Firm Shocks, Workers' Earnings and the Extensive Margin*

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Abstract

We study how idiosyncratic firm shocks transmit to workers' earnings through both the intensive and extensive margins of employment. Using a matched employer–employee census data for Chile between 2007 and 2019, we estimate the pass-through of firm productivity and sales shocks to the wages of stayers and the displacement risk and earnings losses of leavers. For continuing workers, earnings respond modestly to firm-level shocks, revealing partial wage insurance within firms. However, adverse shocks substantially raise displacement probabilities, and displaced workers suffer persistent earnings losses of 15-20 percent. Combining both margins, we show that the overall sensitivity of expected earnings to firm shocks nearly doubles relative to estimates based on stayers alone. These effects exhibit substantial heterogeneity. Young and short-tenure workers face higher displacement probability but minimal earnings losses upon displacement, while older and long-tenure workers are less likely to be displaced but experience larger and more persistent losses if displaced. Turning to stayers, lower-skilled and lower-ranked workers within firms receive more wage insurance, while higher-skilled and higher-ranked workers receive less wage insurance, except for top earners. Hence, firms appear to insure continuing employees only partially while transferring substantial risk through separations. We conclude that a comprehensive assessment of how firms transmit risk to workers must integrate both wage and employment adjustments.

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1 Introduction

Volatility in labor earnings is a source of relevant financial risk for workers, especially for those who face liquidity constraints and cannot smooth out consumption. Earnings risk might not only generate short-term welfare costs for workers but can also reduce incentives to invest in human capital, whether in formal education or on-the-job learning, as well as parental investments in children or assets requiring long-term financial obligations (Levahri and Weiss, 1974; Carneiro and Ginja, 2016). In this context, a large body of literature has examined the role of firms in the instability of workers earnings and, in particular, whether firms insure employees against idiosyncratic fluctuations in firm performance, testing the extent to which wages respond to firm-level shocks.

Previous studies—most using matched employer–employee data from advanced economies—suggest that the pass-through from firm productivity to workers' wages is rather limited. Empirically, firms appear to buffer incumbent workers from transitory shocks; therefore, they offer partial insurance (e.g., Guiso et al., 2005; Juhn et al., 2018; Chan et al., 2023; Lamadon et al., 2022). However, most of this literature has focused on firm adjustment over the intensive margin, concentrating on the earnings of job stayers. However, as firm shocks also lead to reallocation, there is also earnings uncertainty regarding the extensive margin. In the aftermath of a negative shock, workers face the risk of losing their jobs. This separation can potentially result in larger earnings losses than those observed for job stayers. Consequently, in addition to stayers' wage elasticity to firm shocks, estimates of risk pass-through from firms to their pre-shock workers should also account for the effect on the expected displacement costs for leavers.

This paper proposes a simple, unified empirical framework to measure how firm shocks affect workers' expected earnings. This framework jointly accounts for both the intensive (earnings of stayers) and extensive (displacement and associated costs) margins. Using a census of matched employer–employee tax records for Chile between 2007 and 2019, we estimate how changes in firms' total factor productivity (TFP) and sales transmit to (i) the earnings of incumbent workers and (ii) the probability and earnings costs of job losses. We then combine both margins to compute a measure of the overall elasticity of expected earnings with respect to firm shocks. We believe this approach provides a more comprehensive assessment of how firms idiosyncratic risk is reflected in the workers earnings profile.

We highlight three main results. In line with previous results for high-income countries using matched employer–employee data, the earnings elasticity of staying workers to both TFP and sales shocks are relatively modest, although the magnitudes are not economically negligible. Additionally, there is a significant degree of heterogeneity in the elasticity of earnings to shocks, with the earnings of workers with short tenures or those at the lower end of the within firm wage distribution being more affected by negative shocks.

Second, firm shocks have a relevant effect on risk over the extensive margin. On average, job loss events generate persistent earnings losses of 15-20 percent, consistent with previous findings in the job-displacement literature (Jacobson et al., 1993; Couch and Placzek, 2010a; Schmieder et al., 2023). There is also a significant degree of heterogeneity: while losses for older workers and workers with long tenures are very significant, young workers or workers with a short history at the firm are almost unscathed.

Third, combining both margins nearly doubles the average estimated sensitivity of workers' expected earnings to firm-level shocks. In other words, studies that focus on job stayers capture only a portion of the risk actually borne by workers. Heterogeneity once again plays an important role, as both the intensive/extensive composition and the size of the total effect vary significantly across tenure, age, and the earnings distribution. Workers who appear largely buffered from risk on the intensive margin can face relevant risks when one considers the extensive margin.

We rely on data for Chile, which offers an interesting context to study the labor market effects of firm-level shocks. Chile is a small open economy characterized by high earnings inequality, strong exposure to commodity-price fluctuations, and substantial labor mobility. These features can magnify the interaction between firm heterogeneity and worker risk exposure, while the administrative data allow us to follow all formal employment spells and uncapped earnings over fifteen years.

Together, our results show that firm shocks can generate meaningful earnings risk even in labor markets with considerable mobility and limited wage rigidity. Accounting for the extensive margin—displacement and the earnings costs of job loss—reveals that the insurance firms provide to continuing workers can mask substantial risk transferred through separations. Hence, a full understanding of how firms shape individual income volatility requires analyzing wages and employment jointly.

The rest of the paper is organized as follows. Section 2 discusses the data. Section 3 presents our empirical strategy. Section 4 presents the results on stayers, while Section 5 focuses on the extensive margin and the cost of displacement. Section 6 takes stock of the results and calculates overall earnings risk profiles. Section 7 concludes.

2 Data

2.1 General Characteristics

The empirical analysis is based on a matched employer–employee dataset constructed using data provided by the Chilean Internal Revenue Service (SII, by its Spanish acronym) between the years 2005 and 2019[12]. Because all formal firms must report to the SII, the data cover all workers with a formal wage contract. Workers with a formal contract correspond to more than 80% of wage employment in the country.[3]

The main source of information is the labor compensation report (DJ1887[4]) which must be filed annually by each firm in the formal sector. DJ1887, which is used to calculate the total taxable labor income of individuals, records the annual compensation paid to each employee and the specific months during which he was employed at the firm throughout the year. Annual taxable earnings in DJ1887 are the sum of all forms of worker compensation, excluding social security payments. The aggregate compensation cannot be separated into individual components and includes the base salary, incentive pay, bonuses, employer-provided benefits, and overtime pay.

Therefore, for each worker/firm relationship, we can calculate the worker's monthly average earnings in any given year. Notice that this differs from a measure of monthly wages, which typically refers to the worker's base salary. Earnings arguably provide a better representation of the relevant economic concept underlying labor compensation, both in terms of the income flow received by the worker and the marginal cost faced by the firm. Therefore, we think earnings provide a good representation of the overall labor income risk faced by workers, as well as the implications of shocks for firm labor costs.

Each firm and worker in the dataset is assigned a unique, anonymized identifier by the Chilean tax authority (SII), distinct from actual tax IDs. These identifiers enable us to track individual labor histories and firm-level payroll details over time. The dataset does not inform on the precise status of individuals during the months in which they are not formally employed. As a result, we cannot distinguish whether non-employed wage

[1] Affidavit N. 1887 of *Servicio de Impuestos Internos*. To secure the privacy of workers and firms, the Central Bank of Chile mandates that the development, extraction, and publication of the results should not allow for the identification, directly or indirectly, of natural or legal persons. Officials of the Central Bank of Chile processed the disaggregated data. All the analyses were implemented by the authors and did not involve nor compromise the Chilean IRS. The information contained in the databases of the Chilean IRS is of a tax nature originating in self-declarations of taxpayers presented to the Service; therefore, the veracity of the data is not the responsibility of the Service.

[2] For other recent uses of the same dataset, see Albagli et al. (2023) and Albagli et al. (2025).

[3] Given our interest in the effects of firm shocks on workers' earnings, our focus is directly on wage employment, which represents 70% of total employment. For details, see Central Bank of Chile (2018).

[4] Servicio de Impuestos Internos (2024a).

workers are unemployed, self-employed, working informally, or inactive. Nonetheless, during any spell of non-employment, it is reasonable to assume that the chosen alternative dominates the available opportunities in the formal sector at that time.

The tax dataset is matched with information provided by the Chilean Register Office (*Servicio de Registro Civil e Identificación* in Spanish), to obtain basic demographic characteristics (gender and date of birth) of each worker.

Finally, we combine worker-level information with the firms annual tax statement (F22[5]), which presents information on each firm's balance sheet, including data on sales, expenditures in intermediate inputs, wage bill, and a proxy for the capital stock (immobile assets). Using a firm directory provided by the Central Bank of Chile, we can also classify firms across industries.[6] Tax statement F22 can be used to estimate firm-level production functions at an annual frequency that can be used to obtain firm-level productivity measures, as done with the same dataset in the productivity analysis in Albagli et al. (2025). We use this estimated productivity, as well as firm-level sales directly reported in the data, to calculate the shocks that drive our empirical exercise.

Spanning the years 2005 to 2019, the initial dataset comprises approximately 600,000 firms, 9 million workers, and 36 million employment relationships.

2.2 Sample

We apply several filters to the data. At the firm level, we drop firm-year observations that have negative values for sales or intermediate goods expenditures, as well as any observation coming from a firm with less than five employees.[7]

On the worker side, we focus on males aged 25 to 64 years employed in full-time jobs, a group with high participation rates and labor market attachment. Since tax records do not provide information on hours worked, we remove all employment relationships in which the worker earns an implied full-time wage that is less than the minimum wage for 80% of his tenure. These jobs, which account for 20% of the initial set of observations, are probably part-time. We also drop earnings changes above (below) the 99.5 (0.05) percentile. Our final sample includes 11,870,357 employer–employee matched observations for 2005-2019.

[5] Servicio de Impuestos Internos (2024b).

[6] Central Bank of Chile (2024).

[7] We exclude firms with a very small number of workers given the difficulty in separating indicators of aggregate firm performance from the performance of individual workers in those cases. We also trim firm sales data, dropping observations ten times larger than the 99th percentile. As our interest lies in firm shocks, defined either as changes in firm productivity or firm sales, we also trim extreme events, dropping changes above (below) the 99.5 (0.05) percentile.

3 Empirical Strategy

To analyze the extent of firm-risk pass-through to workers, we define two types of firm-level shocks: changes in sales and changes in estimated (revenue) total factor productivity (TFP). Changes in sales have been used in most of the previous literature, making our results directly comparable to those found for other countries. Changes in TFP can help address endogeneity concerns regarding the nature of the shocks experienced by the firms. In fact, in line with most of the literature on production function estimations (Olley and Pakes, 1996; Ackerberg et al., 2015), we assume that the TFP at the firm level is an exogenous variable that follows a stochastic process and is therefore unaffected by firm decisions.

As discussed in more detail below, we first estimate the impact of these shocks on the intensive margin of workers' earnings: the change in earnings for workers who remain in the firm after the shock. However, our interest extends beyond the earnings effects for workers who remain with the firm after a shock. We also want to examine how (negative) shocks can impact the earnings trajectories of potentially displaced workers. To this end, we analyze the extensive margin by estimating the effect of shocks on the separation probabilities of all employees present at the time of the event. Finally, to quantify the potential earnings consequences of job separations, we follow the methodology of Jacobson et al. (1993) and track the earnings trajectories of workers who lose their jobs in large-scale layoffs.

Specifically, we focus on the aftermath of negative shocks that can lead to involuntary transitions into unemployment, as separation risk can constitute a significant component of overall earnings risk for workers. This issue is particularly salient if legal constraints limit firms' ability to adjust existing employment contracts—whether in terms of hours worked or contracted wages. In such settings, nominal rigidities in the fixed component of earnings hinder rapid downward wage adjustments, which can only occur, in real terms, through inflation. These constraints become even more binding when nominal wages are close to regulatory thresholds, such as the minimum wage. As a result, firms facing adverse shocks may be more likely to adjust through the extensive margin—by reducing headcount or replacing workers with new hires at lower wages.

3.1 Measuring Firm Shocks

3.1.1 TFP shocks

We build on the extensive literature on firm-level production function estimation (e.g., Ackerberg et al., 2015; Olley and Pakes, 1996; Gandhi et al., 2020) to calculate unobserved total factor productivity (TFP) as the residual from estimated production functions, conditional on observable inputs. Specifically, we estimate firm-level production and TFP using the methodology proposed by Ackerberg et al. (2015), incorporating an adjustment to the labor input for worker quality.[8] Specifically, we follow Chan et al. (2023) and use an *ability-adjusted labor input* (A_{jt}) as the labor component in the production function. Crucially, this ability measure is not affected by the wage firm-specific component of the workers' current employer but is calculated from their wage history across jobs, netting out firm fixed effects.

