The Effects of Firm Volatility on Workers*

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Abstract

While many recent papers have demonstrated the effects of volatility on firms, there has been less attention on the effects of volatility on workers, and on which workers bear this form of risk. Using linked employee-employer data from the United States, we document causal evidence that increases in an employer's stock price volatility negatively affect workers' earnings growth. Low-earning workers experience the largest losses, especially workers who separate from their employers. To study the macroeconomic effects of an increase in firm dispersion, we use a dynamic contracting model with worker moral hazard, fixed per-worker operating costs, and human capital scarring. Our calibrated model qualitatively and quantitatively matches our empirical findings. We feed the path of idiosyncratic firm volatility observed around the financial crisis into our model and find that this alone accounts for 1.06 percentage points (19 percent) of the rise in unemployment between 2007-2009. Taken together, these findings lend support to the connection between increases in cross-sectional firm dispersion in times of crisis and adverse labor market outcomes.

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1 Introduction

Substantial increases in the cross-sectional dispersion of firm-level outcomes have accompanied recent economic crises (Bloom et al. (2018)). A large literature has documented the effects of increased volatility on firms. Economists have consistently found that shocks affecting firms transmit to workers, but there has been much less attention on the effects of volatility on workers. Who bears this risk across the income distribution? Why? Can answering these questions provide insights into how shocks to firms are transferred to workers?

This paper aims to answer these questions. We estimate the effect of firm volatility on workers' long-run earnings growth, and find that workers are negatively affected by their firm's volatility. We find particularly large effects for low-earning workers and job leavers using an instrumental variables approach. We then rationalize these findings in a dynamic contracting model of firm-worker insurance, and demonstrate the importance of human capital scarring and fixed costs in matching the empirical patterns that we document. Finally, we feed the observed rise in cross-sectional firm dispersion around the global financial crisis into the model and show that the model predicts an economically substantial increase in the unemployment rate, demonstrating that part of the observed increase in unemployment was directly driven by increased firm volatility. We find that the recovery of unemployment was slow, as in the data, and find that low human-capital workers were particularly affected by this shock.

This paper makes four contributions to the literature. First, we measure the heterogeneous effects of firm volatility on workers. We combine detailed earnings records covering virtually all jobs in the United States with detailed firm financial data. By linking these two datasets, we are able to measure the causal effect of employers' stock price volatility fluctuations on their employees' long-run earnings growth. To do so, we adopt the instrumental variables approach from the corporate finance literature developed by Alfaro et al. (2024) which exploits heterogeneous industry-level commodity exposure.[1] We find that a one-standard-deviation annual increase in a firm's stock price volatility reduces workers' earnings growth over the next five years by 0.357 percent on average, but this average effect hides substantial heterogeneity across the within-firm earnings distribution. Workers at the bottom of the earnings distribution experience a 1.12 percent decline in earnings while those at the top experience only a 0.19 percent decline. Further, we find that the earnings losses are especially concentrated within-job leavers, with leavers at the bottom experiencing five-year earnings losses of 1.91 percent. We explain these losses among leavers by showing that

[1] This IV approach allows us to take seriously the concerns of potential endogeneity between volatility and workers' earnings growth. Two endogeneity concerns typically discussed in this literature are reverse-causality and simultaneity.

volatility increases the likelihood of adverse forms of leaving a job, such as increasing the probability of low-earning workers experiencing a nonemployment spell by 0.71 percentage points.

The empirical evidence suggests substantial transmission of firm volatility to workers' earnings. Our second contribution is explaining how and why firms transmit fluctuations in risk to workers. To do so, we develop a quantitative model of firm-worker long-term dynamic contracts, where risk-neutral multi-worker firms explicitly insure the consumption stream of risk-averse workers. Firms produce and compensate workers, who privately provide effort (at a cost) to increase the probability of their match surviving between periods, and privately search on-the-job for a new match. Workers have human capital which depreciates in unemployment, and matches can endogenously separate. In the model, adverse tail events receive more probability mass when a firm has elevated productivity volatility. Realization of these adverse events induces firm and worker separations, and the workers' income is no longer insured by the firm post-separation. Following separation, the workers' human capital depreciates, resulting in a reduction in the workers' permanent earnings.

Our third contribution is to show that our quantitative dynamic contracting model can rationalize the empirical facts that we document. Rather than calibrating our model to hit these empirical moments, we leave these effects as untargeted in our model's calibration and instead target relatively standard moments shown by related papers to identify parameters of interest. We then show that our model qualitatively and quantitatively replicates the results of our empirical regressions run on model-simulated data. Next, we highlight the importance of certain model features in generating these effects. We shut down these parts of our model, human capital scarring and per-worker fixed costs, and show that, without either of these model ingredients, the model fails to generate a larger effect of volatility fluctuations on low-earning workers within the firm. Without human capital scarring, the model fails to generate a larger effect of volatility on job-leavers versus stayers, whereas without per-worker fixed costs, the firm fails to generate nonemployment in response to volatility fluctuations.

Our final contribution is to use our model to assess whether the level of increased cross-sectional firm dispersion observed during the global financial crisis can have economically relevant effects on the unemployment rate, as suggested by the models of Schaal (2017) and Arellano et al. (2019). We feed the average idiosyncratic component of firm risk, as measured by Dew-Becker and Giglio (2023), during the financial crisis into our model. We find that increased cross-sectional firm dispersion alone accounts for about 1.06 percentage points of the increase in unemployment over the period (5.5 percentage points between 2007Q1-2009Q4). The unemployment rate in the model features a slow recovery, consistent with the evolution of the unemployment rate observed over the period. We find substantial heterogeneity in the welfare consequences of the transition; low-earning workers are made worse off while high-earning workers benefit. We compute the transition in the alternative models, which we previously showed to be inconsistent with our empirical evidence, and find less severe and less prolonged effects of firm idiosyncratic volatility on the unemployment rate, suggesting that the mechanisms behind the effects of firm volatility that we measure empirically have important implications for the macroeconomic effects of increased firm dispersion on the unemployment rate.

Related Literature.

Our work lies at the intersection of several fields, each of which we contribute to. First, our work relates to the literature describing the contracting relationships between workers and firms. Dating back at least as far as Knight (1921), economists have long theorized that firms play a critical role in insulating workers from fluctuations. The advent of linked employee-employer datasets beginning in the early-2000s enabled the direct empirical testing of implications from these theoretical models. It has generally been found that firms play an important role in absorbing risk from workers, although firms provide incomplete insurance to their workers. Recent papers have closed the gap between the literature on the relationships between workers and firms and the literature documenting the macroeconomic effects of volatility. Building off of the seminal work of Bloom et al. (2007), Bloom (2009), and Baker et al. (2016), this literature has found that second-moment fluctuations in the economy can have first-moment effects on a variety of economic and financial outcomes. Important recent contributions to this literature have made the connection between volatility fluctuations and outcomes for workers, such as job flows and the unemployment rate. Our work aims to connect the final dots linking these literatures together by providing empirical evidence with detailed administrative data on firms and workers, and applying a quantitative theoretical model of firm-worker interaction.

We firstly contribute to the empirical literature quantifying the transmission of shocks from firms to workers. Building off of the work of Guiso et al. (2005), this literature has shown not only that firm shocks transmit to workers, but also that this transmission has great heterogeneity across workers. Juhn et al. (2018) and Kogan et al. (2024) provide recent examples of this in the United States, and have shown that shocks to firms' first moments (revenue, and successful innovation) transmit to workers, but in particular to high-earning workers within the firm. We contribute to this literature by documenting the effects of firm volatility fluctuations to workers' long-run earnings growth, and by measuring the heterogeneous effect of volatility on high-versus low-earning workers within the firm. We then use the detailed nature of our administrative earnings dataset to trace out the mechanisms underlying the effects that we document.

Theoretical work formalizing the ideas of Knight (1921) has detailed the relationship between firms and workers for over 50 years, with early contributions from Baily (1974), Azariadis (1975), Harris and Holmström (1982), and Fernandes and Phelan (2000). Burdett and Coles (2003), Stevens (2004), and Shi (2009) have early contributions of deriving optimal wage-tenure contracts in a frictional search environment. Tsuyahara (2016) studies a contract where non-contractable worker effort affects the job retention probability. Balke and Lamadon (2022) build upon this literature, characterizing and estimating a quantitative dynamic contracting model which forms the starting point from which our theoretical model builds to match our empirical facts. We add to this literature by highlighting the components required for this class of models to match the transmission of firm volatility to workers' earnings growth.

An emerging strand of literature uses empirical findings of shock transmission from firms to workers to inform theoretical models of long-term contracts between workers and firms, such as the work of Souchier (2023) and Citino and Malgieri (2025). Relative to these papers, we use our empirical findings not only to match the transmission of a shock to pin down model forces, but to match the mechanisms underlying this transmission and to rule out alternative candidate models. We then use our validated model of firm-worker interaction to assess the macroeconomic effects of a rise in cross-sectional firm dispersion as observed in recent economic downturns.

We help bridge the gap between the literatures just discussed, which examine the relationship between workers and firms, and the literature documenting the effects of volatility on economic and financial outcomes spearheaded by Bloom et al. (2007), Bloom (2009), and Baker et al. (2016), with other recent contributions by Julio and Yook (2012), Ludvigson et al. (2021), and Baker et al. (2024). We relate most closely to Di Maggio et al. (2022), who empirically documents the short-run pass through of firm volatility fluctuations to workers' earnings. Relative to this literature, we make several contributions. First, we take seriously concerns of the endogeneity between firm volatility fluctuations and outcomes (see, e.g., Leahy and Whited (1996), Bloom et al. (2007), Bachmann and Moscarini (2012), Stein and Stone (2013), Gilchrist et al. (2014), Orlik and Veldkamp (2015), Berger et al. (2016), Fajgelbaum et al. (2017)) and instrument for firm volatility fluctuations using the instruments developed by Alfaro et al. (2024). Secondly, we focus on the effects of volatility on long-run earnings growth. This focuses our analysis on effects of volatility on workers' permanent earnings. Recent papers such as Braxton et al. (2025a) and Braxton et al. (2025b) show that permanent earnings changes, as opposed to temporary earnings changes, are the form of earnings changes to which individuals respond in terms of pulling economic levers such as moving to worse neighborhoods, withdrawing early from 401(k)s, and defaulting on various forms of debt. Third, we trace out the mechanisms through which this transmission occurs, leveraging the strengths of our datasets and demonstrating that these effects are concentrated within-job leavers.

Finally, our paper relates to the literature explaining the connection between the unemployment rate and economic uncertainty. Much of this literature shows how fluctuations in aggregate uncertainty or risk premium can generate fluctuations in unemployment, relating to the solution proposed by Hall (2017) to the Shimer (2005) puzzle (see, e.g., Leduc and Liu (2016), Basu and Bundick (2017), Meeuwis et al. (2025), Kehoe et al. (2023), Di Della and Hall (2022)). A branch of this literature to which this paper most clearly relates (Schaal (2017); Arellano et al. (2019)) seeks to explain the relationship between firm idiosyncratic risk (that is, cross-sectional dispersion of firm-level outcomes) and the dynamics of the unemployment rate. To this literature, we make several contributions. First, we use detailed administrative microdata to directly assess the impact of firm volatility fluctuations on their workers. Next, we rationalize these findings within a model of firm-worker interactions in which firms are explicitly providing consumption insurance to their workers, and show that this model can rationalize the micro-evidence that we provide. We then quantify the effect that an increase in cross-sectional firm dispersion as observed in the financial crisis can have on the unemployment rate. Finally, we show that the effects of such fluctuations are very heterogeneous, with low-earning workers negatively affected by such fluctuations whereas high-earning workers are positively affected.

The paper proceeds as follows. Section 2 describes our dataset, empirical strategy, and results. Section 3 describes our theoretical model, the calibration of which we describe in Section 4. In Section 5, we show that our model can replicate our empirical facts. We use the model to quantify the macroeconomic implications of increases to a common component of firm idiosyncratic volatility in Section 6. Finally, Section 7 concludes.

2 Estimating the Impact of Volatility Fluctuations on Workers' Earnings

We begin by empirically estimating the direct effect of firm volatility fluctuations on workers' earnings growth. We do so by constructing a dataset linking U.S. administrative earnings data to detailed data on workers' employers.

2.1 Administrative Earnings Dataset

The Longitudinal Employer-Household Dynamics (LEHD) database, accessed through the U.S. Census Bureau, comprises our starting point. The LEHD database is a matched employee-employer dataset covering over 95% of jobs. Our sample consists of all 50 states, plus Washington D.C., from 1990-2014.[2] We draw a random five percent sample of individuals for convenience. For each individual drawn, we observe all earnings from all employers in the LEHD, from all years.

The LEHD is a panel dataset that contains not only information on workers' earnings, but also, critically, on employers. We use this information to link individuals' earnings records to financial data for public firms available through Compustat. We perform this merge by first defining individuals' *primary employer* as the unique federal employer identification number (FEIN) from which the individual received the most income in a calendar year. We then compute the total amount of earnings received in a calendar year for each individual as the individual's annual labor earnings, including earnings received from employers that are not the individual's primary employer. Finally, we use internal Census crosswalks to merge FEINs reported in the LEHD to the Compustat identifier, $GVKEY$, for each calendar year. This process results in a panel dataset of worker earnings where employees that work for a public firm as their primary employer in a year are tagged with that firm's identifier, and Compustat data for that firm-year are merged in a straightforward way. We will henceforth refer to $GVKEY$ as the definition of a firm for the rest of the paper, except when specified otherwise, but note that our dataset also contains workers' earnings for workers who work for firms other than Compustat firms, with the $GVKEY$ identifier coded as missing for these workers. Hence, while workers will need to be employed at a Compustat firm for at least a period to be included in our regression specifications, we can track the evolution of their earnings before and after regardless of whether or not the worker works in a Compustat firm.

After merging the LEHD with Compustat, other merges based on the $GVKEY$ identifier are straightforward. We perform one such merge to the replication files from the supplementary materials of Alfaro et al. (2024). This provides us with key variables used in our analysis, including their firm-level volatility measures, controls, and instruments. The data provided by Alfaro et al. (2024) are described in detail in their paper and appendix, but we also summarize this information below.

[2] States enter the LEHD in a staggered fashion at the beginning of our sample, but our baseline volatility measure (described in detail in the next subsection) enters the sample in 1996 so for the relevant portion of our sample, our dataset covers almost the entirety of all jobs in the United States.

2.2 Firm Volatility Data

We use two variables provided by Alfaro et al. (2024) as proxies for underlying firm fundamental volatility: option-implied stock price volatility and realized stock price volatility. The use of high-frequency equity market data for the measurement of firm volatility allows for well-measured time-varying volatilities at the firm level which would be otherwise impossible to obtain from the firm data available from the Census Bureau directly, such as the annual Longitudinal Business Dynamics (LBD) dataset.

Alfaro et al. (2024) construct implied volatility from options data obtained from OptionMetrics. They define annual implied volatility as the 12-month average of firms' daily option-implied volatility, where daily implied volatility is the average of the implied volatility from forward 365-day-horizon at-the-money call and put options. They define realized volatility as the annualized 12-month standard deviation of firms' cum-dividend daily stock returns. Implied volatility is available beginning in 1996, whereas realized volatility is available throughout our full sample.

In addition to measures of firm-level volatility, Alfaro et al. (2024) provide two other critical sets of variables that we will now describe. We use the instruments from Alfaro et al. (2024) to isolate the true effect of volatility on outcomes from potentially substantially endogenous relationships between firm volatility and outcomes of interest. The second critical set of measures are controls for correlated first-moments related to the instruments.

Volatility Instruments. Here we summarize the intuition behind and construction of the instruments from Alfaro et al. (2024). The instruments exploit heterogeneous exposure to macroeconomic sources of variation in volatility, with a shift-share-style design. Consider, for example, oil prices. Some firms' stock prices are positively correlated with oil prices, some are negatively correlated, while others are uncorrelated. When uncertainty over oil prices rises, the uncertainty over stock prices for firms with positive and negative correlation rises, while for uncorrelated firms uncertainty over stock prices is unchanged. Crucially, year fixed effects absorb the change in macro volatility induced by this increase in oil price volatility, which we include in all regression specifications. Changes in the level of oil prices, which correlate with second-moment fluctuations, are controlled for by heterogeneous exposure to oil price changes. In addition to oil prices (measured by West Texas Intermediate), the macro-sources of volatility exploited in a similar way by Alfaro et al. (2024) include the volatility of the exchange rate versus the U.S. dollar for the seven major currencies as defined by the Federal Reserve Board[3] as well as the changes in economic policy uncertainty from Baker et al.

[3]These currencies are the euro, British pound, Japanese yen, Swiss franc, Swedish krona, and Canadian and Australian dollars.

(2016).

To construct these instruments, Alfaro et al. (2024) begin by measuring the exposure of firms' first moments to the first-moment changes in the sources of macroeconomic fluctuations. Specifically, they estimate the following:

$$r_{i,t}^{risk\_adj} = \alpha_n + \sum_c \beta_n^c r_t^c + \epsilon_{i,t}, \tag{1}$$

where $r_{j,t}^{risk\_adj}$ is firm j's risk-adjusted daily stock returns and r_t^c is the daily price change of commodity c, and where n is the 2-digit Standard Industrial Classification (SIC) code of the firm. Risk-adjusted stock returns are the residuals from firm-level regressions of the firm's stock returns on the four-factor asset pricing model of Carhart (1997). The regressions are run at the industry-level to reduce the role of idiosyncratic noise in driving the exposure estimates, and rolling five-year windows are used so that the exposure estimates for each industry are time-varying. Exposures used in the analysis are lagged by three years to predate control and outcome variables.

After estimating the exposures to sources of macro-variation, the instruments $z_{j,t}^c$ are constructed as follows:

$$z_{j,t}^c = |\beta_n^c| \times \Delta\sigma_t^c, \tag{2}$$

where the volatility term σ_t^c is the 252-trading day (number of trading days in one year) standard deviation of daily returns on crude oil prices, the 252-trading day standard deviation of daily changes in bilateral exchange rates against the U.S. dollar, and the 252-trading day average of the EPU index from Baker et al. (2016). The instruments thus have the structure of a shift-share instrument, where the "shift" is the change in volatility originating from a source of macroeconomic fluctuations, and the "share" is the magnitude of the exposure of the firm's 2-digit SIC industry to that source of variation.

