Are women more exposed to firm shocks?[*]

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Abstract

Workers care deeply about job and pay stability. Given potentially differing risk attitudes, we investigate whether firm wage and employment insurance enjoyed by workers differs by gender. We find that women are less protected than men against idiosyncratic shocks to their employers—a gender gap in firm insurance. The elasticity of women's wages with respect to variations in firm's performance is 95% higher than that of men, and the sensitivity of dismissal to firm shocks is 37% higher for female than for male employees. These gender differences are larger for employees with children, in small firms, and in firms without female executives.

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1 Introduction

Job security and stable pay are highly valued by workers. In surveys, respondents often deem these two dimensions as the most important characteristics of a job. For example, in a 2019 survey conducted by Gallup (Rothwell and Crabtree, 2019) the two dimensions of jobs that were marked as important by the largest share of respondents were "stable and predictable pay" (92% of respondents) and "job security" (91% of respondents). In contrast, only 86% percent of workers viewed the "level of pay" as an important job dimension.[1] Despite its importance for workers, wage and employment stability are contractual dimensions that have received much less attention in the literature than the level of pay.

In this paper, we study the degree to which firms provide workers with pay and employment stability. Our primary goal is to test whether firms provide an equal level of insurance to all their employees, or if instead, some workers are more exposed than others to fluctuations in firm's fortunes through their wages and employment. In particular, we investigate whether male and female workers experience the same protection against firms' idiosyncratic shocks. Experimental and survey evidence has indicated that women are more risk averse than men (e.g., Croson and Gneezy, 2009, and Eckel and Grossman, 2008). Therefore, given the role of the firm as an insurance provider to risk averse workers, an idea going back to Knight (1921), the optimal employment contract may feature a higher level of firm-provided insurance for women than it does for men. If that is the case, the gender wage gap could be, at least in part, a manifestation of a compensating differential for a higher level of stability provided (implicitly or explicitly) in women's labor contracts. In contrast, we may observe a positive correlation between the level of wages and the stability of pay and employment, if differences in the way men and women are treated by firms are due to managerial practices, for example. Gender differences in commitments to home production or different preferences in terms of work-life balance may also result in contracts that feature higher income volatility for women relative to those of men.

[1] This pattern is observed in other surveys on employee satisfaction. As Clark (2001) highlights, using data from the first British Household Panel Survey of 1991, "Job Security is most often cited as the first most important aspect of a job, followed by the work itself, and then pay."

We investigate these conflicting predictions using detailed employer-employee matched data from Sweden over the period 1990-2011. Our main finding is that the pass-through of fluctuations in firm performance is larger for women than for men—a gender gap in firm insurance. Female workers' wages are 90% more sensitive to firm shocks than those of men, and women are 36% more likely to lose their job than men in response to a negative shock to the firm. The granularity of our data allows us to show that these findings are not due to gender differences in occupation or seniority, as the results continue to hold when we include firm-occupation-year fixed effects or firm-hierarchy-year fixed effects.

To shed light on the potential economic mechanisms behind this gender risk gap, we exploit the richness of our employer-employee matched data and test which types of workers and which types of firms drive our results. First, we study the role of family constraints. It is well documented that women's careers are significantly affected by motherhood (e.g., Kleven et al., 2019). However, past research has focused on labor market participation and the *level* of wages, not whether children affect the *riskiness* of the employment contracts. We test whether the difference in the *stability* of wages and employment of women relative to men depends on whether there are children in the household. We find that the difference in the pass-through of firm shocks to women relative to men is magnified when workers have children, especially small children. This suggests that gender differences in time devoted to home production may be an important determinant of the gender gap in firm insurance.

While the previous tests suggest that constraints on the part of workers help explain the gender differences in risk sharing between firms and employees, we also test for the role of corporate policies. We document that the gender differences in exposure to firm shocks are larger in small firms than in large firms, as well as in firms in which all senior executives are male. These findings point to managerial practices as part of the explanation for the gender gap in firm insurance.

We also test for alternative explanations for our findings, but fail to find supporting evidence. Do women receive a lower level of protection against shocks to their employer because they are already insured by their spouses? To test whether insurance within the family substitutes for insurance within the firm, we focus on the subsample of employees who are the main breadwinners of their household. In this sample of employees who cannot rely on insurance from their partner, we continue to find a gender difference in exposure to firm shocks. Furthermore, we exclude the possibility that tenure-dependent labor regulations, and in particular last-in-first-out (LIFO) rules, are the root cause of the gender differences in pay and employment stability that we document, as the results continue to hold in a sample of small firms which are not bound by LIFO and in a sample of workers with short tenure, who, absent gender differences in risk sharing, should have a similar likelihood of being fired.

Our paper contributes to two strands of the literature in Economics and Finance. First, a long and influential literature has studied the careers of women and documented gender differences in labor market outcomes. Blau and Kahn (2017) and Goldin (2021) provide recent reviews of this literature. While most prior work studied gender differences in the *level* of pay, we focus on wage and employment *risk*. Specifically, we analyze the degree to which workers' employment and wages are exposed to idiosyncratic variations in the performance of their employers.

Our paper also contributes to the literature that studies the role of firms as determinants of income and employment risk. Past research has documented that firms partially insure workers against shocks (see Guiso, Pistaferri and Schivardi, 2005; Cardoso and Portela, 2009; Kátay, 2016, for evidence from Italy, Portugal, and Hungary, respectively). In addition, it has been shown that the pass-through rate is larger in firms located in countries with stronger social safety nets (Ellul, Pagano and Schivardi, 2018), suggesting that social insurance and firm insurance are substitutes. Consistent with this hypothesis, Balke and Lamadon (2022) show that firm policies along this dimension can undo a large part of government-provided insurance. For recent reviews of this literature see Pagano (2020) and Guiso and Pistaferri (2020).[2]

[2]In addition to the work on firm insurance, there is an active literature on the (macroeconomic) determinants of labor income risk. Recent work in this literature documents, among other things, that the pay of high (male) earners is more sensitive to business cycles than that of the rest of the (male) population,

We depart from most of the existing literature by studying *heterogeneity* in the provision of firm-insurance across *different workers of the same firm*. In that regard, our paper is closest to a small recent line of work that investigates which workers are rewarded for the success of their employers. In particular, Kline et al. (2019) and Howell and Brown (2020) show that firms share some of the rents of positive (innovation) shocks with employees and investigate which employees are more likely to be rewarded. Our paper differs from their work in several important dimensions. First, while they study the sharing of rents that occurs following positive permanent shocks, our focus is on firm-insurance which may be especially valuable when bad shocks occur. Indeed, one of our main findings is that firings in the aftermath of negative shocks are more likely to be experienced by women than by men. Second, in contrast to our analysis, which is focused on gender differences, these authors focus on hierarchy and tenure within the firm. The focus on gender instead of tenure is also a feature that distinguishes our work from that of Caggese, Cunat and Metzger (2019), who document that tenure-based labor regulations affect the order in which firms lay off workers.

Because idiosyncratic shocks, including those suffered by one's employer, constitute some of the most important determinants of consumption fluctuations and individual welfare (Constantinides, 2021), understanding who bears such risks is an important question. To our knowledge, we are the first to document (i) that the wages of female workers are more exposed to firm performance fluctuations than the wages of their male colleagues; (ii) that dismissal probabilities vary more for women than for men in response to an idiosyncratic shock to the firm; and (iii) that this heightened exposure to firm fluctuations experienced by women is to some extent driven by managerial practices and gender differences in the time allocated to home production.

that there is significant variation across industries (Guvenen, Kaplan and Song, 2014), and that men are more exposed to business cycle risk than women (Guvenen et al., 2017). In contrast with this strand of the literature, which quantifies the elasticity of pay with respect to macroeconomic fluctuations, we focus on idiosyncratic firm shocks. This distinction matters. We document that female workers are more exposed than male workers to firm idiosyncratic risks, while Guvenen et al. (2017) find that males are more exposed to business cycle risk than females.

2 Data

2.1 Data sources

The main data used to perform our analysis combines information from several sources. We obtain information on socioeconomic outcomes for Swedish individuals from 1990 to 2011 from the Longitudinal Database on Education, Income and Occupation (LISA) from Statistics Sweden (SCB). LISA contains information on several individual level characteristics, such as age, gender, marital status, employment, uncensored wages, and social security. It also contains information on the identity of the partner and their earnings. These data, which cover the entire Swedish population aged 16 years or older, allow us to track individuals over time and study their career paths. We link each individual to their respective employer (if they have one). Information on firms comes from the Serrano database. Serrano contains financial statement data on all limited liability firms in Sweden, both public and private, between 1998 and 2011. To be included in the sample we require firms to have at least 5 employees and non-missing data on total assets.