The input quality-adjusted labor input A_{jt} at the firm level is constructed from the *ability unit* of each worker in the firm j at time t as:

$$A_{jt} = \sum_{i \in J_t} \exp(\hat{\alpha}_i + \hat{\gamma} X_{it}) E_{ijt} \tag{1}$$

where J_t is the set of workers in firm j at time t, $\hat{\alpha}_i + \hat{\gamma} X_{it}$ is the estimated ability unit of worker i at time t, and E_{ijt} is the share of months worked of worker i in firm j in year t.

We compute a variant of the AKM methodology of Abowd et al. (1994) in which the monthly wage of worker i working in firm j in period t is given by:

$$w_{ijt} = \alpha_i + \gamma X_{it} + \psi_{j(i,t)t} + \xi_{ijt} \tag{2}$$

where $\alpha_i + \gamma X_{it}$, the worker fixed effect and worker observables define the worker's *ability units*. The sum of the firm-by-time fixed effect and the residual, $\psi_{j(i,t)t} + \xi_{ijt}$, can be interpreted as a *per-unit ability price* paid by firms. The high degree of labor market mobility in Chile implies that the connected set of firms required for estimation covers almost 99% of the workers in the sample.

We then follow Ackerberg et al. (2015) to estimate the coefficients of a Cobb-Douglas production function for real revenues, using the measure of quality-adjusted labor and

[8] As discussed in Chan et al. (2023), the exact measure of labor input L_{ij} chosen in productivity estimations should be considered carefully. Two measures traditionally used in the literature, total working hours and total wage bill, can introduce a significant bias in any estimate of firm productivity, as they cannot correctly address the endogeneity of labor quality. Moreover, under imperfect competition, wages can be affected by the firm, as is implicitly assumed throughout this paper.

a proxy for the capital stock from tax form F22 (immobile assets), and then identify the residuals as the firm's estimated total factor productivity.

Panel (b) from Figure 1b shows the distribution of the log change of the estimated TFP. The standard deviation of log TFP growth is 0.075 log points per year, or approximately 8%.

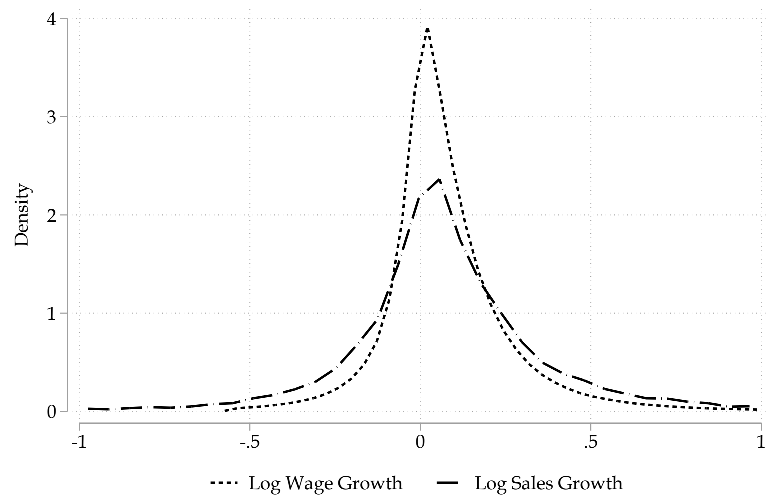
3.1.2 Sales

Data on firms' annual revenue comes from the tax information reported in form F22. Following previous literature, sales shocks are defined as the annual change in the log of a firm's total earnings. Panel (a) of Figure 1a presents the distribution of the firm level sales shock, and compares it with the change in the average wages paid by firms included in our sample. The sales growth distribution (the dashed line) is clearly flatter and has fatter tails than the wage distribution: the standard deviation of log sales growth is 0.31 in log points per year, while for our sample, the log wage growth distribution is 0.18. Both distributions are slightly skewed towards the right, reflecting the increase over time in both average wages and revenues. Still, annual sales and wages variation are concentrated around zero, although the variance of revenue is much larger than the variance of average wages. This provides early insight into the notion that the impact of shocks to firm profitability on worker earnings is likely to be muted.

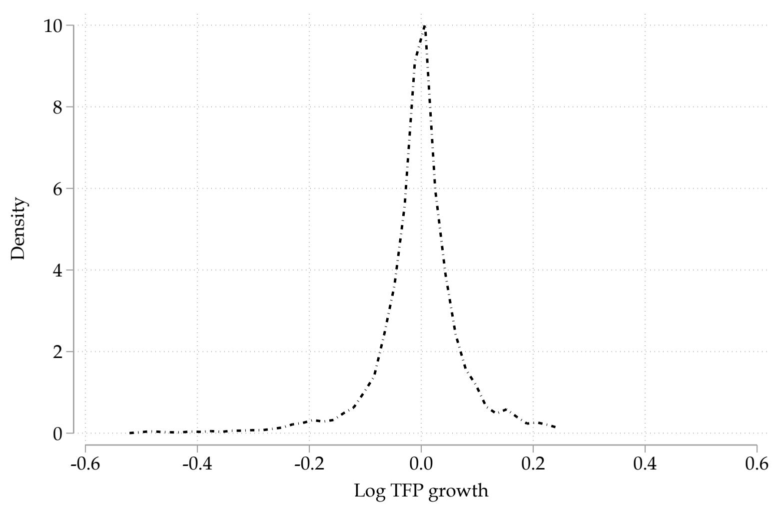
As an additional exercise, we follow Juhn et al. (2018) and use past revenue growth as an instrument for the shock, estimating in the appendix an IV regression that complements our baseline OLS estimates.

Figure 1: Log growth distributions of wages, firm sales and TFP.

(a) Log sales and log wages growth distribution



(b) Log TFP growth distribution



3.2 Wage Pass-Through Estimations on Stayers

To estimate the effects on firm shocks over the intensive margin of earnings, we run worker-level equations of the form:

$$\Delta ln(w_{ijt}) = \alpha + \beta \Delta F_{jt} + X_{it}\sigma + Z_j\gamma + \theta_t + \epsilon_{ijt} \tag{3}$$

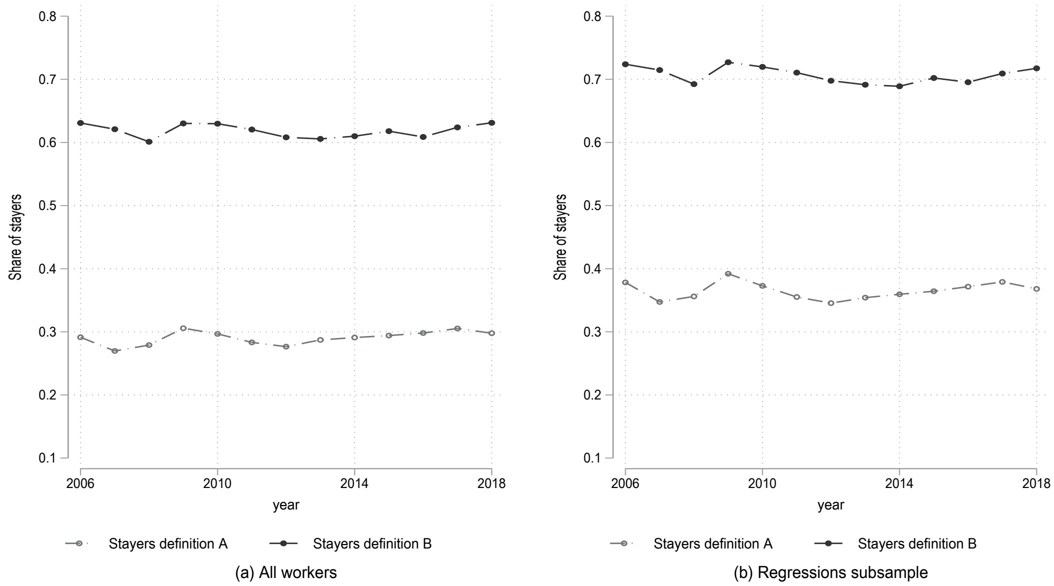
where w_{ijt} are the earnings of worker i in firm j at time t. This baseline regression, directly comparable to most of the previous literature, focuses on job stayers—workers who were employed in the firm during the previous period and remain employed in the current period. Given the nature of the data, a period is defined by a calendar year. The change in the logarithm of the worker's average monthly earnings is a function of a vector of worker characteristics, X_i, such as age and gender; a vector of firm characteristics, Z_j, including size and industrial sector; and time fixed effects, θ_t. Our coefficient of interest is β, which measures the earnings effect of the shock faced by the firm, ΔF_{jt} (measured as the change in estimated TFP or the change of reported sales). This baseline specification provides comparability with previous literature. As shown later, we extend the baseline specification on several dimensions, including asymmetries and non-linearities in the effects of shocks.

3.2.1 Stayers definition

Previous literature has adopted different criteria to define stayers. Under *definition A*, as in Juhn et al. (2018), a worker is considered a stayer in year t if he worked for firm j in the last quarter of year $t-1$ and remained with that same firm for at least the first quarter of year $t+2$. Under *definition B*, used by Chan et al. (2023), a worker is considered a stayer in year t if he worked for firm j during the years t and $t+1$.

Figure 2 shows the share of stayers under both definitions, using the complete data set as well as the sub-sample of firms used in our estimations. Under *definition A*, about 30% of the workers are stayers in a given year, while under *definition B*, twice as many workers meet the requirements. Throughout the rest of the paper, we use *definition B*, as it includes a larger sample of workers, and is also more representative of the comparatively large turnover in the Chilean labor market.

Figure 2: Share of firms' stayers, by selected sub-sample.



Notes: Stayers are defined as the proportion of workers staying in the firm at least 10 consecutive quarters (Def.A); or, two consecutive years after their firm suffered a shock on its sales (Def.B). Panel (a) takes into account all the workers observed in the data. Panel (b) takes into account only the sub-sample of workers with earnings above the minimum wage and working in firms with at least 5 workers.

3.3 Estimated Effects on Workers that Leave the Firm

3.3.1 Extensive margin estimation

As argued earlier, the effects of firm shocks on workers are not limited to the impact on the earnings of employees who stay in the firm, but can also have a relevant impact on the extensive margin. This margin can be especially important in the aftermath of negative shocks, as workers might be forced to leave the firm for unemployment and potentially experience significant earnings losses. Therefore, we want to provide an approximation of the earnings risk over the extensive margin by estimating the effects of shocks on the likelihood of involuntary job losses and the potential earnings consequences of separation.

We estimate the effects of shocks on the firm's extensive margin through a linear probability model. As our interest lies in the potential costs for workers who lose their jobs, rather than those who leave the firm voluntarily, we focus on job separations that are not associated with direct job–to–job transitions. In particular, we run regressions to assess the effect of shocks on the probability of a worker leaving the firm during the first quarter of the year after the shock and not being reemployed in a new firm in the next quarter, controlling for worker and firm characteristics. We also use year, industry, and year–industry fixed effects to control for business cycle and industry-specific trends.

3.3.2 Intensive margin estimations of the earnings costs of displacement

To assess the potential cost of unemployment, we proxy the wage losses suffered by workers who lose their jobs due to a firm shock by estimating the earnings costs of job displacement. To do so, we follow the seminal work of Jacobson et al. (1993) and rely on mass layoffs to proxy for involuntary separations that are not directly related to the worker's individual performance. In particular, we focus on mass layoffs in which firms lose more than 30% of their workforce in a given quarter.[9] Workers in the treatment group (displaced workers) are those in firms experiencing massive layoffs. We also require that they obtain a new job before the end of our sample and restrict our sample to separations that took place before the last quarter of 2016. Considering all job separations at the quarterly level, displaced workers represent about 0.1% of the sample.

We then use an exact matching procedure to identify the control group. Workers in the control group must belong to firms that did not experience mass layoffs. The match is based on firm characteristics such as industry classification, geographical area, size (using IRS classification), and our available observable worker variables such as age, tenure, and wage in $t-1$.

Under our approach, the estimated losses from displacement after a mass layoff proxy the earnings risks faced by agents who lose their jobs due to firms' idiosyncratic shocks. The key assumption for this identification is that the specific nature of the firm shock has no bearing on the future job trajectory of a worker who loses his job. Therefore, earnings losses for a displaced worker are, at least to a large extent, independent of the size of the firm shock that caused the job separation.