The second critical set of variables provided by Alfaro et al. (2024) used in our analysis are first-moment controls related to each instrument. These controls isolate the second-moment effects from the correlated first-moment changes. To understand the intuition of how the first- and second-moment effects are disentangled, let us revisit our example of firms and the oil industry. When firms are positively affected by oil prices, neutral with respect to oil prices, or negatively affected by oil prices, their second-moments are positively exposed to increased uncertainty over oil prices, unexposed, and positively exposed, respectively. Since firms that are positively and negatively exposed to the first moment of oil price changes are both positively exposed in terms of volatility to increases in oil price uncertainty, the separate effects of first-moment and second-moment changes in uncertainty can be disentangled by controlling for first-moment exposure to oil price changes. More generally speaking, controls for first moment exposures to commodity changes are given by the product of the firm's exposure to the commodity and the change in first moment of the commodity:

$$x^c_{j,t} = \beta^c_n \times r^c_t, \tag{3}$$

where r^c_t are the annual growth rates in oil prices, foreign currency prices, and four-quarter average of government expenditures as a share of gross domestic product for the nine sources of macroeconomic uncertainty.

In addition to the volatility instruments $z^c_{i,t}$ and first-moment controls x^c_t, we additionally merge in all firm controls used by Alfaro et al. (2024). These controls include additional first-moment controls at the firm level (the firm's 12-month compounded stock return and Tobin's Q to capture the changes and level of the firm's first moment), financial controls following Leary and Roberts (2013) (tangibility, book leverage, return-on-assets, firm size), and other firm controls (investment rate, change in employment, change in intangible investment, change in cost of goods and services, change in sales, change in corporate payout, change in debt, and change in cash holdings). We include all firm controls in all specifications.

2.3 Sample and Variable Definitions

While the LEHD covers nearly all jobs in the U.S. in our sample, it is impossible to tell whether an individual who permanently leaves our dataset has remained in the labor force but made zero income, or has exited the labor force due to retirement, health issues, or any other reason. Hence, we impose relatively few sample restrictions to attempt to ensure that individuals in our sample have some attachment to the labor force. First, we require that workers be of prime working age, which we define as being between the ages of 25 and 60, inclusively. Next, we require that they earn at least $3350 in 2005 dollars, deflated with PCE, in at least two calendar years.[4] We consider each year (inclusively) between the first and last instance of earning above $3350 to be the individuals' *interior years*. We then only include individuals' interior years in our analysis file. Given our focus on long-run earnings changes, an individual must have at least six interior years to be in our least restrictive sample, and at least eight interior years to be in our longest-horizon sample.

We focus on long-run earnings changes in order to focus on the effect of firms' volatility

[4]This is roughly the average real earnings amount to qualify for four Social Security Administration credits within a year over our sample.

fluctuations on workers' *permanent* earnings changes.[5] We define earnings growth rates for individual i for the time horizon $t : t+h$, $g_{i,t+h}$, as the log difference between the individual's three most recent years of income at t and their h-year forward income:

$$g_{i,t:t+h} = \log\left(\sum_{\tau=t+1}^{t+h} Y_{i,\tau}\right) - \log\left(\sum_{\tau=t-2}^{t} Y_{i,\tau}\right),$$

where $Y_{i,\tau}$ is individual i's real earnings in year τ, and where $h \in \{3,4,5\}$. Longer horizons (larger h) put more weight on permanent earnings changes, as opposed to temporary earnings changes.

For our analysis, we focus on the heterogeneous impact of volatility fluctuations on workers' earnings growth, across the distribution of income within the firm. Our baseline approach ranks workers within Compustat firm j by the workers' *recent earnings* $w_{i,t}$, the three most recent years of income for the worker with an adjustment for the worker's age:

$$w_{i,t} = \log\left(\sum_{\tau=t-2}^{t} Y_{i,\tau}\right) - \log\left(\sum_{\tau=t-2}^{t} \bar{Y}(\text{age}_{i,\tau})\right), \tag{4}$$

where $\bar{Y}(a)$ is the average real earnings of an individual in our sample years of the LEHD at age a, $\text{age}_{i,\tau}$ is the age of individual i in year τ, and where the second sum is an age-adjustment.[6] The age adjustment terms need not be included in our definition of earnings growth $g_{i,t:t+h}$ as they are absorbed by age fixed effects which are included in every regression specification. After ranking individuals by their recent earnings $w_{i,t}$ within their firm j in year t, we bin the individuals according to their percentiles within firm j's recent earnings distribution in year t. We require that we observe at least 50 individuals in each firm-year in order to have accurate rankings, and we bin individuals into six bins: percentiles 1-5, 6-10, 11-25, 26-50, 51-75, and 76-100. We have more detailed bins at the bottom of the earnings distribution due to our focus on the pass-through of volatility at the bottom of the earnings distribution.

To be included in the regression, given our focus on regressors derived from public firms' stock price data, individuals must be employed by a Compustat firm in year t, and that

[5] Braxton et al. (2025b) and Braxton et al. (2025a) show that individuals respond much more to persistent and permanent earnings changes as opposed to temporary changes, in the context of foreclosures, chargeoffs, and other forms of default, as well as moving to lower income neighborhoods and withdrawing early from 401ks.

[6] Our baseline results rank individuals with the age adjustment, although the results are very insensitive to this adjustment, and we perform robustness checks with this adjustment turned off.

Compustat firm must be from an SIC code that is not excluded from our analysis.[7] However, we track the individuals' income even when not employed by a Compustat firm. Given that Compustat firms employ approximately 1/3 of the U.S. population in a given year,[8] there is some nontrivial selection into our sample although our sample also exhibits great heterogeneity and describes individuals across the unconditional earnings distribution. We describe the individuals in our samples and in our recent earnings bins in Table 1.

Table 1 provides summary statistics on age, sex and real earnings in year t across recent earnings bins, for different earnings growth horizon samples. The recent earnings bins included here are our baseline bins, where recent earnings $w_{i,t}$ are age-adjusted. Several patterns are clear from this summary. First, the age-adjustment of earnings helps to keep the distribution of ages relatively flat across recent earnings bins. Men make up a larger share of the highest earning group within a firm (about 71-72 percent of individuals in percentiles P76-100 for all samples). This pattern suggests that it will later be important to control for permanent differences across individuals in our analysis. We include individual fixed effects in all specifications to do so. Finally, Table 1 reports the average real earnings in date t for individuals in each recent earnings bin. Although recent earnings rankings use age-adjusted recent earnings, the level of current earnings varies dramatically across recent earnings bins.[9] We will also later account for this difference in earnings across bins by including cubic polynomials of age-adjusted recent earnings in each specification, as well as recent earnings bin fixed effects to account for any other permanent differences across recent earnings bins.

2.4 Empirical Approach

Let $\sigma_{j,t}$ be a measure of firm j's volatility in year t, $\Delta\sigma_{j,t}$ the first difference $\Delta\sigma_{j,t} = \sigma_{j,t} - \sigma_{j,t-1}$, and let $X_{i,t}$ be a vector of controls (a third degree polynomial in age-adjusted recent earnings $w_{i,t}$, the 23 firm controls from Alfaro et al. (2024), and fixed effects for year, worker's age, firm, individual, and age-adjusted recent earnings bin). We estimate the impact of firm volatility fluctuations on workers' long-run earnings growth $g_{i,t:t+h}$ using the following specification in equation (5):

$$g_{i,t:t+h} = \beta_h \Delta\sigma_{j,t+1} + \Gamma X_{i,t+1} + \varepsilon_{i,t} \tag{5}$$

[7] Consistent with Alfaro et al. (2024), we exclude utilities, finance, and real estate from our analysis. These firms operate in ways that are thought to be fundamentally different from other firms in the economy, and presumably this holds true in terms of the relationship between employer and employee as well.

[8] Davis et al. (2006).

[9] Perhaps unsurprisingly given this fact, our results will later turn out to be robust to whether the ranking within-firm is age-adjusted or not.

Table 1: Baseline Sample Descriptions by Horizon and Earnings Percentile Bins

Variable	All	P1–5	P6–10	P11–25	P26–50	P51–75	P76–100
Panel A: Horizon $h = 3$, N = 7,494,000							
Age	41.49	42.23	42.95	43.06	42.37	40.91	40.12
Female	0.429	0.610	0.613	0.579	0.490	0.386	0.286
Real Earnings	58,760	14,450	21,250	28,220	38,860	53,510	109,500
Panel B: Horizon $h = 4$, N = 6,634,000							
Age	41.05	41.75	42.47	42.55	41.90	40.52	39.75
Female	0.429	0.617	0.618	0.583	0.492	0.385	0.284
Real Earnings	58,690	14,460	21,270	28,250	38,810	53,280	108,400
Panel C: Horizon $h = 5$, N = 5,813,000							
Age	40.61	41.26	41.94	42.03	41.42	40.12	39.39
Female	0.428	0.622	0.623	0.586	0.494	0.385	0.282
Real Earnings	58,600	14,550	21,330	28,280	38,770	53,080	107,200

Notes: Table 1 describes the baseline samples in the analysis. Panel A describes the sample which is matched with a Compustat firm at t and has three-year earnings growth $g_{i,t:t+3}$ defined. Panel B describes the sample which is matched with a Compustat firm at t and has four-year earnings growth $g_{i,t:t+4}$ defined, while Panel C describes the sample which is matched with a Compustat firm at t and has five-year earnings growth $g_{i,t:t+5}$ defined. Averages for descriptive variables are reported for each sample as a whole ("All"), as well as for each recent earnings bin used in the analysis (P1-5, P6-10, P11-25, P26-50, P51-75, P76-100). Recent earnings bins are based on age-adjusted recent earnings $w_{i,t}$ as defined in equation (4). The average age is quite similar across groups for each sample, while the distributions of sex and real earnings vary substantially across groups. In later regressions, permanent differences across individuals are accounted for by individual fixed effects in every regression while mean reversion in earnings is accounted for by polynomial controls for recent earnings, as well as fixed effects for recent earnings bins. All averages reported in this table have been rounded to four significant digits for disclosure reasons.

In equation (5), β_h captures the effect of firm volatility fluctuations on workers' earnings growth at an h-year horizon. If workers were unaffected by idiosyncratic firm volatility innovations, we would expect $\beta_h = 0$. If instead increases in firm volatility transmit negatively to workers' earnings growth, we would observe $\beta_h < 0$.

The firm volatility literature has demonstrated an endogenous relationship between firm volatility and firm outcomes. This endogeneity may then persist in equation (5), which violates the OLS assumption of orthogonality between the regressor and residual and induces bias in estimates of β_h using OLS. To tackle this challenge, we apply a 2SLS approach using the vector of instruments $Z_{j,t} = [z^1_{j,t}, z^2_{j,t}, \ldots, z^9_{j,t}]$ from Alfaro et al. (2024), also described in Section 2.2, and estimate the following systems of equations:

$$g_{i,t:t+h} = \beta_h \widehat{\Delta\sigma_{j,t+1}} + \Gamma X_{i,t+1} + \varepsilon_{i,t} \tag{6}$$

$$\Delta\sigma_{j,t+1} = \gamma Z_{j,t} + \zeta X_{i,t+1} + u_{i,t}, \tag{7}$$

where $\widehat{\Delta\sigma_{j,t+1}}$ in the second stage regression (6) is the predicted value from the first stage regression (7). The validity of our instruments relies on the assumptions of relevance and exogeneity. We demonstrate the validity of our instrument by directly testing the relevance in Section 2.5 and estimate a series of extensive robustness checks to provide evidence as to the instruments' exogeneity.

Heterogeneous impact. We empirically estimate the heterogeneous impact of volatility on workers as a function of the workers' recent earnings. To do so, we define indicator variables B_p which take a value of 1 if the worker is in recent earnings bin p, and 0 otherwise. As before, we use percentile bins $p \in \{\mathrm{P1}-5, \mathrm{P6}-10, \mathrm{P11}-25, \mathrm{P26}-50, \mathrm{P51}-75, \mathrm{P76}-100\}$. We then estimate the following regression:

$$g_{i,t:t+h} = \sum \beta_{h,p} \Delta\sigma_{j,t+1} \times B_p + \Gamma X_{i,t+1} + \varepsilon_{i,t}, \tag{8}$$

where the heterogeneous impact of volatility fluctuations is given by $\beta_{h,p}$. We note that the base terms of the interactions in (8) are the bin fixed effect terms included in $X_{i,t+1}$. We again estimate this regression via 2SLS IV, and construct our instruments for the heterogeneity analysis by interacting the instruments from Alfaro et al. (2024) with the indicators B_p for recent earnings bin. That is, we use 9×6 instrumental variables which are defined as $z^c_{j,t} \times B_p$, for all (c, p) pairs, where c are the commodities underlying each instrument and p are the recent earnings percentile bins.

2.5 Estimates: Volatility Fluctuations and Workers' Earnings

We next turn to our empirical estimates of the impact of firm volatility fluctuations on workers' earnings. We estimate this using the IV approach defined in Section 2.4. The results of the IV regression are reported in Table 2.

Table 2: 2SLS: Effect of a one standard deviation Implied Vol Δ on $g_{i,t:t+h}$ (as a %)

	$h = 3$	$h = 4$	$h = 5$
Implied Vol Δ	-0.573***	-0.465***	-0.357***
	(0.134)	(0.107)	(0.115)
23 Firm Controls	Y	Y	Y
Recent Earnings Cubic	Y	Y	Y
Firm Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Individual Fixed Effects	Y	Y	Y
Age Fixed Effects	Y	Y	Y
Recent Earnings Bin Fixed Effects	Y	Y	Y
Kleibergen-Paap rk Wald F Stat	489.4	428.9	394.1
Observations	7494000	6634000	5813000
Within R^2	0.206	0.257	0.313

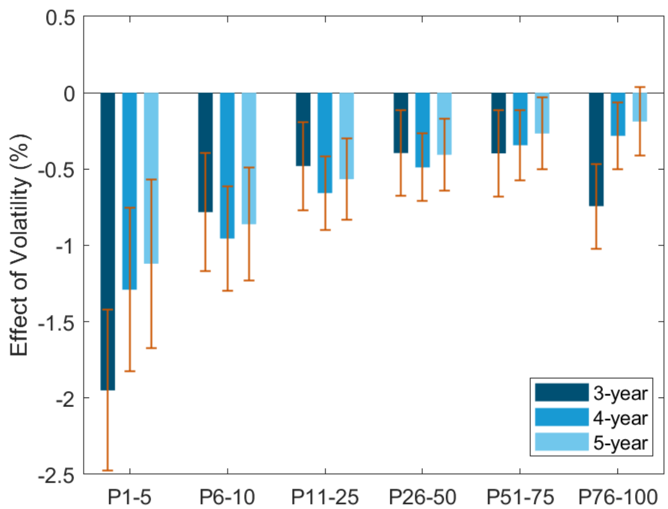
Notes: Implied Vol Δ is scaled to have unit standard deviation; coefficients interpreted as the effect of a unit standard deviation change in implied volatility on h-year real earnings growth (as a percent). From left to right, columns indicate a horizon of three, four, and five years. All specifications include 23 firm controls from Alfaro et al. (2024), a cubic polynomial in age-adjusted recent earnings, and fixed effects for firm, year, individual, age, and recent earnings bin. The Kleibergen-Paap rk Wald Statistic values well above 10 indicate that the instruments are not weak. Standard errors are clustered at the establishment level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2 reports the results of running the 2SLS IV regression from (6), (7). Implied volatility changes are scaled to have unit standard deviation entering the regression and are reported in percents. We find that, on average, volatility negatively affects workers' real earnings growth. The magnitude of the effect is largest for the growth of three-year earnings, but remains substantial for longer horizons. We estimate that a one standard deviation change in volatility reduces three-, four- and five-year real earnings growth by -0.573 percent, -0.465 percent, and -0.357 percent, respectively. All specifications include the 23 firm controls from Alfaro et al. (2024), a cubic polynomial in age-adjusted recent earnings, and fixed effects for firm, year, individual, age, and recent earnings bin. The estimated effects are significant at the 1 percent level for all horizons.

Additionally, Table 2 reports the Kleibergen-Paap rk Wald F Statistic, which tests for weak instruments. All specifications have the F stat above 350, well exceeding the rule-of-thumb threshold of 10 and suggesting the instruments are not weak.

Heterogeneous impact. We now present our main results on the heterogeneous impact of volatility fluctuations on workers' long-run real earnings growth. We estimate equation (8) using the instrumental variables approach as described in Section 2.4. The results are presented in Figure 1.

Figure 1: Heterogeneous Effect of Volatility on Workers



Notes: Figure 1 reports the results of estimating equation (8), instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with workers' recent earnings bins. The grouped bars, from left to right, report the estimated coefficients for the effect of a one standard deviation increase in volatility on real earnings growth over three-, four-, and five-year horizons, respectively. The effect of volatility increases on real earnings growth is most negative for low-earning workers within the firm (percentiles 1-5 of the within-firm recent earnings distribution), and generally the magnitude of the effect declines as the level of recent earnings for the workers increases. The exception is a slight inverted-U-shaped effect for the three-year horizon where workers in percentiles 76-100 experience a relatively large in magnitude, negative effect - that this feature dies out for longer horizons suggests that this effect is transitory in nature. Standard errors are clustered at the establishment level and 95 percent confidence intervals are reported.

Figure 1 shows that, for all horizons, the impact of volatility fluctuations is the most negative for workers at the bottom of the (age-adjusted) recent earnings distribution, percentiles 1-5, and the magnitude of the impact generally declines as the recent earnings percentile of the worker increases. For the shortest horizon, three years, there is a slight inverted U-shape where the impact at the top of the earnings distribution ticks up slightly. This feature does not survive when looking at the longer four- and five-year horizons, suggesting that this impact at the top of the distribution for the three-year horizon is temporary in nature.

There exists a substantial difference between the average impact of volatility and the impact of volatility for workers at the bottom of the recent earnings distribution. A one-standard deviation volatility fluctuation reduces real earnings growth for workers in P1-5 at a three-, four-, and five-year horizon by 1.95, 1.29, and 1.12 percent, respectively. This suggests that the impact of volatility at the bottom of the firm's earnings distribution is between 2.8 and 3.4 times the magnitude of the average effect for different earnings growth horizons.

We provide extensive robustness checks for these results in Appendix A. First, we show that these patterns of heterogeneous impact are not driven by any instrument or group of instruments that may violate the exclusion restriction. We do so by showing that our results are robust to leaving any one instrument out of the regression, and to only including the foreign-exchange based instruments, or by leaving out the foreign-exchange based instruments and only including oil and economic policy uncertainty.

We next address potential violations of the exclusion restriction owing to omitted variables that may be correlated with the instrument, endogenous explanatory variable, and residual. We consider two robustness checks. First, we remove the year fixed effects in our regression and replace them with 1-digit SIC sector-by-year fixed effect. As the instruments vary at the 2-digit SIC industry-by-year level, this 1-digit SIC sector-by-year fixed effect controls all time-varying effects, such as technological change, that are common to a sector over time while not absorbing all of the variation within the instruments. The results hold in this exercise as well.

