.102*	2.730*	1.927*	1.736*	3.925*	3.274*	375,843
	(0.023)	(0.023)	(0.027)	(0.102)	(0.053)	(0.048)	(0.139)	(0.217)	
Quartile 2 Firm Premium	1.764*	1.747*	1.786*	2.734*	2.617*	2.362*	4.823*	4.773*	410,770
	(0.027)	(0.027)	(0.023)	(0.105)	(0.047)	(0.041)	(0.195)	(0.253)	
Quartile 3 Firm Premium	1.362*	1.345*	1.366*	1.863*	2.020*	1.885*	2.816*	2.991*	418,745
	(0.053)	(0.053)	(0.037)	(0.107)	(0.046)	(0.041)	(0.144)	(0.137)	
Quartile 4 Firm Premium	1.193*	1.172*	1.632*	1.264*	0.778*	0.696*	1.224*	1.076	388,278
	(0.021)	(0.021)	(0.039)	(0.035)	(0.013)	(0.012)	(0.040)	(0.034)	
By 75-25 Skill Differential Quartiles									
Quartile 1 Firm Premium	1.400*	1.368*	1.355*	2.224*	2.312*	2.088*	3.783*	3.838*	352,309
	(0.031)	(0.030)	(0.024)	(0.123)	(0.062)	(0.055)	(0.189)	(0.256)	
Quartile 2 Firm Premium	1.489*	1.470*	1.703*	2.131*	1.703*	1.565*	2.756*	1.990*	451,213
	(0.024)	(0.023)	(0.026)	(0.079)	(0.043)	(0.037)	(0.109)	(0.108)	
Quartile 3 Firm Premium	1.375*	1.365*	1.581*	1.459*	1.548*	1.438*	2.180*	1.576*	444,207
	(0.025)	(0.025)	(0.032)	(0.064)	(0.042)	(0.038)	(0.111)	(0.083)	
Quartile 4 Firm Premium	1.618*	1.606*	1.895*	1.824*	1.330*	1.217*	2.151*	1.807*	345,907
	(0.024)	(0.024)	(0.026)	(0.056)	(0.034)	(0.032)	(0.072)	(0.076)	

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 measures of the average worker skill level. The top panel shows results estimated by quartile of the firm's average worker fixed effect distribution. The bottom panel shows estimates by quartile of the firm's 75-25 skill differential distribution, which captures the degree of similarity across workers. The bottom panel additionally controls for the mean worker fixed effect. 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 firms with an average of at least 10 employees in 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 A15: Effect of Firm Premium on Number of Leave-Taking Claims, Controlling for Log Number of Movers

	Female Claims				**Male Claims**			
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring
Baseline								
Firm Premium	1.486*	1.465*	1.536*	2.113*	1.748*	1.609*	2.542*	2.493*
	(0.013)	(0.013)	(0.015)	(0.039)	(0.029)	(0.027)	(0.055)	(0.063)
With Log Movers								
Firm Premium	1.684*	1.671*	1.832*	2.021*	1.771*	1.636*	2.579*	2.397*
	(0.018)	(0.018)	(0.021)	(0.044)	(0.035)	(0.032)	(0.078)	(0.080)
Mean Number of Claims	4.805	4.611	1.226	0.137	2.786	2.275	0.446	0.065

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 667,826 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 firms with an average of at least 10 employees in fiscal years 2004-2013. All regressions include firm size, year fixed effects, industry fixed effects, and the share of women in the industry-year. The bottom panel additionally includes the log number of movers from firms in the top quartile of the firm premium distribution and the log number of movers from firms in the bottom three quartiles of the firm premium distribution. The baseline sample uses the same specification as Table 2 but restricts the analysis to the same sample of firms with movers as in the bottom panel. 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 A16: Effect of Firm Premium on Number of Leave-Taking Claims, by Estimated Change in Firm Premium from 2000-2006 to 2007-2014

	Female Claims				**Male Claims**				**Observations**
	Any Claim	DI	Bonding	Caring	Any Claim	DI	Bonding	Caring	
Lowest 25%									
Firm Premium	1.573*	1.558*	1.821*	2.006*	1.566*	1.441*	2.601*	2.180*	535,231
	(0.025)	(0.025)	(0.025)	(0.076)	(0.036)	(0.033)	(0.075)	(0.114)	
Mean Number of Claims	0.441	0.428	0.129	0.007	0.295	0.253	0.037	0.005	
Middle 50%									
Firm Premium	1.327*	1.305*	1.342*	1.998*	1.881*	1.733*	2.780*	2.722*	1,266,885
	(0.014)	(0.014)	(0.014)	(0.049)	(0.031)	(0.030)	(0.062)	(0.073)	
Mean Number of Claims	2.420	2.323	0.621	0.068	1.353	1.110	0.213	0.031	
Top 25%									
Firm Premium	1.349*	1.333*	1.494*	1.828*	1.961*	1.824*	2.856*	3.255*	527,049
	(0.029)	(0.028)	(0.031)	(0.089)	(0.037)	(0.032)	(0.128)	(0.223)	
Mean Number of Claims	0.552	0.533	0.144	0.013	0.370	0.320	0.043	0.007	

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 distribution of change in the firm premium estimated as the difference in the fixed effect estimated from 2000-2006 and 2007-2013. Sample includes only firms that appear in both periods. 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 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. * $p<0.01$.