We think this is a reasonable assumption, as there are no clear theoretical reasons to assume that future job opportunities for a particular worker will be significantly affected by the specifics or size of the firm-level shock that led him to lose his job. Mass layoffs provide an identification strategy that offers estimates addressing endogeneity concerns; however, the actual consequences of displacement—and therefore the potential earnings

[9] To facilitate identification of the displacement event as occurring in a specific quarter, as well as to exclude firms with volatile employment patterns that could be associated with predictable seasonal patterns, we also require that the firm experiences only moderate changes in the number of employees three quarters before and after the mass layoff quarter. Specifically, we require that the change in headcount in the three quarters prior to the displacement period be in the range of -10 to 10%, and that in the three quarters after the negative shock occurs, its headcount does not grow by more than 10%.

costs faced by workers—are assumed to be the same regardless of the magnitude of the shock experienced by the firm.

3.4 Overall Expected Earnings Effects of Firm Shocks

Finally, our strategy combines all the previous results to provide an overall measure of the expected effects of firm-level shocks.

We can write the expected log wage in period $t+1$ of worker i employed in firm j at period t as:

$$E_t(w_{ijt+1}) = (1 - P_t(d_{ij}))w^s_{ijt+1} + P_t(d_{ij})w^d_{it+1} \tag{4}$$

In the next period, the worker faces two potential states. He either remains employed at the same firm, with probability $(1 - P_t(d_{ij}))$, and receives the stayer wage w^s_{ijt+1}. Alternatively, he is displaced (with probability $P_t(d_{ij})$). In that case, the worker earns the wage associated with displacement, w^d_{it+1}. Conceptually, this wage could represent the wage in a new formal job following an involuntary job transition, flows from unemployment, or work in the informal sector. For simplicity, this expression abstracts from explicitly addressing direct job–to–job transitions and the potential wage changes associated with them. Those cases are implicitly included in the scenario where the worker stays in the job, as $P_t(d_{ij})$ only refers to job transitions in which the worker goes through a non-employment spell in the formal sector.

The sensitivity of the expected wage to a change in current firm sales/TFP can be represented by the partial derivative:

$$\frac{\partial E_t(w_{ijt+1})}{\partial \gamma} = \frac{\partial w^s_{ijt+1}}{\partial \gamma}(1 - P_t(d_{ij})) - \frac{\partial P_t(d_{ij})}{\partial \gamma}w^s_{ijt+1} + \frac{\partial w^d_{it+1}}{\partial \gamma}P_t(d_{ij}) + \frac{\partial P_t(d_{ij})}{\partial \gamma}w^d_{it+1} \tag{5}$$

where γ represents the firm parameter (sales or TFP).

As discussed earlier, we assume that earnings losses for a displaced worker are independent of the size of the firm shock that caused the job separation. Therefore, we assume:

$$\frac{\partial w^d_{it+1}}{\partial \gamma} = 0 \tag{6}$$

In summary, the effect of the firm shock on expected wages can be expressed as:

$$\frac{\partial E_t(w_{ijt+1})}{\partial \gamma} = \frac{\partial w^s_{ijt+1}}{\partial \gamma}(1 - P_t(d_{ij})) + \frac{\partial P_t(d_{ij})}{\partial \gamma}(w^d_{it+1} - w^s_{ijt+1}) \tag{7}$$

The first term, the effect of the shock on the earnings of stayers wages, can be proxied with intensive margin estimates described in Section 3.2. These effects are weighted by the unconditional probability of not being displaced, which is obtained from the data. The second term represents the marginal effect of the shock on the probability of being displaced, multiplied by the earnings cost of displacement. The effect on displacement probabilities is captured by the linear probability model discussed in Section 3.3.1. The earnings losses of displacement, the difference between the log displacement wage and the stayer wage, can be recovered from the job displacement exercise described in Section 3.3.2.

4 Results

4.1 Intensive Margin: Wages Elasticity to Firm-Level Shocks

4.1.1 Average effects, asymmetries and nonlinearities

We start by analyzing the effects of firm shocks on the earnings of job stayers. Throughout this section, we present the effects of shocks for all firms in the sample, as well as only for firms in manufacturing.

Average firm shock effects. Table 1 presents the baseline regressions of the change in the log of real earnings to changes in the log of TFP and real firm sales for job stayers between 2007 and 2019. The sample includes more than 11 million year-worker observations across all industries. The regression controls for polynomials of age and tenure, the number of workers in the firm, the year, the firm's industry, and year–industry fixed effects.

Consistent with most existing literature, the average effects of firm-level shocks on the earnings of job stayers are relatively modest. The first panel of Table 1 shows the earnings implications of TFP shocks for stayers, as defined in Section 3.2. The average estimated elasticity in all sectors (column (1)) is 6.1%, slightly smaller than the figure in Chan et al. (2023) for Norway, but in the same ballpark. The estimated average elasticity is stronger in manufacturing (column (3)), reaching 9.9%. This means that a worker in a firm experiencing a one standard-deviation shock in TFP (8% variation) experiences, on average, a 0.5% change in real earnings. Therefore, the impact on the earnings of continuing workers from firm-level productivity shocks is modest but not economically negligible. Sales shocks (bottom panel) tell a similar story. For the whole economy, the elasticity of the earnings of stayers to sales shocks is 5.0% (column (1)), a figure that increases to 6.1% when we focus on the manufacturing sector (column (3)). It implies that, on average across all industries, a worker who remains employed in a company experiencing a change in

Table 1: Elasticity of earnings to firm shocks, stayers in the firm.

	All sectors		Manufacturing	
	(1)	(2)	(3)	(4)
productivity shock	0.061***		0.099***	
	(0.010)		(0.018)	
Positive productivity shock		0.097***		0.143***
		(0.014)		(0.027)
Negative productivity shock		0.030***		0.066***
		(0.011)		(0.025)
Sales shock	0.050***		0.061***	
	(0.002)		(0.004)	
Positive Sales shock		0.045***		0.049***
		(0.002)		(0.005)
Negative Sales shock		0.059***		0.081***
		(0.004)		(0.006)
N	11,206,172	11,206,172	2,484,457	2,484,457

Notes: Sample includes workers employed at same firm in consecutive years, 2007-2019. All specifications include controls for worker's age, age^2, tenure, tenure^2, number of workers in the firm, year, industry, and year–industry fixed effects. Robust standard errors clustered at firm level in parentheses; ***p<0.01, **p<0.05, *p<0.1

sales equal to one standard deviation (31%), experiences a 1.6% reduction (or increase) in earnings. This is somehow larger than the effects found for the US in Juhn et al. (2018). As shown in Appendix 8.2 Table 12, instrumental variable estimates using past revenue growth, as in Juhn et al. (2018), produce results consistent with our main estimates for the effect of sales shocks: while the OLS estimate is 5.7%, the IV coefficient is 5.2%. As mentioned earlier, the instrumental variable approach significantly reduces the sample size, as sales lags are used as instruments. Therefore, we rely on OLS estimates throughout the rest of the paper, with IV results available upon request.

Our results do not necessarily imply that workers suffer an explicit wage cut after the firm faces a negative shock. First, earnings can decrease due to a reduction in their variable component, even if base salaries are unaffected. As our measure of earnings does not only include base-rate wages but also any taxable components, it seems likely that the variable components of labor earnings, such as performance bonuses or sales commissions, can be especially affected. Second, since wages are typically contracted in nominal terms, a reduction in real earnings can be achieved by keeping nominal wages constant or growing below inflation.[10]

Nevertheless, considering that in our sample and period of study, total earnings

[10] The average annual inflation in Chile was 3.2% throughout the period

volatility—measured as the standard deviation of log wages—is close to 18%, the 0.5% earnings change from a one-standard-deviation TFP shock represents between 2 and 3% of the total annual earnings volatility experienced by Chilean workers. Similarly, the 1.6% earnings change from a one-standard-deviation sales shock represents about 9% of the total annual earnings volatility experienced by Chilean workers.

Asymmetries with respect to the direction of the shock. Similarly to Juhn et al. (2018) and Chan et al. (2023), the point estimates for the effect of shocks are asymmetric (columns (2) and (4)). The asymmetric responses, however, differ between TFP and sales shocks. For TFP shocks, earnings appear to respond more strongly to positive changes: the elasticity to negative shocks (3%) is less than one third of the sensitivity to positive shocks (9.7%). This statistically significant difference seems consistent with the notion of downward nominal wage rigidities, in which statutory minimum wage regulations constrain firms' ability to cut nominal wages (Bewley, 1999; Akerlof et al., 1996; Cruz et al., 2017). Manufacturing exhibits a similar pattern, though the asymmetry is less pronounced than that for all industries (6.6% vs 14.3%). However, the asymmetry is reversed and becomes less striking in the case of sales shocks. Across all sectors, the elasticity to negative sales shocks is 5.9%, roughly a third greater than the elasticity of 4.5% to positive shocks. Similarly, the earnings of workers in manufacturing respond to a negative shock almost 50% more than to a positive shock of the same size (an 8.1% elasticity to sales reductions, compared to a 4.9% elasticity to sales increases).

This difference in asymmetry patterns may reflect potential differences in how sales and productivity shocks affect firm decision-making. The greater sensitivity toward sales declines could reflect variable compensation components that directly respond to sales fluctuations and target goals. Additionally, cash flow constraints are an immediately observable consequence of revenue drops that could threaten firms' ability to cover operational expenses, particularly for smaller firms that represent a substantial fraction of our sample.

Nonlinear firm shock effects. Our results also suggest that wage insurance may vary with shock severity, consistent with recent empirical evidence in how firm shocks transmit to worker earnings. Indeed, Chan et al. (2023) find heterogeneous responses across the shock distribution in Norwegian data while Lamadon et al. (2022) develop theoretical frameworks showing that wage insurance may deteriorate as shock severity increases. Juhn et al. (2018) focus on average linear effects but acknowledge that pass-through rates may vary with shock magnitude, particularly when firms face financing constraints or when insurance arrangements approach sustainability limits.

Table 2 shows the estimated shock effects when we also include a quadratic term. For

TFP shocks (upper panel), the point estimate is positive and significant, indicating that the elasticity of earnings to shocks is convex overall. However, a closer look at asymmetries tells a different story, as seen in columns (3) and (6) of Table 2. Point estimates for positive and negative TFP shocks have opposite signs, though only the quadratic coefficient for negative shocks is statistically significant.

The negative quadratic term with positive shocks suggests that firms may increasingly retain gains from large positive productivity improvements rather than sharing them with workers. For negative shocks, considering the empirical range we observe of firms TFP as shown in Figure 1b, the estimated coefficients *negative* imply that, as negative TFP shocks become larger, earnings fall less than proportionally.

As before, the lower panel of Table 2 presents the results of sales shocks. Unlike in the case with TFP shocks, the estimated quadratic effect of both positive and negative sales shocks on workers' earnings is statistically significant, whether we include all firms or only those in the manufacturing sector. Yet, when looking at asymmetries, the results are qualitatively similar to the TFP estimates.

In the case of positive sales shocks, the elasticity of workers' earnings exhibits concavity. The estimated quadratic term coefficient is -0.037 for the full economy, roughly half the magnitude of the linear term (0.076), as shown in column 3 of Panel B. This result suggests that as firms experience larger positive sales shocks the earnings elasticity tends to be muted since firms transmit their gains less than proportionally to their incumbent workers' earnings. As previously mentioned, such concavity is consistent with the idea that firms extract a larger share of rents as they become more profitable.

In the case of negative sales shocks, the response of earnings also becomes relatively more muted as negative shocks become larger. The quadratic estimated coefficients, 0.043 for all industries and 0.081 for manufacturing exceed half the size of the corresponding linear coefficients. Hence, wage losses increase as negative sales shocks deepen, but less than proportionally. For example, based on column (3) of Panel B, for the whole economy, a 10%, 20% and 30% drop in sales are expected to reduce wages by about 0.7, 1.3 and 1.6 percentage points, respectively. This pattern in the earnings adjustment of staying workers' wages to negative shocks is consistent with the existence of institutional barriers or wage-setting frictions against lowering wages.

Table 2: Asymmetries and non-linearities in the elasticity of earnings to firms' shocks.