In our second robustness exercise, we exclude the firm and year fixed effects but include firm-by-year fixed effects. This absorbs much of the variation within our regressions, including that of the 23 firm controls from Alfaro et al. (2024) as well as that of the original nine volatility instruments. Despite the reduction in variation, we still identify heterogeneous impacts of volatility on workers within a firm relative to a base group, which we take to be the top group within the firm, P76-100. The firm-by-year fixed effects absorb time-varying factors affecting each firms' workers. Then, firms' volatility is allowed to heterogeneously affect the other groups within the firm (i.e. P1-5, 6-10, etc.) *relative to the base group.* In running these regressions, we exclude the firm controls, the heterogeneity term for the base group (e.g. $\Delta\sigma_{j,t+1} \times B_p$ for the top percentile bin), and the instruments interacted with the top group's indicators. We are left with controls for the workers' (age-adjusted) recent earnings as well as the firm-by-year, individual, age, and recent earnings bin fixed effects. Our results are very robust to the inclusion of either 1-digit SIC fixed effects or 2-digit-by-year fixed effects, as we show in Appendix A.

The results of this section show that workers at the bottom of firms' recent earnings distribution suffer a large decline in real earnings growth over three-, four-, and five-year horizons. This pattern contrasts with the standard finding in the firm pass-through literature studying the incidence of first-moment shocks, which typically find larger incidence at the top of the firm's recent earnings distribution.[10] We next explore the mechanisms through

[10] We show in Appendix A that this pattern from the literature, that first-moment fluctuations pass-through at the top of firms' recent earnings distribution, does hold for our sample as well.

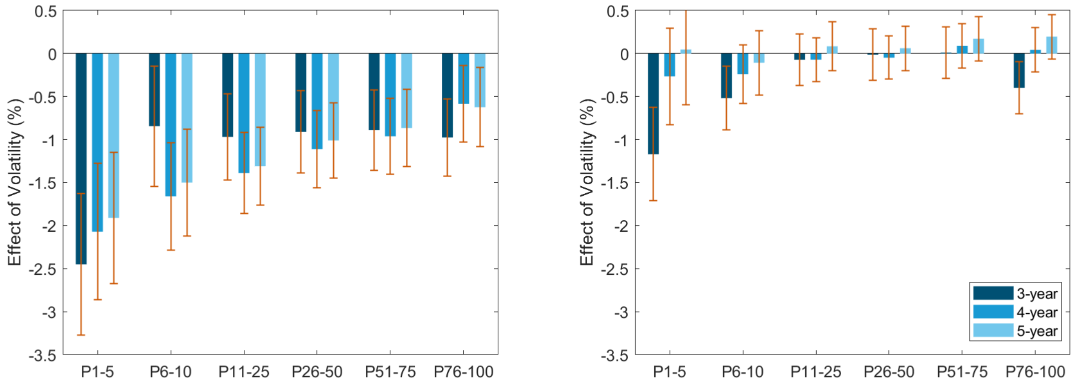
which volatility fluctuations impact low-earning workers.

2.6 Mechanisms

The labor literature has long understood job transitions as a key determinant of changes in workers' labor earnings. We therefore explore job transitions among low-earnings workers in the wake of a firm's increased volatility.

We begin our investigation by conditioning the effect of volatility fluctuations on workers' earnings growth on whether or not a worker has left the firm by our shortest horizon of interest, three years out (we will refer to this as the worker's *leaver/stayer status*). We define a stayer as an individual whose primary employer in $t+3$ is the same as their primary employer in t. We estimate heterogeneity of the effect along this dimension by redefining the bins of workers B_p to be over the interaction of their recent earnings bin and leaver/stayer status. We then estimate $6 \times 2 = 12$ coefficients of interest, instrumenting for the potentially endogenous volatility terms with $9 \times 6 \times 2 = 108$ instrumental variables which are defined as the instruments from Alfaro et al. (2024) interacted with the recent earnings bin-by-leaver/stayer indicators. The recent earnings bin fixed effects are then replaced with recent earnings bin-by-leaver/stayer fixed effects. We present the results of this 2SLS IV regression in Figure 2.

Figure 2: Effects within Leavers and Stayers



(a) Leavers

(b) Stayers

Notes: Figure 2 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. Within each panel, the effects are reported across recent earnings percentile bins, and each group of bars represents the effect of volatility fluctuations on three-, four-, and five-year real earnings growth from left to right. The effect of volatility fluctuations is almost entirely incident upon job leavers, as reflected by the much larger magnitudes of the effect of these workers relative to job stayers. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

As Figure 2 verifies, the impact of volatility fluctuations on workers' real earnings changes is almost entirely driven by leavers, especially at the bottom of the recent earnings distribution. Panel (a) shows the effect within-leavers, with results for three-, four-, and five-year horizons presented from left to right within each bar grouping, where each bar grouping is for the (age-adjusted) recent earnings bin of the workers. For each horizon, the largest impact is at the bottom of the earnings distribution for leavers. For the three-year horizon, the effect is relatively flat for percentile bins above the bottom group (P6 and above), whereas for the four- and five-year horizons, the effects are largest in magnitude at the bottom and decline in magnitude as the recent earnings of the workers increases. Panel (b) of Figure 2 shows the estimated effect of volatility fluctuations on job stayers. At the shorter three-year horizon, workers experience a nontrivial negative effect of volatility on real earnings growth, especially for very low-earning workers (P1-5 and P6-10) and for the highest earning workers (P76-100). For longer horizons, the effect of volatility fluctuations on workers' earnings growth is very small and both economically negligible and statistically insignificant. Hence, we conclude that the effect of volatility fluctuations on workers' real earnings growth is driven by job leavers, especially for long horizons.

While Figure 2 is highly suggestive, it does not explain why the effect of volatility is so highly concentrated within-leavers. On the surface, it is not obvious why a firm's volatility would matter after a worker leaves the firm. Thus far, we have made no distinction between job leavers who make job-to-job transitions and those who separate into nonemployment. We posit that increases in firm volatility impact the types of separations, leading for example to more separations into nonemployment, or to job-to-job transitions to lower-paying positions. While workers may no longer be directly affected by their prior firm's volatility, their reason for separation has a substantial impact on their earnings growth.

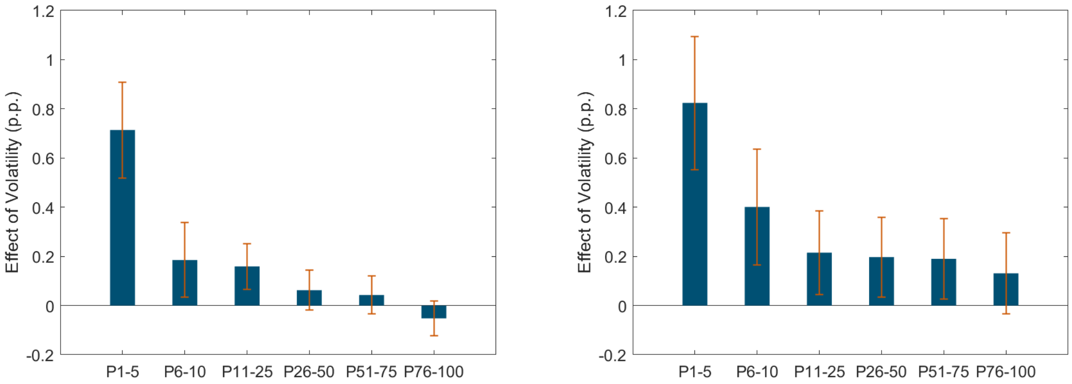
We define proxies for adverse separations to help us evaluate this possible mechanism.[11] In particular, we define a *nonemployment spell* as a worker undergoing a full calendar year with no income. We also define a *costly separation* as a change in primary employer occurring in the same year as a substantial real earnings decline.[12] We consider both of these as adverse separations, and proceed by estimating whether volatility fluctuation induce higher probabilities of these events occurring.

For both the nonemployment spells and costly separations, we estimate the effect of volatility fluctuations on the likelihood of these events occurring by estimating equation (8), replacing workers' real earnings growth on the left-hand-side with an indicator variable for whether the worker experienced the event of interest within three years. As before, we instrument for the uncertainty terms with the fifty-four instruments constructed as the interaction between the recent earnings bins and the volatility instruments from Alfaro et al. (2024). We present the results of the effect of volatility fluctuations on nonemployment spells and costly separations in Figure 3.

[11] Our dataset does not contain information on whether the worker was fired or left voluntarily, so we cannot use *being fired* as an adverse event to check for.

[12] A drop in earnings worse than the tenth-percentile of the log real earnings change distribution.

Figure 3: Heterogeneous Effect of Volatility on Nonemployment and Costly Separations



(a) Nonemployment

(b) Costly Separation

Notes: Figure 3 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. Increases in volatility are associated with increases in both indicators for adverse events, especially for workers at the bottom of the within-firm recent earnings distribution. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure 3 shows that increases in a firm's volatility increases the probability of adverse separations, especially for workers at the bottom of the within-firm recent earnings distribution. Panel (a) shows that increases in volatility have a substantial impact on workers' future nonemployment spells. A one standard deviation increase in firm volatility increases the probability of nonemployment in the next three years for a worker at P1-5 of their firm's recent earnings distribution by 71.4 basis points.[13] The effect is much smaller for workers in higher earnings percentile bins. A similar pattern holds true also for costly separations in panel (b). A one standard deviation increase in firm volatility increases the probability of a costly separation in the next three years by 82.4 basis points, with an average three-year frequency of a costly separation in-sample of 1190 basis points.

Together, Figure 2 and Figure 3 explain the patterns documented in Figure 1: when firm volatility rises, low-earning workers are more likely to leave the firm for adverse reasons, at a substantial cost to their long-run earnings growth.

[13]To interpret magnitude, the unconditional probability of nonemployment spells within this sample is 440 basis points.

2.7 Additional Results, Robustness, and Taking Stock

We conclude this section by discussing several additional results and robustness exercises, then summarize our empirical findings.

First-moment pass-through. Within our sample and using our definitions of earnings growth, we find a similar pattern to the existing literature in terms of the pass-through of first moment fluctuations to workers' earnings growth. In particular, we find a larger pass-through of firm production function residual changes to high-earning workers within the firm, relative to low-earning workers. We present these results in Appendix A.

Job leaving. Our baseline results show the effect of volatility fluctuations within-leavers versus within-stayers, and the effect of volatility on adverse separations. In Appendix A, we show the effect of volatility fluctuations on all forms of job-leaving. We find that increases in volatility lead to an increase in separations across all earnings groups. Given our finding that adverse separations rise substantially more for low-earnings workers than high-earnings workers, this suggests that non-adverse job transitions rise more for high-earners than low earners.

Heterogeneous first-moment controls. Our main specification includes several first-moment controls, but does not condition these controls on the workers' recent earnings bins. To show that our results are robust to such controls, we add the TFP-by-bin proxies from our first-moment pass-through robustness in as extra controls in our volatility heterogeneity regressions. When we add extra controls for changes in a productivity proxy interacted with recent earnings bin, we recover coefficients almost identical to our baseline specifications. This exercise is presented in more detail in Appendix A.

Non-age-adjusted recent earnings. Our main specification adjusts recent earnings for the individual, computing average log earnings relative to the log of expected earnings for an individual of the same age in our sample. We perform a robustness check where we do not age-adjust the recent earnings of individuals in Appendix A. We find very similar results, with a negative effect of volatility particularly affecting low-earning workers, especially leavers, and with volatility increasing the probability of adverse separations for low-earning workers within the firm.

Realized volatility. Our baseline volatility measure is the option-implied volatility of a firm's stock price. We perform a robustness check where we instead use the realized volatility of the firm's stock price as an alternative volatility measure in Appendix A. We find very similar results both qualitatively and quantitatively.

Tenure and firm attachment. Our baseline specification requires workers to be at the firm in t but does not require the workers be at the firm in $t+1$, nor for any periods before t. We check our results to ensure that they are not driven by these assumptions in two ways. First, we add an additional requirement that workers receive some income from the firm in $t+1$ to be in the sample. We find that this requirement has a negligible impact on our results. Next, we add fixed effects for years of tenure with the firm to our baseline specification, and again we recover almost identical results. We summarize both of these exercises and present results in Appendix A.

Taking stock. Our empirical results show that workers are negatively affected by increases in their employers' volatility. The effects on workers' long-run earnings growth is most prominent for low-earning workers within the firm, and is particularly incident within-job leavers, as the probability of (especially low-earning) workers leaving their job for adverse reasons increases with firm volatility. We next write down a model of firm-worker insurance, and show that the calibrated model can replicate these findings.

3 Structural Model

To evaluate the aggregate implications of our empirical results, we add a small number of ingredients to an otherwise standard model of worker-firm interaction. Specifically, we add human capital scarring in unemployment, per-worker operating costs, and heteroskedastic productivity shocks to the dynamic contracting model of Balke and Lamadon (2022), where risk-neutral firms insure risk-averse workers. When the variance of firms' productivity shocks rises, the probability of receiving a severe negative shock rises and, if the shock occurs, workers and firms separate. Upon separation, workers' human capital falls on average and their permanent income falls. Because costs of production are fixed in *absolute* size, they are larger *relative to production* for lower human capital workers. As a result, low human capital workers are more likely to separate when a severe shock occurs.

3.1 Model Overview

Time is discrete and infinite horizon. Each model period corresponds to one quarter.

Agents and preferences. A unit measure of workers consume c, receiving utility from consumption $u(c)$, where the utility function is increasing and concave $u(c)$. Workers lack access to asset markets and hence cannot borrow or save. Workers are either unemployed or employed, with unemployed workers consuming their home production b and employed workers consuming their wage w. Workers are born unemployed and later find employment. Agents differ in terms of their human capital, $h \in \{\underline{h}, \underline{h}+\Delta, \underline{h}+2\Delta, \ldots, \bar{h}\}$, which evolves over time with transition probabilities that depend upon the worker's employment status and current human capital level. Specifically, employed workers have their human capital rise by Δ with probability p_e and otherwise remains the same; unemployed workers have their human capital fall by Δ with probability p_u and otherwise remains the same.[14] Employed workers exert effort $e \geq 0$ which incurs a utility cost $c(e)$ where $c(0) = 0, c' \in [0, \bar{c}'], c'(0) = 0, c'' > 0$. Effort determines the job separation rate $\delta(e)$, where $\delta(0) = 1, \delta' \in [\underline{\delta}', 0)$ and $\delta'' \leq 0$. Workers can search on-the-job with search efficiency of $\iota \in [0, 1]$ while unemployed workers also search, with efficiency normalized to one. Workers maximize the expected sum of utility from consumption net of the cost of effort, discounted at rate $\beta \in (0, 1)$. Workers survive from one period to the next with probability $\lambda \in (0, 1)$ and the mass $(1 - \lambda)$ of workers that die from one period to the next are replaced with the same mass of unemployed workers with the minimum level of human capital $h = \underline{h}$.

There is a large mass of ex-ante identical potential firms. Firm j is matched with a mass of workers $l_{j,t}(h)$ of varying human capital levels. The firm has a single productivity $z_{j,t}$ common to all workers. Each firm's log productivity process is a discretized AR(1) process with heteroskedastic shocks. Transition probabilities are given by $\zeta(z'|z, \sigma)$, where $\sigma_{j,t} \in \{\sigma_L, \sigma_H\}$ governs the variance of the shocks to productivity and follows a 2-state Markov process $Pr(\sigma' = \sigma_{k'}|\sigma = \sigma_k) = \Pi(\sigma_{k'}|\sigma_k)$. Productivity transitions then follow a transition rule dependent on both the current level of productivity $z_{j,t}$ and the current variance $\sigma^2_{j,t}$ of shocks facing the firm. Firms produce output using a production technology that features constant returns to scale across workers,

$$Y_{j,t} = \sum_h l_{j,t}(h) f(z_{j,t}, h), \tag{9}$$

where $f(z_{j,t}, h) = y^g(z_{j,t}, h) - c_f$ is the production (net of fixed costs) of each worker of type h given firm j's productivity level in t, $y^g(z_{j,t}, h)$ is the firm's gross output per-worker of human capital level h, and c_f is the per-worker fixed cost. Each worker's compensation is set dynamically and hence workers of the same human capital level h may receive different wage payments w. Firms maximize their net discounted profits, sharing a common discount factor, β, with the workers.

All wage postings are assumed to be made by unmatched firms. Firms do not draw their

[14] Naturally, given the finite number of human capital grid points, an employed worker already at the top of the human capital grid $h = \bar{h}$ will have their human capital remain the same with probability one. Unemployed workers with human capital at the bottom of the grid $h = \underline{h}$ remains the same with probability one.

initial states until after matching with workers. We define multi-worker firms to be a cohort of workers, and assume that potential firms that choose to enter make a symmetric measure of postings in each market. Unmatched firms decide how many vacancy postings to make, and each post costs $\kappa > 0$ units of the consumption good and lasts for a single period. We next describe the search market between workers and firms in more detail.

Frictional labor market. Labor markets are frictional and feature a directed search technology. Workers and unmatched firms direct their search over submarkets indexed by worker human capital h and a promised value V to be delivered to the worker. We follow Balke and Lamadon (2022) and directly assume that there exists a matching technology with the following properties. In a given submarket (h, V), a worker of type h successfully matches with a firm with probability $p(\theta(h, V))$ and a firm fills a vacancy with probability $q(\theta(h, V))$, with submarket tightness $\theta(h, V)$ determining each rate. The job finding rate, $p(\theta)$, is assumed to be twice continuously differentiable, strictly increasing and strictly concave with $p(0) = 0$ and $p'(0) < \infty$. The vacancy filling rate, $q(\theta)$, is twice continuously differentiable, strictly decreasing, and strictly convex such that $q(\theta) = p(\theta)/\theta$, $q(0) = 1$ and $p(q^{-1}(\cdot))$ is concave.

The values in a submarket are delivered by history-contingent contracts between the worker and the firm. We next discuss the information structure and commitment assumptions, then define the contracts within the model.

Information, commitment, and contracts. The firm does not observe an employed worker's effort e and search V^e choices. These form the moral hazard frictions in the model. This assumption implies that workers cannot credibly commit to a sequence of effort and search choices which maximize match surplus. Instead, contracts suggest effort and search choices. We focus on incentive-compatible contracts between firms and workers.

Firms commit fully to delivering a promised value to the worker, and will choose to deliver that value in a way which maximizes their share of the surplus. The firm thus credibly commits to a wage policy to deliver this value.

Now define a state as $s_t = (z_t, \sigma_t, h_t)$, and a history as $s^\tau = (s_1, \ldots, s_\tau)$. A contract $\mathcal{C}$ offered by a firm to a worker consists of wage policies $w^\tau(s^\tau)$ and suggested actions $e^\tau(s^\tau)$, $V^{e,\tau}(s^\tau)$ for all match periods $\tau \in \mathbb{N}$ and all possible histories s^τ while the match survives.

Timing. Within a period, the model timing proceeds as follows.

