Are Women More Exposed to Firm Shocks?

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Abstract

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Keywords: Insurance Within the Firm, Wage and Employment Stability, Labor and Finance, Shock Pass-Through, Household Finance

JEL Classifications: G30, G52, J16, J28, J32

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1 Introduction

Around the world, most households rely on labor income for their livelihood. In the United States, wages and salaries are the primary income source for households in the top four income quintiles (only in the bottom income quintile do social security and retirement income contribute more; e.g., Dueholm, 2025). This makes human capital the most valuable asset for the vast majority of people in the economy. In most cases, this asset is not only large relative to other assets, but also highly specific: it depends on a particular occupation, employer, industry, and local labor market. As a result, shocks to the value of human capital—manifesting as labor income risk—are a crucial source of financial risk for individuals and households.

Labor income risk is financially consequential because it directly affects the ability to meet ongoing obligations and to smooth consumption over time. Income shocks can take many forms: long-term unemployment or temporary job loss, reductions in hours, wage cuts, delayed promotions or bonus volatility. Unlike many financial risks, these shocks are difficult to diversify or insure: households cannot readily "sell" claims on their future labor income, and formal insurance (e.g., unemployment insurance or severance pay) is often incomplete and short-lived.

Job security and stable pay are valuable to workers because they limit this risk. Indeed, in surveys, these attributes are consistently considered the most important job characteristic, even ranking above pay levels.[1]

This paper examines the degree to which employment contracts provide pay and employment stability. Firms act, to varying degrees, as providers of implicit insurance

[1] For example, in a 2019 Gallup survey, 92% of respondents valued "stable and predictable pay" and 91% valued "job security" as key features of a job, compared to 86% who prioritized the "level of pay" (Rothwell and Crabtree, 2019). This pattern is also 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."

to risk-averse workers, an idea originating with Knight (1921) and supported by evidence from Guiso et al. (2005) as well as subsequent studies.[2] Our primary goal is to test whether firms provide uniform insurance across employees, or if instead, some workers are more exposed than others to fluctuations in firms' fortunes through their wages and employment. In particular, we investigate whether male and female workers experience the same level of exposure to firms' idiosyncratic shocks.

Experimental and survey evidence suggests that, on average, women are more risk averse than men (e.g., Croson and Gneezy, 2009, and Eckel and Grossman, 2008). Therefore, optimal employment contracts may feature (implicitly or explicitly) higher levels of firm-provided insurance for women than for men. This would imply greater wage and job stability for women and could potentially explain part of the gender wage gap (e.g., Goldin, 2021) as a compensating differential for enhanced job security.

However, when we bring this prediction to the data, we find the opposite. Using detailed employer-employee matched data from Sweden over the period 1990-2011, we find 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 25% more sensitive to firm shocks than those of men, and women are 34% 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 confirm that these findings are not due to innate time-invariant differences across workers, gender differences in seniority, or occupational choices of workers.[3]

[2] In contrast to aggregate macroeconomic fluctuations that are challenging to hedge, idiosyncratic shocks present opportunities for risk sharing between well-diversified corporate owners and employees. Firms can shield workers from idiosyncratic shocks through policies such as maintaining liquidity reserves, smoothing cash flows, and financial hedging. These measures help retain skilled employees, reduce turnover costs due to labor market frictions, and maintain a stable, productive workforce, thereby enhancing operational efficiency.

[3] This is evidenced by the robustness of our results to the inclusion of firm-occupation-year and individual worker fixed effects.

To explain this result, we develop a search and matching model in the spirit of Diamond-Mortensen-Pissarides (e.g., Mortensen and Pissarides, 1994; Mortensen and Pissarides, 1999). A key feature of our model is that jobs vary in flexibility. Some jobs require workers to be always available; others allow workers discretion over when and how much to work. These differences in flexibility matter for understanding gender gaps in the labor market, as a robust body of evidence shows that women value flexibility more than men (Goldin, 2014). The main prediction of the model is that the pass-through of firm-specific shocks is greater for workers in flexible jobs. Because women are more likely to hold flexible jobs, this mechanism may help explain our findings.

Guided by the model predictions, we conduct three sets of tests. First, we construct an occupation-specific flexibility score following Goldin (2014) and Bang (2021). To test whether job flexibility helps explain the gender gap in exposure to firm shocks, we split the sample into high- and low-flexibility occupations. We find that the gender gap in shock pass-through is larger in low-flexibility jobs, where women may be less willing or able than men to fully commit to their career. This mirrors Goldin (2014), who used a similar approach to study gender pay gaps. Second, we examine whether family constraints known to drive women's demand for flexibility (proxied by marriage and children), help explain the gender gap in risk exposure. Prior work shows that motherhood shapes women's career paths (e.g., Kleven et al., 2019). But while the literature has focused on labor market participation and wage *levels*, less is known about its impact on the *riskiness* of labor income. We test whether wage and employment *stability* differs by gender, conditional on family status. We find that the gender difference in the pass-through of firm shocks is magnified for married workers and those with children, especially young children. Finally, we test whether women's higher exposure to firm shocks is more pronounced in small firms. Lacking deep internal labor markets, small firms may be unable to offer flexible labor contracts. In contrast, large firms can spread workloads across more employees, accommodating temporary absences with less disruption. Consistent with this hypothesis, we find that gender differences in shock pass-through are larger in small firms. Taken as a whole, our tests provide compelling evidence that job flexibility is a key explanation for the gender gap in firm insurance.

Our paper contributes to two main strands of the literature in Economics and Finance. First, a large literature documents gender differences in labor market outcomes; Blau and Kahn (2017) and Goldin (2021) provide recent reviews. We are closest to Goldin (2014) and Bang (2021), who also study job flexibility. While most prior work studied gender differences in the *level* of pay and employment, we focus on wage and employment *risk*.[4] 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 adds to the literature on firms as sources of income and employment risk. Past research has documented that firms partially insure workers against idiosyncratic shocks (see Guiso et al., 2005; Cardoso and Portela, 2009; Kátay, 2016, for evidence from Italy, Portugal, and Hungary, respectively). The degree of pass-through of firm shocks to wages and employment is larger in countries with stronger social safety nets (Ellul et al., 2018), suggesting that social insurance and firm insurance are substitutes. Consistent with this, Balke and Lamadon (2022) argue that firm policies offset much of the insurance provided by the state: firms raise the pass-through of shocks to earnings when government insurance increases. For recent reviews of this literature see Pagano (2020) and Guiso and Pistaferri (2020). Beyond

[4]Other non-wage forms of compensation may also matter for workers. For example, Liu et al. (2023) show that maternity benefits are a vital tool for attracting and retaining scarce female talent.

firm insurance, a large literature studies the (macroeconomic) determinants of labor income risk. Recent work shows that high-earning men are more exposed to business cycle fluctuations than other (male) workers, with notable differences across industries (Guvenen et al., 2014); that men face more business cycle risks than women (Guvenen et al., 2017; Albanesi and Şahin, 2018);[5] and that time-varying risk premia lead to time-varying idiosyncratic income risk (Meeuwis et al., 2023). Unlike these studies, which focus on aggregate shocks, we examine exposure to idiosyncratic firm shocks. This distinction is crucial: we find that women are more exposed to firm-specific risk, in contrast to Guvenen et al. (2017) and Albanesi and Şahin (2018), who report that men bear more macroeconomic risk than women.

We also contribute to the literature by examining *within-firm heterogeneity* in insurance against idiosyncratic shocks: how are different workers of the same firm affected? In this regard, our paper relates to a growing line of research on which workers benefit when firms do well. Prior work shows that firms share rents from positive (innovation-related) shocks with certain employees (Van Reenen, 1996; Kline et al., 2019; Howell and Brown, 2020). Our paper differs from this work in three key ways. First, we study both positive and negative performance fluctuations, rather than focusing solely on the rent division following positive shocks. This is important because firm-insurance may be especially valuable to workers when negative shocks occur. Indeed, we find that women face higher dismissal risk after negative shocks. Second, while prior work emphasizes hierarchy or tenure within the firm, we focus on gender as a key source of heterogeneity. The focus on gender is also a feature that distinguishes our work from Caggese et al. (2019), who explore tenure-based firing regulations; from Card et al. (2014), who examine how rent sharing between firms and

[5]Recent work has also documented that the COVID-19 pandemic was more consequential for women's employment than for men's (Alon et al., 2020; Albanesi and Kim, 2021; Alon et al., 2022; Guisinger, 2020).

workers affects capital investment; from Kogan et al. (2023) who study technological displacement; and from Braxton et al. (2021), who document labor income risk along the skill distribution. Third, unlike Card et al. (2016), who attribute gender wage gaps to bargaining differences, we study gender differences in exposure to firm-specific risk. We document disparities not only in wage sensitivity but also in dismissal risk following firm shocks. We also show that differences in job flexibility may help explain these patterns.

In sum, idiosyncratic shocks, including those experienced by one's employer, are crucial determinants of household financial risk, consumption fluctuations, and individual welfare (Constantinides, 2021). Understanding who bears such risks is therefore essential. We provide the first evidence that (i) women's wages are more exposed to firm-specific performance fluctuations than men's; (ii) women face greater variability in dismissal risk following idiosyncratic firm shocks; and (iii) job flexibility can help explain this gender risk gap.

2 Data

2.1 Data sources

The main data for our analysis combines information from several sources. Information on socioeconomic outcomes for Swedish individuals is obtained from the Longitudinal Database on Education, Income and Occupation (LISA, Longitudinell Integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier) from Statistics Sweden (SCB). The sample available from LISA covers the years from 1990 to 2011 and contains information on individual-level characteristics such as age, gender, marital status, employment, uncensored labor income, and social security. In the case of married couples and couples in a registered partnership, the data also contain information on the identity of the spouse 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). Data on job flexibility comes from O*Net Online. These data contain surveys about the mix of knowledge skills, abilities, and tasks associated with each occupation. We use the occupation codes in O*Net and LISA to merge information across the two data sets. 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. Moreover, we restrict the analysis to working age adults. We consider individuals to be of working age if they are at least 25 years old, younger than 64 years old, and not retired.

By combining detailed information on firms' performance with data on wages and employment outcomes of workers, we can 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 range of firm, occupation, and individual characteristics available in the combined dataset enables us to explore the mechanisms underlying any heterogeneity in risk-sharing arrangements between firms and employees.

2.2 Variable definitions

In this section, we define the main variables. We also summarize the variable descriptions in Appendix Table A1.

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 et al. (2005) and model firms' performance processes as a dynamic panel. In particular, firm performance is measured as sales growth, which evolves according to the following equation:

$$y_{ft} = \rho y_{f,t-1} + F_f + I_{ft} + \delta_t + \epsilon_{ft} \tag{1}$$

where y_{ft} is the growth of sales for firm f in period t. F_f, I_{ft}, and δ_t are firm, industry, and year fixed effects, respectively.[6] We estimate equation (1) using the two-step approach of Arellano and Bond (1991). The variable *Shock* is the residual, $\hat{\epsilon}_{ft}$, for each firm-year; therefore, *Shock* can take both positive and negative values, capturing the extent to which a firm is subject to a "good" or "bad" shock in a given year. Table A2 in the Appendix reports the estimates for equation (1) together with additional specification tests. Figure 1 plots the average absolute value of the variable *Shock*, by industry. The largest shocks, in absolute terms, occur in Finance and insurance, followed by Real estate.

[6] Industry is defined using the Swedish Standard Industrial Classification (SNI) 2007 letter sectors; it is based on NACE Rev.2, the industry standard classification system used by the European Union. Industry fixed effects have a firm and time subscript to allow for the possibility that the main industry of operation of a firm changes over time. However, most firms do not change industry. In cases where a firm operates in the same industry throughout the entire sample period, firm fixed effects absorb the industry dummies.