	All sectors			Manufacturing		
Panel A- Productivity Shock	(1)	(2)	(3)	(4)	(5)	(6)
Productivity shock	0.061***	0.067***		0.099***	0.112***	
	(0.010)	(0.010)		(0.018)	(0.019)	
Productivity shock^2		0.160***			0.308***	
		(0.024)			(0.069)	
Positive productivity shock			0.117***			0.166***
			(0.032)			(0.064)
Positive productivity shock^2			-0.172			-0.337
			(0.119)			(0.379)
Negative productivity shock			0.131***			0.221***
			(0.029)			(0.068)
Negative productivity shock^2			0.410***			0.856***
			(0.082)			(0.243)
Panel B- Sales Shock	(1)	(2)	(3)	(4)	(5)	(6)
Sales shock	0.050***	0.054***		0.061***	0.070***	
	(0.002)	(0.002)		(0.004)	(0.003)	
Sales shock^2		-0.013***			-0.031***	
		(0.002)			(0.006)	
Positive Sales shock			0.076***			0.114***
			(0.005)			(0.008)
Positive Sales shock^2			-0.037***			-0.082***
			(0.004)			(0.010)
Negative Sales shock			0.080***			0.111***
			(0.009)			(0.015)
Negative Sales shock^2			0.043***			0.081***
			(0.011)			(0.021)
N	11,206,172	11,206,172	11,206,172	2,484,457	2,484,457	2,484,457

Notes: Estimations include controls for worker's age, age^2, tenure, tenure^2, total number of workers in the firm, year, industry, and year–industry fixed effects. Robust standard errors clustered at the firm level in parentheses; ***p<0.01, **p<0.05, *p<0.1

4.1.2 Heterogeneity in earnings elasticities by worker's characteristics

We now examine the heterogeneity in earnings elasticities for stayers across four worker characteristics: age (25-39, 40-54, 55+), tenure at the firm (up to 1 year, more than 1 and up to 3 years, more than 3 years), earnings rank within the firm, and worker skills rank based on the economy-wide distribution (using quintiles constructed using AKM worker fixed effects from our wage decomposition). Results are reported in Tables 3 through 6. We find evidence of heterogeneity in wage elasticities, particularly concerning the asymmetric responses to positive and negative shocks.

Vulnerability to negative shocks declines systematically with age, tenure, and earnings rank, suggesting that firm-specific relationships—and presumably firm-specific skills—provide protection against earnings volatility for workers who remain employed. For both productivity and sales shocks, younger workers, workers with short tenures (up to a year), and workers at the bottom of the within–firm earnings distribution have the largest sensitivity to negative shocks, while enjoying minimal benefits from positive shocks. By contrast, continuing workers with longer tenure (over three years), ranked at the upper end of earnings within the firm (top quintile and top 5%), and greater experience (55+) have earnings that respond less to negative shocks, often with statistically insignificant effects, while benefiting more from positive firm performance.

For instance, workers over 55 years old appear fully insulated from negative productivity shocks in both the full sample and manufacturing-only estimates, with point estimates not statistically different from zero (Table 3, columns (4) and (8), Panels A and B). For sales shocks, the group shows statistically significant elasticities, though the coefficients are smaller than those of younger workers (Table 3, Panels C and D). In contrast, youngest workers (25-39) face statistically significant elasticities of 3.8% and 6.6% to negative productivity and sales shocks, respectively (Table 3, Panels A and C, column (2)). In the manufacturing sector, the magnitudes are larger, reaching 8.8% and 9.5%, respectively (Table 3, Panels B and D, column (6)).

The most substantial heterogeneity is associated with tenure at the time of the shock. Workers with up to a year of tenure barely gain from positive shocks (not at all in manufacturing) and are more affected by negative shocks. Their elasticity to positive productivity shocks is roughly one third of the average effect (0.035 vs 0.097), while their elasticity to negative productivity shocks is about three times as large (0.107 vs 0.035). A similar pattern holds for sales shocks: the earnings of short-tenure workers do not respond to positive shocks (0% for all firms and -1.7% for manufacturing firms), whereas long-tenure workers exhibit relatively large wage gains, with elasticities of 6.6% and 8.6% for all firms and manufacturing firms, respectively. For negative sales shocks, all stayers show statistically significant wage elasticities, but point estimates are statistically larger for short-tenure workers, with differences of more than 50% when compared to those of long-tenure workers. These results are consistent with the notion that firms place greater value on workers with longer tenures, who are more likely to represent better matches for the firm. Their earnings respond more to positive shocks and less to negative shocks. Conversely, earnings risk from negative firm shocks is stronger among workers with weaker firm attachment.

Table 3: Heterogeneity of wages' elasticity to firm shocks, by workers' age

Dependent variable: Δlog wages	(1) All workers	(2) Age: 25-39	(3) Age: 40-54	(4) Age: 55+	(5) All workers	(6) Age: 25-39	(7) Age: 40-54	(8) Age: 55+
	Panel A - All industry sectors				*Panel B - Manufacturing*			
Positive productivity shock	0.097***	0.097***	0.101***	0.085***	0.143***	0.153***	0.145***	0.105***
	(0.014)	(0.014)	(0.015)	(0.017)	(0.027)	(0.030)	(0.030)	(0.027)
Negative productivity shock	0.030***	0.038***	0.028**	0.012	0.066***	0.088***	0.057**	0.035
	(0.011)	(0.013)	(0.012)	(0.010)	(0.025)	(0.030)	(0.024)	(0.027)
	Panel C - All industry sectors				*Panel D - Manufacturing*			
Positive sales shock	0.045***	0.043***	0.046***	0.043***	0.049***	0.048***	0.050***	0.044***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)	(0.006)	(0.006)
Negative sales shock	0.059***	0.066***	0.058***	0.047***	0.081***	0.095***	0.077***	0.057***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)	(0.007)	(0.007)
N	11,206,172	4,836,864	4,776,061	1,593,247	2,484,457	1,030,620	1,096,502	357,335

Notes: All specifications include controls for number of workers in the firm, sales, year, industry, and year–industry fixed effects. Robust standard errors clustered at the firm level in parentheses;*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Heterogeneity of wages' elasticity to firm shocks, by workers tenure

Dependent variable: Δlog wages	(1) All workers	(2) Short tenure	(3) Medium tenure	(4) Long tenure	(5) All workers	(6) Short tenure	(7) Medium tenure	(8) Long tenure
	Panel A - All industry sectors				*Panel B - Manufacturing*			
Positive productivity shock	0.097***	0.035**	0.120***	0.099***	0.143***	-0.016	0.172***	0.200***
	(0.014)	(0.016)	(0.016)	(0.020)	(0.027)	(0.051)	(0.041)	(0.036)
Negative productivity shock	0.030***	0.107***	-0.002	0.031*	0.066***	0.157***	-0.019	0.119***
	(0.011)	(0.013)	(0.014)	(0.016)	(0.025)	(0.025)	(0.027)	(0.040)
	Panel C - All industry sectors				*Panel D - Manufacturing*			
Positive sales shock	0.045***	-0.004	0.056***	0.066***	0.049***	-0.017**	0.072***	0.086***
	(0.002)	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)	(0.006)	(0.004)
Negative sales shock	0.059***	0.075***	0.055***	0.049***	0.081***	0.107***	0.063***	0.071***
	(0.004)	(0.005)	(0.003)	(0.005)	(0.006)	(0.009)	(0.008)	(0.007)
N	11,206,172	2,244,206	3,533,177	5,428,789	2,484,457	420,739	777,741	1,285,977

Notes: All specifications include controls for number of workers in the firm, sales, year, industry, and year–industry fixed effects. Robust standard errors clustered at the firm level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Short tenure are workers with a tenure of less than a year at the time of the shock. Long tenure are workers with a tenure of more than a year at the time of the shock.

To further characterize the link between earnings risk and firm–worker matches, we rank workers by within firm earnings quintiles. As we do not have data on occupations, this provides a proxy for the organizational structure of the firm, from workers in the lower rungs (quintiles 1-2) to those in the highest echelons (quintile 5), distinguishing workers at the very top 5%, likely managers and high-skilled professionals with specialized human capital. Our results show that risk exposure decreases monotonically with earnings rank. Across all industry sectors and in manufacturing, the earnings of workers in the bottom quintile are the most affected by negative shocks and least rewarded by positive shocks, as shown in Table 5. Bottom quintile workers face elasticities to negative shocks roughly twice the average effect, whereas top quintile workers experience minimal exposure. The reverse pattern emerges for workers at the top, consistent with a greater role of performance-based earnings components. While not all differences in the estimated coefficients are statistically significant, results suggest systematic variation in risk exposure within the firms' compensation structure. Notably, point estimates reveal that the top 5% workers benefit disproportionately from positive shocks (12% elasticity for all industry sectors, 16.7% in manufacturing firms) while keeping their earnings unaffected by adverse shocks. This last result contrasts with findings from high-income countries, where top 5% earners are significantly exposed to negative firm shocks (Juhn et al., 2018; Chan et al., 2023).

Finally, we consider heterogeneity by worker skills, proxied using AKM worker fixed effects, which can be interpreted as the systematic market valuation of the worker associated to his human capital derived from education, ability, and experience. Unlike the previous within–firm rank analysis, this classification captures workers' relative position across the overall earnings distribution. We estimate elasticities for five quintiles plus the top 5%,[11] as shown in Table 6. For positive productivity shocks, elasticities are largest for the middle quintiles (3-4), with an estimated elasticity of 10.5%, though differences are not statistically significant. For negative productivity shocks, bottom-quintile workers show smaller and insignificant elasticities, likely reflecting minimum wage constraints and the use of informal employment as a buffer when formal sector conditions deteriorate. For positive sales shocks, elasticities increase monotonically with skills, although differences are only statistically significant in the manufacturing sector, where elasticity ranges from 4.4% (quintiles 1-2) to 6.7% (top 5%), as shown in Panel D of Table 6. For negative sales shocks, estimates are relatively larger and more variable, particularly in manufacturing, where workers in the skill quintiles 3-4 show nearly twice the elasticity of the top 5% (9.4% vs 4.9%).

In summary, across specifications, the earning elasticities for job stayers present consistent patterns: skilled, longer-tenure, higher-rank, and older workers gain more from positive firm shocks and are better shielded from negative shocks; in contrast, younger, short-tenure, and lower ranked workers face the opposite—minimal upside benefits combined with maximum downside exposure. These patterns are stronger in manufacturing, where tenure gaps reach an elasticity of 15.7% vs near-zero for short versus long-tenure workers, suggesting that industry characteristics amplify within–firm inequality in risk exposure.

[11] While by construction each quintile has the same number of workers, observations vary significantly, being lower for bottom quintiles due to their more frequent employment gaps and higher job turnover, making them less likely to be stayers.

Table 5: Heterogeneity of wages' elasticity to firm shocks, by workers' earnings rank in the firm (men).

Dependent variable: Δlog wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All workers	Quintiles 1-2	Quintiles 3-4	Quintile 5	Top 5%	All workers	Quintiles 1-2	Quintiles 3-4	Quintile 5	Top 5%
	Panel A: All Sectors, Productivity Shocks					*Panel B - Manufacturing, Productivity Shocks*				
Positive shock	0.097***	0.067***	0.099***	0.115***	0.120***	0.143***	0.086***	0.152***	0.176***	0.167***
	(0.014)	(0.019)	(0.013)	(0.013)	(0.020)	(0.027)	(0.033)	(0.028)	(0.025)	(0.028)
Negative shock	0.030***	0.057***	0.030***	0.018**	0.010	0.066***	0.134***	0.060**	0.007	-0.016
	(0.011)	(0.019)	(0.011)	(0.008)	(0.011)	(0.025)	(0.035)	(0.024)	(0.020)	(0.023)
	Panel C: All Sectors, Sales Shocks					*Panel D - Manufacturing, Sales Shocks*				
Positive shock	0.045***	0.029***	0.043***	0.050***	0.052***	0.049***	0.021***	0.051***	0.066***	0.075***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Negative shock	0.059***	0.069***	0.060***	0.050***	0.039***	0.081***	0.104***	0.078***	0.059***	0.039***
	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)	(0.009)	(0.007)	(0.005)	(0.007)

Notes: Quintiles and rankings are constructed based on the within–firm wage distribution in the period preceding the shock. Estimations include controls for worker's age, age^2, tenure, tenure^2, total number of workers in the firm; year, industry, and year–industry fixed effects. Robust standard errors clustered at the firm level in parentheses;*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Heterogeneity of wages' elasticity to firm shocks, by workers' skill quintile (men).