1) Stochastic death occurs. Human capital h is realized for all surviving workers, and productivity z and volatility σ are realized for continuing firms.

2) Firm-worker pairs produce $f(z, h)$ on-net and firms pay a worker a wage w. Unemployed workers produce b at home.

3) Workers in existing matches choose effort levels e and search values V^e, unobservable by the firm. Unemployed workers choose a value V^u to search for.

4) Jobs are destroyed with probability $\delta(e)$.

5) Successful search results in the formation of new matches.

We next formalize the recursive formulation of the worker's problem.

3.2 Worker's Problem

First, consider an unemployed worker. Their value $U(h)$ at the beginning of the period can be written recursively as:

$$U(h) = u(b) + \lambda\beta\left[\max_{V^u}\left\{p(\theta(h, V^u))V^u + (1 - p(\theta(h, V^u)))\mathbb{E}[U(h')]\right\}\right] \tag{10}$$

We focus on the recursive form of the contract. Workers matched with firms receive a wage payment w and promises for the future that are conditional on the future realizations of the stochastic variables $W(h', z', \sigma')$. Workers form expectations over the value of remaining in the match given the promises committed to by the firm, $W = \mathbb{E}[W(h', z', \sigma')]$, which summarizes the information necessary to describe their optimal effort and search policies. The moral hazard problem of an employed worker is given by the following optimization problem:

$$\max_{e,V^e} u(w) - c(e) + \lambda\beta\left[\delta(e)\mathbb{E}[U(h')] + (1 - \delta(e))[\iota p(\theta(h, V^e))V^e + (1 - \iota p(\theta(h, V^e))W]\right] \tag{11}$$

Noting that the term $u(w)$ is a constant in (11), we define the policies which solve the maximization problem given by (11) as $e^*(h, W)$, $V^{e*}(h, W)$. We then define, as in Balke and Lamadon (2022), the job retention probability $\tilde{p}(h, W)$ and utility return to the worker $\hat{r}(h, w)$ as:

$$\tilde{p}(W, h) = (1 - \delta(e^*(W, h)))(1 - \iota p(\theta(h, V^{e*}(W, h)))) \tag{12}$$

$$\begin{aligned}\hat{r}(W, h) = &-c(e^*(W, h)) + \lambda\beta\delta(e^*(W, h))\mathbb{E}[U(h')] \\ &+ \lambda\beta(1 - \delta(e^*(W, h)))[\iota p(\theta(h, V^{e*}(W, h)))V^{e*}(W, h)\end{aligned} \tag{13}$$

$$+ (1 - \iota p(\theta(h, V^{e*}(W, h))))W]$$

While the firm has no direct control over the worker's effort e and search V^e choices, they internalize how promises made to the worker influences the worker's choices.

We next summarize the recursive form of the firm's problem.[15]

3.3 Firm's Problem

The firm faces a promised value V to which they have committed to delivering to the worker. They deliver this promise through wage payments w in the current period, as well as in all periods where the firm and worker remain matched. A firm with productivity z facing volatility σ, matched with a worker of human capital h solves the following optimization problem:

$$J(V, h, z, \sigma) = \max_{w, W, \{W(h', z', \sigma')\}} f(z, h) - w + \lambda\beta\tilde{p}(W, h)\mathbb{E}[J(W(h', z', \sigma'), h', z', \sigma')] \tag{14}$$

subject to productivity, volatility, and human capital laws of motion, as well as:

$$V \leq u(w) + \hat{r}(W, h) \qquad \text{(promise-keeping)}$$

$$W = \mathbb{E}[W(h', z', \sigma')] \qquad \text{(rational expectations)}$$

Importantly, the firm is able to provide value promises to the worker that depend on the future realizations of variables, i.e. $W(h', z', \sigma')$. The worker's expected value of continuing in the match, W, is the expectation of these conditional promises and summarizes the information that the worker needs to know to optimally determine their private actions.

When firms enter in our model, they have not yet drawn their volatility σ or their productivity z. In the first period after successfully matching, these variables are drawn from a fixed multivariate distribution $Q(z, \sigma)$. Immediately before this, but after successfully matching with a worker, firms determine a set of conditional promises to provide to the worker to solve:

[15] When describing the firm's problem, we abstract from randomizations over lotteries, which are minor details but necessary for some of the derivations for the characterization. We introduce these randomizations in Appendix C, but ignore them here as they are irrelevant for the rest of the paper outside of the technical details of the model characterization.

$$J^e(V,h) = \max_{\{W^e(h',z',\sigma')\}} \beta\lambda q(V,h)\mathbb{E}[J(W^e(h',z',\sigma'),h',z',\sigma')] - \kappa \text{ s.t. } V = \mathbb{E}[W^e(h',z',\sigma')] \tag{15}$$

Competitive entry with a posting cost implies the following free-entry condition:

$$0 \geq J^e(V,h) \tag{16}$$

New firms enter occurs until the inequality (16) condition binds with equality, or no new firms enter the market. As is standard in directed search frameworks, this condition pins down the market tightness function $\theta(h,V)$.

3.4 Equilibrium

Due to the block-recursive nature of the model, it is unneccessary to track which worker is matched with which firm, and instead we can track the distributions of workers, employed and unemployed, over states. Denote by $\mathcal{W}(V,h,z,\sigma)$ the measure of workers over promised values, human capital, and firm states. Denote by $\mu(h)$ the measure of unemployed workers of human capital h. Let the measure operators governing the law of motions of these distributions be denoted $T^{*,e}(\mathcal{W},\mu)$ and $T^{*,u}(\mathcal{W},\mu)$, such that $\mathcal{W}' = T^{*,e}(\mathcal{W},\mu)$ and $\mu' = T^{*,u}(\mathcal{W},\mu)$. Using the state vector $s = (V,h,z,\sigma)$, $T^{*,e}$ can be written as:

$$\begin{aligned}(T^{*,e}(\mathcal{W},\mu))(V',h',z',\sigma') = &\underbrace{\lambda \int \mathbb{1}_{\{V'=(W(h',z',\sigma'))(s)\}}\tilde{p}(W(s),h)Pr(h'|h,\text{employed})\zeta(z'|z,\sigma)\Pi(\sigma'|\sigma)d\mathcal{W}(s)}_{\text{Retention by current firm}} \\ &+ \underbrace{\lambda \int \mathbb{1}_{\{V'=(W^e(h',z',\sigma'))(V^e(h,W(s)),h)\}}\iota p(\theta(h,V^e(h,W(s))))Q(z',\sigma')Pr(h'|h,\text{employed})d\mathcal{W}(s)}_{\text{New on-the-job-search matches}} \\ &+ \underbrace{\lambda \int \mathbb{1}_{\{V'=(W(h',z',\sigma')(V^u(h),h))\}}p(\theta(h,V^u(h)))Q(z',\sigma')Pr(h'|h,\text{unemployed})d\mu(h)}_{\text{New matches from unemployment}}\end{aligned}$$

We can then write $T^{*,u}$ as:

$$(T^{*,u}(\mathcal{W},\mu))(h') = \underbrace{\lambda \int \delta(e(W(s)),h)Pr(h'|h,\text{employed})d\mathcal{W}(s)}_{\text{Job separations}}$$

$$+\underbrace{\lambda\int(1-p(\theta(h,V^u(h))))Pr(h'|h,\text{unemployed})d\mu(h)}_{\text{Unsuccessful job search of unemployed}}$$

$$+\underbrace{(1-\lambda)\mathbb{1}_{\{h'=\underline{h}\}}}_{\text{Newborn workers}}$$

A stationary distribution $(\mathcal{W},\mu)$ of workers over employed and unemployed states can then be defined as the following:

$$\mathcal{W}=T^{*,e}(\mathcal{W},\mu), \tag{17}$$

$$\mu=T^{*,u}(\mathcal{W},\mu). \tag{18}$$

Finally, the mass of vacancies posted in a submarket $\phi(h,V)$ can be written as:

$$\begin{aligned}\phi(\tilde{h},V)=\theta(\tilde{h},V)\Bigg[&\mathbb{1}_{V=V^{*,u}(\tilde{h})}\mu(\tilde{h})\\ &+\iota\int\mathbb{1}_{\tilde{h}=h}\mathbb{1}_{V=V^{*,e}(h,W(s))}d\mathcal{W}(s)\Bigg].\end{aligned} \tag{19}$$

We now define the relevant concept of equilibrium.

Definition 1. *A **stationary recursive search equilibrium** consists of firm value functions $J(V,h,z,\sigma)$ and $J^e(V,h)$, an unemployed worker value $U(h)$, a job retention probability $\tilde{p}(h,V)$, a worker return function $\hat{r}(W,h)$, optimal contract policy functions $\mathcal{C}=\{w^*,e^*,V^{e,*},W^*,W^*(h',z',\sigma'),W^{e,*}(h',z',\sigma')\}$, worker submarket choice when unemployed $V^{u*}(h)$, market tightness function $\theta(h,V)$, distribution of employed workers $\mathcal{W}$, measure of unemployed workers μ and measure of vacancies in each submarket $\phi(h,V)$ such that:*

i. $J(V,h,z,\sigma)$, $J^e(V,h)$, and $U(h)$ satisfy (14), (15), and (10),

ii. $\tilde{p}(h,V)$ and $\hat{r}(W,h)$, given by (12) and (13) satisfy (11),

iii. $\mathcal{C}$ and $V^{u*}(h)$ contain the associated policies implied by the solution to these problems,

iv. $\theta(h,V)$ and $\phi(h,V)$ satisfy the free entry condition (16).

v. The distribution of employed $\mathcal{W}$ and unemployed μ workers are stationary (17), (18),

vi. $\mathcal{W}$, μ, and $\phi(h,V)$ clear the market (19).

The directed search structure of the model naturally lends itself to *block recursivity*, the property that the equilibrium values and policies are independent of the distributions of workers over states of the economy (Shi (2009), Menzio and Shi (2011)). This greatly improves tractability of the model, as is discussed in the computational appendix (Appendix D). We next summarize a few points on the model before moving on to calibration and validation exercises.

3.5 Model Characterization

The model closely follows Balke and Lamadon (2022) so that the characterization of our model follows immediately from their theorems, which in turn are based heavily on the work of Menzio and Shi (2011) and Tsuyahara (2016).[16] These propositions, while not our contribution, are useful for the computation of our model. We hence apply Balke and Lamadon (2022) Proposition 1 to prove that there exists an equilibrium. Additionally, we apply Balke and Lamadon (2022) Proposition 2, which demonstrates the following equations holds for a match that continues with any positive probability:[17]

$$\left(\frac{\partial \log \tilde{p}(h,W)}{\partial W}\right)\mathbb{E}[J(W(h',z',\sigma'),h',z',\sigma')|h,z,\sigma] = \frac{1}{u'(w'(\hat{h}',\hat{z}',\hat{\sigma}'))} - \frac{1}{u'(w)}\ \forall(\hat{h}',\hat{z}',\hat{\sigma}') \tag{20}$$

The left-hand side of equation (20) is the product of the semi-elasticity of the retention probability with respect to the expected continuation value of the worker in the match, and the firm's expected value conditional on the match continuing. The right-hand side of equation (20) is the difference in inverse marginal utilities between tomorrow and today. The left-hand side of this equation is in expectations from today into tomorrow, whereas the right-hand side of the equation holds true for *all* realizations of the firm's state variables tomorrow. In other words, a worker's wage tomorrow, conditional on remaining matched with the same firm, is perfectly insured with respect to the evolution of the firm's and worker's state variables. This insight provides the basis of our computational algorithm, described in more detail in Appendix D.

[16] We explain in more detail the application of the proofs of Balke and Lamadon (2022) to our specific context in Appendix C. The proofs are applicable after introducing lotteries over the firm choices which are omitted from the main text for expositional reasons, but are introduced in Appendix C.

[17] The version of the model for which Balke and Lamadon (2022) prove their Proposition 2 is the version with randomizations as presented in Appendix C, the optimality condition presented here is for the version of the model without randomizations, which is the same except the randomization subscript i is dropped throughout.

4 Calibration of the Model

In this section, we discuss how the model is calibrated. We leave our empirical results untargeted and evaluate whether our calibrated model can produce these estimates. We instead target standard moments used in the literature to identify key model parameters.

Our calibration strategy follows a two-step process. First, we calibrate parameters, when possible, outside of the model. We then calibrate our remaining parameters within the model to match moments using model-simulated data. We calibrate our model to the quarterly frequency.

Calibration outside the model and functional forms. We assume that the consumer has log preferences, $u(c) = \log(c)$. We set the quarterly discount factor to $\beta = 0.987$ following Balke and Lamadon (2022). We set the survival probability to $\lambda = 0.993$ so that an average worker, entering the labor force at 25, "dies" or leaves the labor force at age 60 on average.

We assume that the gross output is the scaled product of human capital and firm productivity, $y^g(z,h) = Azh$ and normalize the level of productivity to one ($A = 1$). Net production then takes the form $f(z,h) = Azh - c_f$. We assume that human capital has lower and upper bounds given by $\underline{h} = 1, \bar{h} = 2$ and the human capital grids has 11 points, so that $\Delta = 0.1$.

We adopt parameters for the firms' productivity and volatility processes from Bloom et al. (2018). This gives us the persistence of log productivity, $\rho = 0.95$, the low level of firm volatility $\sigma_L = 0.051$, the high level of firm volatility $\sigma_H = 0.209$, and the probability of having the high volatility next period when the current volatility is low $P(\sigma' = \sigma_H | \sigma = \sigma_L) = 0.026$ and when the current volatility is high $P(\sigma' = \sigma_H | \sigma = \sigma_H) = 0.943$.

For a newly entering firm, we assume first that the volatility is drawn from the ergodic distribution of the volatility process, then that firm productivity is drawn from the ergodic distribution of the conditional productivity process conditional on their drawn volatility state.

We assume three additional functional forms. First, we assume that $q(\theta) = \frac{1}{(1+\theta^{\varphi})^{1/\varphi}}$, and calibrate $\varphi = 0.8$ following Balke and Lamadon (2022). We further follow Balke and Lamadon (2022) and assume that the destruction rate as a function of effort is given by $\delta(e) = 1 - e$ and the utility cost of effort is given by

$$c(e) = \frac{\gamma_0}{\gamma_1 - 1} + \gamma_0(1-e) - \left(\frac{\gamma_0}{1 - \frac{1}{\gamma_1}}\right)(1-e)^{1-\frac{1}{\gamma_1}}.$$

We are left with eight free parameters to be estimated within the model: home production b, the per-worker fixed operating cost c_f, the relative efficiency of on-the-job-search ι, the probability of human capital rising when employed p_e, the probability of human capital falling when unemployed p_u, the vacancy posting cost κ, and the parameters governing the cost of effort γ_0 and γ_1. We will next discuss the calibration of these parameters within the model.

Calibration within the model. We calibrate our eight remaining parameters using moments standard to literature. We do so to emphasize that the empirical patterns we document are not explicitly targeted. Our estimation of the eight remaining free parameters is just identified, we use only eight moments. Rather than overidentifying our parameters by introducing additional moments, we adopt the just-identified approach to ensure our results do not depend upon the weighting matrix in the estimation. While we describe certain moments as key for identifying specific parameters, all moments jointly identify all parameters.

We first identify the home production parameter, b, by targeting the replacement rate of unemployed income relative to the average wage. We take the estimate of this moment from Braxton et al. (2024), and implement this in the model by dividing the home production parameter b by the average earnings of the employed the period before they become unemployed.

Next, we identify the fixed cost of operating a firm-worker relationship by targeting the layoff rate. We calculate the layoff rate ourselves in the United States using the Current Population Survey (CPS), which asks unemployed workers for the reason for their unemployment. We count all workers who report their reason for unemployment as being attributed to a layoff, and compute the probability of transitioning from employed to unemployed due to a layoff in a 3-month span conditional on being in the labor force in both periods. We compare this definition to a definition in the model, of the fraction of employed workers that have probability zero of being employed in the following period. We consider these workers to have been laid off in the sense that the promises made to them are so bad that the firm has ensured that the match will end entering the next period.

We then identify the on-the-job-search efficiency, ι, by targeting the job-to-job flow rate. We compute this moment using the public-use version of the LEHD Job-to-Job Flows data. We implement this in the model by computing the probability of a successful on-the-job search for the employed conditional on the worker not dying between periods.

The Ljungqvist and Sargent (1998) human capital process features two parameters which we calibrate next. First, we identify the probability of human capital rising when employed by targeting the age semi-elasticity of real earnings. We take the empirical estimate of this moment from Braxton et al. (2024). We compare this estimate to the estimated parameter of an equivalent model regression run on simulated data. We then identify the probability of human capital falling when unemployed by targeting the five-year drop in real earnings after job loss, the moment of which is also estimated by Braxton et al. (2024). We compare this to the average earnings decline five years out after a layoff, defined as an event where a worker was promised such low value such to have zero probability of remaining with the employer with any positive probability in the next period.

Next, we identify the cost of posting by targeting the unemployed-to-employed transition rate. In order to be able to estimate the transition rate from unemployment, as opposed to nonemployment (i.e. non-employed workers searching from jobs vs those who may or may not be searching for jobs), we use the labor force indicator from the CPS. This also has the advantage of lining up with our calculation for the layoff rate, used previously, and the employed-to-unemployed (EU) rate, soon to be discussed. We compare this moment to a model moment computed as the average rate of successfully matching with a firm out of unemployment, conditional on not dying.

We finally calibrate the parameters of the function governing the utility cost of effort. We identify γ_0 by targeting the EU rate. We compare an estimate of this rate, computed ourselves using the CPS, to the average rate of all model employed-to-unemployed transitions, including both workers who separated with a positive probability of remaining in their match and with zero probability of remaining in their match. We then calibrate γ_1 by targeting the variance of log real wage changes between two quarters within an employment relationship. We target an estimate of this parameter from Juhn et al. (2018), and compare this directly within the model. Balke and Lamadon (2022) show that these moments identify these parameters.

We describe our model solution method and calibration strategy in Appendix D. The resulting calibration and model fit from this exercise are presented in Table 3 and Table 4, respectively.

The estimated model matches the targeted moments well. We next evaluate the ability of our calibrated structural model to replicate our empirical results.