By combining detailed information on firms' performance with data on wages and employment outcomes of employees, we are able to identify shocks to firms and study the degree to which these shocks are passed-through to employees. In addition, because the data include information on the gender of each worker, we can study whether firms transmit shocks to male and female employees equally. Furthermore, the wide array of individual characteristics in our data allows us to shed light on the mechanisms that drive any heterogeneity in the risk sharing arrangements between firms and employees.

2.2 Variables definition

Firm-level data

The main firm-level variable that we employ in our analysis is *Shock*, which captures idiosyncratic shocks to the firms. To create this variable we follow Guiso, Pistaferri and Schivardi (2005). We model firms' performance process as a dynamic panel. In particular, firm's performance is measured as sales growth, which evolves according to the following process:

$$y_{jt} = \rho y_{j,t-1} + f_j + I_{jt} + \delta_t + \epsilon_{jt} \tag{1}$$

where y_{jt} is the growth of sales for firm j in period t. f_j, I_{jt}, and δ_t are firm, industry, and year fixed effects, respectively. We estimate equation (1) using the two-step approach of Arellano and Bond (1991). The variable *Shock* is the estimated error, $\hat{\epsilon}_{jt}$, for each firm-year. For further details on the estimation approach and additional results, including tests of whether lagged ys can be used as instruments, see Appendix 1.

We report summary statistics for the firm-level variables in Panel A of Table 1.

Individual-level data

The two main outcome variables that we employ in our tests are *Wage* and *Dismissed.* These variables allow us to study the intensive and extensive margins of risk sharing between firms and workers. *Wage* is defined as the natural logarithm of the total compensation a worker receives from its employer in a given year. A worker's "employer" in a given calendar year is the firm that provides an individual with the most labor income in that year.[3] *Dismissed* is an indicator variable that takes the value of one if a worker is dismissed in that year, and zero otherwise. While our dataset does not explicit distinguish between voluntary and involuntary departures, we classify a worker as being dismissed in a given year if the worker is not employed by the firm in the following year and the worker collects unemployment benefits in the current year or the next. We show, in Section 5, that our findings are robust to defining a dismissal in several different ways.[4] The main explanatory variable at the individual-level is *Female*, an indicator variable that takes the value of one if the individual

[3]Most workers have only one source of labor income in any given year. For the small number of cases when a worker receives labor income from multiple firms, we assume that the worker's main employer is the firm that provides the largest income in that year.

[4]In addition, we also conduct placebo tests based on voluntary departures, which we define as workers transitioning to a new employer without collecting unemployment benefits and without experiencing a wage drop. We discuss these results in Section 5.

is female and takes the value of zero if the individual is male. We also define a set of additional variables that measure individual characteristics. *Married* is an indicator variable that takes the value of one if the worker is married or is in a cohabitating relationship, and takes the value of zero otherwise. *Age* is the worker's age in years. *Ln(Education)* is the natural logarithm of the number of years of education associated with the person's highest educational attainment. Finally, *Experience* and *Tenure* measure the years a worker has been in the labor force and in the current firm, respectively.

We restrict the analysis to working age adults. We consider individuals to be of working age if they are at least 24 years old, younger than 64 years old, and not retired.

We report summary statistics for the individual-level variables in Panel B of Table 1.

3 Main Results

Our main goal is to empirically study the degree to which firms insulate workers against corporate idiosyncratic shocks. Idiosyncratic shocks are an important source of risk in the economy (Constantinides, 2021). In contrast with aggregate macroeconomic fluctuations, which may be difficult to hedge against, idiosyncratic shocks create opportunities for risk sharing between well-diversified corporate owners and employees.

Given that workers' earnings are tightly linked to their employer, understanding whether and to what extent firms insure workers against idiosyncratic shocks is an important economic question. Indeed, survey evidence indicates that wage and employment stability are key determinants of worker welfare (Clark, 2001).

In this section, we investigate the existence and quantify the magnitude of the heterogeneity in the provision of firm insurance across workers, a question where evidence is scant. We primarily focus on differences across male and female workers and test whether firms provide differential levels of wage and employment security to these two groups of workers. In particular, we are interested in estimating the following equation:

$$z_{ijt} = \alpha + \beta Female_{ijt} \times Shock_{jt} + \gamma_1 Female_{ijt} + \gamma_2 Shock_{jt} + \theta X + f_j + IY_{jt} + LY_{jt} + u_{ijt} \tag{2}$$

where z_{ijt} is the natural logarithm of worker's wage (variable *Wage*) or a dismissal dummy (variable *Dismissed*) for individual i in firm j in period t, X is a vector of control variables, and f_j, IY_{jt}, and LY_{jt} are firm, industry-year, and local labour market $\times$ year fixed effects, respectively. Our main parameter of interest is β, which measures gender differences in the pass-through rate of idiosyncratic shocks faced by the firm. A positive value of β implies a higher pass-through rate of a corporate shock to women than to men. By focusing on employees who work for the same firm at the same point in time, we can test whether exposure to the same firm-shock leads to differential effects on the male and female workers of the firm. The identifying assumption is that *Female* $\times$ *Shock* is conditionally random, that is, for employees working at the same firm at the same point in time, after controlling for employee characteristics as well as industry- and labor market-specific trends, the estimated parameter β captures differences in the employment relation between male and female workers.

3.1 Idiosyncratic shocks and firm-level outcomes

We identify firm-specific revenue shocks by employing the approach proposed by Guiso, Pistaferri and Schivardi (2005). To ensure that this empirical methodology does indeed capture significant shocks to the performance of firms in our setting, we start by showing that firms' employment, wage bill, profitability, financial slack and liquidity are affected by *Shock* in the manner that we would expect, if this variable was indeed capturing idiosyncratic fluctuations in revenue. In these firm-level regressions, we include firm fixed effects and industry-year fixed effects. The inclusion of firm fixed effects allows us to exploit variation within firms over time and absorb any time-invariant differences across the firms in our sample. The industry-year fixed effects control for industry-specific time trends that may impact firms' performance in the absence of a shock.

Consistent with the notion that the methodology we employ identifies relevant shocks to the firms, in Table 2, we find that idiosyncratic revenue shocks are positively associated with increases in employment (column 1), wage bill (column 2), profitability (column 3), financial slack (as measured by interest coverage in column 4), and liquidity (as measured by $\frac{Cash}{Assets}$ in column 5). These results reassure us that, like in the setting of Guiso, Pistaferri and Schivardi (2005), shocks to firm revenues significantly impact firms' financial performance and firm-level labor outcomes.

3.2 The gender gap in firm insurance

Having shown that the variable *Shock* does indeed identify firm-level idiosyncratic shocks, we focus on the main question: are revenue shocks equally transmitted towards all workers within the firm?

Lab and survey evidence suggests that women are more risk averse than men (Croson and Gneezy, 2009, and Eckel and Grossman, 2008). Therefore, one may expect firms to provide more comprehensive wage and employment stability to women than to men. As a way to compensate the firm for this increased level of protection against idiosyncratic fluctuations, female workers may be willing to accept a lower salary. This negative compensating differential for wage and employment stability could explain part of the gender wage gap that has been extensively documented in the literature. However, it is not ex-ante theoretically obvious that women will enjoy more income and employment stability than men. For example, if firms perceive men as the breadwinners of families, they may be more inclined to offer more insurance to male than to female workers. Prejudice and discrimination is another factor that may influence the degree to which firms protect different types of workers against idiosyncratic business fluctuations.

Our empirical tests compare the sensitivity of individual worker labor outcomes to idiosyncratic shocks suffered by their employers. Using information on the gender of each worker, we test whether male and female workers enjoy the same level of protection against these corporate shocks. Because our goal is to study differences across workers within the same firm, we include firm fixed effects in all regression specifications. We also account for any factors that may affect wages and employment at the industry or geographical levels with the inclusion of industry × year and local labor market × year fixed effects. We measure labor income risk across two important dimensions: wages and employment. While one can think of *Wage* as capturing an intensive margin adjustment which occurs while workers remain employed, firms can make extensive margin adjustments by dismissing workers.