Dependent variable: Δlog wages	(1) All Workers	(2) Quintiles 1-2	(3) Quintiles 3-4	(4) Quintile 5	(5) Top 5%	(6) All Workers	(7) Quintiles 1-2	(8) Quintiles 3-4	(9) Quintile 5	(10) Top 5%
	Panel A - All Industry Sectors, Productivity Shocks					*Panel B - Manufacturing, Productivity Shocks*				
Positive productivity shock	0.097***	0.099***	0.105***	0.080***	0.057***	0.143***	0.136***	0.126***	0.153***	0.130***
	(0.014)	(0.016)	(0.018)	(0.015)	(0.015)	(0.027)	(0.031)	(0.034)	(0.029)	(0.036)
Negative productivity shock	0.030***	-0.015	0.041***	0.051***	0.053***	0.066***	0.003	0.103***	0.063***	0.055**
	(0.011)	(0.013)	(0.014)	(0.012)	(0.010)	(0.025)	(0.023)	(0.034)	(0.023)	(0.023)
	Panel C - All Industry Sectors, Sales Shocks					*Panel D - Manufacturing, Sales Shocks*				
Positive Sales shock	0.045***	0.041***	0.043***	0.048***	0.046***	0.049***	0.044***	0.045***	0.060***	0.067***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)
Negative Sales shock	0.059***	0.050***	0.067***	0.055***	0.046***	0.081***	0.072***	0.094***	0.064***	0.049***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.007)	(0.008)

Notes: All specifications include controls for number of workers in the firm, sales, year, industry, and year–industry fixed effects. Robust standard errors clustered at the firm level in parentheses;*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2 Extensive Margin: Firm-Level Shocks and Employment Responses

4.2.1 Firm-level shocks average effect on individual separation probabilities

As argued in the introduction, the potential effects of firm shocks on the earnings of workers are not limited to the wages of employees who stay in the firm but can also have a relevant effect on the extensive margin. Therefore, an overall assessment of risk must take into account the likelihood of job displacement and its potential costs.

The analysis of displacement responses focuses on sales shocks.[12] Our interest does not lie in workers who change jobs directly in the aftermath of a shock (which are likely to represent voluntary transitions), but rather in workers who might lose their jobs involuntarily after a shock. We proxy this by looking at workers who leave the firm and are not immediately (in the next month) reemployed at another firm. As mentioned earlier, our dataset does not allow us to distinguish transitions to unemployment/out of the labor market from transitions to informal employment. All those cases can be associated to transitions to non-employment, the state in which workers are not employed in any given month in a firm in the formal sector.

Tables 7 to 10 present linear probability estimates of how sales shocks affect separation into non-employment.[13] On average, across all industries, negative sales shocks increase workers' displacement probability by 27.2 percentage points (first column of Panel A for Tables 7 to 10). Counterintuitively, positive sales shocks also increase the average separation probability, although only by 3.7 percentage points. These effects are slightly amplified in the manufacturing sector (first column of Panel B for Tables 7 to 10). In our sample, the annual baseline displacement probability is 27%, consistent with turnover rate estimates at the national level (Albagli et al., 2023). Therefore, on average, a one standard deviation drop in sales would increase workers' separation probability to 35%.

4.2.2 Heterogeneity in displacement risk following firm sales shocks

As in the intensive margin section, we consider four dimensions of possible heterogeneity in the effect of firm shocks on the probability of separation: age, tenure, earnings rank, and skills. Overall, the marginal effects vary only modestly across worker characteristics, ranging from 0.24 to 0.29 across age, tenure, earnings rank, and skills. Skills are the

[12]This reflects the concern of a potential endogeneity problem between employment in the firm and measured TFP. If firms are already adjusting employment downward (upward), productivity mechanically increases (decreases), making it difficult to establish whether displacement follows the shock or whether the measured shock partly reflects the displacement decision itself. Using sales shocks mitigates this concern: revenue changes are directly observable and exogenous to subsequent employment decisions.

[13]As mentioned, firm-to-firm transitions are excluded from our analysis.

dimension where we observe relatively more heterogeneity, with coefficients ranging from -0.20 for the top 5% to -0.292 for quintiles 3-4, a difference of 9 percentage points.

However, these similar marginal responses compound dramatically different baseline displacement probabilities, generating substantial heterogeneity in total displacement risk. Three examples illustrate this pattern:

- Tenure (Table 8): workers with up to one year of tenure face a 44.8% baseline separation probability versus 17.3% for workers with over three years of tenure. Following a 30% negative sales shock (one standard deviation), total displacement probability becomes 53.1% for short-tenured workers and 24.8% for long tenured workers.

- Earnings rank (Table 9): Baseline average probabilities of separation vary non-monotonically across earning ranks, although the lowest two quintiles and top 5% earners show the highest estimates (32.3% and 33.3% vs 24.3%, 25.2% for earnings ranks in quintiles 1-2, 3-4 and 5, respectively). The estimated effect of negative sales shocks decreases as workers' earnings rank increases, but point estimates remain close in magnitude and are not statistically distinguishable from the average effect of -0.272. Consequently, sales shocks accentuate differences in displacement likelihood only modestly: after a 30% negative sales shock, separation probability becomes 40.6% vs 32.4%, 32.7%, and 40.3% for earnings ranks in quintiles 1-2, 3-4, and 5 and the top 5%, respectively.

- Skills (Table 10): Skills provide little protection for workers against the average effect of negative sales shocks on the likelihood of being displaced, which has a point estimate of -0.272. However, skills do protect workers against displacement through baseline rates: the bottom two skill quintiles face twice the separation risk of the highest quintile, with a 37.0% baseline separation probability versus 18.4% and 16.9% for the highest quintile and top 5% skilled workers, respectively. After a 30% negative sales shock, those separation probabilities become 44.3%, 25.7% and 22.9%, respectively, leaving lower-skilled workers facing roughly twice the displacement probability of higher-skilled workers.

Overall, *ex ante* displacement risk varies drastically across worker types. However, this does not reflect large differences in sensitivity to sales shocks, but rather that shocks compound large baseline differences in job stability. Workers with weaker firm attachment—short tenure, lower skills—face substantially higher displacement risk, largely because they begin with much higher baseline separation rates.

Table 8: Displacement probability responses to firm sales shocks, by tenure group

Dependent variable: $Pr(D_{i,j} = 1)$	(1) All Workers	(2) Tenure: < 1 year	(3) Tenure: 1-3 years	(4) Tenure: > 3 years	(5) All Workers	(6) Tenure: < 1 year	(7) Tenure: 1-3 years	(8) Tenure: > 3 years
	Panel A - All industry sectors				*Panel B - Manufacturing*			
Positive Sales shock	0.037***	0.004	0.027***	0.053***	0.064***	0.037***	0.048*	0.080***
	(0.006)	(0.006)	(0.007)	(0.009)	(0.017)	(0.014)	(0.025)	(0.030)
Negative Sales shock	-0.272***	-0.275***	-0.291***	-0.249***	-0.289***	-0.320***	-0.288***	-0.263***
	(0.008)	(0.007)	(0.010)	(0.011)	(0.015)	(0.011)	(0.021)	(0.023)
N	14,870,930	4,346,789	4,603,924	5,920,217	3,140,015	780,233	988,544	1,371,238
Mean prob. leave	*0.275*	*0.448*	*0.244*	*0.173*	*0.320*	*0.483*	*0.291*	*0.247*

Notes: Table reports marginal effects (linear probability model coefficients) of firm sales shocks on a displacement indicator, estimated separately by tenure group and industry scope. Robust standard errors clustered at the firm level in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Regressions control for firm size and sales, with year, industry, and year–industry fixed effects. Mean displacement probabilities by group are shown at the bottom.

Table 7: Displacement probability responses to firm sales shocks, by age group

Dependent variable: $Pr(D_{i,j} = 1)$	(1) All Workers	(2) Age: 25-39	(3) Age: 40-54	(4) Age: 55+	(5) All Workers	(6) Age: 25-39	(7) Age: 40-54	(8) Age: 55+
	Panel A – All industry sectors				*Panel B – Manufacturing*			
Positive Sales shock	0.037***	0.033***	0.037***	0.039***	0.064***	0.063***	0.063***	0.059***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.017)	(0.018)	(0.017)	(0.017)
Negative Sales shock	-0.272***	-0.277***	-0.272***	-0.255***	-0.289***	-0.295***	-0.286***	-0.274***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.015)	(0.016)	(0.016)	(0.015)
N	14,870,930	6,704,230	6,150,498	2,016,202	3,140,015	1,377,588	1,340,324	422,103
Mean prob. leave	*0.275*	*0.300*	*0.246*	*0.284*	*0.320*	*0.347*	*0.288*	*0.327*

Notes: Table reports marginal effects (linear probability model coefficients) of firm sales shocks on a displacement indicator, estimated separately by age group and industry scope. Robust standard errors clustered at the firm level in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. All regressions include controls for firm size and sales, and fixed effects for year, industry, and year–industry. Mean displacement probabilities by group are reported at the bottom.

Table 9: Displacement probability responses to firm sales shocks, by within–firm earnings rank

Dependent variable: $Pr(D_{i,j} = 1)$	(1) All Workers	(2) Earn.rank Quintiles 1-2	(3) Earn.rank Quintiles 3-4	(4) Earn.rank Quintile 5	(5) Earn.rank Top 5%
	Panel A - All industry sectors				
Positive Sales shock	0.037***	0.049***	0.052***	0.046***	0.011*
	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
Negative Sales shock	-0.272***	-0.278***	-0.270***	-0.251***	-0.234***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
N	14,870,930	5,629,357	6,382,974	2,858,599	639,845
Mean prob. displacement	*0.275*	*0.323*	*0.243*	*0.252*	*0.333*
	Panel B - Manufacturing				
Positive Sales shock	0.064***	0.069***	0.079***	0.085***	0.041**
	(0.017)	(0.019)	(0.017)	(0.016)	(0.016)
Negative Sales shock	-0.289***	-0.301***	-0.283***	-0.276***	-0.245***
	(0.015)	(0.017)	(0.016)	(0.016)	(0.019)
N	3,140,015	1,199,042	1,349,511	591,462	129,571
Mean prob. displacement	*0.320*	*0.355*	*0.293*	*0.308*	*0.377*

Notes: Table reports marginal effects (linear probability model coefficients) of firm sales shocks on a displacement indicator, estimated separately by earnings rank group and industry scope. Earnings rank defined relative to within–firm distribution. Robust standard errors clustered at the firm level in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. All regressions include firm size and sales as controls, and fixed effects for year, industry, and year–industry. Mean displacement probabilities by group reported at bottom. See text for definitions.

5 Earnings Effects of Job Losses

We now turn our attention to the potential earnings costs for workers who lose their jobs and enter non-employment following a negative firm shock. As discussed earlier, we follow the identification strategy in Jacobson et al. (1993) and examine the differential earnings trajectories of workers displaced in mass layoff events relative to those in a control group.

Studying mass layoffs offers a valuable identification strategy by providing exogenous variation in job displacement. However, there is nothing inherently unique about mass layoffs with respect to their impact on earnings: that is, the consequences of displacement on the worker are not driven by the size of a firm-level shock or the associated mass layoff,

Table 10: Displacement probability responses to firm sales shocks, by skill rank (AKM worker FE quintiles)

Dependent variable: $Pr(D_{i,j} = 1)$	(1) All Workers	(2) Skills rank: Quintiles 1-2	(3) Skills rank: Quintiles 3-4	(4) Skills rank: Quintile 5	(5) Skills rank: Top 5%
	Panel A - All industry sectors				
Positive Sales shock	0.037***	0.029***	0.043***	0.035***	0.015*
	(0.006)	(0.005)	(0.006)	(0.008)	(0.009)
Negative Sales shock	-0.272***	-0.244***	-0.292***	-0.243***	-0.200***
	(0.008)	(0.007)	(0.009)	(0.011)	(0.014)
N	14,870,930	4,545,928	6,406,623	3,826,367	1,048,847
Mean prob. displacement	*0.275*	*0.370*	*0.254*	*0.184*	*0.169*
	Panel B - Manufacturing				
Positive Sales shock	0.064***	0.053***	0.071***	0.056**	0.046*
	(0.017)	(0.015)	(0.018)	(0.022)	(0.024)
Negative Sales shock	-0.289***	-0.264***	-0.300***	-0.263***	-0.218***
	(0.015)	(0.014)	(0.017)	(0.023)	(0.026)
N	3,140,015	944,577	1,397,132	780,245	191,726
Mean prob. displacement	*0.320*	*0.399*	*0.300*	*0.244*	*0.230*

Notes: Marginal effects (linear probability model coefficients) of sales shocks on a displacement indicator, estimated separately by skills rank group and industry scope. Skill rank defined as quintiles of AKM worker fixed effects, see text for definitions and details on AKM construction of skills rank. Robust standard errors clustered at the firm level in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Regressions control for firm size and sales, with year, industry, and year–industry fixed effects. Mean displacement probabilities by group reported at bottom.

but by displacement itself. Therefore, the earnings costs of job losses should not depend on the scale of the sales or productivity shock that pushed workers away from the firm. We leverage this insight to use these estimates towards our overall assessment of worker risk.