5 Model Evaluation

Here we show that the calibrated structural model is consistent with our empirical evidence of the direct effect of volatility fluctuations on worker outcomes. Given our calibration does not make use of our empirical estimates, these model results are entirely untargeted. After demonstrating that our baseline model is consistent with the effects that we document empirically, we show the importance of our particular choice of model ingredients by compare to alternative models where we have removed these key ingredients (fixed operating costs and human capital scarring) one at-a-time. The alternative models fail to reproduce the

Table 3: Model Parameters

Variable	Value	Description
		Calibrated Outside Model
$u(c)$	$\log(c)$	Worker utility function
β	0.987	Discount factor (quarterly)
λ	0.993	Probability of stochastic death
A	1	Level of productivity
$\underline{h}$	1	Human capital lower bound
$\bar{h}$	2	Upper bound of human capital
Δ	0.1	Human capital ladder rung distance
ρ	0.95	Persistence of log productivity
σ_L	0.051	Low firm volatility state
σ_H	0.209	High firm volatility state
$P(\sigma' = \sigma_H \mid \sigma = \sigma_L)$	0.026	Probability of transitioning, $L \rightarrow H$ volatility
$P(\sigma' = \sigma_H \mid \sigma = \sigma_H)$	0.943	Probability of remaining in H volatility state
φ	0.8	Matching function curvature
		Calibrated Within Model
ι	0.7011	Job-to-job search efficiency
b	0.3440	Home production per quarter
c_f	0.7160	Fixed operating cost per worker (per quarter)
p_e	0.06763	Prob. of human capital increase when employed
p_u	0.9245	Prob. of human capital decrease when unemployed
κ	0.4036	Cost of Vacancy Posting
γ_0	1.186×10^{-3}	Effort cost parameter
γ_1	0.5272	Effort cost curvature

Notes: Table 3 presents the calibration of model parameters. The top panel displays the values of parameters set outside of the model. The bottom panel displays the description and values of the parameters calibrated within the model. See the text for more explanation of the parameters, and see Table 4 for a summary of the model fit.

Table 4: Calibration Fit

Parameter	Value	Moment	Model	Data	Source
ι	0.7011	J2J rate	0.04964	0.0495	LEHD Job-to-job
b	0.3440	UI replacement	0.3553	0.412	Braxton, Herkenhoff, Phillips (2024)
c_f	0.7160	Layoff rate	0.01110	0.01343	Current Population Survey
p_e	0.06763	Earnings–age semielasticity	0.01030	0.0095	Braxton, Herkenhoff, Phillips (2024)
p_u	0.9245	Earnings loss after layoff	-0.08302	-0.089	Braxton, Herkenhoff, Phillips (2024)
κ	0.4036	UE rate	0.3778	0.4090	Current Population Survey
γ_0	1.186×10^{-3}	EU rate	0.0211925	0.02012	Current Population Survey
γ_1	0.5272	Within-spell var. of $\Delta \log w$	0.02508	0.03028	Juhn, McCue, Monti, Pierce (2018)

Notes: Table 4 presents the fit of the moment matching algorithm, which identifies the parameters calibrated within the model. See the text for more details on the moments and sources, and see Table 3 for a description of the parameters.

qualitative patterns we find empirically.

Baseline model evaluation. To cleanly compare the model to the data, we replicate the data construction and regression specification used in our empirical analysis in model-simulated data. We begin by defining a multi-worker firm in our simulated data. Due to the block recursive nature of our model, each worker-firm relationship is independent and thus firm size, as defined by the number of workers per firm, is indeterminate. We assume that, when each infinitesimal potential firm posts vacancies, they post a large number of vacancies and that all firms post a symmetric measure of vacancies in each submarket over which workers search. A cohort of workers, drawn independently from the distribution of workers successfully matching with a firm, comprises a firm. [18]

After drawing a cohort of workers for each firm, we simulate each firm forward in time assuming a common productivity and volatility process for each worker within the firm. In each period, we compute the distribution of recent earnings, defined as the (age-adjusted) three-year sum of recent earnings for the workers, and compute forward-looking earnings growth variables following the definitions in our empirical analysis. We then run OLS regressions in the model to estimate the parameters in equation (6),[19] including controls for the polynomial in recent earnings as well as firm controls (in the model, the lag of log productivity and cubic polynomial of current log productivity are the included controls) as well as fixed effects for the individual, firm, worker age, and worker recent earnings bin. Given the model is in steady state, we do not include year fixed effects. We focus on the five-year

[18] Workers successfully matching out of unemployment and on-the-job search comprise this distribution.
[19] In the model, the volatility fluctuations are exogenous and hence do not need to be instrumented.

effect of volatility fluctuations on recent earnings growth as our baseline estimate, although the qualitative patterns for all horizons are very similar.

The average effect of volatility fluctuations on earnings growth, as measured in the data and the baseline model, is compared in Table 5.

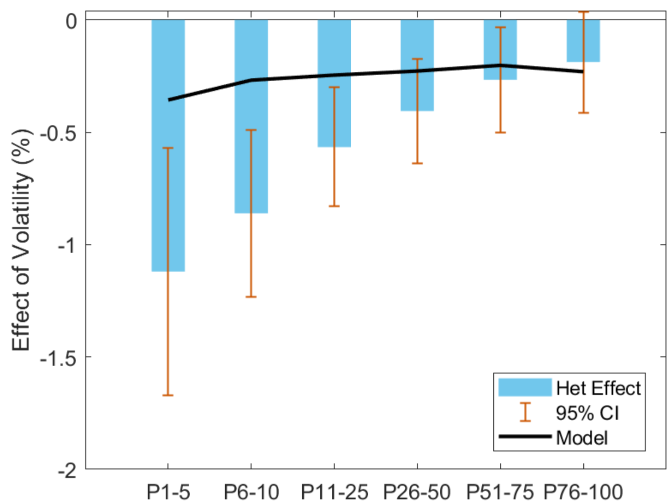
Table 5: Effect: 1 Standard Deviation Volatility Change on Workers' 5-year Earnings Growth

	Data	Baseline Model
Effect (%)	-0.357	-0.233
Standard Error	(0.115)	-

Notes: Table 5 compares the estimated average effect of a one standard deviation annual change in firm volatility on five-year real earnings growth between the data, and baseline model. The model generates a negative impact of volatility on earnings growth, with a magnitude that is close to the magnitude in our empirics, and well within the 95 percent confidence interval.

We find similar average effects of volatility fluctuations on workers' earnings growth in the data and the model. While the point estimate of the empirical estimate is slightly lower than the model, the coefficients are quite close and the model is within the 95 percent confidence interval. We next compare the heterogeneous effect of volatility fluctuations on workers' income growth in Figure 4.

Figure 4: Model Comparison: Leavers and Stayers: Effect of Volatility on Earnings



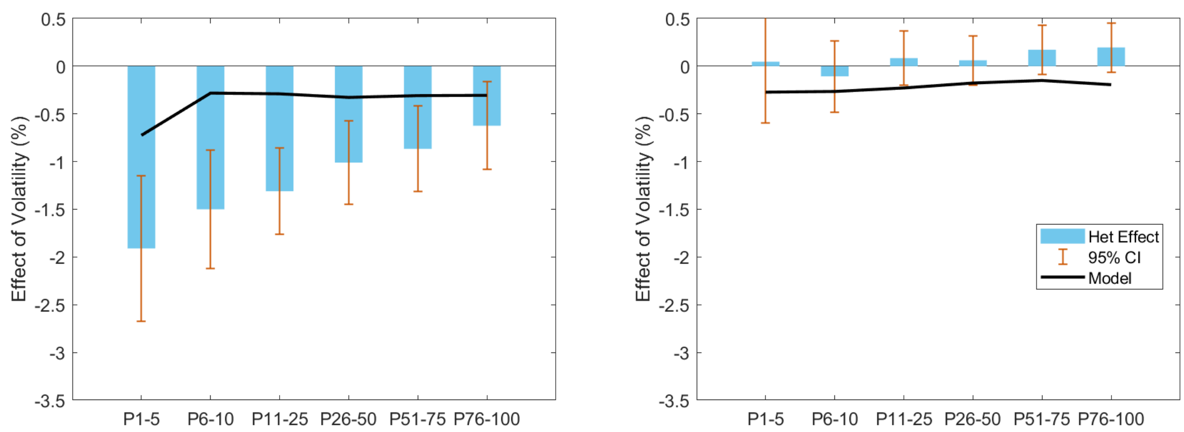
Notes: Figure 4 compares the effect of volatility fluctuations as measured in the data to that as implied by model-simulated data. The model is able to generate a larger impact of volatility fluctuations on the bottom of the within-firm earnings distribution than the top, as is in the data. Many of the model coefficients lie within the 95 percent confidence intervals of the empirical estimates despite the fact that all model coefficients are untargeted.

Figure 4 reports the results of estimating equation (8) via 2SLS IV on our data, against the result of running the same regression on model-simulated data. In both the empirical estimate and the model, volatility affects the bottom of the within-firm earnings distribution more than the top. The model does not quite match the steepness of the empirical relationship, but is quantitatively quite close overall - for three-quarters of the distribution, the model estimate is within the 95 percent confidence interval of the empirical estimate. We next validate that the model's mechanisms match the data by comparing the effect of volatility within leavers and stayers in Figure 5.

Figure 5: Model Comparison: Heterogeneous Effect of Volatility on Earnings

(a) Leavers

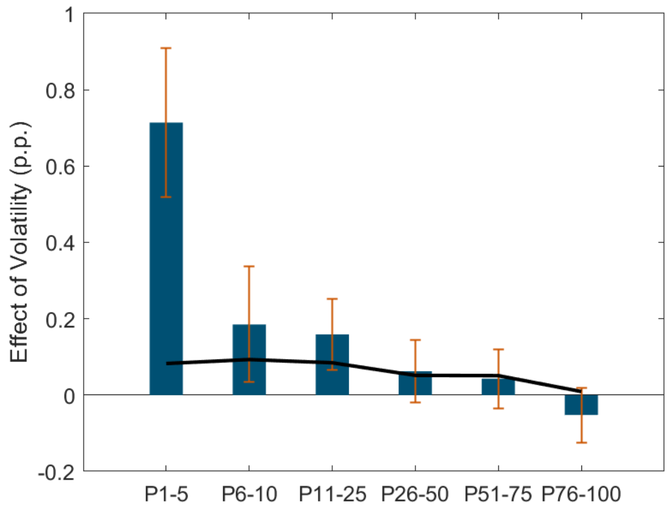
(b) Stayers



Notes: Figure 5 compares the effect of volatility fluctuations among job leavers (Panel (a)) and job stayers (Panel (b)) as measured in the data to that as implied by model-simulated data. In the model, volatility fluctuations have a larger effect on job leavers compared to job stayers. As with the rest of the model coefficients, these are entirely untargeted.

Figure 5 compares the results of estimating the model analogue of Figure 2 to the empirical estimates. The model succeeds in the sense that leavers, especially those at the bottom of the within-firm recent earnings distribution, are more affected than stayers. The model's effects are attenuated for leavers, but larger for stayers. Nevertheless, as we will show when comparing to alternative models, recovering this qualitative relationship is nontrivial. Finally, we compare the model estimates of the results displayed in Figure 3 to the model analogue in Figure 6.

Figure 6: Model Comparison: Heterogeneous Effect of Volatility on Nonemployment



Notes: Figure 6 compares the effect of volatility fluctuations on nonemployment, across low- and high-earners within the firm, between the empirical estimates and model analogue. The model is able to replicate the empirical pattern of generating nonemployment in response to volatility fluctuations, and almost all of the model-implied coefficients lie within the 95 percent confidence interval of the empirical estimates. The primary data feature that the model fails to generate is the extreme spike in nonemployment for the very bottom workers within the firm. As with the rest of the model coefficients, these are entirely untargeted by the model calibration.

Figure 6 shows the model does a good job at matching the empirical relationship between volatility fluctuations and nonemployment. While the empirical estimates display a spike in the bottom five percentiles that the model does not match, the estimated effect on the remaining 95 percent of the within-firm earnings distribution lies within the 95 percent confidence interval of the empirical estimates.

Comparing to alternative models. In order to demonstrate the importance of human capital scarring and fixed per-worker operating costs in matching these empirical facts, we replicate the validation exercise turning off key aspects of the model mechanism.

To study the role of fixed operating costs, we set the parameter c_f to zero. To study the role of human capital scarring, we set the parameter governing the reduction of human capital loss under unemployment to zero, and to remove any residual scarring effect of unemployment in terms of human capital accumulation during unemployment, we equate the probability of human capital rising when employed and unemployed. We recalibrate the alternative models to ensure that they remain consistent with our targeted moments, dropping one moment for each model alternative which corresponds to the dropped model parameter.[20] When removing fixed costs, we drop the layoff rate moment. When we recalibrate while when recalibrating human capital scarring we drop the earnings loss after layoff. The model fit for the recalibration exercises are presented in Appendix E. We compare the average effect of volatility on workers, in the data versus in our baseline and two alternative models, in Table 6.

Table 6: Effect of 1 s.d. Volatility Fluctuation on Workers' Five-year Earnings Growth

	Data	Baseline	No fixed costs	No scarring
Effect (%)	-0.357	-0.233	-0.0885	-0.225
Standard Error	(0.115)	-	-	-

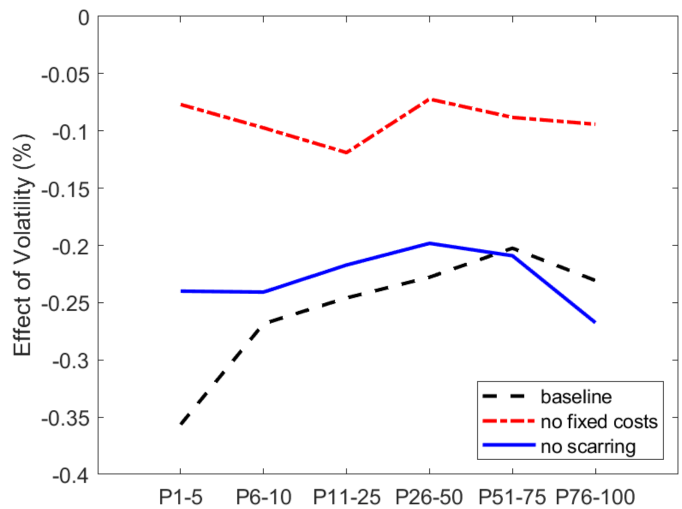
Notes: Table 6 compares the estimated average effect of a one standard deviation annual change in firm volatility on five-year real earnings growth (expressed as a percent) between the data, baseline model, and alternative models where key ingredients in the model are turned off. The model moments are untargeted in all cases. The two alternative models remove either the operating fixed costs or human capital scarring, recalibrating the model parameters to hit the remaining subset of relevant moments (see text). The effect of firm volatility on workers' earnings growth is larger in the baseline model (closer to the data) than the alternative models.

Table 6 verifies that the model generates a negative effect of volatility fluctuations on workers' real earnings growth. The model is able to generate a negative effect of volatility on real earnings growth even with removing parts of the model mechanism. However, the estimated effect is smaller taking out either model feature.

We next turn to our effect heterogeneity to further evaluate the predictions of our baseline and alternative models. The results of this exercise are presented in Figure 7.

[20] We show that we get very similar results without recalibrating the alternative models in Appendix E.

Figure 7: Model Comparison: Heterogeneous Effect of Volatility on Earnings



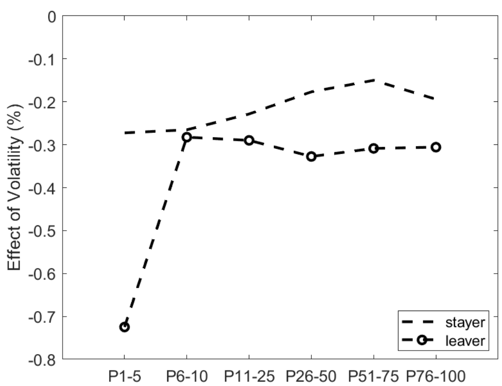
Notes: Figure 7 reports the effect of volatility fluctuations on real earnings growth in our baseline and alternative models. The black dashed line represents the heterogeneous effect of volatility on workers' earnings growth as implied by the baseline model. The baseline model replicates the empirical finding that the incidence of volatility fluctuations is larger in magnitude on low-earnings workers, and the baseline model is compared to the empirical estimates in Figure 4. The red dash-dotted line is the alternative model with no fixed costs, whereas the blue solid line is the alternative model with no human capital scarring. Neither alternative model is able to replicate the larger incidence of volatility fluctuations at the bottom of the within-firm earnings distribution relative to the middle and top.

As Figure 7 verifies, the baseline model generates more pass-through of firm volatility on workers' earnings growth at the bottom of the within-firm recent earnings distribution. Comparing the baseline model to the alternative models, one can see that the alternative models fail to replicate the key empirical finding that volatility fluctuations pass-through at the bottom of the firm's recent earnings distribution. Instead, these models generate more pass-through of volatility at the top of the firm's recent earnings distribution. We next investigate further by replicating our mechanism analysis in model-simulated data.

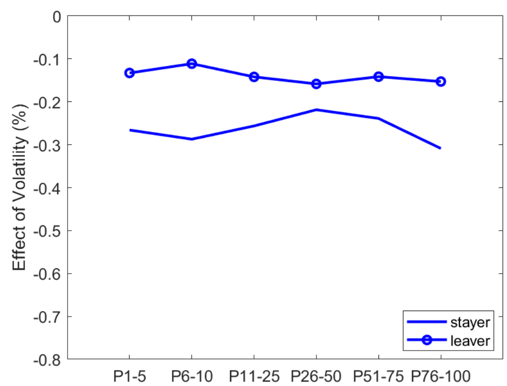
As in our empirical analysis, we identify workers in our models' samples as leavers or stayers. Consistent with Figure 2, we define leaver-stayer status by whether a worker remains with the same firm three-years later. We then redefine the (age-adjusted) recent earnings bins with indicators for the interaction of recent earnings bin-leaver/stayer status. While the model with no fixed costs (but human capital scarring) has a similar leaver/stayer pattern as our baseline model, the model without human capital scarring (but with fixed costs) has quite a different prediction. We compare the estimated effects including the leaver/stayer distinction, for baseline and alternative model without human capital scarring, in Figure 8.[21]

Figure 8: Model Comparison: Heterogeneous Effect, Leavers vs Stayers

(a) Baseline



(b) No Scarring



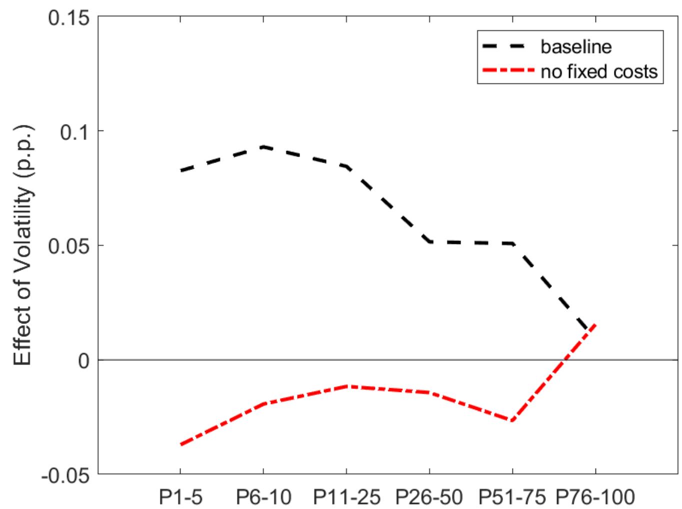
Notes: Figure 8 compares the effect of volatility fluctuations on real earnings growth among leavers versus stayers for our baseline and alternative model without human capital scarring. Panel (a) presents the effect of volatility fluctuations in the baseline model, comparing the effect within-stayers (dashed line) to the effect within-leavers (dashed line with dot markers). As in the data, the effect of volatility is more incident amongst leavers than stayers. Panel (b) reports the effect in the alternative model without human capital scarring, with the solid line presenting the effect within-leavers and the solid line with circle markers presenting the effect within-stayers. This alternative model is unable to generate the model prediction that the effects of volatility fluctuations are incident upon leavers as opposed to stayers, and instead predicts the opposite relationship which is inconsistent with our empirical findings.