We construct the following additional firm-level variables using data from Serrano: $\frac{Cash}{Assets}$ is cash divided by total assets. *Int. cov.* is EBITDA divided by interest expense. *Ln(Employment)* is the natural logarithm of the total number of workers employed by a firm (according to the financial statements). *Ln(Wage bill)* is the natural logarithm of the total labor compensation paid by a firm in a given year. *Return on assets* is EBITDA divided by total assets. We also construct two measures of financial constraints. *High leverage* is a dummy variable taking the value of one if the net leverage (total debt minus cash holdings, divided by total assets) of a firm in a given year is above the median net leverage in that year in the industry the firm belongs to, and zero otherwise. *Financially constrained (H&P)* is a dummy variable that takes the value one if a firm is both small and young in a year, and zero if it is large and old. In other cases (that is, small and old or large and young) this variable is set to missing. This measure is based on Hadlock and Pierce (2010). A firm is considered to be young if its age (years since incorporation) in a year is below the median firm age in the sample; a firm is small if the value of its assets in a year is below the median of the sample (asset value deflated to 1998 SEK).

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

Individual-level data

We use data from LISA to construct the following variables. The two main outcome variables 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 their 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.[7] *Dismissed* is an indicator variable that takes the value of one if a worker is dismissed in that year, and zero otherwise. This indicator is then multiplied by 100 for ease of interpretation. While our dataset does not explicitly 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 7, that our findings are robust to defining dismissals in alternative ways. In addition, we conduct tests based on voluntary departures, which we define as workers transitioning to a new employer without collecting unemployment benefits. We discuss these results in Section 6. The main explanatory variable at the individual-level is *Female*, an indicator variable that takes the value of one if the individual 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 that takes the value of one if the worker is married or is in a cohabiting relationship, and it 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 in a given year. Finally, *Experience* and *Tenure* measure the years a worker has been in the labor force and in the current firm, respectively.

Following Goldin (2014) and Bang (2021), we construct an occupation-specific flexibility measure as the average of five normalized O*NET characteristics based on Work Activity characteristics "Establishing and Maintaining Interpersonal Relationships" and on Work Context characteristics "Time Pressure", "Contact with Others",

[7]Most workers have only one source of labor income in any given year. For the limited number of cases when a worker receives labor income from multiple firms (this may occur, for example, if a worker has two part-time jobs, or in years when an employee transitions across jobs), we assume that the worker's main employer is the firm that provides the largest income in that year.

"Structured versus Unstructured Work", and "Freedom to Make Decisions".[8] High index scores imply low flexibility. Starting in 2001, LISA includes the Swedish Standard Classification of Occupations 1996 (SSYK) code for each worker, which allows us to link the flexibility measure to our sample.[9] Based on this measure, we construct two variables. *High flex* is an indicator variable that takes the value of one if the flexibility index is below the median flexibility measure in a given year, and zero otherwise. In contrast, *Low flex* is an indicator variable that takes the value of one if the flexibility measure is above the median flexibility measure in a given year, and zero otherwise.

We report summary statistics for the individual-level variables in Panels B and C of Table 1. For convenience, variable definitions are also summarized in Appendix Table A1.

3 Main results

The objective of this study is to examine the extent to which firms insulate different workers against corporate idiosyncratic shocks. Idiosyncratic shocks are an important source of risk in the economy (Constantinides, 2021). Unlike aggregate macroeconomic fluctuations that are difficult to hedge, idiosyncratic shocks create opportunities for risk sharing between well-diversified corporate owners and employees. Given that workers' earnings are closely tied to their employer, understanding the extent to which firms pass through idiosyncratic shocks to their workers is an impor-

[8]We use data on Work Activity and Work Context characteristics from July 2011 (version 16.0) to match the latest year in our sample.

[9]SSYK is based on the International Standard of Occupations (ISCO-88 (COM)). There are very small differences between ISCO-88 and ISCO-88 (COM) at the three-digit level (Tåg, 2013). Using the SSYK at the three-digit level, we can link SSYK and the O*NET Standard Occupation Classification codes, which are aligned with the federal 2010 Standard Occupation Classification codes, using a crosswalk from the Bureau of Labor and Statistics: https://www.bls.gov/soc/soccrosswalks.html.

tant economic question. Indeed, survey evidence indicates that wage and employment stability are key determinants of worker welfare (e.g., Clark, 2001).

In this section, we examine whether firms insure some workers more than others, a question with limited empirical evidence. Our focus is on gender disparities: do firms offer different degrees of wage and employment stability to men and women?

3.1 Idiosyncratic shocks and firm-level outcomes

We follow Guiso et al. (2005) to identify firm-specific revenue shocks. First, we validate that this empirical methodology accurately captures significant shocks to firm performance. To do so, we investigate whether the *Shock* variable affects firms' employment, wage bill, profitability, financial slack, and liquidity, outcomes expected to respond to idiosyncratic fluctuations in revenue. The inclusion of firm fixed effects in these regressions allows us to exploit variation within firms over time and to absorb time-invariant differences across firms. The industry-year fixed effects control for common industry trends.

Table 2 reports the results. We observe that idiosyncratic revenue shocks are positively associated with increases in wage bill (column 1), employment (column 2), return on assets (column 3), financial slack (as measured by interest coverage in column 4), and liquidity (as measured by the ratio of cash to assets in column 5). These results affirm that, consistent with Guiso et al. (2005), shocks to firm revenues significantly impact firms' financial performance and firm-level labor outcomes.

3.2 The gender gap in firm insurance

Next, we address the central question of our study: Do idiosyncratic firm shocks affect all workers within a firm equally, or are there gender disparities?

Laboratory and survey evidence suggests that women are more risk averse than men (Croson and Gneezy, 2009, and Eckel and Grossman, 2008). Consequently, one may expect firms to offer women greater wage and employment stability. In exchange, women may accept lower pay. This negative compensating differential for wage and employment stability could help explain the gender wage gap 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, family constraints may limit women's availability to the firm, reducing the incentive for firms to insure them against idiosyncratic shocks. Instead, workers who are more available to the firm may receive priority in protection.

We assess how individual labor outcomes respond to idiosyncratic shocks experienced by employers. Using information on the gender of each worker, we test whether men and women enjoy the same level of protection against these corporate shocks. In particular, we estimate the following baseline equation:

$$\begin{aligned} y_{ift} = \alpha + \beta Female_i \times Shock_{ft} + \gamma_1 Female_i + \gamma_2 Shock_{ft} + \theta X \\ + F_f + IY_{ft} + LY_{ift} + u_{ift} \end{aligned} \tag{2}$$

To examine differences across workers within the same firm, all regressions include firm fixed effects (F_f). We also control for industry-by-year and local labor market-by-year fixed effects (IY_{ft} and LY_{ift}, respectively) to capture broader wage and employment trends. Labor income risk (y_{ift}) is measured along two margins: wages and employment. *Wage* captures intensive-margin adjustments from continuing workers, while firms can make extensive margin adjustments by dismissing workers.[10]

[10] Swedish labor protection is comparable to Continental Europe, less stringent than Southern Europe, and more stringent than Anglo-Saxon countries. The country has liberalized labor regulations

Our main parameter of interest, β, measures gender differences in the pass-through of idiosyncratic firm shocks. A nonzero value of β implies a differential pass-through rate of corporate shocks to women relative to men. By comparing workers within the same firm and year, we test whether exposure to the same firm-specific shock leads to differential effects on male and female employees. 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, wage and employment of male and female workers differ only due to the impact of the shock. The rich list of firm and individual controls that are included in the regression (which are also interacted with the variable *Shock*) makes it implausible that omitted variables correlated with the shock could differentially affect male and female workers' wages and likelihood of dismissal. That is, we believe that the estimated parameter β captures differences in the employment relation between male and female workers.

First, we investigate whether firms provide wage insurance to their workers, on average. In these tests, we restrict the sample to "stayers": workers who remain with the employer throughout the year of the shock. That is, we exclude sample years in which the worker joins or exits the firm (voluntarily or involuntarily), because the recorded annual compensation may be mechanically lower in such years for reasons unrelated to the firm shocks. We estimate regression model (2) using *Wage* as the dependent variable and report the coefficient estimates in Table 3. Observed changes in labor income may result from variations in both hourly rates and the number of hours worked. Because both of these adjustments—in hours worked and wage rate—constitute ways through which a worker's total income can fluctuate with

over the past three decades, notably legalizing temporary work agencies in 1993 and introducing fixed-term employment in 1997. For more details on the labor law in Sweden, see, e.g., Baghai et al. (2021).

firm performance, we consider total annual compensation the most appropriate and encompassing measure of income risk, conditional on being employed.

Column 1 reports the average pass-through of firm shocks to wages, irrespective of worker gender. A two standard deviation idiosyncratic shock (that is, an increase in *Shock* of 0.54) is associated with a 4% increase in worker compensation, which is comparable in sign and magnitude to estimates from Guiso et al. (2005) for Italy. In column 2, we incorporate an interaction between *Shock* and *Female* into the regression model to assess whether wage sensitivity to firm shocks differs between genders. We find that women's wages are more sensitive to firm shocks than men's. The difference is both statistically and economically significant: women are about 25% more exposed to idiosyncratic firm shocks than men.[11]

In column 3, we add individual controls (*Experience*, *Tenure*, *Ln(Education)*, and *Age*) that are known to affect wages, together with their interactions with the variable *Shock*. While most of the coefficients associated with these variables are statistically significant, their inclusion does not alter the magnitude or statistical significance of our main variable of interest.[12] The estimated gender gap in shock exposure remains: women's wages are still about 25% more exposed to firm shocks than men's. In column 4, we add individual worker fixed effects to account for time-invariant, unobservable individual characteristics, such as innate ability or worker quality. The inclusion of

[11]The coefficient on the variable *Female* corroborates the magnitude of the gender wage gap documented in other Swedish studies over the same period, specifically the findings reported by Fortin et al. (2017). When excluding workers in parental leave, educational training, and partial employment, our estimates of the gender wage gap narrow to about 20% in otherwise similar specifications. In our main sample, we do not impose these restrictions as such responses may reflect firms' shock-related adjustments (e.g., reduced hours following a negative firm shock). Nevertheless, Appendix Table A3 confirms that our conclusions remain robust under these alternative sample definitions.

[12]The magnitude of the coefficient on the (non-interacted) variable *Shock* changes from 0.07 in column 1 to 0.26 in column 3. This comparison, however, is not meaningful due to the interaction of the variable *Shock* with *Female*, *Experience*, *Tenure*, *Education*, and *Age* in column 3. Evaluated at the sample means (Panel B, Table 1), the elasticity of wages to *Shock* is $0.258 + 0.017 * 0.339 - 0.003 * 14.482 - 0.001 * 7.567 - 0.033 * 2.427 - 0.001 * 43.509 = 0.09$, which is comparable to column 1.

these fixed effects absorbs the *Female* dummy variable in this specification. However, our finding remains that the pass-through of shocks to wages is larger for women.

Finally, in column 5, the regression model includes occupation fixed effects interacted with year fixed effects.[13] The coefficient on the $Female \times Shock$ interaction remains statistically significant in this specification, but it declines in magnitude. This suggests that while gender differences in shock exposure are not exclusively driven by occupational sorting, occupation-specific characteristics contribute meaningfully to the observed gap.

Next, we investigate whether women and men face equal dismissal risk in response to idiosyncratic firm shocks. First, column 1 of Table 4 confirms prior findings: firms (partly) insure workers' employment against idiosyncratic revenue shocks. Specifically, a two-standard-deviation increase in *Shock* (an increase in *Shock* of 0.7) is associated with a 2 percentage point increase in the probability of dismissal (39% of the sample mean of *Dismissed*). This suggests that there is limited pass-through of shocks to dismissal and that firms significantly shield workers from these shocks. However, column 2 of Table 4 reveals substantial heterogeneity: the dismissal probability for women is about 34% more sensitive to firm shocks than that of men. This gender gap remains robust after controlling for individual worker characteristics and their interactions with *Shock* (in column 3); including worker fixed effects (in column 4); and adding occupation-by-year fixed effects (column 5).