First, we start by investigating whether firms insure the wages of their workers. In these tests, the sample is restricted to workers who do not leave the firm in the year of the shock (we refer to these workers as "stayers"). We estimate regression model (2) and report the coefficient estimates in Table 3. In the first column, we report coefficients from regressions that estimate the average pass-through of firms' shocks to the wages of workers. We find that an idiosyncratic shock corresponding to two standard deviations of *Shock* (i.e., an increase in *Shock* of 0.596) is associated with a 1.7% increase in salaries. The sign and magnitude of this effect is in line with the estimates of Guiso, Pistaferri and Schivardi (2005) for Italy. In column 2, we add to the regression model an interaction between *Shock* and *Female* to test whether the exposure to firm shocks is similar for both women and men. We find that women's wages are more sensitive to firm shocks than male wages are. The difference is not only highly statistically significant, it is also economically significant, with women being almost twice as exposed to idiosyncratic firm shocks as men.

In column 3, we add several individual controls that have been shown to explain wages. These controls are *Experience*, *Tenure*, *Education*, and *Age*. While these variables are positive and statistically significant, they do not affect our main finding, that women's wages are about twice as exposed to firm shocks as men's wages are. It is perhaps unsurprising that individual-level controls do not affect the magnitude or statistical significance of the firm-insurance coefficients, since these individual controls are unlikely to be correlated with the sign or severity of firms' revenue shocks. In column 4, we include occupation fixed effects. Because the distribution of male and female workers across occupations and hierarchies may not be comparable, the estimates in columns 2 and 3 could simply be picking up the fact that some types of occupations have higher-powered incentives than others. However, we continue to find that even within occupation classification, women's wages are more exposed to fluctuations in firm's revenues than those of men.

We do not observe the number of hours that each employee works. Therefore, a change in wages could be due to both changes in the wage per hour and to changes in the number of hours of work. Since both of these types of adjustments (hours and wage per hour) constitute ways through which a worker's overall income fluctuates with firm performance, wages are the most encompassing measure of income risk, conditional on being employed.

Next, we investigate whether women and men are equally exposed to changes in the probability of dismissal in response to an idiosyncratic shock experienced by their employer. First, the regression coefficients reported in column 1 of Table 4 document that firms (partly) insure workers' employment against idiosyncratic revenue shocks. On average, a two standard deviation increase in the variable *Shock* is associated with a 0.93 percentage point increase in the probability of being fired, which corresponds to 17% of the sample mean of *Dismissal*. Column 2 of Table 4 reveals that the average elasticity of employment to firm's revenue shocks hides important heterogeneity. We find that women's dismissal probability is about 37% more sensitive to firms' shocks than that of men. These results remain virtually unchanged when we control for individual worker characteristics in column 3, and occupation fixed effects in column 4.

The regression specifications in Tables 3 and 4 control for a large set of individual characteristics and fixed effects. In Table 5, we document that our findings continue to hold when we saturate the regression specifications with additional fixed effects. First, in column 1 of Panel A, we show that the higher elasticity of female wages to firm-level shocks continues to hold when we add to our regression specification firm-by-year fixed effects. In this specification, we compare male and female workers of the same firm at the same point in time. This test rules out the possibility that firm-level unobservable factors (that affect both male and female workers equally) could be biasing our estimates.[5] In addition, we show, in column 2, that the gender gap in firm insurance is not driven by the gender composition of the different hierarchies of a firm. In columns 3 and 4, we include occupation-by-year and firm-by-occupation fixed effects, respectively. Our main findings remain unchanged. Finally, in column 5, we compare the impact of firm shocks across workers employed in the same occupation of the same firm in the same year; this specification captures variation for relatively large firms, which are those that have employees of different gender within the same occupation and year. Even in these restrictive specifications, the sign and statistical significance of the main effect remains unchanged. In terms of economic magnitude, the coefficient on the interaction *Female* $\times$ *Shock* is about 25% smaller than the coefficient reported in the less saturated specification of column 2 of Table 3.

In Panel B of Table 5, we repeat these empirical exercises for the dependent variable *Dismissed*. As in the case of wages, we document that the gender gap in the sensitivity of dismissal to corporate idiosyncratic shocks is not driven by unobservable effects at the occupation, hierarchy, or firm levels. In column 5, we report coefficients from our tightest regression specification. Even when workers in the same occupation of the same firm in the same year are compared, female employees experience a larger increase in the probability of dismissal in response to negative firm shocks than male employees do. In terms of economic magnitude, the coefficient on column 5 of Panel B of Table 5 is about half of that in column 2 of Table 4. This suggests that occupational sorting explains some, but certainly not all, of the gender differences in the exposure to firm shocks.

One important determinant of the ability of a firm to provide insurance to its workers is its financial position. Firms that are financially constrained may not have the necessary slack to absorb idiosyncratic shocks. As a result, these firms may be forced to pass-on to their employees any shock that they experience. In contrast, firms that are financially healthy have the ability to absorb temporary revenue shocks and offer stable wage and employment contracts. As an additional validation of our methodology, we study whether

[5] Because the firm-year fixed effects absorb all firm-level variation, the coefficient on the variable *Shock* cannot be estimated in this specification.

financial constraints affect the level of insurance that firms provide to workers. We first categorize firms into those that have high leverage and those that have low leverage, based on whether the leverage ratio of the firm is above or below the respective industry median. While large interest and principal payments may prevent highly levered firms to insure their workers, firms with low leverage are more likely to be able to, if they so wish, absorb revenue shocks and offer wage and employment stability to their employees. In columns Table 7, we find that highly levered firms on average offer less insurance to workers, as the coefficient on the variable *Shock* is larger for firms that have high leverage than for those that have low leverage. In Panel B of Table 7, we construct an alternative measure of financial constraints following Hadlock and Pierce (2010). We categorize firms as constrained if they are small and young, and categorize them as unconstrained if they are large and old.[6] Using this alternative measure of financial constraints we confirm that, on average, constrained firms offer less insurance to employees than unconstrained firms do.

The gender differences in the pass-through of firm shocks that we documented so far may result from higher sensitivity to the shocks in the top of the distribution or more exposure to the shocks in the bottom of the distribution. To test whether there is a symmetric response to firm idiosyncratic shocks, we separate the variable *Shock* into two sub-variables that capture the top 20th percentile of shocks (*Top shock*) or the bottom 20th percentile of shocks (*Bottom shock*). We then interact these variables with the *Female* dummy. The evidence, reported in Table 6, points to a symmetric effect. The incremental risk borne by women is driven both by the fact that in bad times women experience a larger wage decline and larger increase in the probability of being fired, and also by the fact that in good times, women's wages increase more and dismissal probability decreases more than those of men.

[6] Hadlock and Pierce (2010) "recommend that researchers rely solely on firm size and age, two relatively exogenous firm characteristics, to identify constrained firms." Small firms are defined as firms that have assets below the median of firms' assets; young firms are firms whose age is below the median of firms' age.

4 Why are female workers less insured by firms?

In this section, we investigate potential channels that may explain why firms provide less wage and employment insurance to women than they do to men. Given that after decades of research, the determinants of the gender wage gap are still under investigation, we must acknowledge that we will not be able to fully explain the gender gap in firm insurance. Instead, below, we make a first attempt to test the underlying mechanisms for this newly documented phenomenon.

4.1 Gender differences in home production

It has been extensively documented that children have a detrimental impact on the career outcomes of women (e.g., Kleven, Landais and Søgaard, 2019; Kleven et al., 2019). Therefore, it is natural to ask whether family constraints, and in particular, intra-household differences in the distribution of home production associated with children help explain our findings.

The time that a firm suffers a shock may be precisely when it requires unconditional dedication from employees. However, family constraints may make women unwilling or unable to dedicate themselves to their careers to the same extent that men do. In Table 8, we document that like in other countries, in Sweden, women are more likely than men to take sick days and family days to support children. Specifically, for workers with children up to (and including) the age of ten, we estimate Poisson regressions using as dependent variables the number of days of parental leave taken by a worker per annum (column 1) and the number of days taken to care for a sick child (column 2).[7] The main explanatory variable is *Female*. In addition, we control for firm $\times$ occupation, industry-year, and labor market $\times$ year fixed effects. The estimates suggest that women take more than double the amount of parental leave than men in Sweden, while they take about 15% more time off

[7] Parental leave benefit is paid out for a maximum of 480 days (to be shared between the two parents) for one child. Parents in Sweden can also receive compensation for caring for a sick child ("VAB") for a maximum of 120 days per year, until the child is 12 years old. The compensation for both parental leave and VAB leave is paid by the Swedish Social Insurance Agency (Försäkringskassan); it is based on the annual income of the worker and is capped. For details, please see *Försäkringskassan*.

than men to care for sick children.