As Figure 8 shows in Panel (a), the baseline model replicates the qualitative prediction that the effect of volatility is felt more by leavers than by stayers. In Appendix E, we show that the alternative model without fixed costs is also consistent with this fact. However, Panel (b) shows that the alternative model without human capital scarring is inconsistent with this fact. Without human capital scarring, workers that leave when volatility is elevated are more likely to be unemployed, but without human capital scarring this is not detrimental to their human capital accumulation. This helps to explain why the model without human capital scarring is inconsistent with the heterogeneity analysis as shown by Figure 7.

We then evaluate whether the alternative models can match the qualitative prediction that uncertainty increases the probability of nonemployment spells. For each model, we construct the nonemployment indicator in the simulated data. We then replace the left-hand-side variable in equation (8) and estimate the coefficients using OLS. We compare the ability of the baseline and alternative models to match our empirical evidence in Figure 9.

[21]The comparison of all three models is presented in Appendix E.

Figure 9: Model Comparison: Heterogeneous Effect of Volatility on Nonemployment



Notes: Figure 9 compares the effect of volatility fluctuations on nonemployment for our baseline model and the alternative model without fixed costs. The black dashed line reports the heterogeneous effect in the baseline model. As in the data, volatility fluctuations induce layoffs, in particular at the bottom of the within-firm recent earnings distribution. The red dash-dotted line reports the heterogeneous effect of volatility on layoffs in the alternative models without fixed costs. This alternative model is unable to generate the prediction that volatility fluctuations induce layoffs for low-earning workers.

As Figure 9 shows, our baseline model successfully generates nonempoyment spells in response to volatility fluctuations, especially at the bottom of the firm's recent earnings distribution. We also show in Appendix E that the alternative model without human scarring, but with fixed costs, also generates nonemployment in response to increased volatility. However, the model without fixed costs completely fails to generate nonemployment for low-earning workers in response to volatility fluctuations. Fixed costs are important for generating endogenous separations in this model, and without them volatility does not generate enough separations. This explains why, even with human capital scarring, the model without fixed costs fails to match the greater pass-through of volatility at the bottom of the recent earnings distribution.

The Effects of Volatility on Workers' Earnings Risk. As we showed empirically, when firm volatility increases, workers' earnings are negatively affected. In Appendix F, we discuss in detail the effects that firm volatility fluctuations have on workers' earnings risk. In particular, we show that when firm volatility is elevated, firms respond by reducing the transmission of a given productivity shock to workers' long-run earnings. In so doing, firms absorb a substantial portion of the increase in risk (60 percent), passing on only a fraction

(40 percent) to workers' long-run earnings risk.

Now that we have demonstrated that our baseline model can generate effects of volatility on workers consistent with our empirical evidence, and shown the importance of our particular choices of model ingredients for generating such responses, we use the model to evaluate the labor market consequences of an increase in firm dispersion.

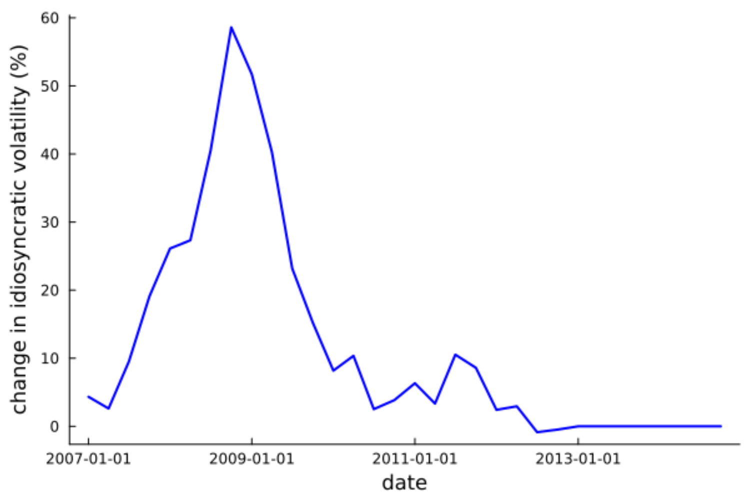
6 Aggregate Implications of Idiosyncratic Volatility

In this section, we take our model out of steady state to quantify the macroeconomic effects of common increases in idiosyncratic volatility. Researchers commonly find that economic downturns are associated with increased macroeconomic uncertainty of various forms. The literature has focused much of its attention on the interaction between economic downturns and increases in aggregate uncertainty, for example, increased uncertainty over forward-looking changes in macroeconomic aggregates such as output, or the changes in implied volatility of the market portfolio (e.g. VIX). In this section, we instead focus on common changes in the volatility of idiosyncratic firm outcomes, as motivated by Schaal (2017), Bloom et al. (2018), and Arellano et al. (2019).

To assess the macroeconomic implications of idiosyncratic volatility, we feed in the path of idiosyncratic volatility from the Global Financial Crisis (GFC). We take our measure of time-varying idiosyncratic volatility from Dew-Becker and Giglio (2023). Using an option-implied firm volatility measure, as used in our empirical strategy, Dew-Becker and Giglio (2023) compute a monthly measure of firm idiosyncratic volatility, disentangled from aggregate volatility (the volatility of the S&P 500, similar to the VIX). To incorporate their time-varying series into our model, we make several modifications. First, we convert the series to standard deviations to match the units of our firm volatility variable, σ. Then, we aggregate the series to a quarterly level by averaging the standard deviations within a quarter. Finally, we scale the series by the average value between 2013 and 2014. The volatility measure during the time span we consider, 2007 through 2012, is then a quarterly relative measure of firm idiosyncratic volatility. We feed this path of firm idiosyncratic volatility into our model, multiplying each firm volatility state σ by this relative value in each period along the transition, assuming perfect foresight upon the beginning of the transition in 2007. Figure 10 displays the evolution of firm idiosyncratic volatility fed into the model, assuming a constant level of volatility at the 2013-2014 level for all periods after 2012.

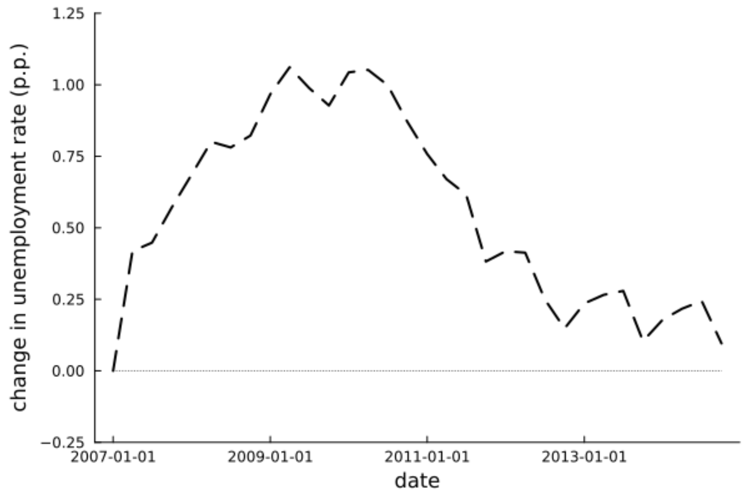
The path of idiosyncratic firm volatility has substantial fluctuations around the time of the great financial crisis. In particular, idiosyncratic volatility begins to rise around late-2007, peaking in late-2008 before falling through 2009 back to lower levels. As suggested by Schaal

Figure 10: Aggregate Scenario: Path of Idiosyncratic Volatility



Notes: Figure 10 displays the path of idiosyncratic volatility fed into the model in the macroeconomic response scenario. The path of idiosyncratic volatility follows the estimated path of the average idiosyncratic component of option-implied volatility (in standard deviations) as estimated by Dew-Becker and Giglio (2023) from 2005 to 2012, scaled relative to the average idiosyncratic volatility from 2013 to 2014. This path is fed into the dynamic contracting model, fixing the relative standard deviation at one for all periods beginning in 2013. The economy begins in the stationary distribution in the first quarter of 2005 and has perfect foresight over the evolution of idiosyncratic volatility over the transition. See the main text for more details.

Figure 11: Aggregate Scenario: Path of Unemployment

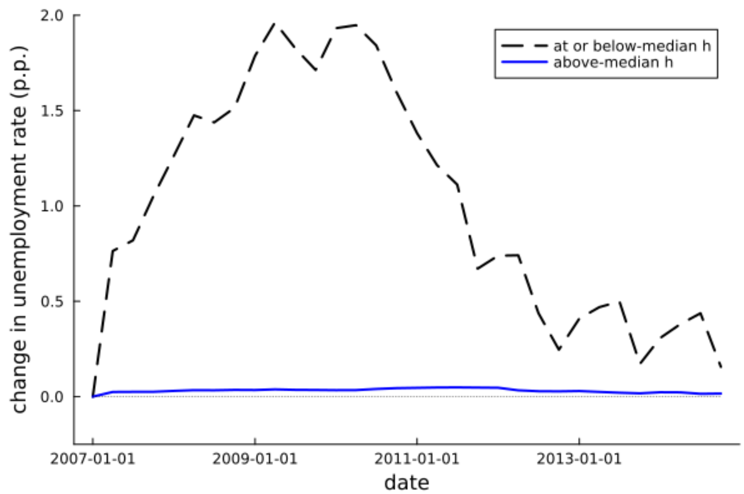


Notes: Figure 11 displays the path of unemployment in response to the aggregate scenario, defined by the path of average idiosyncratic volatility as displayed in Figure 10. The unemployment rate does not jump upon impact, as the announcement of the path of volatility affects search and retention decisions on impact but these affect the unemployment rate with a delay. As firm volatility shocks become more dispersed, the unemployment rate rises. The unemployment rate rises to a peak of 106 b.p. above the stationary level (rises to above 6 percent, where the stationary unemployment rate is about 5 percent). After firm volatility begins to decline, the unemployment rate begins falling back to its stationary level. However, this decline is not immediate, rather, it falls slowly back to the stationary level. This reflects both search frictions and human capital decay.

(2017) and supported by our empirical analysis, firm idiosyncratic volatility fluctuations may have implications for job transitions for workers, and in particular on the evolution of the unemployment rate. We hence focus on the effect of this volatility path on unemployment within the model. We illustrate the implications of a common increase in idiosyncratic volatility on unemployment in Figure 11.

In response to an increase in firm-level idiosyncratic volatility, unemployment rises substantially. Unemployment rises over the entire transition, peaking at a level about 106 b.p. above the stationary unemployment level in 2009 and 2010. The unemployment rate moves in a much more persistent way than the path of volatility over the transition, remaining elevated by over 50 basis points through 2010 and by over 20 basis points through 2013 despite firm volatility falling close to its stationary value around the beginning of 2010. As we have shown heterogeneity in the direct effect of volatility on workers in our empirical analysis, we similarly show heterogeneity in the effect of this volatility path on workers. We demonstrate this heterogeneous effect in Figure 12, where we compute the unemployment

Figure 12: Aggregate Scenario: Path of Unemployment, by Human Capital



Notes: Figure 12 displays the path of unemployment in response to the aggregate scenario, defined by the path of average idiosyncratic volatility as displayed in Figure 10, by workers' human capital levels. The increase in unemployment, as detailed in Figure 11, is almost entirely driven by low-human capital workers.

rate among low-human capital and high-human capital workers.

As is verified by Figure 12, there is heterogeneity across high- versus low-human capital workers in the response of unemployment to firm idiosyncratic volatility. In particular, low human-capital workers drive almost all of the unemployment response.

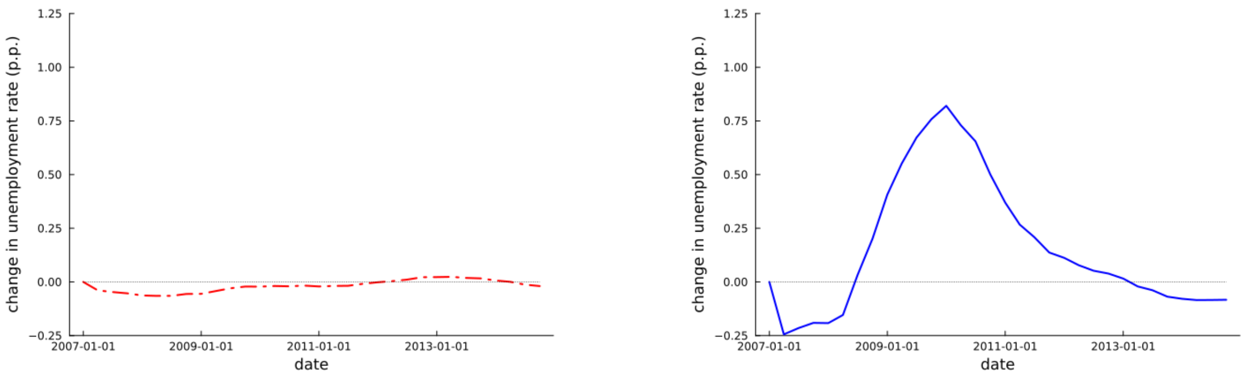
Finally, we feed the same path of firm volatility into the two alternative models without our benchmark model's key ingredients. We present the path of unemployment across the transition of idiosyncratic volatility in these models in Figure 13.

As is demonstrated in Figure 13, the alternative models have different implications for the path of unemployment to a fluctuation in idiosyncratic firm volatility. In the alternative model without fixed costs, unemployment is almost unaffected as firms do not lay off workers when volatility increases. Meanwhile, in the model without human capital scarring, unemployment does increase when firm dispersion increases, but it more quickly rebounds to its stationary level. The return to stationary unemployment in this alternative model is only hindered by search frictions, thus enabling a faster recovery.

We hence conclude that common fluctuations in firms' idiosyncratic volatility can have substantial implications for the evolution of the unemployment rate. In particular, our benchmark model suggests that short-lived spikes in firm idiosyncratic volatility can induce increases in unemployment that are substantial in magnitude and drawn-out in duration,

Figure 13: Aggregate Scenario: Path of Unemployment: Alternative Models

(a) No Fixed Costs (b) No Scarring



Notes: Figure 13 displays the path of unemployment in response to the aggregate scenario, defined by the path of average idiosyncratic volatility as displayed in Figure 10, under the two alternative models from Section 5. In the model without per-worker fixed costs, the unemployment rate is almost entirely unchanged across the transition. In the model without human capital scarring, the unemployment rate does rise when average idiosyncratic volatility increases. This increase, however, is smaller than the increase in unemployment as predicted by the baseline model as displayed in Figure 11, Additionally, while the unemployment rate does not fall immediately back down to the stationary level in the alternative without human capital due to search frictions, the lack of human capital scarring implies that the unemployment rate falls back to its stationary level much faster than in the baseline model, with a full recovery by 2013 whereas unemployment in the baseline model remains elevated beyond 2014.

consistent with the pattern of unemployment that we observed after the GFC. This mechanism explains 1.06 percentage points of the peak rise in unemployment in the GFC.

7 Conclusion

We document that workers' labor earnings move negatively in response to increases in their employer's stock price volatility. The magnitude of this finding is strongest at the bottom of the within-firm earnings distribution. We show that the effect is more incident upon job leavers as opposed to stayers, and volatility induces adverse separations.

We then write down a dynamic contracting model between workers and firms, where risk-neutral firms insure the income of risk-averse workers subject to worker moral hazard. We add heteroskedastic productivity volatility and human capital scarring to the model of Balke and Lamadon (2022).

In calibrating the model, we avoid targeting moments from our empirical evidence, and instead calibrate to match standard moments. We then look at the untargeted model analogues of our empirically estimated moments. We find that the model replicates the key relationships that we document empirically. We then compare to alternative models where we remove human capital scarring and fixed operating costs from the model. We find that these alternative models are unable to replicate the empirical findings, suggesting that this combination of ingredients is indeed important for matching the data.

Finally, we assess the macroeconomic implications of a widening of cross-sectional firm dispersion by feeding in the observed path of idiosyncratic volatility in the United States around the GFC into our model. In response to a common increase in volatility, our model suggests that an increase in firm idiosyncratic volatility alone can increase the unemployment rate by 1.06 percentage points. We document substantial heterogeneity in the unemployment response, with the increase almost entirely concentrated among low-human capital workers. We find that the response of unemployment to a common increase in firm volatility is larger and more prolonged than the alternative models which are inconsistent with this evidence, suggesting that our empirical findings have nontrivial implications for the macroeconomic consequences of increased dispersion of firm outcomes.

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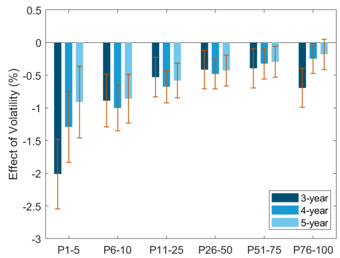
A Robustness of Empirical Estimates

In this appendix, we provide evidence supporting the robustness of our main empirical results, the heterogeneous impact of firm volatility fluctuations on workers' real earnings growth. We begin by detailing the results of key robustness exercises defending the validity of our instrumental variables approach as explained in Section 2.5, and then provide other robustness with respect to specification details as explained in Section 2.6 and Section 2.7.

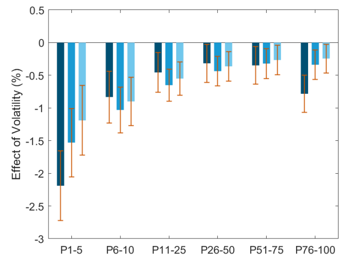
A.1 Robustness: Leave-one-out exercise

Here we present the results of our leave-one-out exercise, related to our instruments. In order to show that our results are not driven by any one instrument that violates the exogeneity assumption, we run our main regression (8) via 2SLS IV, removing one instrument at-a-time from the set of instruments used. Reassuringly, our results are very similar across all specifications. We present the results of this exercise in Figure A1.