The regressions in Tables 3 and 4 include a comprehensive set of individual characteristics and fixed effects. In Table 5, we test the robustness of our results to employing an alternative set of fixed effects. Specifications 1, 2 and 3 study the elasticity of wages to shocks. First, in column 1, we add firm-by-year fixed effects,

[13] Occupations are defined at the two-digit level, covering 27 unique occupations. Because occupation data are only available from 2001 onward, this specification uses a smaller sample.

comparing male and female workers within the same firm and year. This specification rules out the possibility that firm-level unobservable factors (that affect all workers equally) could be biasing our estimates. Column 2 includes interactions of occupation dummies with the variable *Shock*, allowing for different occupations to be differentially exposed to firm shocks. Column 3 includes firm-by-occupation-by-year fixed effects, allowing comparisons among workers in the same firm, occupation, and year. This analysis confirms that the gender gap in firm insurance is not driven exclusively by the gender composition across different firm hierarchies or occupations (in the same year). The results hold in both cases; 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 19% smaller than the coefficient reported in the less saturated specification of column 2 of Table 3.

Columns 4 to 6 of Table 5 repeat the analysis using *Dismissed* as the outcome. Column 6 presents our most restrictive regression specification, comparing workers in the same occupation and firm in the same year. We continue to find that female employees show a larger sensitivity in the probability of dismissal in response to firm shocks compared to their male counterparts. Economically, the coefficient of interest is about 30% of that reported in column 2 of Table 4, indicating that occupational sorting explains a substantial, albeit not complete, share of the gender differences in the exposure to firm shocks.[14]

In sum, we find that women are more exposed than men to idiosyncratic firm shocks, both in wages and dismissal risk. This gender gap persists after controlling for individual characteristics, various fixed effects, and occupational sorting. This evidence motivates the theoretical and empirical analysis that we develop below, in

[14]Could women self-select into firms with smaller shocks? Appendix Table A4 shows that male and female workers experience similar average shocks and shares of negative shocks. This reflects the unpredictable nature of idiosyncratic shocks and supports our identification strategy.

Sections 4 and 5, to rationalize this gender risk gap.

4 Model

To rationalize women's greater exposure to firm shocks, we develop a search-and-matching model in which job flexibility plays a central role.

The model is motivated by evidence that gender differences in job flexibility explain much of the wage gap (Goldin, 2014), and by our own finding that controlling for occupation attenuates the gender gap in firm insurance. We thus ask whether differences in job flexibility can account for the gender gap in the elasticity of wages and employment to firm shocks.

We formalize this idea in a Diamond–Mortensen–Pissarides search-and-matching model with endogenous separations (Mortensen and Pissarides, 1994, and Mortensen and Pissarides, 1999). Occupations come in two types. High-flexibility occupations feature a high elasticity of substitution across workers, while low-flexibility occupations have a low elasticity of substitution. As a result, a worker's inability to fully commit to the job is more costly in low-flexibility occupations, where firms cannot easily replace an unavailable worker.

4.1 Model Setup

We study a continuous time, infinite horizon economy with risk neutral agents. Workers can be employed in two different types of occupations j; let $j = H, L$ denote high and low flexibility jobs, respectively. Unemployed workers are matched to job vacancies according to matching function m:

$$flow\ rate\ of\ matches = m(u_j, v_j)$$

where u_j and v_j are the unemployment and vacancy rate, respectively. We assume that $m(u_j, v_j)$ exhibits constant returns to scale, as is standard in the literature (e.g., Petrongolo and Pissarides, 2001). Furthermore, occupations are segmented, with the fraction of the population that could be employed in segment j being defined as the sum of unemployment (u_j) and employment (e_j) rates in the sector: $u_j + e_j = n_j$. The mass of workers employed in the high- and low-flexibility sectors equals 1: $n_H + n_L = 1$.

Labor market tightness for job type j, denoted by θ_j, is defined as $\theta_j = \frac{v_j}{u_j}$, the ratio of vacancy rate to unemployment rate. We also define $q(\theta_j) \equiv \frac{m_j}{v_j} = m(\frac{1}{\theta_j}, 1)$, which is the Poisson arrival rate of a match for a vacancy; and $\theta_j q(\theta_j) \equiv \frac{m_j}{u_j} = \frac{v_j}{u_j} m(\frac{1}{\theta_j}, 1)$, the Poisson arrival rate of a match for an unemployed worker. The likelihood of matching depends on labor market tightness, with $q'(\theta_j) < 0$. In turn, job creation occurs when an unemployed worker is matched with a job, that is, $job\ creation = u_j \cdot \theta_j q(\theta_j)$.

Because we want to study how firm shocks affect dismissals, we endogenize job separations.

The productivity of a match for an occupation and firm is given by:

$$productivity_{jf} = p_j + \sigma \times \epsilon_f$$

where p_j is the common productivity element for occupation j, ϵ_f are firm specific shocks, and σ captures the importance of firm-specific shocks to productivity. To avoid notational clutter, we remove the firm subscripts f henceforth.

Firm-specific productivity shocks, denoted ϵ, arrive at a constant Poisson rate of

λ and are independently drawn from a cumulative distribution function $F(.)$ with support $\underline{\epsilon}, \overline{\epsilon}$. Profit maximization at the time of job creation requires that a job is created when $\epsilon = \overline{\epsilon}$.

Workers can either be employed or unemployed. We call W the present value of a job to an employed worker and U the present value of being unemployed. Let r be the discount rate, $w_j(\epsilon)$ the wage paid for a filled job with productivity draw ϵ, and b the unemployment benefits or value of leisure. The corresponding Bellman equations are:

$$rW_j(\epsilon) = w_j(\epsilon) + \lambda \left[\int_{\underline{\epsilon}}^{\overline{\epsilon}} max\{W_j(x), U_j\} dF(x) - W_j(\epsilon) \right] \tag{3}$$

$$rU_j = b + \theta_j q(\theta_j) \left[W_j(\overline{\epsilon}) - U_j \right] \tag{4}$$

Firms have filled and vacant positions. We call J the present value of a filled job for a firm, and V the present value of a vacant job. The corresponding Bellman equations are:

$$rJ_j(\epsilon) = p_j + \sigma\epsilon - w_j(\epsilon) + \lambda \left[\int_{\underline{\epsilon}}^{\overline{\epsilon}} max\{J_j(x), V_j\} dF(x) - J_j(\epsilon) \right] \tag{5}$$

$$rV_j = -\gamma_j + q(\theta_j) \left(J_j(\overline{\epsilon}) - V_j \right) \tag{6}$$

We assume that low flexibility jobs are more productive than high flexibility jobs: $p_L > p_H$. Moreover, the cost of recruiting a worker expressed as a fraction of the worker's productivity, which we denote as γ_j, is larger for low flexibility workers than for high flexibility workers, that is, $\gamma_L > \gamma_H$. This is due to low flexibility workers being inherently more difficult to replace. Finally, we assume that $p_L - p_H \geq \gamma_L - \gamma_H$ and that $\gamma_H > (\overline{\epsilon} - \underline{\epsilon})\sigma(1 - \beta)$; this implies that recruiting costs are non-negligible and that the net gain (productivity minus recruiting costs) of hiring a low flexibility worker is at least as high as that of hiring a high flexibility worker, so firms gain from employing workers who do not demand flexibility.

4.2 Equilibrium

In equilibrium, firms maximize profits and workers maximize utility. The mass of people in the economy is constant, so labor supply is fixed. Free entry implies that the value of new vacancies is zero in equilibrium.

Wages are determined via Nash bargaining over match-specific surplus $S_j = J_j(\epsilon) + W_j(\epsilon) - U_j - V_j$. Therefore, as shown in Mortensen and Pissarides (1994), the equilibrium wage contract is given by:

$$w_j(\epsilon) = rU_j + \beta\left[p_j + \sigma\epsilon - rU_j - rV_j\right] \tag{7}$$

where β represents the worker's bargaining power, which we assume to be homogeneous across job types.

$\frac{dw_j(\epsilon)}{d\epsilon} = \beta\sigma > 0$ implies that $W_j(\epsilon)$ and $J_j(\epsilon)$ are monotonically increasing in ϵ. In addition, the value of a filled job is higher than a vacancy if and only if the worker's value from employment exceeds that of unemployment. Therefore, equilibrium job destruction is characterized by a cut-off rule, that is, $\exists \epsilon < \epsilon_j^D$ for which job destruction will occur. At the job destruction threshold ϵ_j^D, both the worker and the firm are indifferent between continuing the match and separating:

$$W_j(\epsilon_j^D) - U_j = J_j(\epsilon_j^D) - V_j = 0 \tag{8}$$

Job separations equal total job destruction in equilibrium. In steady state $\dot{u}_j = 0$

and the Beveridge curve is:

$$u_j = \frac{\lambda F(\epsilon_j^D)}{\lambda F(\epsilon_j^D) + \theta_j q(\theta_j)} \tag{9}$$

The labor market equilibrium is characterized by values of u_j, θ_j, ϵ_j^D and $w_j(\epsilon)$ that jointly satisfy the free-entry condition, the wage equation (7), the job destruction condition (8), the Beveridge curve (9), and the value functions (6) and (4).

To study how firm shocks affect the likelihood of dismissal, we derive the equilibrium job creation and job destruction curves. The job creation curve is given by:

$$\gamma_j = \frac{(1-\beta)\sigma}{r+\lambda} q(\theta_j)(\bar{\epsilon} - \epsilon_j^D) \tag{10}$$

and the job destruction curve is given by:

$$p_j + \sigma\epsilon_j^D + \frac{\lambda}{r+\lambda}\sigma \int_{\epsilon_j^D}^{\bar{\epsilon}} (x - \epsilon_j^D) dF(x) = b + \frac{\theta_j \beta \gamma_j}{1-\beta} \tag{11}$$

where the integral term captures the expected gain from future favorable shocks above the destruction threshold, which captures the option value of continuing the match. The right-hand side reflects the worker's outside option and expected surplus from matching.

4.3 Implications for the pass-through of firm shocks to employees

The job creation and job destruction curves derived above have implications for how idiosyncratic firm shocks affect the likelihood of dismissal. Figure 2 contains a graphical representation of the job creation and job destruction curves for high- and low-flexibility occupations.

First, for any given θ, the equilibrium productivity threshold for creating a new vacancy is higher for high flexibility jobs than for low flexibility jobs. Similarly, the productivity threshold to destroy a job is higher for high flexibility jobs than for low flexibility jobs. This means that the minimum level of firm productivity that is required not to dismiss a worker is higher for more flexible jobs. This implies that firms are more likely to dismiss workers in high-flexibility occupations following a low productivity draw. This is the model's first testable prediction that we will examine in the next section: dismissals are more responsive to firm shocks in high-flexibility occupations.

Second, the model has implications for how shocks to firm performance are passed through to worker wages. In the model, the marginal effect of a shock to firm productivity, ϵ, on the level of wages is:

$$\frac{dw_j(\epsilon)}{d\epsilon} = \beta\sigma,$$

which is constant across occupations, so the nominal impact of a firm shock on the level of wages is similar across workers. However, because low flexible jobs command a wage premium, an identical shock to firm productivity leads to a larger percentage change in the wages of workers in high-flexibility occupations than in the wages of low-flexibility occupations. In other words, the model predicts that wage sensitivity to firm performance is larger for more flexible jobs.

These two predictions, greater dismissal sensitivity and greater wage elasticity in high-flexibility occupations, will guide the empirical analysis in the next section.