Given that women take more time off for child care, it could be profit maximizing for firms to offer more insurance to men relative to women: because the provision of insurance should arguably help the firm attract and retain workers, firms may insure men more if they are more able and willing to sacrifice family time and flexibility to fully devote themselves to their careers.

In Panel A of Table 9, we study the provision of firm insurance to individuals with and without children. We find that the gender gap in firm insurance is more pronounced for workers with children. This is particularly the case for employment insurance. Small children may be particularly demanding in terms of parental availability. Recognizing this fact, in Panel B of Table 9, we perform the sample splits based on the number of small children (aged 10 or below) that each employee has. As in Panel A, we find that the difference in the amount of wage and employment insurance obtained by women relative to men is larger in the presence of small children.

These findings are consistent with firms rewarding with pay and employment stability workers who put fewer restrictions on the time devoted to the firm. Because, on average, child-rearing tasks tend to fall mostly on women, female workers effectively experience a double "child penalty," in the form of a lower *level* of wages and, as we now document, lower *stability* of wage and employment.

4.2 Managerial practices

Managerial practices are another potential driver of the gender differences in risk exposure that we document. We conduct two types of tests that suggest that this is indeed be the case.

First, we investigate the role of female leadership. Female leaders may be more aware of potential gender biases within the organization and may therefore implement managerial practices that are more favorable towards other women. We thus test whether firms in which a large fraction of top executives are female operate with a more egalitarian level of stability in labor contracts. We split the sample into firms that have no women in the top two hierarchical levels of the organization and those that have at least one high-ranking woman.[8] Consistent with the evidence in Matsa and Miller (2013), in Table 10, we find that female leadership is associated with more firm insurance, on average. In addition, we find that employment insurance is more egalitarian in firms with larger share of female executives. However, we find no impact of female leadership on the size of the gender differences in wage insurance.

Next, we test whether the gender gap in firm insurance varies with firm size. The role of managers in determining individual worker outcomes may manifest itself more in small than in large firms. The reason is that large firms tend to have dedicated human resources (HR) departments and rules and procedures on how to treat employees under different circumstances. In contrast, smaller firms are more likely to use managerial discretion when dealing with positive and negative idiosyncratic shocks. Therefore, if HR rules are themselves not gender-biased, larger firms may be in a position to offer not only more insurance, but also less gender-biased insurance to its workers. In Table 11, we find evidence consistent with these predictions. In Panel A, firms that are below the median of the distribution of firm size (measured in terms firm's asset value) feature lower levels of insurance for both men and women, and also larger absolute gender gaps in firm insurance than larger firms.

In Panel B of Table 11, we employ an alternative measure of firm size and complexity. We categorize firms into those who have more than two hierarchical levels and those than have only one or two formal hierarchies. Smaller and flatter organizations (in which managers may have more discretion to affect labor policies) are part of the latter group, and larger more hierarchical firms (in which labor policies may be more formalized and standardized) are included in the former group. The findings are consistent with the results documented in Panel A. We find that workers in smaller, flatter firms experience lower levels of wage and employment stability; in addition, this dimension of labor contracts is more gender-biased in smaller and flatter firms than in larger, more hierarchical organizations.

[8] We follow Tåg (2013) and construct a measure of hierarchy by mapping occupational codes into four different hierarchy levels: CEOs and directors, senior staff, supervisors, and clerks and "blue-collar" workers.

In Figures 1 and 2, we check whether the impact of household constraints associated with having children and the presence of female managers on the gender gap in firm insurance is stronger in small than in large firms. Consistent with the notion that these are complementary forces, we document that the impact of children (especially small children) and the impact of female leadership on the gender differences in pass-through of corporate idiosyncratic shocks, is more pronounced in smaller firms than in large firms. This holds true for wages (Figure 1) and even more so for employment (Figure 2).

4.3 Potential explanations for the gender gap in firm insurance not supported by the data

In addition to the channels discussed above, which find some support in the data, we also tested for additional potential drivers of the gender differences in the pass-through of firm shocks which were not supported by the empirical evidence.

Spousal-provided insurance

An additional reason why female workers may have employment contracts that feature a higher pass-through rate with respect to firm shocks than those of their male colleagues is that insurance from the spouse may lead firms to offer less wage and employment protection to women, and women perhaps to demand less protection from firms. In most societies, including Sweden, women earn on average less than their spouses. Therefore, shocks to a woman's income may have less severe repercussions for the household than shocks to the wages and careers of men. Consequently, the optimal risk-sharing arrangement, once insurance by spouses is taken into account, may be one where women are more exposed than men to idiosyncratic firm shocks.

We examine the possibility that insurance within the family is the primary motive why women enjoy less insurance from their employers in two ways. First, we distinguish between workers who contribute more than 50% of the household income versus those who contribute less. If a woman is the main breadwinner, the argument that she does not need firm insurance because she is ultimately insured by her spouse does not apply. Focusing on a subsample of married or cohabitant couples, Panel A of Table 12 documents that the gender gap in firm insurance is larger among workers who contribute most of the household's total income than among those who contribute a smaller share. We also observe that, on average, male workers who are the breadwinners of their household obtain a higher level of firm insurance than those whose contribution to household income is more modest. This result suggests that firms may refrain from passing idiosyncratic shocks onto employees who are unable to use their household as an alternative source of insurance, but only if the workers are men.

In our second test, we divide the sample into married and non-married individuals.[9] If female workers obtain less insurance primarily because they already enjoy high protection against shocks from their spouse, we would expect to find no gender differences in the sample of non-married workers. However, in Panel B of Table 12 we find that the gender gap in firm insurance is present in both the married and non-married subsamples.

Labor regulation

Another potential reason for firms to treat men and women differently has to do with regulation. In particular, it has been documented that severance packages and dismissal laws linked to tenure within the firm may distort firing decisions in Sweden (Caggese, Cunat and Metzger, 2019). While past research did not test whether women are more likely to be dismissed in the aftermath of a negative shock, this is possibly the case. The reason is that, on average, women have shorter tenure at their employers than men do. In our sample, women's average tenure is 5.3 years, while men's is 6.1 years. If firing costs are positively correlated with tenure at the firm, it could be less costly for firms to dismiss women than to dismiss men. Even though this cannot explain gender differences in wage stability, it may help explain gender differences in employment stability. We test whether differences in tenure can account for the gender gap in firm insurance by splitting the sample into those individuals who have long tenure and those with short tenure.[10] The results, presented in

[9]Married refers not only to individuals who are legally married but also to those who live in a cohabitation relationship.

[10]We control for tenure in our main regressions in Tables 3 and 4.

Panel A of Table 13, show that women have lower employment stability than men when the firm faces a revenue shock, regardless of their tenure. In light of this evidence, we conclude that firing costs related to tenure do not explain the gender differences in employment sensitivity to firm shocks.

We additionally employ a feature of the Swedish labor law to reinforce the point that tenure is not driving the results. Firms are required by law to follow a last-in-first-out (LIFO) rule when dismissing workers that have similar roles within the firm. As a result, a worker who recently joined a firm is more likely to be dismissed than a worker who has been at the firm for a long time. To test whether LIFO regulations lead firms to fire women more promptly than men, we exploit the fact that after 2001 firms with less than 11 employees are exempt from the LIFO rule. Therefore, in these tests, we restrict the sample to start in 2002. We separate firms that have more than 10 employees from those that have 10 or fewer employees and test whether gender differences in dismissals are driven by LIFO rules. Consistent with the observation that the gender differences in tenure are small in our sample, we find, in Panel B of Table 13, that the coefficients on the interaction $Shock \times Female$ do not materially change across subsamples. This suggests that LIFO regulations and tenure are not driving our main results.

5 Robustness and discussion

Our main tests identify idiosyncratic shocks to firms which are based on the evolution of sales growth (following Guiso, Pistaferri and Schivardi, 2005, and Ellul, Pagano and Schivardi, 2018). However, we obtain qualitatively similar results, that is, we continue to find a gender gap in firm insurance, when we use an alternative corporate performance measure to identify firm idiosyncratic shocks. In particular, in Tables A3 and A4 in the Online Appendix, we redo our main tests using the level of sales and the natural logarithm of value added to construct the variable *Shock*.