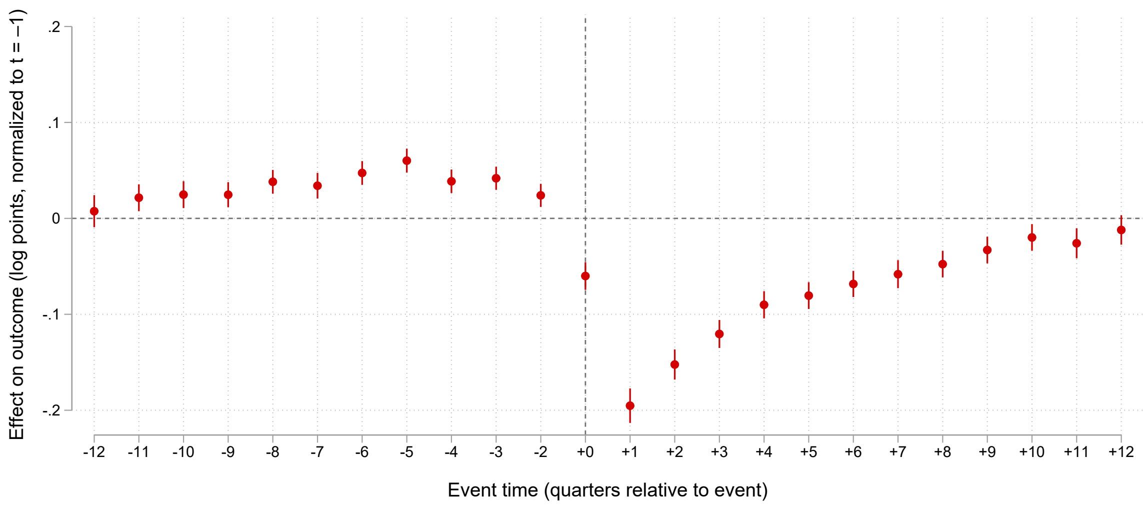
Figure 3 illustrates the earnings trajectory of displaced workers over a three-year period (12 quarters) following the month of displacement, relative to the control group. Differences are normalized to zero at the quarter prior to the displacement event.

Job displacement is associated with substantial earnings losses: workers who are reemployed within the first quarter experience, on average, a reduction in earnings of approximately 20% relative to the matched control group, and losses throughout the first year average 15%. Moreover, the earnings of displaced workers remain persistently below those of the control group for over two years. These patterns are qualitatively and quantitatively very similar to those found in the literature[14] and underscore that

[14]For example, other papers using administrative data, such as Schmieder et al. (2023) and Couch and

the monetary cost of job loss is significant, making displacement risk a non-negligible component of the overall labor market risk faced by workers. Moreover, as found in the literature, the effects of displacement are likely to be heterogeneous, with larger losses for workers facing higher reallocation costs, such as older individuals or those with longer tenures.

Figure 3: Average effects of displacement



Notes: X-axis represents the number of quarters after the displacement event. Balanced panel estimates are normalized at t=-1. Treatment: workers displaced in mass layoffs (employment decline >30%), with tenure ≥1 year, reemployed before 2019:Q4. Displacements restricted to: 2007:Q1- 2016:Q4.

Figures 4 to 7 explore heterogeneity among the dimensions analyzed in the previous sections. Results show that the average cost of displacement varies significantly between workers with different characteristics, consistent with theoretical predictions and results found elsewhere in the literature. Our estimates use balanced samples in order to keep the sample of analysis constant across all pre and post-displacement periods.

Figure 4 examines displacement by age groups. As expected, earnings costs of displacement are larger for older workers. Upon reemployment, young workers experience earnings losses of close to 10%, and their earnings become statistically identical to those of the control group in less than six months. In contrast, workers older than 55 have a harder time coping with losing their jobs: earnings losses relative to their past earnings are greater than 20% after reemployment, and their earnings still lag behind the control group three years after the displacement. Middle-aged workers fare somewhere in between, experienc-

Placzek (2010b), find earnings declines of roughly 20-30 percent in the short run and 10-15 percent even a decade later.

ing similar initial losses but recovering faster than their older counterparts, although their earnings still lag after two years. Therefore, as expected, reallocation seems to be easier for younger workers. Older workers, who are more likely to possess firm-specific human capital that can become obsolete in different firms or to have constructed valuable job ladders that take time to build due to search frictions, may find job reallocation significantly more costly.

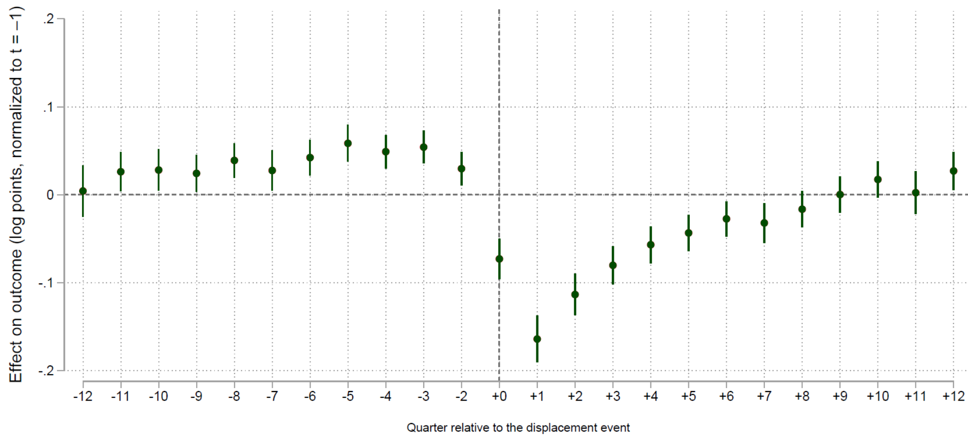
This intuition is reinforced by Figure 5, which analyzes workers by their tenure at the moment of displacement. Workers with longer tenures, which, as discussed earlier, are probably better matches and have more firm-specific human capital, suffer much more from displacement. The wage loss experienced by displaced workers who had a tenure of one year is not statistically significant. In contrast, the earnings losses for workers with tenure between one and three years are close to 30% for those reemployed a quarter after being displaced, and even after three years, the average wage has only recovered by half. For workers with tenures longer than three years, earnings in the first quarter after reemployment drop by 40%, and remain almost 20% below after three years. Therefore, the earnings risk from displacement, associated with a costly process of reallocation, is much larger for workers with longer tenures. While, as we saw earlier, the earnings of those workers are relatively more isolated/protected from the intensive margin effect of firm shocks, in the event of displacement, their earnings costs are much larger.

Figure 6 examines the earnings implications of displacement across skill groups defined in the previous sections. Losses appear to be non-monotonic with respect to skills. Job reallocation seems to be costlier, both in terms of magnitude and persistence, for workers in the middle of the skill distribution (quintiles 3 and 4). Earnings losses in the first quarter exceed 20%, and after two years, their earnings still lag 10% behind. Workers in the lower part of the skill distribution (quintiles 1 and 2) suffer similar losses on impact, but differences with the control group become non-significant within the year. High-skill workers (quintile 5) experience smaller losses on impact, but these losses also persist beyond the first year.

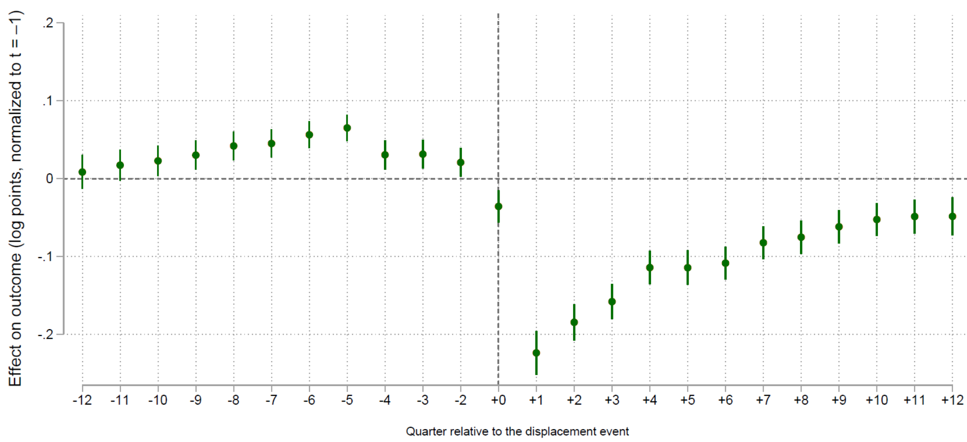
In summary, the evidence shows, consistent with the literature, that earnings losses associated with job displacement can be large and persistent. This is especially true for workers for whom reallocation is likely to be more difficult, such as older workers, workers with longer tenures, or workers with more specialized skills. While the identification of separations that are exogenous to the worker comes from the particular case of mass layoffs, the implications are far more general and can be applied to all involuntary separations associated with events such as firm level shocks that are not directly related to the worker. Therefore, these results highlight the relevance of the extensive margin when examining the earnings risk of workers in the face of firm-level shocks.

Figure 4: Earnings Effects of Displacement by Age Group

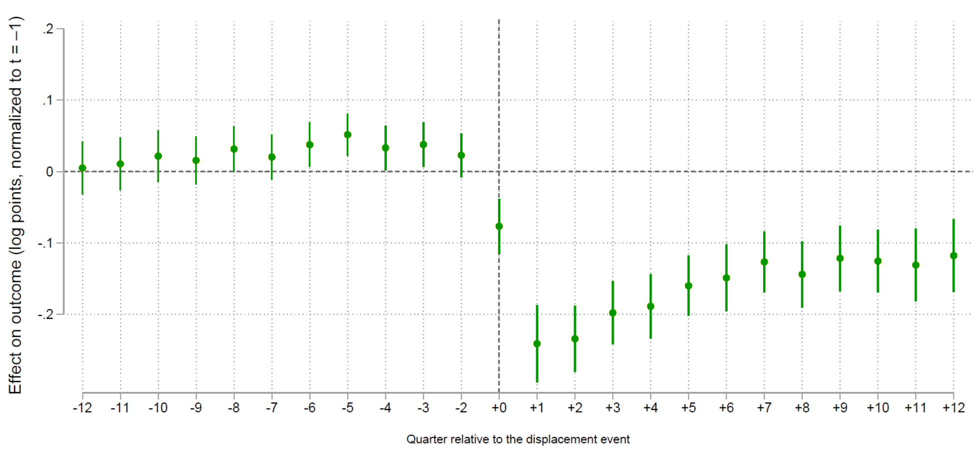
(a) Age group 25 to 39 years old.



(b) Age group 40 to 54 years old.



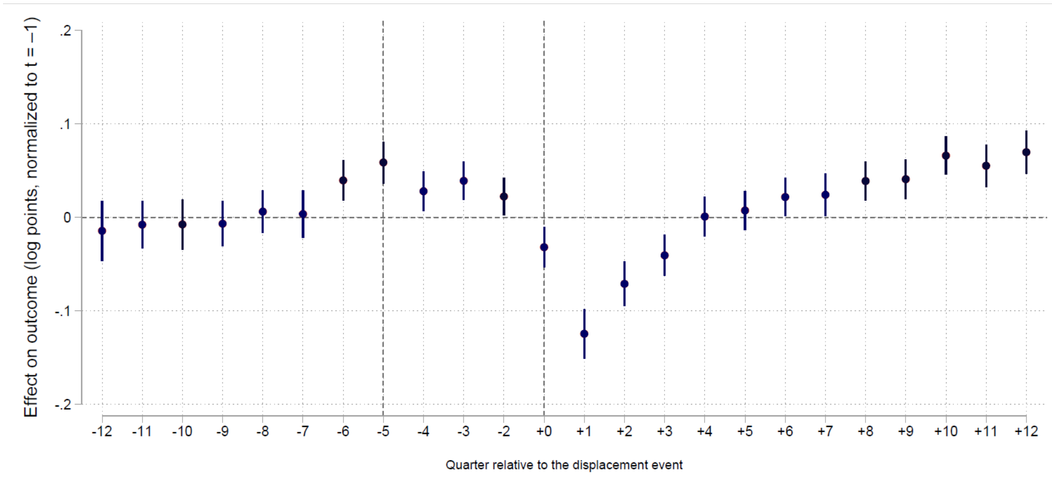
(c) Age group 55+ years old.