5 Job flexibility and the gender gap in firm insurance

The model of the previous section shows that job flexibility can be an important determinant of the pass-through of firm shocks to workers. Given the well-documented gender differences in job flexibility, this job attribute may help explain the gender differences in exposure to firm shocks that we documented in Section 3. In this section, we test the empirical relevance of this channel.

5.1 Occupation flexibility

We begin by testing whether gender differences in exposure to firm shocks vary across occupations with different levels of flexibility. This test leverages the richness and granularity of our data. Starting in 2001, Statistics Sweden records the occupation of each worker. This allows us to create a time-varying measure of job flexibility for every person in our sample. We follow the recent work of Goldin (2014) and Bang (2021) to assign flexibility scores at the occupation level. Using this measure of job flexibility, we examine whether gender differences in shock pass-through are concentrated in low-flexibility occupations. Our tests are inspired by Goldin (2014), who found that gender differences in the *level* of wages are larger in low flexibility occupations. We extend this logic to the risk dimension and test whether job flexibility can also account for differences in the *riskiness* of employment contracts.

In Table 6, we separate occupations into high and low flexibility groups based on the median job flexibility score. We then test whether the gender differences in the pass-through of firm shocks are larger in low flexibility occupations than in high flexibility occupations. We find that both for wages (columns 1 and 2) and dismissals (columns 3 and 4), the gender gap in firm insurance is only statistically significant in low-flexibility occupations. This is consistent with the view that the value of job flexibility differs by gender, and that this may be a primary driver of the gender risk gap that we document in Section 3. Only in occupations where flexibility is limited are women more exposed to firm shocks. In occupations that are inherently flexible, women and men face similar exposures to firm performance shocks. This supports the interpretation that job flexibility is a key channel behind the gender gap in firm shock exposure.

5.2 Home production and household constraints

In addition to the occupation-based measures of job flexibility used above, we also examine alternative proxies. In particular, household constraints associated with marriage and parenthood, which may differ by gender, may impact career commitment and the degree to which workers can devote themselves to their jobs. The occurrence of a firm shock plausibly coincides with a critical period requiring employees' unconditional commitment and full engagement. However, family constraints may limit women's ability to dedicate themselves to their careers as much as men.

We conduct several tests to assess the role of household constraints as a determinant of gender differences in the value of flexibility. First, we divide the sample into "married" and "non-married" individuals.[15] Panel A of Table 7 shows that gender differences in exposure to firm shocks are more pronounced among married workers. This suggests that marital status, and the associated household constraints, may indeed help explain gender differences in exposure to firm shocks.

Having children may impose even greater time constraints than marriage, and

[15] This classification includes individuals who are legally married as well as those in recognized cohabiting relationships.

such constraints may fall disproportionately on women. Child-rearing responsibilities are rarely equally shared within households, and a large body of evidence shows that having children has a detrimental impact on the level of wages of women (e.g., Kleven et al., 2019). Therefore, it is natural to ask whether family constraints, particularly the unequal division of domestic responsibilities and the inherent lack of flexibility that parenting imposes, help explain the gender gap in exposure to firm shocks.

In Sweden, as in many countries, women are more likely than men to take family leave for childcare. In Appendix Table A5, we examine workers with young children (up to, and including, the age of ten). In this sample, we estimate Poisson regressions using as dependent variables the number of parental leave days taken per annum (column 1) and the days taken to care for a sick child (column 2).[16] The specification is otherwise similar to our main regressions. The main explanatory variable is *Female*. In these tests, we control for *Experience*, *Tenure*, *Ln(Education)*, and *Age*. In addition, we control for firm, industry-by-year, and labor market-by-year fixed effects. The estimates indicate that, over the 1994 - 2011 period, women in Sweden took almost triple the amount of parental leave than men, and about 22% more leave to care for sick children.[17]

Given that women more frequently take time off for child care, it could be profit-maximizing for firms to offer more insurance to men relative to women. Because providing insurance should arguably help attract and retain workers, firms may insure men more if they are more able and willing to sacrifice family time and flexibility to

[16]Parental leave in Sweden covers up to 480 days per child (to be shared between the two parents). Parents in Sweden 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 are paid by the Swedish Social Insurance Agency (Försäkringskassan) and are income-based, with caps. See *Försäkringskassan* for details.

[17]This evidence is consistent with Keloharju et al. (2022), who report large gender differences in parental leave, sick leave, unemployment, labor force participation, and working hours; these differences persist years after the birth of the first child.

fully devote themselves to their careers. In Panel B of Table 7, we study the provision of firm insurance to employees with and without children. We observe that the gender gap in firm insurance is limited to workers with children up to age 18, as evidenced by the coefficients on the interaction $Shock \times Female$ in columns 2 and 4. We further refine our analysis by categorizing employees based on the presence of *young* children (aged 10 or below), given that small children often require more intensive care and presence. Results from Panel C of Table 7 corroborate our earlier findings: the difference in wage and employment insurance obtained by women compared to men intensifies in the presence of small children. This pattern is consistent with the view that family constraints, particularly those tied to childcare, limit women's ability to respond flexibly to firm needs, and may thus reduce the insurance firms are willing to offer.

5.3 Heterogeneity in firms' capacity to provide flexibility

Finally, we test whether firm-level differences in the ability to offer flexibility to workers are associated with gender differences in firm insurance. Job flexibility is not only determined by worker characteristics and constraints: firms may also differ in the extent to which they are able to offer flexible work arrangements to their employees.

In particular, small firms may be less able to offer job flexibility, because they do not have the slack to redistribute workload among a large pool of workers. In contrast, large firms, with bigger workforces, may be better equipped to cope with worker absences, as tasks can be performed by the employees who remain available. This greater substitutability means that large firms are in a better position than small firms to offer flexible work contracts without sacrificing operational efficiency. For this reason, if job flexibility is a determinant of firm insurance, we would expect the gender gap in firm insurance to be more pronounced in small firms than in large ones.

Table 8 presents evidence consistent with this prediction. Panel A shows that firms smaller than the median firm size (based on asset value) display larger gender gaps in firm insurance than firms above the median size threshold.[18] Panel B of Table 8 uses an alternative measure of firm size by categorizing firms based on their hierarchical structure. We differentiate between firms that maintain more than two hierarchical levels and those with only one or two levels. The latter represents smaller, flatter organizations, where flexibility may be costly to offer to employees, whereas the former includes larger, more hierarchical firms where tasks are more standardized and substitutable. The findings corroborate those in Panel A: workers in smaller firms experience a larger gender gap in wage and employment stability than those in bigger, more hierarchical organizations.

6 Additional discussion

To better understand the mechanisms behind the gender gap in firm-provided insurance, we present a set of complementary analyses in this section.

First, we examine voluntary employee turnover. Specifically, we test whether women are more likely than men to voluntarily leave the firm amid performance declines, rather than being dismissed. If that was the case, we would expect to observe a similar gender difference in the sensitivity of voluntary departures to firm shocks as we do when studying dismissals and wages. We follow Baghai et al. (2021) in defining voluntary departures as instances where a worker transitions directly to another job without experiencing unemployment. We report regressions with the de-

[18] In unreported results, we also find that smaller firms feature lower levels of insurance overall.

pendent variable *Voluntary leaver* in Table A6. The coefficients for the interaction $Female \times$ *Shock* are both economically and statistically insignificant in all specifications. This suggests that firm shocks do not differentially affect the voluntary exit behavior of women relative to men. Notably, we observe a negative relationship between *Shock* and voluntary departures, on average (see column 1); this indicates that workers are less likely to voluntarily leave a firm performing well and more likely to leave one performing poorly.

The gender differences in the pass-through of firm shocks that we document in Section 3 may stem from higher sensitivity to the shocks in the top or bottom of the firm performance distribution. This distinction matters: more exposure to good performance may reflect more generous rent-sharing between the firm and its workers, while increased exposure to negative shocks could signify weaker insurance. To assess whether the response to idiosyncratic firm shocks is symmetric, we separate the variable *Shock* into three components: *Top shock* (an indicator variable capturing the top quintile of positive shocks), *Bottom shock* (an indicator for the bottom quintile of negative shocks), and the remaining realizations of the shock, closer to zero, serve as our baseline. We then interact these variables with *Female*. The results, reported in Table 9, reveal a nuanced, asymmetric effect. The incremental wage risk borne by women appears to be driven primarily by exposure to positive shocks. Considering the most saturated specifications of columns 2 and 3, we find that the coefficient associated with the interaction $Female \times$ *Top shock* is positive and significant, indicating a larger pass-through of large positive shocks to wages for female workers. In contrast, the interaction $Female \times$ *Bottom shock* is negative but statistically insignificant, suggesting that there is no gender difference in the pass-through of large negative shocks to wages, consistent with downward wage rigidities.

For employment (columns 4 to 6), the asymmetry is reversed: Gender differences in employment responsiveness to firm shocks stem mostly from downside risk. In all specifications, including the most saturated model in column 6 (with individual controls, worker fixed effects, and occupation-year fixed effects), women's dismissal probability is more sensitive to large negative shocks. In terms of magnitudes, according to specification 4, a large negative shock increases the dismissal likelihood for men by roughly two percentage points (roughly 40% of the sample mean of 4.9%); this effect is about 50% larger for women. We conclude that both rent-sharing (associated with positive shocks) and risk sharing (associated with negative shocks) contribute to the gender differences in sensitivity to firm performance and thus to the income variability experienced by women.

In Table A7 of the Online Appendix, we conduct a variation of these tests. Instead of comparing top and bottom shocks to moderate shocks, we contrast negative shocks with positive shocks. We find that while negative shocks have negative consequences for all workers, the magnitude of the effect is larger for women, in line with our main findings.

Are gender differences in exposure to firm shocks driven by transitory fluctuations or more persistent changes in firm performance? In Table A8 in the Online Appendix, we decompose *Shock* into a permanent and a transitory component—*Permanent shock* and *Transitory shock*, respectively. For a given firm-year, *Permanent shock* is the average of the variable *Shock* over the previous, current, and following years; *Transitory shock* is the difference between *Shock* and *Permanent shock*. We find that the pass-through is significantly larger for permanent shocks, consistent with Guiso et al. (2005). Moreover, the gender differences in exposure to firm shocks are primarily driven by exposure to permanent, not temporary, shocks.

One important determinant of the ability of a firm to provide insurance to its workers is its financial health. Financially constrained firms may lack the necessary slack to absorb idiosyncratic shocks, forcing them to pass these shocks onto their employees. In contrast, financially robust firms with the ability to absorb temporary revenue shocks are more likely to maintain stable wage and employment contracts. Thus, as an additional validation of our methodology, we study whether financial constraints affect the level of insurance that firms provide to workers. We first sort firms based on their leverage ratios, categorizing them as "high leverage" if their ratios are above the industry median, and "low leverage" if below. Large debt service obligations may prevent highly levered firms to insure their workers, while firms with low leverage may be more capable of absorbing revenue shocks, allowing them to provide more wage and employment stability to their employees. Consistent with this idea, in Panel A of Table A9 in the Online Appendix, we find that highly levered firms on average offer less insurance to workers, as evidenced by larger coefficients on the variable *Shock* compared to firms with low leverage. In Panel B of Table A9, we adopt an alternative measure of financial constraints, following Hadlock and Pierce (2010). We categorize firms as constrained if they are small and young, and as unconstrained if they are large and old.[19] This measure further corroborates our results: constrained firms offer less insurance to their employees than their unconstrained counterparts.

7 Robustness

In this section, we assess the robustness of our findings to alternative measures of firm performance, dismissal definitions, and empirical specifications to ensure that

[19] 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. Note that the tests in Panel B of Table A9 only contain firms that are young and small (constrained) and those that are old and large (unconstrained), with the remaining two categories excluded from the tests. Because unconstrained firms employ more workers, the regressions using that subsample of firms have more observations.

our results are not driven by modeling choices or data limitations.