The results are also robust to different ways of defining dismissals. Because a key object of study for us is the likelihood that a worker's contract is terminated by the firm, and given that our dataset does not explicitly distinguish voluntary from voluntary departures, it is important to make sure that we are capturing firings, not voluntary exits. We do several tests to ensure that our variable *Dismissed* is indeed identifying dismissals. First, we use alternative definitions of dismissal. In Table A5 in the Online Appendix we show that we continue to find qualitatively similar results if we define dismissal based on whether a worker receives unemployment insurance (variable *Unemployment benefits*) or if we define dismissal for workers who leave a firm to a lower paying job (variable *Worse job*). In addition, we follow Baghai et al. (2021) to define voluntary departures if workers leave to another job without going through unemployment. If what we are capturing is indeed a gender gap in firm insurance, we would not expect to find women to be more likely to voluntarily abandon their jobs than men when their firm suffers a negative shock. That is precisely what we find. In columns (5) and (6) of Table A5 in the Online Appendix we document that women's voluntary departures are not more sensitive to firm performance than those of men. This test, which can be thought of as a placebo, provides further support to our interpretation that it is the firm that is firing women in larger proportion than men when firm performance deteriorates, not that women are more prone to abandoning the firm voluntarily.

Another concern addressed by our robustness tests is that our findings could be driven by part-time workers. Because we cannot observe the number of days or hours of work for each employee, our findings could be picking up gender differences in the distribution of full-time and part-time employment. While it would still be informative to find that women are more likely to absorb shocks to the firm, if this result is driven solely by differences in part-time versus full-time status, the interpretation and implications of our findings could change. To address this possibility we redo our main tests after excluding from the sample workers who make less than 100,000 SEK in 2000 prices for two consecutive years, or workers that suffer a big drop in wage, defined as workers that were less than 100,000 SEK in a year while they were earning at least 150,000 SEK in the previous year. Despite not being precise measures of individual employment status, excluding workers with low annual earnings should reduce the concern regarding part-time employees. Using the restricted sample where we exclude workers earning a low wage for two consecutive years, in Panel A of Tables A6 and A7 we continue to find that women are systematically more exposed than men to shocks to the firm. A similar conclusion is drawn from looking at the restricted sample where we exclude workers who suffered a big drop in wage, in Panel B of Tables A6 and A7.

6 Conclusion

Previous literature has shown that there is a gap in the level of pay of women relative to that of men. However, the level of pay is not the only, and perhaps not even the most important, dimension of a job. Survey evidence suggests that workers care deeply about pay and employment stability. We study the degree to which firms insure workers against idiosyncratic shocks. We find that women receive systematically less insurance from the firm than men do, a pattern we call the gender gap in firm insurance. The difference in firm-insurance is sizeable, with women's wages being 95% more exposed than those of men to shocks to the firm and dismissal probabilities being 37% more dependent on idiosyncratic movements in firm performance than those of men.

These gender differences are more pronounced for workers who have children, work in smaller and hierarchically flatter firms, and work in firms with a lower share of female executives. On the other hand, insurance within the family and labor regulations are factors that do not seem to explain our results.

These findings raise a number of interesting questions for future research. First, more work is needed to further investigate the channels that drive the gender gap in firm insurance that we document. While we take a first step in that direction, understanding the determinants of this gender risk gap is an endeavor that goes beyond the scope of a single paper, considering the amount of work done to explain the gender pay gap. Second, while gender is an important dimension where differences in firm-insurance manifest themselves, other dimensions are worthy of study. Understanding the distribution of firm insurance along individual worker characteristics, such as race, age, and education, remains a fruitful area for future research. Another interesting research avenue that follows from our findings is to understand the consequences of these differences in firm insurance. Do workers who receive less insurance from their firms exhibit different consumption patterns than those who are more protected against fluctuations in the performance of their employer? Are there other personal or family consequences associated with lack of insulation from firm shocks? Future research could shed light on these important issues.

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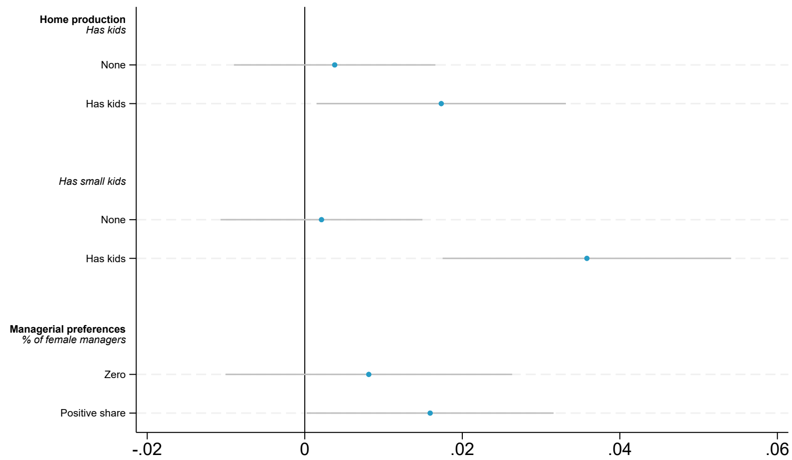
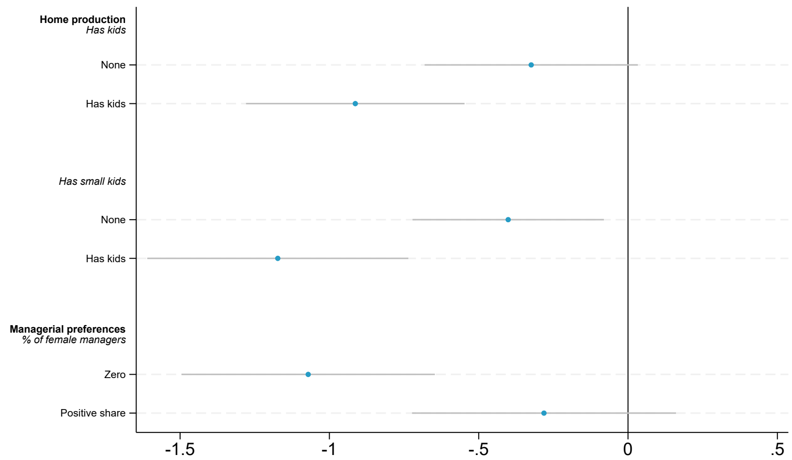
Figure 1: Difference in wage insurance gap for small relative to large firms



This figure depicts the difference in the gender gap in wage shock-passthrough rate between small firms vs large firms for workers with and without kids, with and without small kids, and for workers of firms with and without female managers. The dots represent the coefficient estimates and the solid line represents 95% confidence intervals.

Figure 2: Difference in employment insurance gap for small relative to large firms



This figure depicts the difference in the gender gap in employment shock-passthrough rate between small firms vs large firms for workers with and without kids, with and without small kids, and for workers of firms with and without female managers. The dots represent the coefficient estimates and the solid line represents 95% confidence intervals.

Table 1: Summary Statistics

This table presents the summary statistics — number of observations, mean, and standard deviation — for the variables of interest in the paper. Panel A shows summary statistics for firm-level variables and Panel B shows summary statistics for the employee-level variables. All variables are defined in Section 2.2.

	Panel A: Firm level variables		
	Obs	Mean	Stand. Dev.
Ln(Wage bill)	448,941	8.404	1.062
Ln(Employment)	448,941	2.990	0.993
Interest Coverage	448,941	107.157	360.100
Profitability	448,941	0.125	0.168
Shock	448,941	0.214	0.268
	Panel B: Employee level variables		
	Obs	Mean	Stand. Dev.
Wage	28,121,661	7.592	0.896
Dismissed	25,971,563	5.410	22.622
Female	28,121,661	0.350	0.477
Experience	28,121,661	13.328	4.609
Tenure	28,121,661	5.798	4.790
Ln(Education)	27,976,738	2.436	0.227
Age	28,121,661	41.685	11.100

Table 2: Firm outcomes and Idiosyncratic shock

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and firm performance. The dependent variable is *Wage bill* in column 1, *Employment* in column 2, *Profitability* in column 3, and *Interest coverage* in column 4. All columns include firm and industry × Year fixed effects. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	ln(wage bill)	ln(employment)	Profitability	Interest Coverage	$\frac{Cash}{Assets}$
	(1)	(2)	(3)	(4)	(5)
Shock	0.146***	0.136***	0.096***	43.955***	0.006***
	(0.004)	(0.003)	(0.002)	(1.640)	(0.001)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.937	0.923	0.473	0.366	0.690
Observations	628,217	628,217	628,024	589,369	628,161