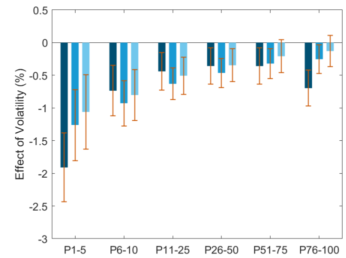
Figure A1: Robustness: Leave-One-Out Exercise



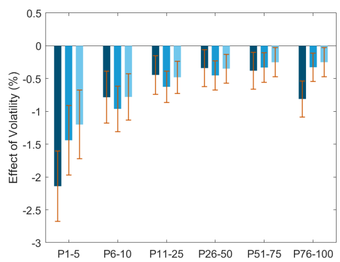
(a) Excluding AUD



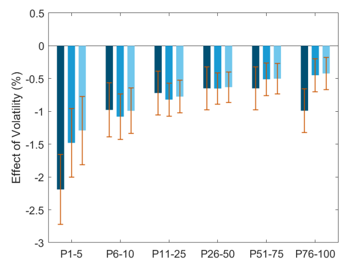
(b) Excluding CAD



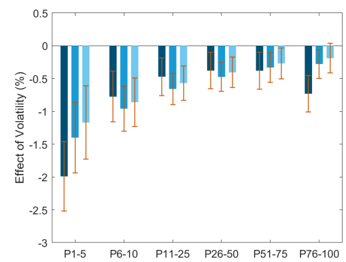
(c) Excluding CHF



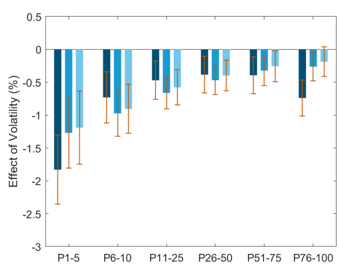
(d) Excluding EPU



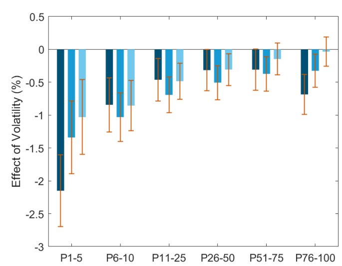
(e) Excluding Euro



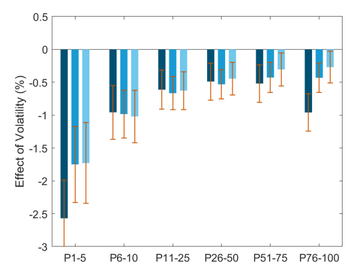
(f) Excluding GBP



(g) Excluding JPY



(h) Excluding Oil



(i) Excluding SEK

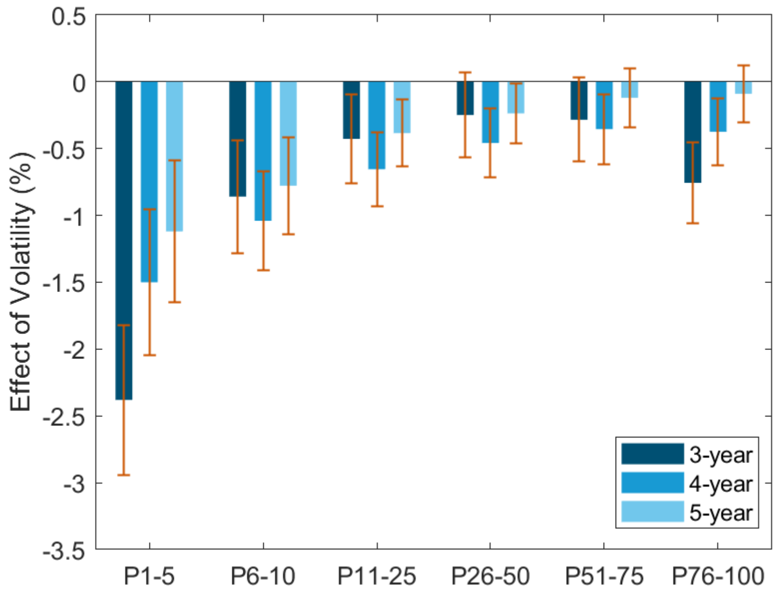
Notes: Figure A1 presents the results of estimating our baseline specification, equation (8), by 2SLS IV where we instrument for volatility by the instruments from Alfaro et al. (2024), excluding one instrument from the full set of instruments at-a-time. Each estimate includes the remaining 8 instruments per recent earnings bin. The estimates are all very similar to one another, suggesting none of the instruments are individually responsible for our results.

As can be seen from Figure A1, the estimated effect of volatility fluctuations on workers by percentile are quite similar, qualitatively and quantitatively, across specifications.

A.2 Robustness: Only Forex

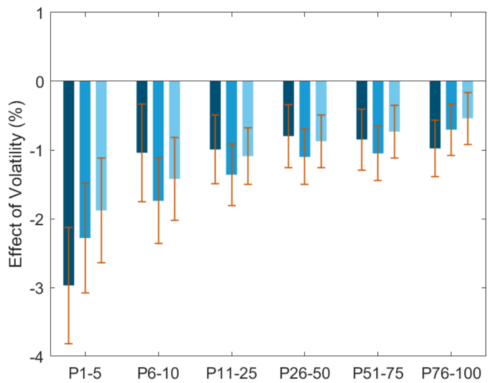
Here we present the results of our robustness exercise where we only include the exchange-rate based instruments from Alfaro et al. (2024), leaving out the oil- and economic policy uncertainty-based instruments. As Figure A2, Figure A4, and Figure A3 verify, this exercise results in similar estimates to our baseline as presented in the main text. This suggests that our results are not driven by the inclusion of the oi- and economic policy uncertainty-based instruments.

Figure A2: Robustness: Only Forex: Heterogeneous Effect of Volatility on Workers

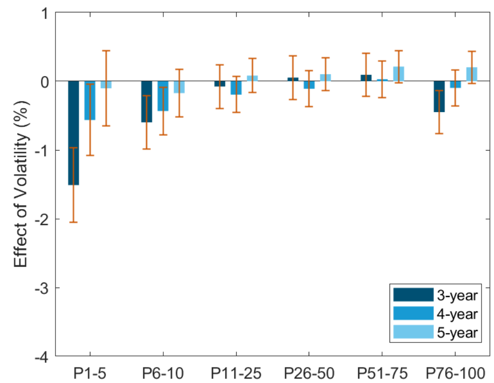


Notes: Figure A2 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we have only included the foreign-exchange based instruments. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A3: Robustness: Only Forex: Effects within-Leavers and -Stayers



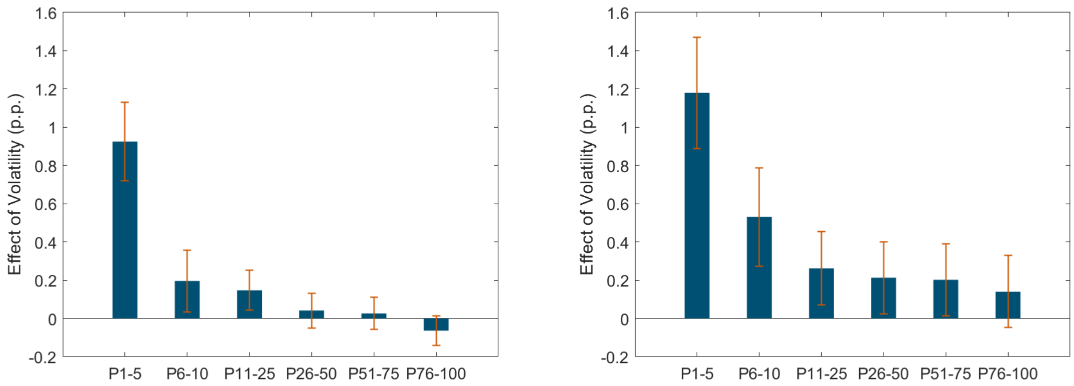
(a) Leavers



(b) Stayers

Notes: Figure A3 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we have only included the foreign-exchange based instruments. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A4: Robustness: Only Forex: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment

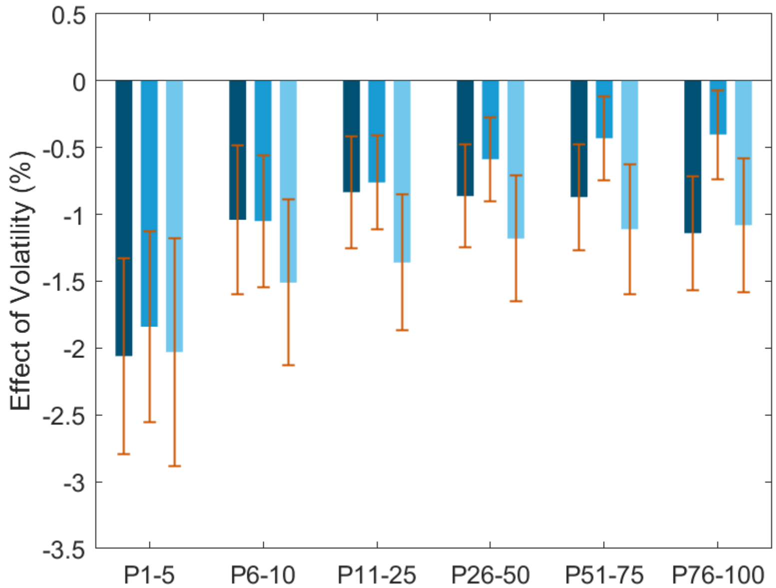
(b) Costly Separation

Notes: Figure A4 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we have only included the foreign-exchange based instruments. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.3 Robustness: No Forex

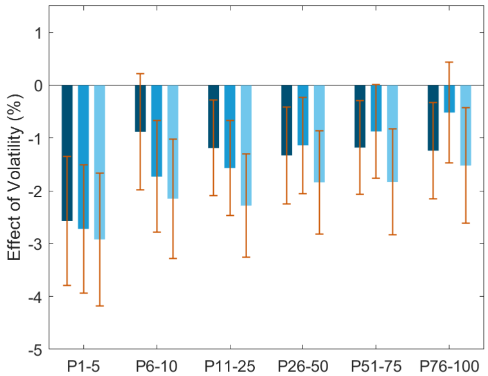
Here we present the results of the robustness exercise where we hold out the exchange rate-based instruments from Alfaro et al. (2024), including only the oil- and economic policy uncertainty-based instruments. The results are displayed in Figure A5, Figure A7, and Figure A6; reassuringly, the results are the same qualitatively and very similar qualitatively which supports that our results are not driven by the inclusion of the exchange-rate based instruments.

Figure A5: Robustness: No Forex: Heterogeneous Effect of Volatility on Workers

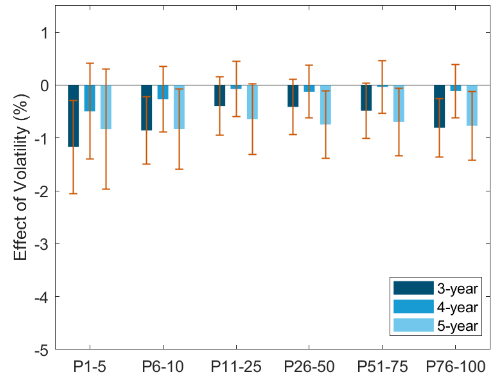


Notes: Figure A5 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we have excluded the foreign-exchange based instruments. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A6: Robustness: No Forex: Effects within-Leavers and -Stayers



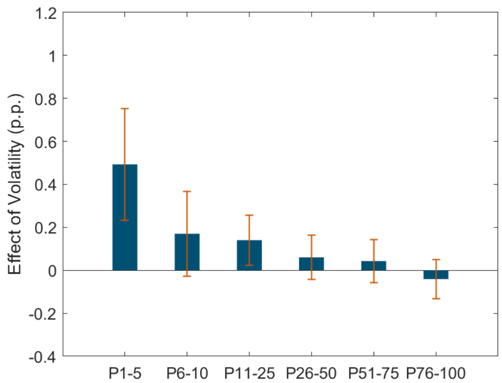
(a) Leavers



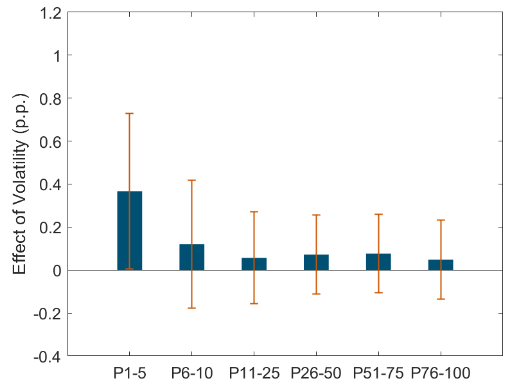
(b) Stayers

Notes: Figure A6 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we have excluded the foreign-exchange based instruments. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A7: Robustness: No Forex: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment



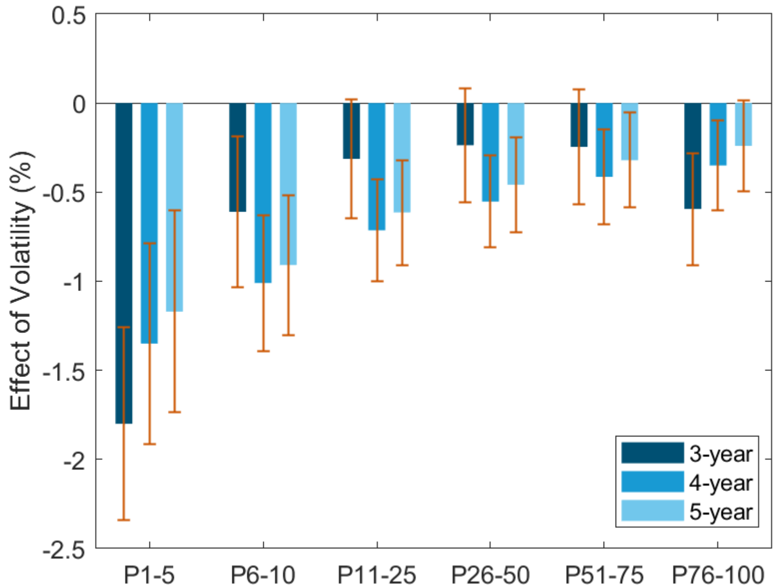
(b) Costly Separation

Notes: Figure A7 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we have excluded the foreign-exchange based instruments. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.4 Robustness: 1-digit SIC Sector-by-year Fixed Effect

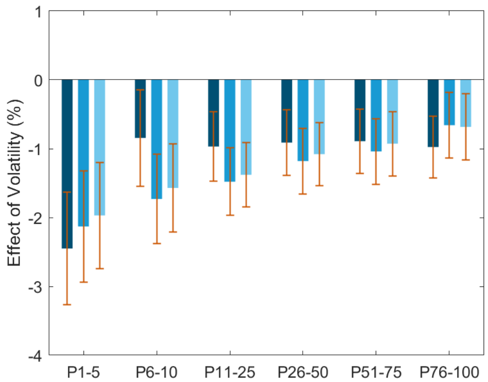
Here, we present the results of our robustness exercise where we include 1-digit SIC sector-by-year fixed effects in place of year fixed effects. Our instruments vary at the 2-digit SIC industry-by-year level, so this fixed effect can be separately identified without any other changes to the specification. Reassuringly, the results of this exercise, presented in Figure A8, Figure A10, and A9, are very similar to those of our baseline as presented in the main text. This suggests that our results are not driven by unobservables which vary at the sector-by-year level, such as sectoral-based technological change or changing industry-specific outside options for workers.

Figure A8: Robustness: 1-digit SIC Sector-by-year Fixed Effect: Heterogeneous Effect of Volatility on Workers

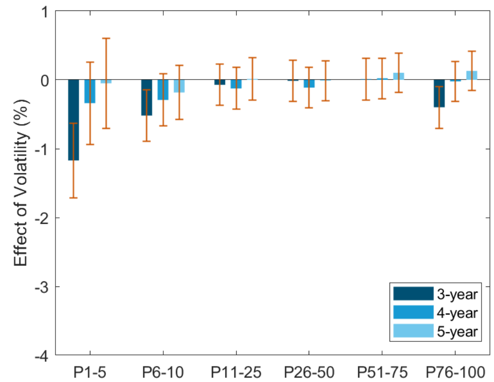


Notes: Figure A8 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, included a 1-digit SIC sector-by-year fixed effect in place of the year fixed effect. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A9: Robustness: 1-digit SIC Sector-by-year Fixed Effect: Effects within-Leavers and -Stayers



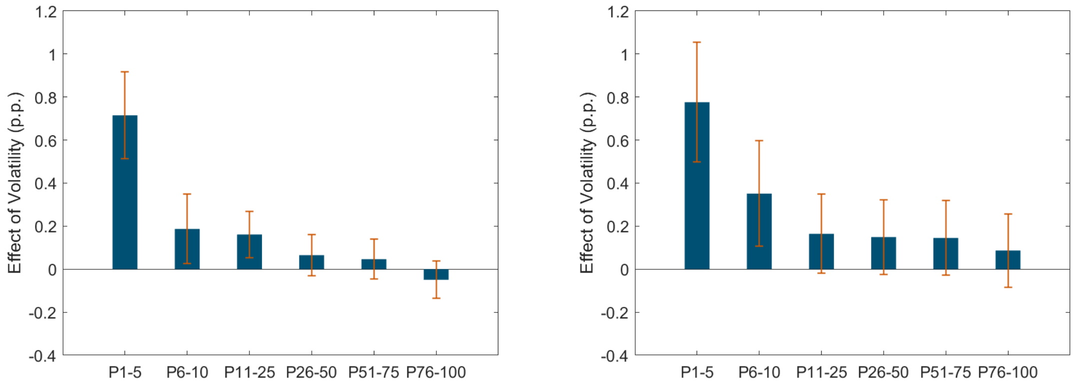
(a) Leavers



(b) Stayers

Notes: Figure A9 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, included a 1-digit SIC sector-by-year fixed effect in place of the year fixed effect. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A10: Robustness: 1-digit SIC Sector-by-year Fixed Effect: Heterogeneous Effect of Volatility on Layoffs



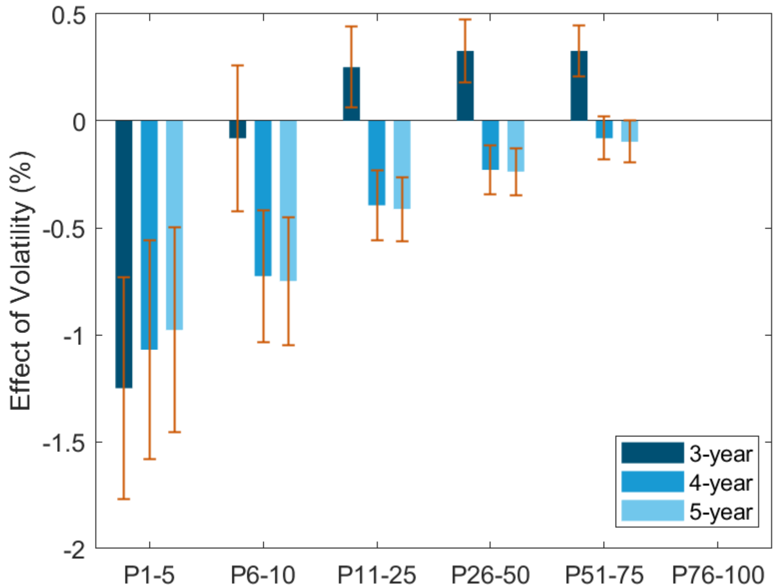
(a) Nonemployment (b) Costly Separation

Notes: Figure A10 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we have excluded the foreign-exchange based instruments. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.5 Robustness: Firm-by-year Fixed Effect

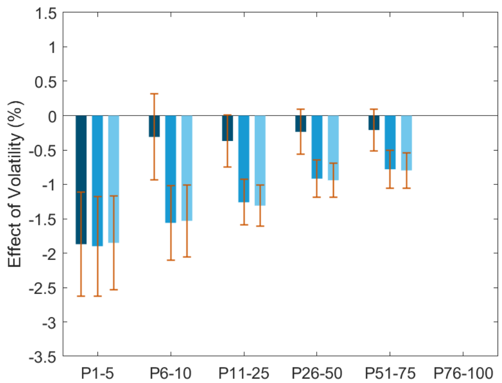
In this section, we present the results of including firm-by-year fixed effects in our regressions, in the place of year and firm fixed effects. As firm-level volatility varies at the firm-by-year level, the instruments vary at the 2-digit SIC industry-by-year level, further changes to the specification are required in order to identify all parameters in the regression. Specifically, we remove all controls which vary at the firm-by-year level, leaving us with just the recent earnings polynomial which varies at the individual-by-year level, and the remaining fixed effects. Then, we remove the endogenous right-hand-side variable for the heterogeneous effect of firm volatility on the highest-income (P76-100) group, as well as their instruments. In this regression, the firm-by-year fixed effect is then the average income growth amongst the highest income group, with the terms for the rest of the groups identified as a function of volatility relative to the top group. As is verified by Figure A11, Figure A13, and Figure A12, the results of this exercise are very similar to our baseline results as presented in the main text. This suggests that our results are not driven by any unobservables which are common to workers within the firm, such as firm-specific effects of technological change or outside options.