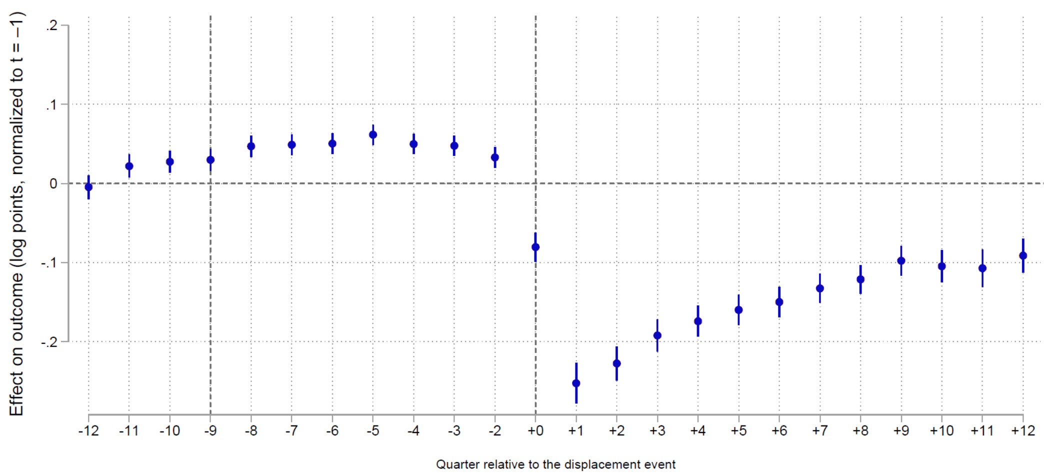
Notes: X-axis represents the number of quarters after the displacement event. Balanced panel estimates are normalized at t=-1. Treatment: workers displaced in mass layoffs (employment decline >30%), with tenure ≥1 year, reemployed before 2019:Q4. Displacements restricted to: 2007:Q1- 2016:Q4.

Figure 5: Earnings Effects of Displacement by Tenure

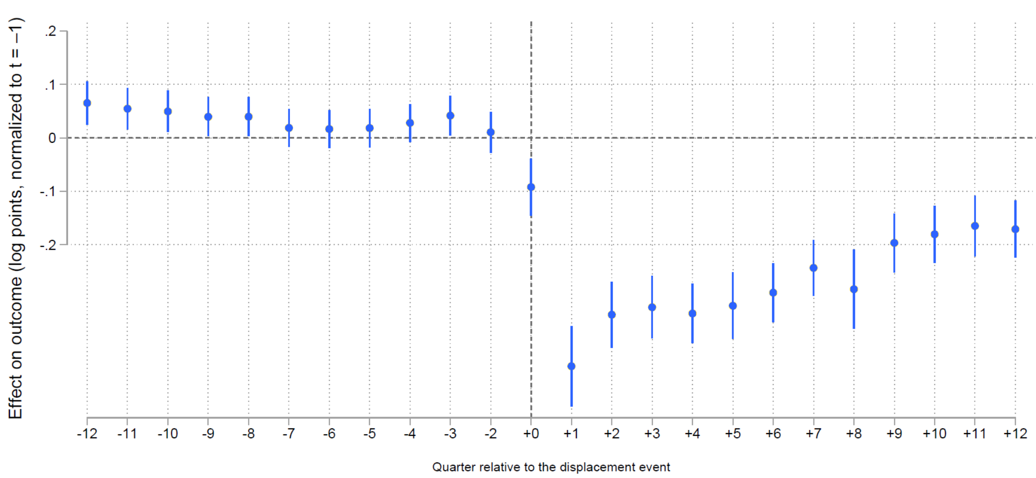
(a) Tenure at displacement: up to one year.



(b) Tenure at displacement: between one and three years.



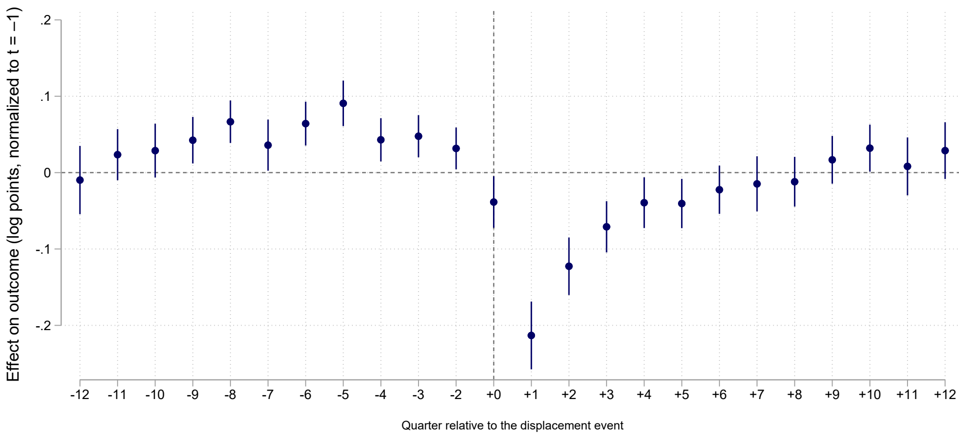
(c) Tenure at displacement: more than three years.



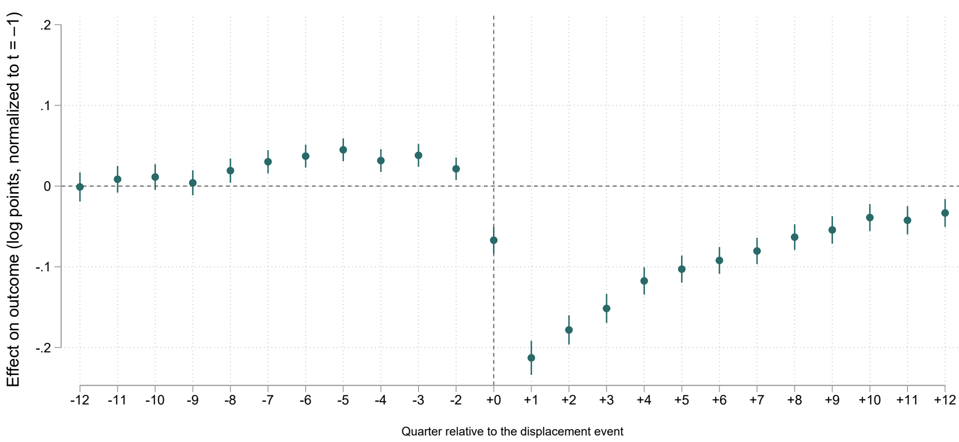
Notes: X-axis represents the number of quarters after the displacement event. Balanced panel estimates are normalized at t=-1. Treatment: workers displaced in mass layoffs (employment decline >30%), with tenure ≥1 year, reemployed before 2019:Q4. Displacements restricted to: 2007:Q1- 2016:Q4.

Figure 6: Earnings Effects of Displacement by Skills

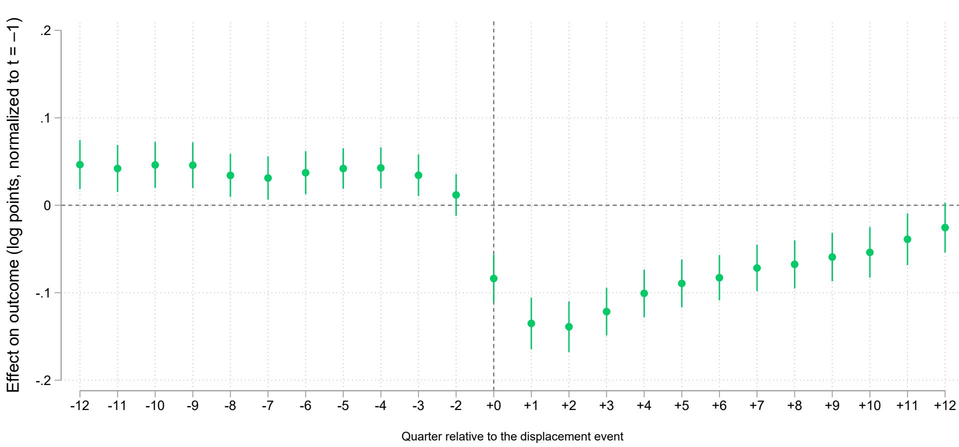
(a) Skill quintile: 1-2 (lowest).



(b) Skill quintile: 2-4 (middle).



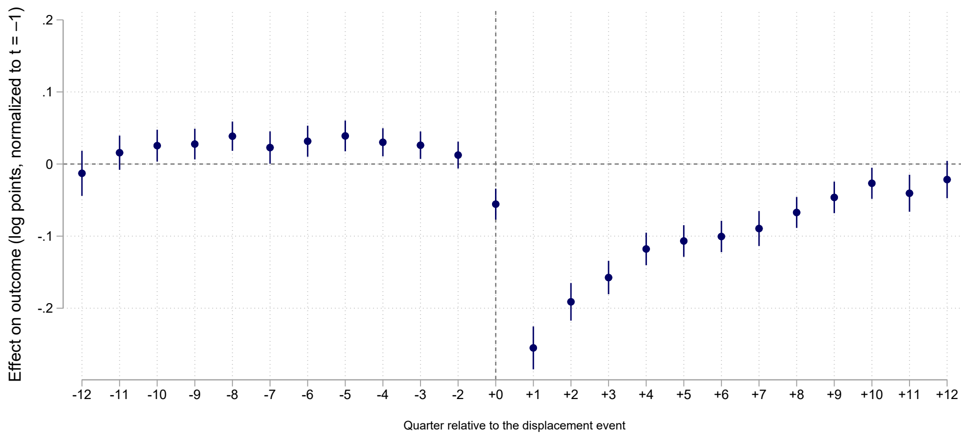
(c) Skill quintile: 5 (highest).



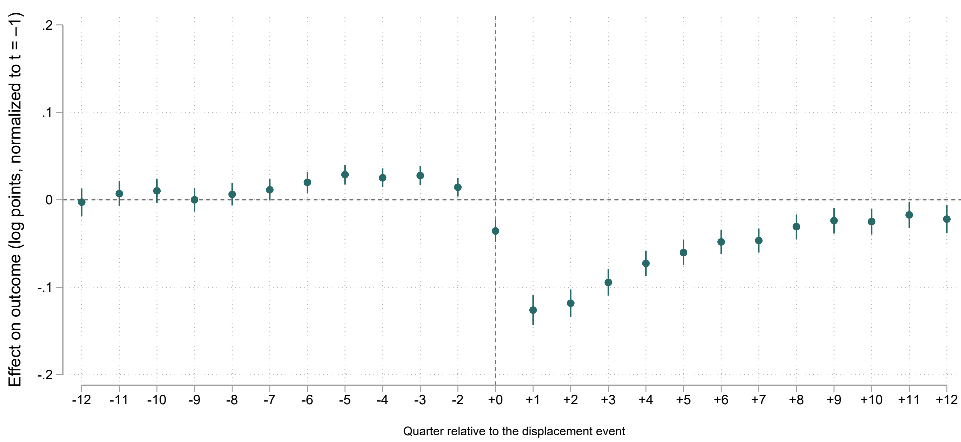
Notes: X-axis represents the number of quarters after the displacement event. Balanced panel estimates are normalized at t=-1. Treatment: workers displaced in mass layoffs (employment decline >30%), with tenure ≥1 year, reemployed before 2019:Q4. Displacements restricted to: 2007:Q1- 2016:Q4.

Figure 7: Earnings Effects of Displacement by Earnings Rank

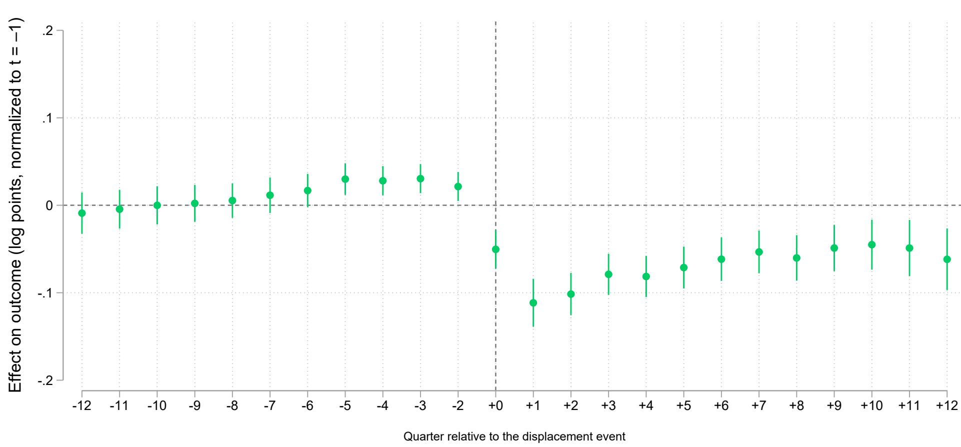
(a) Earnings rank quintile:1-2(lowest).