Table 3: Wage insurance gap - Stayers

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the wages of male and female workers. The dependent variable is *Wage*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Shock	0.028***	0.021***	0.019***	0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
Female		-0.329***	-0.321***	-0.280***
		(0.004)	(0.003)	(0.003)
Female × *Shock*		0.020***	0.021***	0.011***
		(0.004)	(0.003)	(0.003)
Experience			0.019***	0.013***
			(0.000)	(0.000)
Tenure			0.005***	0.004***
			(0.000)	(0.000)
ln(education)			0.439***	0.211***
			(0.013)	(0.008)
age			0.006***	0.004***
			(0.000)	(0.000)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Occupation FE - exc miss	No	No	No	Yes
Adj. R^2	0.247	0.304	0.348	0.402
Observations	13,245,028	13,245,028	13,206,346	11,972,146

Table 4: Employment insurance gap - All adults

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the likelihood of dismissal of male and female workers. The dependent variable is *Dismissal*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Shock	-1.558***	-1.386***	-1.579***	-1.548***
	(0.126)	(0.126)	(0.134)	(0.149)
Female		0.768***	0.113***	0.080***
		(0.027)	(0.022)	(0.019)
Female ×		-0.516***	-0.489***	-0.475***
Shock		(0.081)	(0.084)	(0.087)
Experience			-0.061***	-0.055***
			(0.004)	(0.004)
Tenure			-0.210***	-0.202***
			(0.005)	(0.005)
ln(education)			0.192***	0.467***
			(0.037)	(0.036)
age			0.007***	0.010***
			(0.001)	(0.001)
ln(wage_{t-1})			-1.691***	-1.597***
			(0.028)	(0.030)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Occupation FE - exc miss	No	No	No	Yes
Adj. R^2	0.049	0.049	0.060	0.061
Observations	16,790,445	16,790,445	16,478,688	14,818,367

Table 5: Robustness of gender gaps

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the wages and likelihood of dismissal of male and female workers. In Panel A, the dependent variable is *Wage*; In Panel B, the dependent variable is *Dismissal*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Wage insurance gap - Stayers				
	(1)	(2)	(3)	(4)	(5)
Female	-0.320***	-0.285***	-0.279***	-0.267***	-0.263***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Shock	0.000	0.022***	0.022***	0.020***	0.000
	(.)	(0.002)	(0.002)	(0.002)	(.)
Female ×	0.020***	0.009***	0.008**	0.012***	0.015***
Shock	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	No
Labor mkt × Year FE	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	No	No	No	No
Occupation × Year FE	No	No	Yes	No	No
Firm × Occupation FE	No	No	No	Yes	No
Firm × Occupation × Year FE	No	No	No	No	Yes
Hierarchy × Year FE	No	Yes	No	No	No
Adj. R^2	0.345	0.395	0.403	0.436	0.419
Observations	13,191,440	11,971,225	11,972,146	11,891,964	11,202,779
	Panel B: Employment insurance gap				
	(1)	(2)	(3)	(4)	(5)
Female	0.096***	0.087***	0.077***	0.104***	0.060***
	(0.021)	(0.021)	(0.019)	(0.019)	(0.019)
Shock	0.000	-1.547***	-1.540***	-1.607***	0.000
	(.)	(0.146)	(0.145)	(0.155)	(.)
Female ×	-0.458***	-0.470***	-0.458***	-0.346***	-0.248***
Shock	(0.056)	(0.087)	(0.087)	(0.089)	(0.056)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	No
Labor mkt × Year FE	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	No	No	No	No
Occupation × Year FE	No	No	Yes	No	No
Firm × Occupation FE	No	No	No	Yes	No
Firm × Occupation × Year FE	No	No	No	No	Yes
Hierarchy × Year FE	No	Yes	No	No	No
Adj. R^2	0.102	0.061	0.061	0.079	0.122
Observations	16,472,954	14,816,209	14,818,367	14,702,395	13,914,956

Table 6: Top and bottom shocks

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the wages and likelihood of dismissal of male and female workers. We distinguish between the top 20th percentile and bottom 20th percentile of shocks by employing the variables *Top shock* and *Bottom shock*. In Panel A, the dependent variable is *Wage*; In Panel B, the dependent variable is *Dismissal*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Wage insurance			Panel B: Employment insurance		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.330***	-0.323***	-0.281***	0.707***	0.053**	0.016
	(0.004)	(0.004)	(0.003)	(0.029)	(0.026)	(0.025)
Top Shock	0.010***	0.008***	0.007***	-0.382***	-0.512***	-0.468***
	(0.001)	(0.001)	(0.001)	(0.031)	(0.031)	(0.032)
Female ×	0.010***	0.013***	0.010***	-0.078**	-0.072**	-0.054
Top Shock	(0.003)	(0.003)	(0.003)	(0.037)	(0.037)	(0.037)
Bottom Shock	-0.008***	-0.008***	-0.011***	0.954***	1.024***	1.056***
	(0.001)	(0.001)	(0.001)	(0.045)	(0.046)	(0.052)
Female ×	-0.011***	-0.010***	-0.006**	0.526***	0.510***	0.572***
Bottom Shock	(0.003)	(0.003)	(0.003)	(0.055)	(0.056)	(0.066)
Experience		0.019***	0.013***		-0.061***	-0.055***
		(0.000)	(0.000)		(0.004)	(0.004)
Tenure		0.005***	0.004***		-0.209***	-0.202***
		(0.000)	(0.000)		(0.005)	(0.005)
ln(education)		0.439***	0.211***		0.197***	0.470***
		(0.013)	(0.008)		(0.037)	(0.036)
age		0.006***	0.004***		0.007***	0.010***
		(0.000)	(0.000)		(0.001)	(0.001)
ln(wage_{t-1})					-1.694***	-1.598***
					(0.028)	(0.030)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	No	No	Yes	No	No	Yes
Adj. R^2	0.304	0.348	0.402	0.049	0.060	0.061
Observations	13,245,028	13,206,346	11,972,146	16,790,445	16,478,688	14,818,367

Table 7: Financial constraints

This table reports OLS coefficients of regression models examining the relationship between financial constraints and impact of firm idiosyncratic shocks on the wages and likelihood of dismissal of all workers. The dependent variable is *Wage* in columns 1 and 2, and *Dismissal* in columns 3 and 4. Idiosyncratic firm shocks are captured by the variable *Shock*. In Panel A, we split the sample into workers who work for low-leverage firms, defined as having below median leverage (columns 1 and 3), and those who work for highly-levered firms (columns 2 and 4). In Panel B, we split the sample into workers who work for financially unconstrained firms, defined as firms which are young and small following Hadlock and Pierce (2010) (columns 1 and 3), and those who work for financially unconstrained firms (columns 2 and 4). All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: High leverage			
	Wage insurance		Employment insurance	
	Below median	Above median	Below median	Above median
Shock	0.025***	0.029***	-1.485***	-2.015***
	(0.003)	(0.002)	(0.167)	(0.163)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.293	0.297	0.061	0.068
Observations	7,284,234	5,920,049	8,941,034	7,536,049
	Panel B: Constrained (H&P)			
	Wage insurance		Employment insurance	
	Unconstrained	Constrained	Unconstrained	Constrained
Shock	0.021***	0.088***	-1.282***	-5.368***
	(0.002)	(0.005)	(0.142)	(0.257)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.272	0.318	0.041	0.106
Observations	9,061,934	645,624	11,004,115	865,346

Table 8: Parental leave and days off to care for sick children

This table reports the coefficients from Poisson regressions examining the relationship between days off taken to care for children, and the gender of workers; dependent variable is the number of days of parental leave taken by a worker per annum (column 1) and the number of days taken to care for a sick child (column 2). The sample is workers with children up to (and including) the age of ten. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. The other variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Parental leave	(2) Care of sick children
Female	0.917***	0.123***
	(0.009)	(0.007)
Experience	0.055***	0.051***
	(0.001)	(0.001)
Tenure	0.016***	0.005***
	(0.001)	(0.001)
Ln(Education)	0.818***	-0.073***
	(0.014)	(0.013)
Age	-0.088***	-0.028***
	(0.001)	(0.000)
Wage(t-1)	-0.092***	-0.059***
	(0.003)	(0.005)
Industry × Year F.E.	Yes	Yes
Firm × Occupation F.E.	Yes	Yes
Labor mkt × Year FE	Yes	Yes
Observations	5,960,158	5,995,710