The methodology used to measure idiosyncratic shocks is central to our analysis. Our main tests identify these shocks based on the evolution of sales growth (following Guiso et al., 2005 and Ellul et al., 2018). To ensure the robustness of our results, we employ an alternative measure of corporate performance to identify firm-specific shocks. In particular, in Table A10 in the Online Appendix, we replicate our main tests using the natural logarithm of value added to construct the variable *Shock*.[20] These alternative specifications yield qualitatively similar results, consistently revealing a gender gap in firm insurance.

The results are also robust to alternative definitions of dismissals. A key object of our study are involuntary separations, so it is important to ensure that we accurately capture firings rather than voluntary exits. However, most datasets, including ours, do not record whether departures are voluntary or forced. We therefore use several independent approaches to proxy involuntary departures. Specifically, in Table A11 in the Online Appendix, we replicate our main tests using two alternative proxies for dismissal. First, we define dismissal as instances where workers leave a firm for a lower-paying job (dependent variable *Worse job*, columns 1 and 2); second, we use receipt of unemployment insurance as an indicator of involuntary separations (dependent variable *Unemployed*, columns 3 and 4). In both cases, the results remain qualitatively and quantitatively similar, reinforcing the conclusion that the gender gap in firm insurance is robust to alternative dismissal definitions proxied using observable data.

Finally, to control for unobserved heterogeneity at the individual level, one can use either first differences or worker fixed effects. We opt for fixed effects for several reasons. First, our panel is unbalanced, and first differencing would discard many

[20] Observations with zero or negative value added (1.7%) are excluded from this analysis.

observations. Second, first differences relies only on changes in wages in adjacent years, whereas fixed effects use the full wage profile to establish a worker-specific baseline, potentially yielding less noisy estimates of how firm performance affects wages. Third, fixed effects offer greater flexibility: we can sequentially add different fixed effects (such as worker, occupation-by-year, and firm-by-year) to isolate the variation driving our results and assess the role of factors like occupational sorting versus within-firm gender disparities. Despite this, in Table A12 of the Online Appendix, we present results using a first differences estimator; we obtain results that are broadly consistent with our main findings. We only conduct this robustness test for wages because the variable *Dismissed* already captures a change in employment status.

8 Conclusion

Labor income risk is a major determinant of household financial risk. We study the degree to which firms insulate workers from idiosyncratic shocks. Our findings reveal that women's wages and employment are systematically more exposed to idiosyncratic firm shocks than men's, a pattern we term the gender gap in firm insurance. The difference in firm-insurance is sizable: women's wages are 25% more susceptible to firm-specific shocks than men's, and their dismissal probabilities are 34% more sensitive to these idiosyncratic fluctuations in firm performance.

To rationalize these findings, we build a Diamond-Mortensen-Pissarides style model in which flexibility is a defining characteristic of a job. The model predicts that the sensitivity of wages and employment to firm performance should be higher for more flexible occupations. Because the need for flexibility has been documented to be larger for women than for men, the model can help explain the gender gap in firm insurance.

We provide a collage of empirical evidence that suggests that job flexibility is indeed a plausible driver of the gender risk gap. First, the gender differences in exposure to firm shocks are present primarily in occupations with low flexibility. Second, the gender risk gap is larger for workers who are married and have children, groups likely to face greater household constraints and higher costs of inflexibility, particularly for women. Third, we find that the gender gap in firm insurance is smaller in large firms, which have deep internal labor markets and therefore a greater ability to offer more flexibility by redistributing the workload among employees. Taken together, our analysis shows both theoretically and empirically that gender differences in job flexibility can contribute to explaining the gender differences in sensitivity to firm shocks.

These findings open interesting avenues for future research. While gender is an important dimension where differences in firm insurance manifest themselves, worker heterogeneity along race, age, and education also merit exploration. Investigating how firm insurance varies along these characteristics could provide deeper insights into workplace inequalities and the distribution of financial risk in the economy.

References

Albanesi, S. and J. Kim (2021). Effects of the covid-19 recession on the us labor market: Occupation, family, and gender. *Journal of Economic Perspectives 35*(3), 3–24.

Albanesi, S. and A. Şahin (2018). The gender unemployment gap. *Review of Economic Dynamics 30*, 47–67.

Alon, T., S. Coskun, M. Doepke, D. Koll, and M. Tertilt (2022). From mancession to shecession: Women's employment in regular and pandemic recessions. *NBER Macroeconomics Annual 36*(1), 83–151.

Alon, T., M. Doepke, J. Olmstead-Rumsey, and M. Tertilt (2020). This time it's different: the role of women's employment in a pandemic recession. Technical report, National Bureau of Economic Research.

Arellano, M. and S. Bond (1991). Some Tests of Specification for Panel Data: Monte carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies 58*(2), 277–297.

Baghai, R. P., R. C. Silva, V. Thell, and V. Vig (2021). Talent in distressed firms: Investigating the labor costs of financial distress. *The Journal of Finance 76*(6), 2907–2961.

Balke, N. and T. Lamadon (2022). Productivity shocks, long-term contracts, and earnings dynamics. *American Economic Review 112*(7), 2139–77.

Bang, M. (2021). Job flexibility and household labor supply: Understanding gender gaps and the child wage penalty. *Working paper*.

Blau, F. D. and L. M. Kahn (2017). The gender wage gap: Extent, trends, and explanations. *Journal of economic literature 55*(3), 789–865.

Braxton, J. C., K. F. Herkenhoff, J. L. Rothbaum, and L. Schmidt (2021). Changing income risk across the us skill distribution: Evidence from a generalized kalman filter. Technical report, National Bureau of Economic Research.

Caggese, A., V. Cunat, and D. Metzger (2019). Firing the wrong workers: Financing constraints and labor misallocation. *Journal of Financial Economics 133*(3), 589–607.

Card, D., A. R. Cardoso, and P. 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.

Card, D., F. Devicienti, and A. Maida (2014). Rent-sharing, holdup, and wages: Evidence from matched panel data. *Review of Economic Studies 81*(1), 84–111.

Cardoso, A. R. and M. Portela (2009). Micro foundations for wage flexibility: wage insurance at the firm level. *Scandinavian Journal of Economics 111*(1), 29–50.

Clark, A. E. (2001). What really matters in a job? hedonic measurement using quit data. *Labour economics 8*(2), 223–242.

Constantinides, G. M. (2021). Welfare costs of idiosyncratic and aggregate consumption shocks. Technical report, National Bureau of Economic Research.

Croson, R. and U. Gneezy (2009). Gender differences in preferences. *Journal of Economic literature 47*(2), 448–74.

Dueholm, M. (2025). Income sources for the highest- and lowest-earning families. *Federal Reserve Bank of St. Louis Open Vault Blog accessible at: https://www.stlouisfed.org/open-vault/2025/june/income-sources-highest-lowest-earning-families*.

Eckel, C. C. and P. J. Grossman (2008). Men, women and risk aversion: Experimental evidence. *Handbook of experimental economics results 1*, 1061–1073.

Ellul, A., M. Pagano, and F. Schivardi (2018). Employment and wage insurance within firms: Worldwide evidence. *The Review of Financial Studies 31*(4), 1298–1340.

Fortin, N. M., B. Bell, and M. Böhm (2017). Top Earnings Inequality and the Gender Pay Gap: Canada, Sweden, and the United Kingdom. *Labour Economics 47*, 107–123.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American economic review 104*(4), 1091–1119.

Goldin, C. (2021). *Career and Family: Women's Century-Long Journey toward Equity*. Princeton University Press.

Guisinger, A. Y. (2020). Gender differences in the volatility of work hours and labor demand. *Journal of macroeconomics 66*, 103254.

Guiso, L. and L. Pistaferri (2020). The insurance role of the firm. *The Geneva Risk and Insurance Review 45*(1), 1–23.

Guiso, L., L. Pistaferri, and F. Schivardi (2005). Insurance Within the Firm. *Journal of Political Economy 113*(5), 1054–1087.

Guvenen, F., G. Kaplan, and J. Song (2014). How risky are recessions for top earners? *American Economic Review 104*(5), 148–53.

Guvenen, F., S. Schulhofer-Wohl, J. Song, and M. Yogo (2017). Worker betas: Five facts about systematic earnings risk. *American Economic Review 107*(5), 398–403.

Hadlock, C. J. and J. R. Pierce (2010). New evidence on measuring financial constraints: Moving beyond the kz index. *The Review of Financial Studies 23*(5), 1909–1940.

Howell, S. T. and J. D. Brown (2020). Do cash windfalls affect wages? evidence from r&d grants to small firms. Technical report, National Bureau of Economic Research.

Kátay, G. (2016). Do firms provide wage insurance against shocks? *The Scandinavian Journal of Economics 118*(1), 105–128.

Keloharju, M., S. Knüpfer, and J. Tåg (2022). What prevents women from reaching the top? *Financial Management 51*(3), 711–738.

Kleven, H., C. Landais, J. Posch, A. Steinhauer, and J. Zweimüller (2019). Child penalties across countries: Evidence and explanations. In *AEA Papers and Proceedings*, Volume 109, pp. 122–26.

Kline, P., N. Petkova, H. Williams, and O. Zidar (2019). Who profits from patents?

rent-sharing at innovative firms. *The quarterly journal of economics 134*(3), 1343–1404.

Knight, F. H. (1921). *Risk, Uncertainty and Profit.* Houghton Miffin, New York.

Kogan, L., D. Papanikolaou, L. D. Schmidt, and B. Seegmiller (2023). Technology and labor displacement: Evidence from linking patents with worker-level data. Technical report, National Bureau of Economic Research.

Liu, T., C. A. Makridis, P. Ouimet, and E. Simintzi (2023). The distribution of nonwage benefits: maternity benefits and gender diversity. *The Review of Financial Studies 36*(1), 194–234.

Meeuwis, M., D. Papanikolaou, J. Rothbaum, and L. D. Schmidt (2023). Time-varying risk premia, labor market dynamics, and income risk. Technical report, National Bureau of Economic Research.

Mortensen, D. T. and C. A. Pissarides (1994). Job creation and job destruction in the theory of unemployment. *The review of economic studies 61*(3), 397–415.

Mortensen, D. T. and C. A. Pissarides (1999). New developments in models of search in the labor market. *Handbook of labor economics 3*, 2567–2627.

Pagano, M. (2020). Risk sharing within the firm: A primer. *Foundations and Trends in Finance.*

Petrongolo, B. and C. Pissarides (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature 39*, 390—431.

Rothwell, J. and S. Crabtree (2019). Not just a job: New evidence on the quality of work in the united states. *Lumina Foundation, Bill & Melinda Gates Foundation, Omidyar Network and Gallup.*

Tåg, J. (2013). Production hierarchies in sweden. *Economics letters 121*(2), 210–213.

Van Reenen, J. (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.

Figure 1: Idiosyncratic firm shocks by industry

This figure plots the average absolute value of the variable *Shock* by industry. Industries are ordered by the share of female employees, with the industries with highest share of female workers on top and those with the lowest share of female workers at the bottom. Industry is defined using the Swedish Standard Industrial Classification (SNI) 2007 sectors. Data are from LISA and Serrano.