(b) Earnings rank quintile: 2-4 (middle).



(c) Earnings rank quintile: 5 (highest).



Notes: X-axis represents the number of quarters after the displacement event. Balanced panel estimates are normalized at t=-1. Treatment: workers displaced in mass layoffs (employment decline >30%), with tenure ≥1 year, reemployed before 2019:Q4. Displacements restricted to: 2007:Q1- 2016:Q4.

6 Taking Stock: Measuring the Overall Exposure to Earnings Risk

We now combine our results to provide an overall measure of the sensitivity of individual earnings to firm-level shocks, incorporating both the intensive and extensive margins. This exercise is presented for the average worker and for the worker subgroups discussed throughout the paper.

As discussed earlier, the effect of firm shocks on the logarithm of expected earnings for current employees in the following year can be written as

$$\frac{\partial E_t(w_{ijt+1})}{\partial \gamma} = \frac{\partial w^s_{ijt+1}}{\partial \gamma}(1 - P_t(d_{ij})) + \frac{\partial P_t(d_{ij})}{\partial \gamma}(w^d_{it+1} - w^s_{ijt+1}), \tag{8}$$

where the first term captures the impact of shocks on stayers' earnings, weighted by the unconditional probability of not separating, and the second term captures the effect of shocks on displacement probabilities multiplied by the earnings cost of displacement.

We obtain the first component from the linear OLS coefficients of negative sales shocks across all sectors (Tables 3-6), combined with the unconditional probabilities of continued employment from the linear probability models in Tables 7-10. These form the intensive margin of the earnings response, shown as the lighter-shaded (bottom) portions of Figure 8.

The second component measures the earnings cost of displacement, weighted by the change in displacement probability. The latter comes from the estimated effect of sales shocks on transitions to non-employment (Tables 7-10), while the earnings losses are based on difference-in-differences estimates following Jacobson et al. (1993) (Section 5). We use the average earnings loss during the first year after displacement. This extensive margin is represented by the darker-shaded (upper) portions of Figure 8.

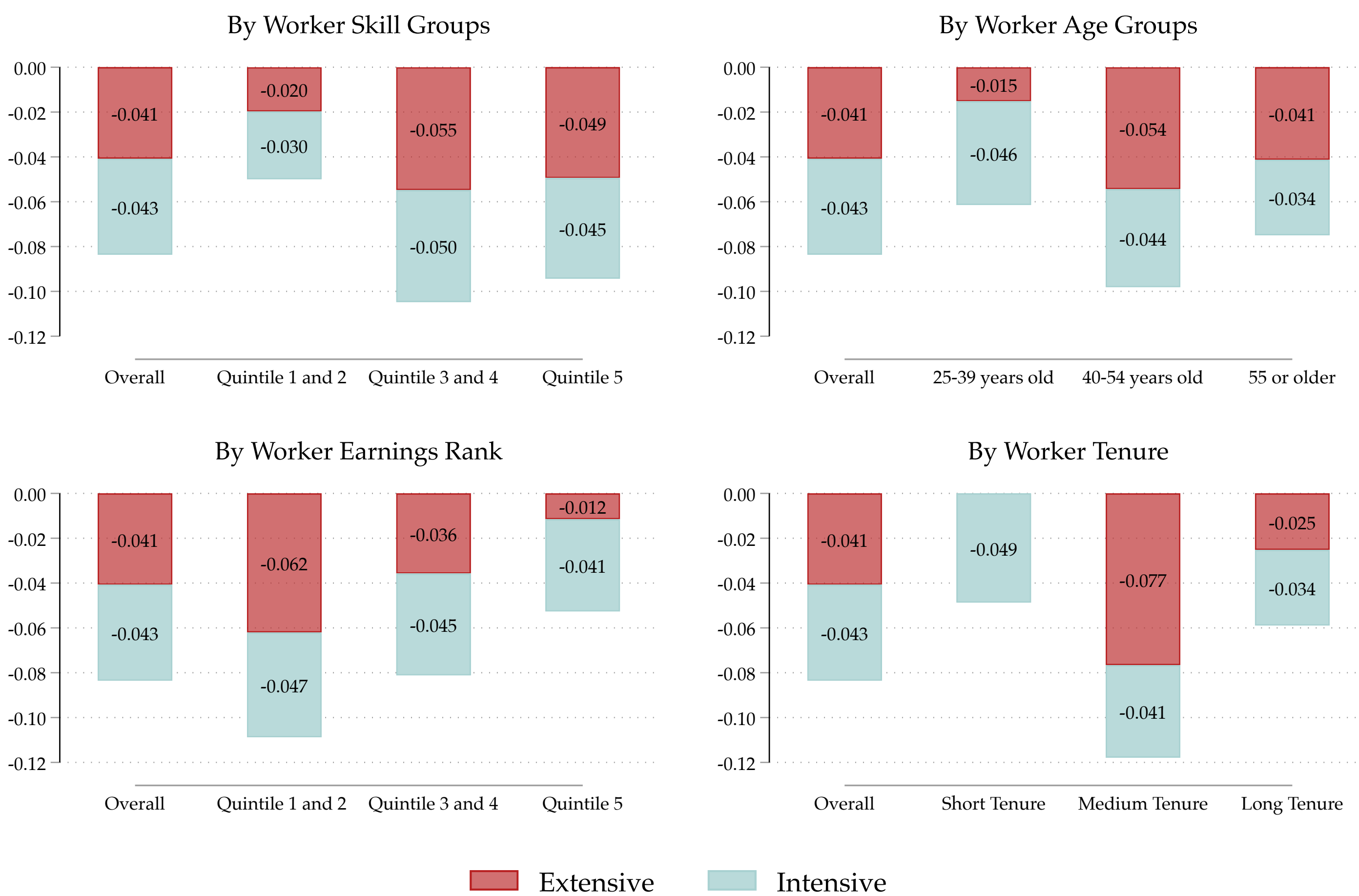
Figure 8 presents four panels, decomposing the overall effect by worker skill, age, within–firm earnings, and job tenure. Each panel includes the average effect as a reference. Because all estimates are linear, they represent constant elasticities with respect to sales shocks.

For the average worker, incorporating the extensive margin nearly doubles the expected effect of a sales shock. The overall sensitivity of expected earnings over the next year is 8.3 percent: this is, the effect of a 20% negative sales shock is a 1.6% reduction in the expected next year earnings of workers currently employed in the firm.

The relative effect of both margins is roughly the same: 4.3 percent of the overall sensitivity comes from the intensive margin, and 4.0 percent from the extensive margin.

The latter reflects the combination of large short-run earnings losses from displacement (15 percent) and the elasticity of the displacement probability (27.2 percent). Thus, accounting for the extensive margin substantially amplifies the estimated exposure of earnings to firm risk.

Figure 8: Earning effects of negative sales shocks on the intensive and extensive margins, by worker categories



Notes: The figures present the estimated effects of firm shocks over the intensive and extensive margin. The intensive margin represents the elasticity of the earnings of stayers to a sales shock, weighted by the probability of being a stayer. The extensive margin represent the effect of a shock on the probability of displacement, times the average earnings cost of displacement over the first year.

The first panel shows heterogeneity by skills. Workers in the bottom skill quintiles have the lowest overall sensitivity—roughly half the effect for higher-skill groups. This arises from both margins. On the intensive margin, their earnings as stayers are less sensitive to shocks and their unconditional job-retention probability is significantly smaller (0.63 for quintiles 1-2 vs. 0.75 for quintiles 3-4 and 0.82 for quintile 5). On the extensive margin, low-skilled workers experience smaller earnings losses upon displacement, likely reflecting the binding role of the minimum wage in reemployment and the informal sector's buffering effect on reservation wages. More broadly, their higher turnover and shorter expected tenures reduce exposure to firm-specific risk.

The second panel shows heterogeneity by age. Younger workers (under 40) have low overall sensitivity (5.8 percent), as their displacement costs are modest—earnings losses average just 4 percent. Therefore, their extensive margin exposure is only 1.5 percent. Middle-aged workers (40 to 54) face similar intensive-margin effects (4.4 percent) but much larger displacement costs (nearly 17 percent), raising their extensive margin to 5.4 percent and overall exposure to 9.0 percent, 50% higher than the youngest group. Older workers (55+) have lower sensitivity on the intensive margin but incur the largest displacement costs, reflecting the difficulties of being reemployed in the later part of a workers life cycle. Extensive margin effects account for almost two thirds of their overall exposure.

The third panel presents results by tenure. Due to the extensive margin, overall sensitivity is increasing with tenure. As the earnings losses from displacement for workers with tenures of 1 year are very small, 85% of earnings sensitivity to shocks comes from the intensive margin. Despite having the lowest probability of staying in the firm next year (0.65), workers with short tenures still have the highest exposure on the intensive margin due to the greater sensitivity of their earnings, conditional on remaining at the firm. Workers with longer tenures might be more isolated from shocks on the intensive margin but can suffer significantly from displacement, as they lose valuable matches or firm-specific human capital. Overall, workers with the longest tenures have the largest overall sensitivity (12.1%), more than double the sensitivity of workers with short tenures (5.8%). Almost two thirds of their exposure comes from the extensive margin.

Finally, the fourth panel examines heterogeneity across the within–firm earnings distribution. Overall sensitivity declines monotonically with earnings rank. Workers in the top quintile show half the sensitivity of those in the bottom two quintiles (5.1 vs 9.6 percent). Differences stem primarily from the extensive margin: while it accounts for more than half of total exposure among the bottom quintiles, it represents only about 20 percent for top-quintile workers.

Overall, incorporating the extensive margin substantially increases the estimated exposure of workers' earnings to firm shocks and reveals meaningful heterogeneity across worker groups. Analyses that focus solely on stayers' earnings dynamics omit a central channel through which firm-level risk translates into earnings risk.

Two caveats apply. First, our decomposition considers only two worker states—staying with the same firm or moving to non-employment. Earnings dynamics of job–to–job movers are implicitly proxied by stayers. Second, we restrict attention to one-year effects. Longer-term consequences—especially for displaced workers who do not reenter formal employment—are excluded and may be particularly important for certain groups. Similarly, and as discussed earlier, the displacement effects on earnings focus only on workers who find a new job and become reemployed. Therefore, they do not take into account the earnings costs for workers who, after displacement, are not reemployed in the formal sector within the first year.

7 Conclusions

This paper contributes to the literature that studies the effect of idiosyncratic firm shocks on the earnings risk faced by workers. Our main contribution is to complement the analysis on the effects of shocks on the earnings of stayers with a measurement of impacts over the extensive margin, providing a more comprehensive assessment of the exposure of workers' earnings to firm risk. We show that the risks over the extensive margin, associated with foregone earnings due to job displacement, are relatively large. Accounting for these costs can significantly increase the measured risk exposure of workers.

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8 Appendix

8.1 Descriptive statistics

Table 11: Earnings evolution by categories

Category	Number of workers	Mean monthly real wage (USD 2015)	Number of workers	Mean monthly real wage (USD 2015)
	2007		**2018**	
Panel A				
Age [25, 40]	551,941	$ 952	509,338	$ 1,330
Age [36, 55]	160,905	$ 1,209	145,260	$ 1,850
Age [56, 65]	281,600	$ 1,276	410,264	$ 1,704
Panel B				
High Tenure	709,560	$ 1,211	819,702	$ 1,683
Low Tenure	284,886	$ 773	245,160	$ 1,084
Panel C				
Quintile 1	209,146	$ 536	232,374	$ 891
Quintile 2	210,699	$ 746	216,218	$ 1,234
Quintile 3	197,635	$ 947	213,624	$ 1,435
Quintile 4	192,044	$ 1,186	212,239	$ 1,642
Quintile 5	184,922	$ 2,136	190,407	$ 2,711

Notes: the figures include workers in our sample, that is, men, stayers, with incomes above the minimum wage. We also restrict our analysis to firms with more than 5 workers.

8.2 IV estimates on sales shocks

Table 12: Earnings effects of sales shocks: IV estimates

	All sectors		Manufacture	
	OLS	IV	OLS	IV
Sales shock	0.057***	0.052***	0.073***	0.069***
	(0.002)	(0.005)	(0.004)	(0.008)
N	9,909,494	9,909,494	2,194,732	2,194,732
Adjusted R2	0.052	0.052	0.066	0.066

Notes: We control for age, age^2, tenure, tenure^2, and number of workers in the firm. We also use year, industry, and year–industry fixed effects. The instrument is a long-term shock (3 years).