Table 9: Home production

This table reports OLS coefficients of regression models examining the relationship between having children and impact of firm idiosyncratic shocks on the wages and likelihood of dismissal of male and female workers. The dependent variable is *Wage* in columns 1 and 2, and *Dismissal* in columns 3 and 4. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. In Panel A, we split the sample into workers who do not have children (columns 1 and 3), and those who do (columns 2 and 4). In Panel B, we split the sample into workers who do not have small children (columns 1 and 3), and those who do (columns 2 and 4). All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: All kids			
	Wage insurance		Employment insurance	
	None	Has kids	None	Has kids
Female	-0.196***	-0.406***	0.140***	0.129***
	(0.003)	(0.004)	(0.029)	(0.022)
Shock	0.015***	0.020***	-1.715***	-1.440***
	(0.002)	(0.002)	(0.156)	(0.120)
Female ×	0.021***	0.024***	-0.188*	-0.755***
Shock	(0.004)	(0.004)	(0.102)	(0.093)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.351	0.383	0.065	0.065
Observations	6,200,968	6,995,194	7,803,636	8,667,419
	Panel B: Small kids			
	Wage insurance		Employment insurance	
	None	Has small kids	None	Has small kids
Female	-0.215***	-0.529***	0.083***	0.275***
	(0.003)	(0.005)	(0.025)	(0.027)
Shock	0.014***	0.023***	-1.656***	-1.393***
	(0.002)	(0.002)	(0.146)	(0.116)
Female ×	0.025***	0.026***	-0.281***	-0.951***
Shock	(0.004)	(0.005)	(0.089)	(0.110)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.369	0.393	0.063	0.071
Observations	9,390,813	3,805,029	11,639,122	4,830,909

Table 10: Managerial practices - Share of female managers

This table reports OLS coefficients of regression models examining the relationship between managerial preferences and impact of firm idiosyncratic shocks on the wages and likelihood of dismissal of male and female workers. The dependent variable is *Wage* in columns 1 and 2, and *Dismissal* in columns 3 and 4. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. split the sample into workers who work for firms with zero female executives (columns 1 and 3), and those who work for firms with at least one female executive (columns 2 and 4). Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage insurance		Employment insurance	
	None	Positive share	None	Positive share
Female	-0.346***	-0.306***	0.187***	0.055*
	(0.001)	(0.005)	(0.022)	(0.029)
Shock	0.032***	0.010***	-2.518***	-1.074***
	(0.002)	(0.003)	(0.122)	(0.151)
Female ×	0.019***	0.018***	-0.842***	-0.408***
Shock	(0.004)	(0.005)	(0.115)	(0.090)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.365	0.337	0.079	0.048
Observations	5,541,632	7,664,182	6,968,347	9,510,149

Table 11: Managerial preferences - Size

This table reports OLS coefficients of regression models examining the relationship between managerial preferences and impact of firm idiosyncratic shocks on the wages and likelihood of dismissal of male and female workers. The dependent variable is *Wage* in columns 1 and 2, and *Dismissal* in columns 3 and 4. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. In Panel A, we split the sample into workers who work for small firms, defined as having below median firm asset value (columns 1 and 3), and those who work for large firms (columns 2 and 4). In Panel B, we split the sample into workers who work for small firms, defined as having 2 hierarchies or fewer within the firm (columns 1 and 3), and those who work and those who work for large firms, defined as having more than 2 hierarchies within the firm (columns 2 and 4). Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Firm size using assets			
	Wage insurance		Employment insurance	
	Below median	Above median	Below median	Above median
Female	-0.325***	-0.316***	0.260***	0.034
	(0.001)	(0.005)	(0.020)	(0.036)
Shock	0.031***	0.008***	-2.606***	-0.796***
	(0.002)	(0.003)	(0.126)	(0.117)
Female ×	0.028***	0.015***	-0.897***	-0.191**
Shock	(0.003)	(0.006)	(0.124)	(0.085)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.357	0.335	0.073	0.030
Observations	6,068,000	7,138,296	7,762,530	8,716,144
	Panel B: Firm size using hierarchies			
	Wage insurance		Employment insurance	
	$\leq$ 2 hierarchies	$>$ 2 hierarchies	$\leq$ 2 hierarchies	$>$ 2 hierarchies
Female	-0.316***	-0.315***	0.201***	0.091***
	(0.002)	(0.004)	(0.035)	(0.024)
Shock	0.050***	0.015***	-3.021***	-1.275***
	(0.002)	(0.002)	(0.124)	(0.142)
Female ×	0.024***	0.013***	-1.697***	-0.382***
Shock	(0.005)	(0.004)	(0.198)	(0.086)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.382	0.332	0.093	0.051
Observations	2,050,003	9,920,266	2,555,028	12,260,866

Table 12: Insurance from the spouse

This table reports OLS coefficients of regression models examining the relationship between spousal income and impact of firm idiosyncratic shocks on the wages and likelihood of dismissal of male and female workers. The dependent variable is *Wage* in columns 1 and 2, and *Dismissal* in columns 3 and 4. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. In Panel A, we split the sample into workers who contribute less than 50% of the household income (columns 1 and 3), and those that contribute more than 50% of the household income (columns 2 and 4). In Panel B, we split the sample into married (columns 2 and 4) and non-married workers (columns 1 and 3). All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Share of household income for married adults			
	Wage insurance		Employment insurance	
	<50% of inc.	>50% of inc.	<50% of inc.	>50% of inc.
Female	-0.108***	-0.252***	-0.659***	-0.054*
	(0.003)	(0.004)	(0.053)	(0.029)
Shock	0.043***	0.012***	-2.166***	-1.133***
	(0.005)	(0.001)	(0.185)	(0.106)
Female ×	-0.020***	0.030***	0.169	-0.549***
Shock	(0.006)	(0.005)	(0.145)	(0.097)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.212	0.465	0.074	0.064
Observations	1,845,329	4,279,049	2,285,554	5,098,476
	Panel B: Marital status			
	Wage insurance		Employment insurance	
	Single	Married	Single	Married
Female	-0.273***	-0.370***	0.306***	-0.028
	(0.003)	(0.004)	(0.025)	(0.026)
Shock	0.021***	0.018***	-1.806***	-1.317***
	(0.002)	(0.002)	(0.157)	(0.115)
Female ×	0.021***	0.018***	-0.400***	-0.583***
Shock	(0.003)	(0.004)	(0.106)	(0.082)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.322	0.382	0.066	0.062
Observations	6,918,242	6,277,995	8,890,432	7,580,338

Table 13: Regulation

This table reports OLS coefficients of regression models examining the relationship between labor regulations and impact of firm idiosyncratic shocks on the likelihood of dismissal of male and female workers. The dependent variable is *Dismissal*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. In Panel A, we split the sample into workers who have low tenure (column 1) and high tenure (column 2). In Panel B, we split the sample into workers of firms that are not subject to LIFO rules in column 3 and workers of firms who are subject to LIFO rules in column 4. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Tenure		Panel B: LIFO firms	
	Low	High	No LIFO	LIFO
Female	0.632***	0.002	0.364***	0.334***
	(0.039)	(0.022)	(0.051)	(0.060)
Shock	-1.704***	-1.670***	-2.366***	-2.152***
	(0.203)	(0.097)	(0.166)	(0.182)
Female ×	-0.593***	-0.515***	-1.446***	-1.322***
Shock	(0.109)	(0.109)	(0.237)	(0.234)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.070	0.050	0.112	0.103
Observations	5,912,200	10,558,850	1,042,503	757,720

A Internet Appendix

A.1 Estimation of *Shock*

We model firm's performance process as a dynamic panel model, following Guiso, Pistaferri and Schivardi (2005), as:

$$y_{jt} = \rho y_{j,t-1} + f_j + I_{jt} + \delta_t + \epsilon_{jt} \tag{3}$$

We measure firm performance, y_{jt}, as the growth of sales for firm j in period t. f_j, I_{jt} and δ_t are firm, industry, and year fixed effects, respectively.

Since OLS provides inconsistent estimates due to the lagged dependent variable being used as a regressor, (3) is estimated using the two-step approach of Arellano and Bond (1991). We take first differences and apply the Windmeijer correction to the standard errors (Windmeijer (2005)). Furthermore, since our data is an unbalanced panel with gaps and taking first differences has the drawback of magnifying gaps in unbalanced panels, we apply the forward orthogonal transformation (see Arellano and Bover (1995) and Roodman (2009)), as well as the backward orthogonal deviations transform to the instruments for the transformed equation (Hayakawa et al. (2009)).