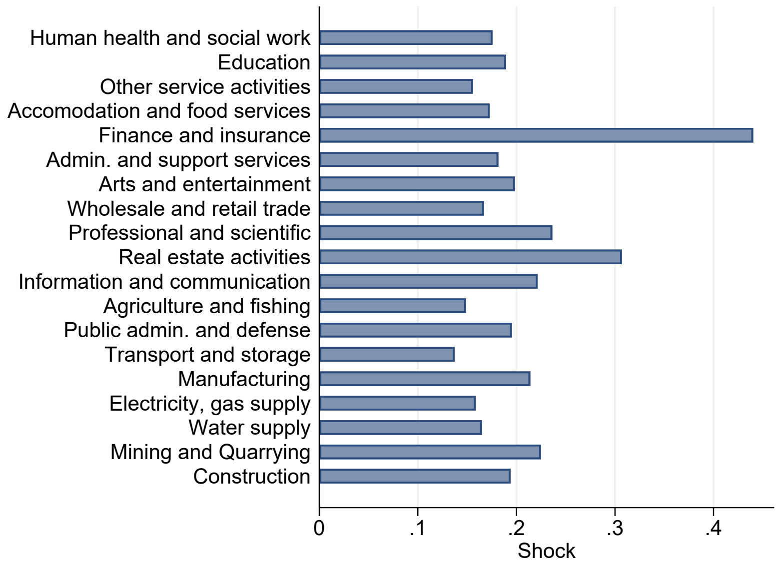

Figure 2: Equilibrium dismissal threshold for low and higher flexibility occupations

This figure plots the job creation and job destruction curves in blue for high flexibility occupations and in red for low flexibility occupations resulting from the model presented in section 4.

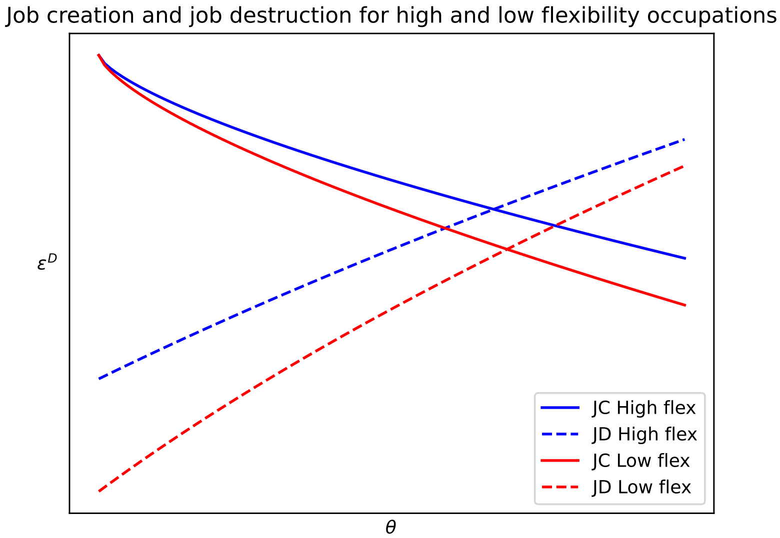

Table 1: Summary Statistics

This table presents the summary statistics — number of observations, mean, and standard deviation — for the variables of interest in the paper. Panel A reports summary statistics for firm-level variables, Panel B resports summary statistics for the employee-level variables for the sample used in wage regressions (dependent variable *Wage*), and Panel C reports summary statistics for the employee-level variables for the sample used in dismissal regressions (dependent variable *Dismissed*). All variables are defined in Section 2.2 and in Appendix Table A1.

	Panel A: Firm-level variables		
	Obs.	Mean	SD
Shock	650,793	-0.051	0.318
Ln(Wage bill)	650,793	10.340	1.130
Ln(Employment)	650,793	2.745	0.938
Int. cov.	611,923	92.409	315.833
Return on assets	650,551	0.132	0.183
$\frac{Cash}{Assets}$	650,735	0.163	0.183
High leverage	650,727	0.498	0.500
Financially constrained (H&P)	385,573	0.377	0.485

	Panel B: Employee-level variables Wage regressions sample		
	Obs	Mean	SD
Shock	13,674,313	-0.061	0.272
Wage	13,674,313	7.819	0.662
Female	13,674,313	0.339	0.473
Experience	13,674,313	14.482	3.872
Tenure	13,674,313	7.567	4.807
Ln(Education)	13,635,061	2.427	0.228
Age	13,674,313	43.509	10.662
Low flex	11,127,354	0.538	0.499
Married	13,674,313	0.478	0.500
Has kids	13,674,313	0.530	0.499
Has small kids	13,674,313	0.289	0.453
Firm size > median	13,674,313	0.538	0.499
> 2 hierarchies	12,350,617	0.827	0.378
Top shock	13,674,313	0.058	0.233
Bottom shock	13,674,313	0.103	0.304

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	Panel C: Employee-level variables Dismissal regressions sample		
	Obs	Mean	SD
Shock	18,638,302	-0.046	0.338
Dismissed	18,638,302	4.931	21.651
Female	18,638,302	0.351	0.477
Experience	18,638,302	13.976	4.152
Tenure	18,638,302	6.386	4.923
Ln(Education)	18,554,058	2.439	0.227
Age	18,638,302	42.362	10.826
Low flex	14,764,478	0.538	0.499
Married	18,638,302	0.457	0.498
Has kids	18,638,302	0.522	0.500
Has small kids	18,638,302	0.294	0.456
Firm size > median	18,638,302	0.520	0.500
> 2 hierarchies	16,474,061	0.825	0.380
Top shock	18,638,302	0.077	0.266
Bottom shock	18,638,302	0.109	0.312

Table 2: Idiosyncratic shock and firm outcomes

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and firm performance. The dependent variable is *Ln(Wage bill)* in column 1, *Ln(Employment)* in column 2, *Return on assets* in column 3, *Int. cov.* in column 4, and $\frac{Cash}{Assets}$ in column 5. All specifications include firm and industry-year fixed effects. All variables are defined in Section 2.2 and in Appendix Table A1. 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) (1)	Ln(Employment) (2)	Return on assets (3)	Int. cov. (4)	$\frac{Cash}{Assets}$ (5)
Shock	0.187***	0.144***	0.088***	41.534***	0.005***
	(0.004)	(0.004)	(0.002)	(1.607)	(0.001)
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.932	0.916	0.460	0.365	0.688
Observations	634,084	634,084	633,855	594,755	634,028

Table 3: Wage sensitivity to firm shocks

This table reports coefficients of OLS 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*. The sample includes workers who do not join or leave the firm in the current year (i.e., stayers). All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage				
	(1)	(2)	(3)	(4)	(5)
Shock	0.070***	0.063***	0.258***	0.203***	0.252***
	(0.003)	(0.003)	(0.038)	(0.023)	(0.023)
Female		-0.341***	-0.331***		
		(0.004)	(0.004)		
Female × Shock		0.016***	0.017***	0.014***	0.008**
		(0.004)	(0.004)	(0.003)	(0.003)
Experience			0.027***	-0.090***	-0.090***
			(0.001)	(0.003)	(0.004)
Tenure			0.009***	-0.006***	-0.005***
			(0.000)	(0.000)	(0.000)
Ln(Education)			0.435***	0.725***	0.557***
			(0.014)	(0.037)	(0.030)
Age			0.005***		
			(0.000)		
Experience × Shock			-0.003***	0.003***	0.003***
			(0.001)	(0.001)	(0.001)
Tenure × Shock			-0.001**	0.001	
			(0.001)	(0.000)	(0.000)
Ln(Education) × Shock			-0.033**	-0.017**	-0.043***
			(0.013)	(0.007)	(0.007)
Age × Shock			-0.001***	-0.004***	-0.003***
			(0.000)	(0.000)	(0.000)
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes	Yes
Worker F.E.	-	-	-	Yes	Yes
Occupation × Year F.E.	-	-	-	-	Yes
Adj. R^2	0.227	0.271	0.313	0.660	0.664
Observations	13,674,313	13,674,313	13,635,018	13,237,063	11,950,383

Table 4: Employment sensitivity to firm shocks

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the employment status of male and female workers. The dependent variable is *Dismissed*. *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 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dismissed				
	(1)	(2)	(3)	(4)	(5)
Shock	-2.818***	-2.512***	-11.551***	-10.841***	-11.945***
	(0.314)	(0.296)	(2.686)	(3.366)	(3.150)
Female		1.487***	1.322***		
		(0.051)	(0.047)		
Female × Shock		-0.858***	-0.742***	-0.373**	-0.356**
		(0.151)	(0.143)	(0.181)	(0.179)
Experience			-0.211***	4.959***	6.080***
			(0.007)	(0.074)	(0.097)
Tenure			-0.494***	0.260***	0.294***
			(0.011)	(0.011)	(0.011)
Ln(Education)			-1.295***	-9.134***	-9.666***
			(0.069)	(0.906)	(0.977)
Age			0.007***		
			(0.002)		
Experience × Shock			0.069	-0.015	-0.007
			(0.042)	(0.048)	(0.047)
Tenure × Shock			0.007	-0.105**	-0.098**
			(0.044)	(0.053)	(0.047)
Ln(Education) × Shock			2.090**	2.201**	2.722***
			(0.839)	(1.108)	(1.014)
Age × Shock			0.064***	0.077***	0.070***
			(0.010)	(0.009)	(0.008)
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes	Yes
Worker F.E.	-	-	-	Yes	Yes
Occupation × Year F.E.	-	-	-	-	Yes
Adj. R^2	0.054	0.055	0.066	0.228	0.232
Observations	18,638,302	18,638,302	18,554,047	18,127,856	16,060,073

Table 5: Wage and employment sensitivity to firm shocks – Robustness

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in the regression specifications reported in columns 1, 2, and 3 and *Dismissed* in columns 4, 5 and 6. *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 addition to the (non-interacted) variables *Female* and *Shock*, the control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Shock* are included in all specifications, but not reported for brevity. In columns 1, 2 and 3, the sample includes workers who do not join or leave the firm in the current year (i.e., stayers). All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage			Dismissed		
	(1)	(2)	(3)	(4)	(5)	(6)
Female × Shock	0.017***	0.008***	0.013***	-0.424***	-0.216*	-0.251***
	(0.002)	(0.003)	(0.003)	(0.089)	(0.128)	(0.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Occupation × Shock	-	Yes	-	-	Yes	-
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	-	Yes	-	-	Yes	-
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year F.E.	Yes	-	-	Yes	-	-
Firm × Occupation × Year F.E.	-	-	Yes	-	-	Yes
Adj. R^2	0.666	0.663	0.672	0.264	0.232	0.297
Observations	13,218,927	11,950,383	11,103,448	18,124,824	16,060,073	14,977,994

Table 6: Job Flexibility and firm insurance

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in the regression specifications reported in columns 1 and 2 and *Dismissed* 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 addition to the (non-interacted) variables *Female* and *Shock*, the control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Shock* are included in all specifications, but not reported for brevity. In columns 1 and 3, the sample includes workers in low flexibility occupations, while in columns 2 and 4, the sample includes workers in high flexibility occupations. We separate occupations into high and low flexibility groups based on the median of the job flexibility index following Goldin (2014). All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage		Dismissed	
Sub-sample:	Low Flex (1)	High Flex (2)	Low Flex (3)	High Flex (4)
Female × Shock	0.012***	0.002	-0.657***	-0.034
	(0.003)	(0.007)	(0.141)	(0.326)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.690	0.623	0.246	0.256
Observations	5,710,946	4,853,302	7,649,129	6,478,099

Table 7: Household outcomes and the gender differences in sensitivity to firm shocks

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of male and female workers. In Panel A, we study whether marital status impacts the gender differences in exposure to firm shocks, in Panel B, we separately study the sensitivity of wages and employment for workers with and without children, and in Panel C, for workers with small children and without children. In all panels, the dependent variable is *Wage* in specifications 1 and 2, and *Dismissed* in specifications 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 columns 1 and 2 of all panels, the sample includes workers who do not join or leave the firm in the current year (i.e., stayers). In addition to the (non-interacted) variables *Female* and *Shock*, the control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Shock* are included in all specifications, but not reported for brevity. All variables are defined in Section 2.2 and in Appendix Table A1. 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: Marital status			
	Wage		Dismissed	
Sub-sample:	Single (1)	Married (2)	Single (3)	Married (4)
Female × Shock	-0.001	0.027***	-0.274	-0.536***
	(0.004)	(0.005)	(0.197)	(0.199)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.636	0.704	0.239	0.233
Observations	6,782,764	6,290,373	9,711,430	8,229,847