Consistent estimates of the first difference of $y_{j,t-1}$ can be obtained by instrumenting with the lags of y that are no serially correlated. Since we fail to reject the null of no serial correlation of orders 2 and 3 and to avoid the instrument proliferation problem (Ziliak (1997), Bowsher (2002), among others), we instrument using lags of y dated $t-2$ and $t-3$. The Hansen test of overidentifying restrictions fails the reject the null of misspecification of our model. The table below shows the results of the estimation, along with the test statistics for the autocorrelation of the errors in first differences and the overidentifying Hansen-J statistic. p-values are in square brackets.

Appendix Table A1: DPD for estimation of idiosyncratic shock

This table reports coefficients from estimating a Dynamic Panel Data model of *Sales growth (%)*. We present tests of serial correlation of orders 1 through 4, as well as the Hansen test of overidentifying restrictions in the bottom of the table. All variables are defined in Section 2.2. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. P-values are reported in square brackets.

	Sales growth (%)
L.Sales growth (%)	0.041***
	(0.008)
Year FE	Yes
Industry FE	Yes
Observations	533,418
Test for AR(1) in FD	-36.296
	[0.000]
Test for AR(2) in FD	-0.556
	[0.578]
Test for AR(3) in FD	0.608
	[0.543]
Test for AR(4) in FD	1.693
	[0.090]
Hansen Overid. rest. test	2.611
	[0.106]

A.2 Robustness

Appendix Table A2: Summary Statistics

This table presents the summary statistics — number of observations, mean, and standard deviation — for the *Shock* varibale measured using alternative performance measures of the firm, *ln(sales)* and *ln(value added)*

	Obs	Mean	Stand. Dev.
Shock - ln(sales)	772,157	2.273	0.396
Shock - ln(value added)	772,157	1.583	0.401

Appendix Table A3: Wage insurance gap robustness to *Shock* - Stayers

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the wages of male and female workers. The dependent variable is *Wage*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock* computed using the firm's *ln(sales)* in columns (1) and (2), and firm's *ln(value added)* in columns (3) and (4). All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: *Shock* on Sales		Panel B: *Shock* on Value Added	
	(1)	(2)	(3)	(4)
Female	-0.350***	-0.351***	-0.353***	-0.355***
	(0.013)	(0.013)	(0.010)	(0.010)
Shock	0.030***	0.034***	0.011***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Female ×	0.006	0.009*	0.010	0.015**
Shock	(0.005)	(0.005)	(0.006)	(0.006)
Experience		0.019***		0.019***
		(0.000)		(0.000)
Tenure		0.005***		0.005***
		(0.000)		(0.000)
ln(education)		0.432***		0.428***
		(0.012)		(0.012)
age		0.006***		0.006***
		(0.000)		(0.000)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.314	0.357	0.312	0.355
Observations	14,924,033	14,880,391	14,701,921	14,659,201

Appendix Table A4: Employment insurance gap robustness to *Shock* - Stayers

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the wages of male and female workers. The dependent variable is *Dismissal*. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock* computed using the firm's *ln(sales)* in columns (1) and (2), and firm's *ln(value added)* in columns (3) and (4). All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: *Shock* on Sales		Panel B: *Shock* on Value Added	
	(1)	(2)	(3)	(4)
Female	2.604***	1.697***	2.184***	1.355***
	(0.120)	(0.127)	(0.102)	(0.100)
Shock	-1.649***	-2.003***	-0.718***	-0.913***
	(0.105)	(0.116)	(0.114)	(0.137)
Female ×	-0.587***	-0.512***	-0.632***	-0.562***
Shock	(0.045)	(0.047)	(0.053)	(0.053)
Experience		-0.060***		-0.060***
		(0.004)		(0.004)
Tenure		-0.214***		-0.212***
		(0.006)		(0.006)
ln(education)		0.196***		0.215***
		(0.034)		(0.033)
age		0.005***		0.004***
		(0.001)		(0.001)
ln(wage$_{t-1}$)		-1.760***		-1.764***
		(0.029)		(0.030)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.053	0.064	0.052	0.063
Observations	19,186,444	18,813,700	18,862,921	18,498,179

Appendix Table A5: Employment insurance gap robustness to *Dismissal* variables

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the likelihood of dismissal of male and female workers. The dependent variable is *Dismissal* is an indicator variable that takes the value of one if the worker receives unemployment benefits in column (1) and if the worker is employed at a worse job in column (2). The dependent variable is *Leaver* defined as an indicator variable that takes the value of one if the worker leaves to another job without going through unemployment in column (3). *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. Idiosyncratic firm shocks are captured by the variable *Shock*. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Unvoluntary leavers				Panel B: Voluntary leavers	
	Unemployment benefits		Worse job		Voluntary leavers	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.864***	0.418***	0.395***	-0.020	-0.002***	-0.009***
	(0.031)	(0.026)	(0.016)	(0.013)	(0.001)	(0.001)
Shock	-0.818***	-0.990***	-0.495***	-0.564***	-0.052***	-0.054***
	(0.116)	(0.122)	(0.051)	(0.057)	(0.006)	(0.006)
Female × *Shock*	-0.391***	-0.355***	-0.240***	-0.181***	-0.004	-0.003
	(0.087)	(0.087)	(0.047)	(0.048)	(0.004)	(0.004)
Experience		-0.209***		-0.188***		-0.001***
		(0.007)		(0.005)		(0.000)
Tenure		-0.190***		0.008***		-0.002***
		(0.005)		(0.001)		(0.000)
ln(education)		-0.851***		0.164***		0.027***
		(0.058)		(0.035)		(0.001)
age		0.032***		0.062***		-0.001***
		(0.001)		(0.001)		(0.000)
ln($wage_{t-1}$)		-1.127***		-1.250***		-0.018***
		(0.018)		(0.020)		(0.000)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.041	0.048	0.016	0.021	0.125	0.132
Observations	16,790,445	16,478,688	16,790,445	16,478,688	16,790,445	16,478,688

Appendix Table A6: Insurance gap without workers with low labour market participation

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and the wages of male and female workers. In Panel A, we exclude workers who made less than 100,000 SEK in 2000 prices for two consecutive years. In Panel B, we exclude workers who made less than 100,000 SEK in 2000 prices and were making at least 150,000 SEK in the previous year. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Two years low wage		Panel B: Big drop in wage	
	(1)	(2)	(3)	(4)
Female	-0.307***	-0.300***	-0.318***	-0.311***
	(0.004)	(0.004)	(0.003)	(0.003)
Shock	0.024***	0.022***	0.022***	0.020***
	(0.002)	(0.002)	(0.002)	(0.002)
Female × *Shock*	0.012***	0.012***	0.018***	0.019***
	(0.004)	(0.003)	(0.004)	(0.003)
Experience		0.018***		0.019***
		(0.000)		(0.000)
Tenure		0.005***		0.005***
		(0.000)		(0.000)
ln(education)		0.439***		0.435***
		(0.012)		(0.013)
age		0.006***		0.006***
		(0.000)		(0.000)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.299	0.348	0.313	0.359
Observations	12,877,202	12,839,816	13,081,750	13,043,387

Appendix Table A7: Insurance gap without workers with low labour market participation

This table reports OLS coefficients of regression models examining the relationship between firm idiosyncratic shocks and likelihood of dismissal of male and female workers. In Panel A, we exclude workers who made less than 100,000 SEK in 2000 prices for two consecutive years. In Panel B, we exclude workers who made less than 100,000 SEK in 2000 prices and were making at least 150,000 SEK in the previous year. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. All variables are defined in Section 2.2. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Two years low wage		Panel B: Big drop in wage	
	(1)	(2)	(3)	(4)
Female	0.709***	0.104***	0.775***	0.131***
	(0.025)	(0.021)	(0.027)	(0.021)
Shock	-1.390***	-1.568***	-1.386***	-1.577***
	(0.127)	(0.134)	(0.126)	(0.134)
Female ×	-0.486***	-0.477***	-0.504***	-0.478***
Shock	(0.080)	(0.084)	(0.081)	(0.084)
Experience		-0.069***		-0.057***
		(0.004)		(0.004)
Tenure		-0.198***		-0.202***
		(0.005)		(0.005)
ln(education)		0.127***		0.241***
		(0.035)		(0.037)
age		0.010***		0.007***
		(0.001)		(0.001)
ln(wage_{t-1})		-1.712***		-1.789***
		(0.026)		(0.030)
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt × Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.049	0.059	0.049	0.060
Observations	16,233,034	15,923,090	16,548,625	16,237,335