	Panel B: All kids			
	Wage		Dismissed	
Sub-sample:	No kids (1)	Has kids (2)	No kids (3)	Has kids (4)
Female × Shock	-0.010***	0.066***	-0.028	-0.776***
	(0.003)	(0.006)	(0.184)	(0.210)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.705	0.675	0.239	0.244
Observations	6,016,902	6,908,063	8,419,914	9,337,078

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	Panel C: Small kids			
	Wage		Dismissed	
Sub-sample:	No kids	Has small kids	No kids	Has small kids
	(1)	(2)	(3)	(4)
Female × Shock	-0.010***	0.105***	-0.028	-0.861***
	(0.003)	(0.010)	(0.184)	(0.218)
Controls	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Labor mkt. × Year FE	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
Adj. R^2	0.705	0.627	0.239	0.253
Observations	6,016,902	3,710,354	8,419,914	5,207,129

Table 8: Firm size and the gender differences in sensitivity to firm shocks

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of male and female workers. We split the sample of firms into small (columns 1 and 3) and large (columns 2 and 4) firms; firm size is measured using total assets in Panel A and number of hierarchical levels in Panel B. In both panels, the dependent variable is *Wage* in columns 1 and 2, and *Dismissed* 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 columns 1 and 2 of both panels, the sample includes workers who do not join or leave the firm in the current year (i.e., stayers). In addition to the (non-interacted) variables *Female* and *Shock*, the control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Shock* are included in all specifications, but not reported for brevity. All variables are defined in Section 2.2 and in Appendix Table A1. 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 measure: assets			
	Wage		Dismissed	
Sub-sample:	Below median (1)	Above median (2)	Below median (3)	Above median (4)
Female × Shock	0.017*** (0.005)	0.008* (0.004)	-1.073*** (0.257)	0.121 (0.142)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.674	0.665	0.254	0.212
Observations	5,951,511	7,080,615	8,441,985	9,336,926

	Panel B: Firm size measure: hierarchies			
	Wage		Dismissed	
Sub-sample:	$\leq$ 2 hierarchies (1)	$>$ 2 hierarchies (2)	$\leq$ 2 hierarchies (3)	$>$ 2 hierarchies (4)
Female × Shock	0.026*** (0.007)	0.008** (0.004)	-2.757*** (0.396)	-0.185 (0.185)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.688	0.670	0.297	0.234
Observations	1,735,355	8,936,959	2,320,039	11,914,458

Table 9: Wage and employment sensitivity to top and bottom firm shocks

This table reports coefficients of OLS regression models examining the relationship between large positive and negative idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in the regression specifications reported in columns 1–3 and *Dismissed* in columns 4–6. *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 variables *Top shock* and *Bottom shock*. *Top shock* is an indicator variable that takes the value of one if the variable *Shock* is in the top 20 percent largest positive shocks. *Bottom shock* is an indicator variable that takes the value of one if the variable *Shock* is in the bottom 20 percent smallest negative shocks. In columns 1–3, the sample includes workers who do not join or leave the firm in the current year (i.e., stayers). The control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Top shock* and with *Bottom shock* are included in columns 2, 3, 5, and 6. All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage			Dismissed		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.340***			1.382***		
	(0.004)			(0.054)		
Top shock	0.021***	0.009	0.021	-0.718***	-3.199***	-3.267***
	(0.003)	(0.016)	(0.013)	(0.085)	(1.216)	(1.021)
Female × Top shock	0.002	0.012***	0.009***	-0.207***	-0.041	0.017
	(0.005)	(0.002)	(0.002)	(0.076)	(0.083)	(0.083)
Bottom shock	-0.039***	-0.066***	-0.113***	2.483***	8.431***	11.720***
	(0.002)	(0.017)	(0.017)	(0.105)	(0.910)	(1.025)
Female × Bottom shock	-0.018***	-0.004	-0.003	1.463***	0.877***	1.182***
	(0.004)	(0.003)	(0.003)	(0.137)	(0.152)	(0.164)
Controls	-	Yes	Yes	-	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Worker F.E.	-	Yes	Yes	-	Yes	Yes
Occupation × Year F.E.	-	-	Yes	-	-	Yes
Adj. R^2	0.271	0.660	0.664	0.055	0.228	0.233
Observations	13,674,313	13,237,063	11,950,383	18,638,302	18,127,856	16,060,073

A Internet Appendix

Appendix Table A1: Definition of Main Variables

Variable	Description
Age_{it}	Worker i's age (in years) in year t.
Bottom shock_{ft}	Dummy variable that takes the value of 1 when the negative idiosyncratic shock is below the 20th percentile of negative shocks for firm f in year t, and 0 otherwise.
$\frac{Cash}{Assets}_{ft}$	Cash divided by total assets of firm f in year t. Winsorized at 1% and 99% yearly.
Dismissed_{it}	Indicator variable that takes the value of one if worker i is dismissed in year t, and zero otherwise. A worker is considered to be dismissed if the worker is not employed by firm f in the following year $t+1$ and the worker collects unemployment benefits in the current year t, or the next year, $t+1$. This variable is multiplied by 100 for ease of interpretation.
Experience_{it}	Number of years of worker i in the labor market as of year t. (Because LISA data starts in 1990 and only covers Swedish firms, only employment in Sweden from 1990 onward is considered.)
Female_{i}	Indicator variable that takes the value of one if the individual i is female and takes the value of zero if the individual is male.
Financially constrained $\text{(H\&P)}_{ft}$	Dummy variable that takes the value 1 if firm f is both small and young in year t, and zero if it is large and old. This measure is based on Hadlock and Pierce (2010). A firm is considered to be young if its age in year t is below the median firm age in the sample. A firm is considered to be small if the value of its assets in year t is below the median of the sample (asset value deflated to 1998 SEK).
Firm size $>$ median_{ft}	Dummy variable that takes the value of one if the firm's size in assets in year t is above the median size of assets in year t weighted by the number of individuals employed by each firm f.
Has kids_{it}	Dummy variable that takes the value of one if worker i has dependent children or children of any age living at home in year t, and zero otherwise.
$\text{Has small kids}_{it}$	Dummy variable that takes the value of one if the worker (i) has children which are 10 years old or younger in year t, and zero if the worker has no dependent children of any age living at home in year t.
$\text{High leverage}_{ft}$	Dummy variable taking the value of one if the net leverage of firm f in year t is above the median net leverage in year t in the industry the firm belongs to, and zero otherwise. Net leverage of firm f in year t is total debt net of cash holdings divided by total assets of firm f in year t. Total debt includes short- and long-term debt of firm f in year t.
Industry_{ft}	Industry definition that uses the Swedish Standard Industrial Classification (SNI) 2007 letter sectors, which is based on NACE Rev.2, the industry standard classification system used by the European Union.
Int. cov._{ft}	EBITDA divided by interest expense for firm f in year t. Winsorized at 1% and 99% yearly.

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Labor mkt.$_{ift}$	Region defined by Statistics Sweden as the local labor market (LAs) based on labor flows.
Ln(Education)$_{it}$	Natural logarithm of an individual i's years of schooling as of year t. We consider the number of "scheduled" schooling years required by an individual to obtain his/her highest earned degree, regardless of how many years it actually took the person to complete the degree (the latter information is unavailable): 12 years for a high school graduate, 15 years for an individual with a bachelor's degree, etc.
Ln(Employment)$_{ft}$	Natural logarithm of the total number of workers employed by firm f in year t. Winsorized at 1% and 99% yearly.
Ln(Wage bill)$_{ft}$	Natural logarithm of the total wages paid by firm f in year t. Winsorized at 1% and 99% yearly.
Low flex$_{it}$	Dummy variable that takes the value one if worker i is in an occupation with a flexibility score above the median score in year t, and zero otherwise. The flexibility score is the average of five normalized O*NET characteristics computed at the 3-digit SSYK occupational codes, following Goldin (2014) and Bang (2021). The five characteristics are "Establishing and Maintaining Interpersonal Relationships", "Time Pressure", "Contact with Others", "Structured versus Unstructured Work", and "Freedom to Make Decisions". High flexibility scores indicate low flexibility occupations.
Married$_{it}$	Dummy variable that takes the value one if worker i is married in year t, and zero otherwise. We considered workers to be married if they are legally married or are in registered partnership.
Return on assets$_{ft}$	EBITDA divided by the total assets of firm f in year t. Winsorized at 1% and 99% yearly.
Shock$_{ft}$	Idiosyncratic shock to firm's performance is the residual, $\hat{\epsilon_{ft}}$, for each firm-year. This variable is created following Guiso et al. (2005): a firm's performance follows the process $y_{ft} = \rho y_{f,t-1} + F_f + I_{ft} + \delta_t + \epsilon_{ft}$, where y_{ft} is sales growth for firm f in year t, and F_f, I_{ft} and δ_t are firm, industry, and year fixed effects, respectively.
Tenure$_{ift}$	Number of years the worker (i) has been employed at firm f in year t.
Top shock$_{ft}$	Dummy variable that takes the value of 1 when the positive idiosyncratic shock is above the 80th percentile of positive shocks for firm f in year t, and 0 otherwise.
Wage$_{ift}$	Natural logarithm of the total compensation worker i receives in a given year t from its employer, which is firm f that provides an individual with the most labor income in that year. Winsorized at 1% and 99% yearly.
>2 hierarchies$_{ft}$	Dummy variable that takes the value of one if in year t the firm f's workers are distributed across 3 or 4 hierarchies, and zero if firm f's workers are distributed across 2 or fewer hierarchies. We follow Tåg (2013) and construct a measure of hierarchy by mapping the occupational codes, using the Swedish Standard Classification of Occupations 1996, into four different levels: CEOs and directors, senior staff, supervisors, and clerks and "blue-collar" workers.

Appendix Table A2: Estimation of idiosyncratic shock

This table reports coefficients from estimating a Dynamic Panel Data model of *Sales growth (%)* in column 1, and *Ln(Value added)* in column 2 of Panel A. In Panel B, we present tests of serial correlation of orders 1 through 6, as well as the Hansen test of overidentifying restrictions in the bottom of the table. 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.

	Panel A: Estimation results	
	Sales growth (%)	Ln(Value added)
	(1)	(2)
Sales growth$_{t-1}$(%)	0.040***	
	(0.008)	
Ln(Value added)$_{t-1}$		0.885***
		(0.037)
Year F.E.	Yes	Yes
Industry F.E.	Yes	Yes
Observations	538,578	651,477
	Panel B: Additional tests	
Test for AR(1) in FD	-36.557	-22.372
	[0.000]	[0.000]
Test for AR(2) in FD	-0.456	5.268
	[0.649]	[0.000]
Test for AR(3) in FD	0.470	3.816
	[0.638]	[0.000]
Test for AR(4) in FD	1.897	2.232
	[0.058]	[0.026]
Test for AR(5) in FD	-2.478	0.480
	[0.013]	[0.631]
Test for AR(6) in FD	1.058	-0.341
	[0.290]	[0.733]
Hansen overid. rest. test	2.456	0.960
	[0.117]	[0.327]

Appendix Table A3: Wage and employment sensitivity to firm shocks – Imposing additional sample restrictions

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in column 1 and *Dismissed* in column 2. *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*. Relative to our main tests, the sample used in this table additionally excludes observations where workers are in part-time unemployment, spend time in parental leave, or are in an educational program. All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage (1)	Dismissed (2)
Female	-0.233***	0.210***
	(0.003)	(0.015)
Shock	0.011	-2.231***
	(0.034)	(0.619)
Female × Shock	0.018***	-0.106**
	(0.004)	(0.045)
Experience	0.025***	-0.058***
	(0.001)	(0.003)
Tenure	0.005***	-0.105***
	(0.000)	(0.003)
Ln(Education)	0.469***	-0.281***
	(0.013)	(0.022)
Age	-0.000	-0.013***
	(0.000)	(0.001)
Experience × Shock	0.000	0.001
	(0.000)	(0.011)
Tenure × Shock	0.003***	-0.008
	(0.000)	(0.011)
Ln(Education) × Shock	0.022*	0.308
	(0.012)	(0.188)
Age × Shock	-0.002***	0.018***
	(0.000)	(0.003)
Industry × Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes
Adj. R^2	0.345	0.037
Observations	9,256,629	12,038,622

Appendix Table A4: Exposure to firm idiosyncratic shocks by male and female workers

This table reports the mean and standard deviation (in parentheses) of the absolute value of the variable *Shock* and the share of observations for which the variable *Shock* is negative, for all workers (column 1), and separately for male (column 2) and female workers (column 3).

	All	Male	Female
	(1)	(2)	(3)
|Shock|	0.197	0.198	0.194
	(0.273)	(0.272)	(0.274)
Share of negative shocks	0.584	0.594	0.564
	(0.493)	(0.491)	(0.496)
Observations	21,306,785	13,852,250	7,454,535

Appendix Table A5: 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; the 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 and in Appendix Table A1. The sample period in these regressions is 1994–2011 (information on the parental leave is available to us from 1994 onward). 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)
	Parental leave	Care of sick children
Female	1.047***	0.199***
	(0.007)	(0.005)
Experience	0.035***	0.038***
	(0.001)	(0.001)
Tenure	0.016***	0.008***
	(0.001)	(0.001)
Ln(Education)	0.867***	-0.425***
	(0.014)	(0.014)
Age	-0.103***	-0.041***
	(0.001)	(0.000)
Industry × Year F.E.	Yes	Yes
Firm F.E.	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes
Observations	7,755,934	7,769,252

Appendix Table A6: Voluntary departures in response to firm shocks

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and voluntary departures of male and female workers. The dependent variable is *Voluntary leaver*, an indicator variable that takes the value of one if a worker leaves the firm without going through unemployment (collecting unemployment benefits). *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 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Voluntary leaver		
	(1)	(2)	(3)
Female	-0.006***		
	(0.001)		
Shock	-0.066***	-0.074	-0.041
	(0.008)	(0.048)	(0.029)
Female × Shock	0.004	0.002	0.003
	(0.004)	(0.004)	(0.004)
Experience		0.018***	0.018***
		(0.001)	(0.002)
Tenure		0.017***	0.017***
		(0.000)	(0.000)
Ln(Education)		0.168***	0.215***
		(0.010)	(0.012)
Experience × Shock		0.000	-0.001
		(0.001)	(0.001)
Tenure × Shock		-0.004***	-0.003***
		(0.001)	(0.001)
Ln(Education) × Shock		-0.002	-0.007
		(0.015)	(0.009)
Age × Shock		0.001**	0.000**
		(0.000)	(0.000)
Industry × Year F.E.	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes
Worker F.E.	-	Yes	Yes
Occupation × Year F.E.	-	-	Yes
Adj. R^2	0.112	0.204	0.212
Observations	18,638,302	18,127,856	16,060,073

Appendix Table A7: Wage and employment sensitivity to positive and negative firm shocks

This table reports coefficients of OLS regression models examining the relationship between positive and negative idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in the regression specifications reported in columns 1–3 and *Dismissed* in columns 4–6. *Female* is an indicator variable that takes the value of one if the worker is female, and zero otherwise. *Negative shock* is an indicator variable that takes the value of one if the variable *Shock* is negative, and zero otherwise. In columns 1–3, the sample includes workers who do not join or leave the firm in the current year (i.e., stayers). The control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Negative shock* are included in columns 2, 3, 5, and 6. All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage			Dismissed		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.319***			1.051***		
	(0.004)			(0.055)		
Negative shock	-0.066*	-0.026***	-0.055***	5.702***	4.897***	5.242***
	(0.038)	(0.008)	(0.008)	(0.461)	(0.569)	(0.512)
Female × Negative shock	-0.020***	-0.018***	-0.014***	0.491***	0.125**	0.152***
	(0.003)	(0.001)	(0.001)	(0.055)	(0.055)	(0.054)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Worker F.E.	-	Yes	Yes	-	Yes	Yes
Occupation × Year F.E.	-	-	Yes	-	-	Yes
Adj. R^2	0.312	0.660	0.664	0.065	0.227	0.231
Observations	13,635,018	13,237,063	11,950,383	18,554,047	18,127,856	16,060,073

Appendix Table A8: Wage sensitivity to permanent and transitory firm shocks

This table reports coefficients of OLS regression models examining the relationship between permanent and transitory idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in the regression specifications reported in columns 1–3 and *Dismissed* in columns 4–6. *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 variables *Permanent shock* and *Transitory shock*. *Permanent shock* is the average of the idiosyncratic shock in the last, current, and following period. *Transitory shock* is the difference between *Shock* and *Permanent shock*. In columns 1–3, the sample includes workers who do not join or leave the firm in the current year (i.e., stayers). The control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age* are included in columns 3 and 5. All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage			Dismissed		
	(1)	(2)	(3)	(4)	(5)	(6)
Permanent shock	0.088***	0.070***	0.059***	-4.204***	-3.757***	-4.112***
	(0.006)	(0.006)	(0.005)	(0.807)	(0.780)	(0.805)
Transitory shock	0.040***	0.044***	0.037***	-0.873***	-0.902***	-1.022***
	(0.003)	(0.003)	(0.003)	(0.221)	(0.206)	(0.214)
Female		-0.337***	-0.327***		1.308***	1.138***
		(0.004)	(0.004)		(0.051)	(0.046)
Female × Permanent shock		0.040***	0.049***		-1.174***	-1.142***
		(0.009)	(0.008)		(0.202)	(0.204)
Female × Transitory shock		-0.011***	-0.009**		0.100	0.119
		(0.004)	(0.004)		(0.139)	(0.141)
Controls	No	No	Yes	No	No	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Labor mkt. F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.221	0.265	0.309	0.038	0.038	0.050
Observations	11,862,647	11,862,647	11,828,713	15,539,730	15,539,730	15,470,519

Appendix Table A9: Financial constraints and the pass-through of firm shocks

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of workers. 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 old and large following Hadlock and Pierce (2010) (columns 1 and 3), and those who work for financially constrained firms (young and small firms, columns 2 and 4). In both panels, the dependent variable is *Wage* in columns 1 and 2, and *Dismissed* in columns 3 and 4. Idiosyncratic firm shocks are captured by the variable *Shock*. In addition to the (non-interacted) variables *Female* and *Shock*, the control variables *Experience*, *Tenure*, *Ln(Education)*, and *Age*, as well as their interactions with *Shock* are included in all specifications, but not reported for brevity. All variables are defined in Section 2.2 and in Appendix Table A1. 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		Dismissed	
Sub-sample:	Below median (1)	Above median (2)	Below median (3)	Above median (4)
Shock	0.189***	0.201***	-8.004**	-17.546***
	(0.034)	(0.026)	(3.614)	(1.761)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.677	0.673	0.248	0.243
Observations	6,926,098	5,814,677	9,319,355	8,153,322

	Panel B: Financially constrained (H&P)			
	Wage		Dismissed	
Sub-sample:	Unconstrained (1)	Constrained (2)	Unconstrained (3)	Constrained (4)
Shock	0.159***	0.206***	-15.017***	-20.531***
	(0.028)	(0.067)	(1.512)	(3.125)
Controls	Yes	Yes	Yes	Yes
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	Yes	Yes	Yes	Yes
Adj. R^2	0.664	0.674	0.221	0.260
Observations	8,978,227	563,423	11,759,540	836,923

Appendix Table A10: Wage and employment sensitivity to firm shocks – Alternative shock definition

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wages and employment status of male and female workers. The dependent variable is *Wage* in columns 1 and 2, and *Dismissed* 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 *Value added shock*. This is defined like our main variable *Shock*, but using variation in value added instead of sales growth to identify firm shocks (see Table A2). All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Wage		Dismissed	
	(1)	(2)	(3)	(4)
Female	-0.369***		2.906***	
	(0.005)		(0.093)	
Value added shock	0.026***	0.111***	-1.270***	-9.063***
	(0.005)	(0.015)	(0.199)	(1.572)
Female × Value added shock	0.018***	0.005***	-0.970***	-0.505***
	(0.006)	(0.001)	(0.077)	(0.099)
Experience		-0.077***		4.484***
		(0.003)		(0.083)
Tenure		-0.004***		0.220***
		(0.001)		(0.038)
Ln(Education)		0.746***		-11.395***
		(0.030)		(1.066)
Experience × Value added shock				0.015
		(0.000)		(0.020)
Tenure × Value added shock		-0.001*		0.007
		(0.000)		(0.028)
Ln(Education) × Value added shock		-0.024***		2.353***
		(0.007)		(0.586)
Age × Value added shock		-0.001***		0.033***
		(0.000)		(0.005)
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	-	Yes	-	Yes
Adj. R^2	0.276	0.652	0.056	0.227
Observations	15,153,946	14,698,898	20,936,057	20,406,659

Appendix Table A11: Employment sensitivity to firm shocks – Alternative dismissal definitions

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the employment status of male and female workers. The dependent variable is *Worse job* in columns 1 and 2, and *Unemployed* in columns 3 and 4. *Worse job* is an indicator variable that takes the value of one if a worker leaves a firm and transitions to a lower-wage job. *Unemployed* is an indicator variable that takes the value of one if a worker leaves a firm and transitions to unemployment. *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 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Worse job		Unemployed	
	(1)	(2)	(3)	(4)
Female	1.161***		1.667***	
	(0.064)		(0.056)	
Shock	-2.358***	-8.465***	-2.771***	-9.798***
	(0.269)	(2.052)	(0.323)	(3.133)
Female × Shock	-0.757***	-0.334**	-0.936***	-0.376**
	(0.164)	(0.161)	(0.169)	(0.181)
Experience		10.983***		4.141***
		(0.154)		(0.066)
Tenure		0.558***		0.701***
		(0.013)		(0.015)
Ln(Education)		-22.397***		-7.992***
		(0.826)		(0.849)
Experience × Shock		0.025		-0.027
		(0.038)		(0.046)
Tenure × Shock		-0.196***		-0.176***
		(0.039)		(0.050)
Ln(Education) × Shock		1.663***		2.097**
		(0.642)		(1.032)
Age × Shock		0.049***		0.074***
		(0.009)		(0.008)
Industry × Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Labor mkt. × Year F.E.	Yes	Yes	Yes	Yes
Worker F.E.	-	Yes	-	Yes
Adj. R^2	0.045	0.171	0.056	0.246
Observations	18,638,302	18,127,856	18,638,302	18,127,856

Appendix Table A12: Wage sensitivity to firm shocks – first differences

This table reports coefficients of OLS regression models examining the relationship between firm idiosyncratic shocks and the wage growth of male and female workers. The dependent variable is $\Delta Wage$, the difference between the natural logarithm of worker compensation in year t and year $t-1$. *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*. The sample includes workers who do not join or leave the firm in the current year (i.e., stayers). All variables are defined in Section 2.2 and in Appendix Table A1. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$\Delta Wage$		
	(1)	(2)	(3)
Shock	0.086***	0.083***	0.461***
	(0.004)	(0.003)	(0.023)
Female × Shock		0.009**	0.007*
		(0.004)	(0.004)
Experience × Shock			-0.003***
			(0.001)
Tenure × Shock			-0.003***
			(0.000)
Ln(Education) × Shock			-0.131***
			(0.007)
Age × Shock			0.000**
			(0.000)
Labor mkt. F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Adj. R^2	0.005	0.005	0.006
Observations	11,594,407	11,594,407	11,566,941

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