Figure A11: Robustness: Firm-by-year Fixed Effect: Heterogeneous Effect of Volatility on Workers

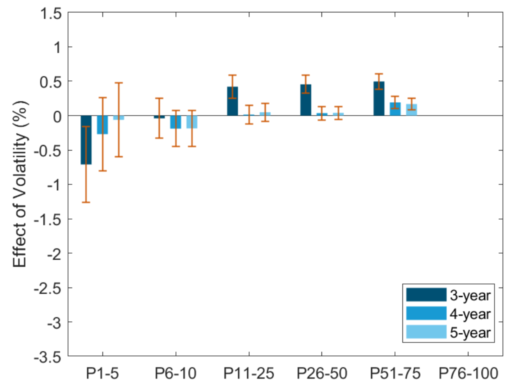


Notes: Figure A11 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we have included a fixed effect for firm-by-year instead of year (see text). The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A12: Robustness: Firm-by-year Fixed Effect: Effects within-Leavers and -Stayers



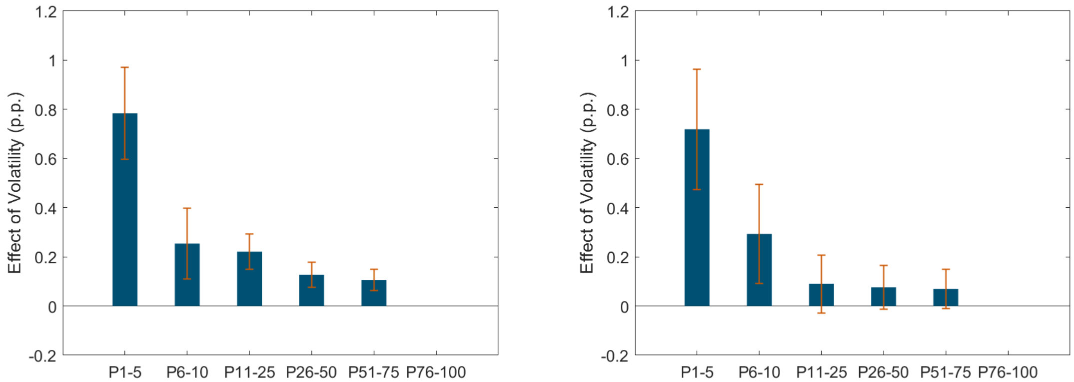
(a) Leavers



(b) Stayers

Notes: Figure A12 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we have included a fixed effect for firm-by-year instead of year (see text). The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A13: Robustness: Firm-by-year Fixed Effect: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment

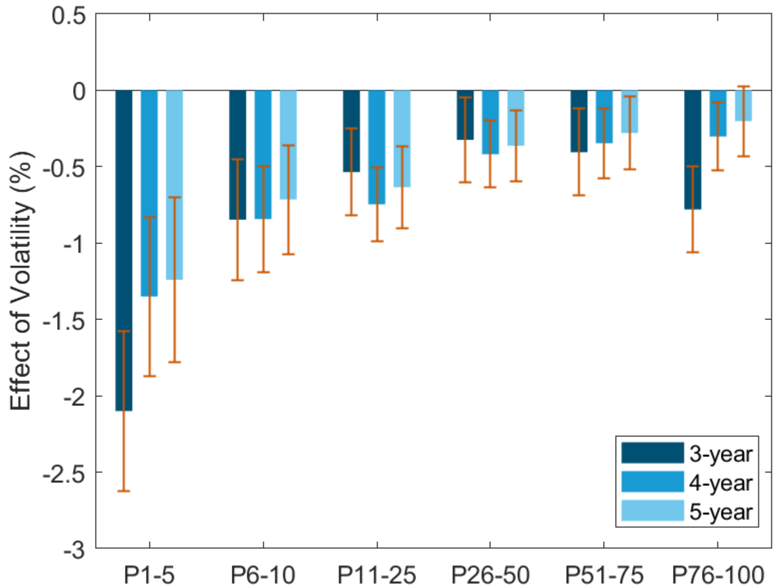
(b) Costly Separation

Notes: Figure A13 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we have included a fixed effect for firm-by-year instead of year (see text). Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.6 Robustness: Non-age-Adjusted Earnings Ranks

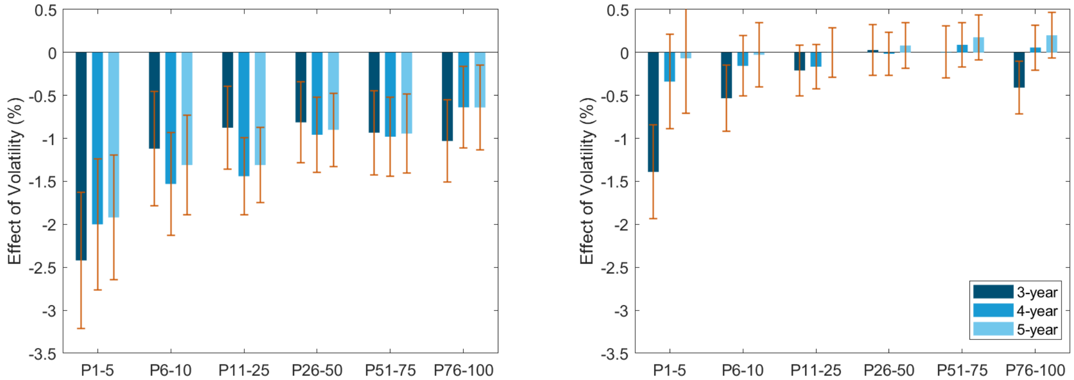
Here we present the results of our robustness exercise, where we do not age-adjust recent earnings ($\xi = 0$). Unlike in our baseline where earnings are age-adjusted to focus on human capital differences in the effect across individuals, we show here that this is not crucial in driving our results. As is verified by Figure A14, Figure A16, and Figure A15, the results of this exercise are very similar to that of the baseline results as reported in the main text.

Figure A14: Robustness: Non-age-Adjusted Earnings Ranks: Heterogeneous Effect of Volatility on Workers



Notes: Figure A14 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we rank workers within a firm in a given year by non-age-adjusted ($\xi = 0$) recent earnings. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A15: Robustness: Non-age-Adjusted Earnings Ranks: Effects within-Leavers and -Stayers

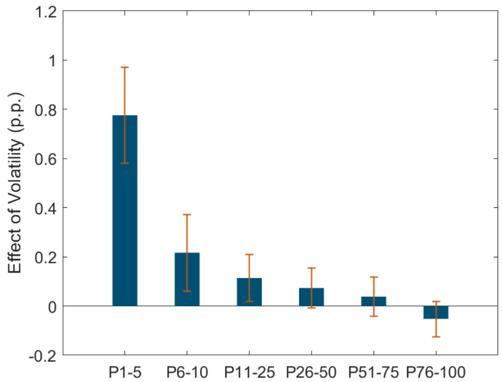


(a) Leavers

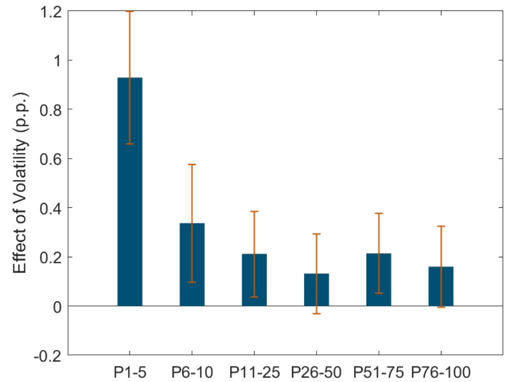
(b) Stayers

Notes: Figure A15 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we rank workers within a firm in a given year by non-age-adjusted ($\xi = 0$) recent earnings. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A16: Robustness: Non-age-Adjusted Earnings Ranks: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment



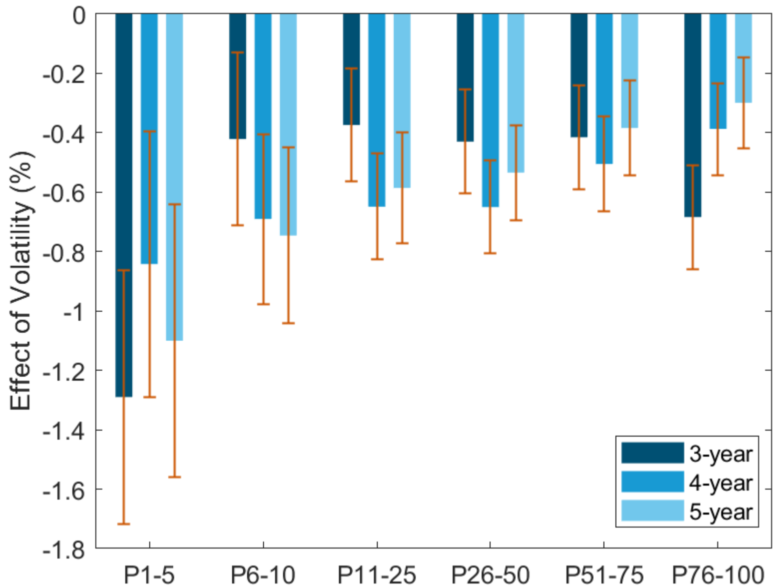
(b) Costly Separation

Notes: Figure A16 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we rank workers within a firm in a given year by non-age-adjusted ($\xi = 0$) recent earnings. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.7 Robustness: Realized Volatility

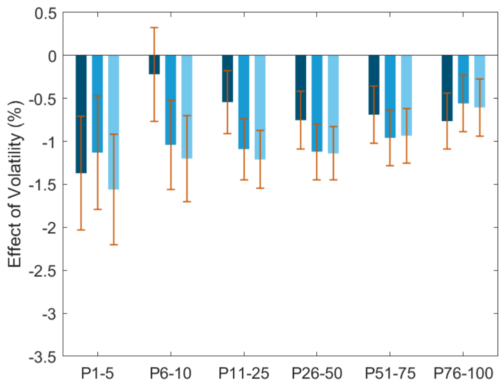
Here, we present the results of our robustness exercise where we use the 1-year average of daily realized volatility in place of the 1-year average of option-implied volatility as a proxy for a firm's fundamental volatility. As is verified by Figure A17, Figure A19, and Figure A18, the results of this exercise are very similar to that of our baseline estimates as presented in the main text.

Figure A17: Robustness: Realized Volatility: Heterogeneous Effect of Volatility on Workers

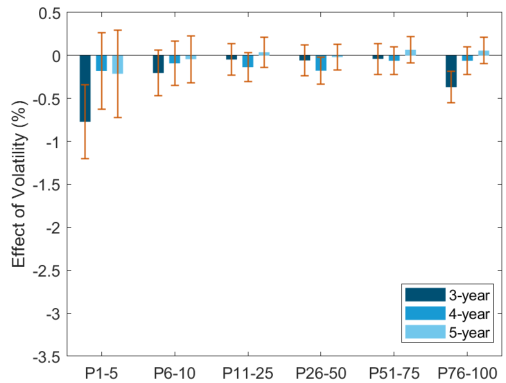


Notes: Figure A17 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we use realized volatility in the place of option-implied volatility. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A18: Robustness: Realized Volatility: Effects within-Leavers and -Stayers



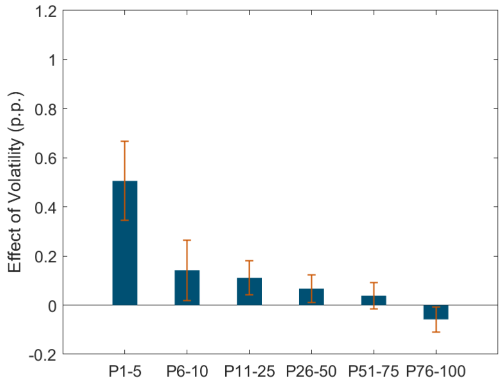
(a) Leavers



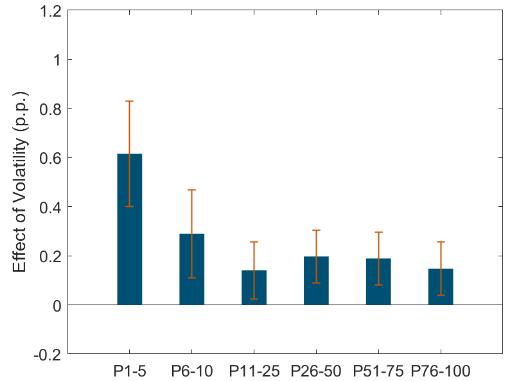
(b) Stayers

Notes: Figure A18 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we use realized volatility in the place of option-implied volatility. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A19: Robustness: Realized Volatility: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment



(b) Costly Separation

Notes: Figure A19 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we use realized volatility in the place of option-implied volatility. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

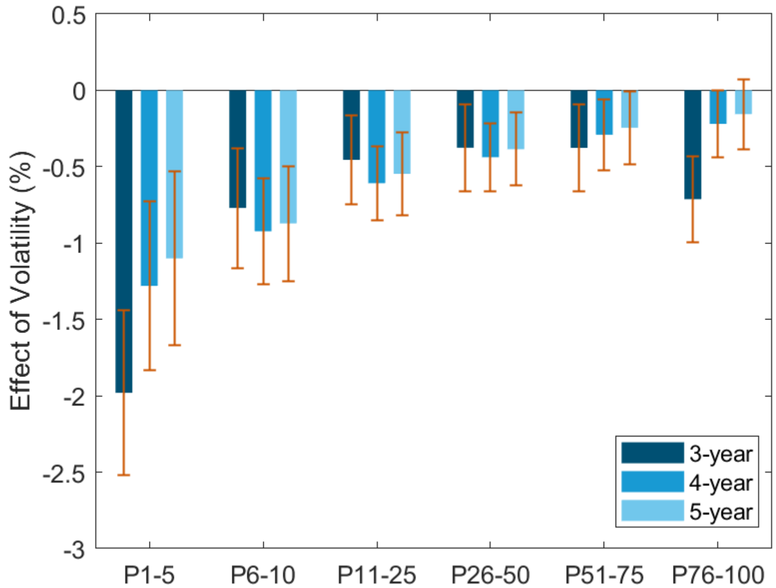
A.8 Robustness: Heterogeneous First-moment Controls

Here we present the results of the robustness exercise where we include heterogeneous first-moment controls to our regression specification. Specifically, we first estimate a naive estimate of TFP as the residual from an OLS estimate of a production function, which we take to be a proxy for firm TFP:

$$\Delta \log(\text{ValueAdded}_{j,t}) = \alpha^{VA} + \beta^{PPENT} \log(PPENT_{j,t}) + \beta^{EMP} \log(EMP_{j,t}) + \epsilon_{j,t}^{tfp}$$

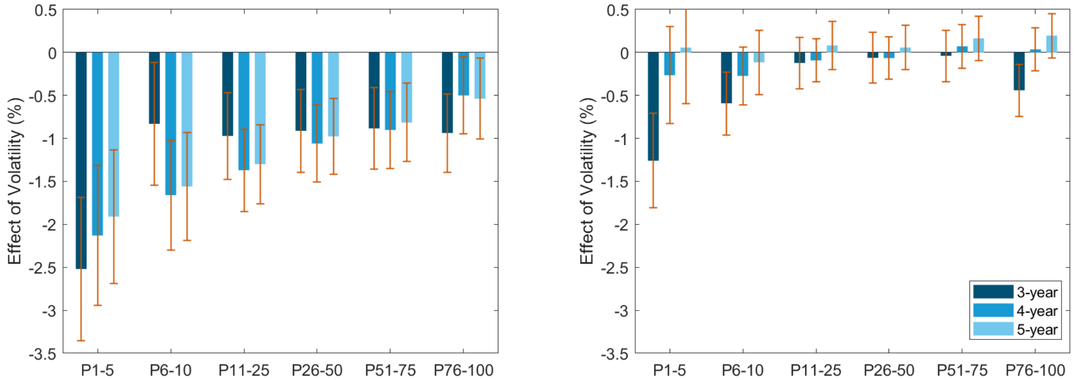
Then, we augment our baseline regression by adding controls for this TFP proxy-by-bin $\epsilon_{j,t}^{tfp} \times B_{p,i,t}$ to our regression specification in equation 8. The estimates for the coefficients on the volatility terms are shown in Figure A20, Figure A22, and A21. Reassuringly, the results are very similar to the results of our baseline regression as reported in the main text. The heterogeneous first-moment response is incident on the top of the recent earnings distribution rather than the bottom, as is consistent with the prior literature. The heterogeneous coefficients on the TFP proxy, both with and without including the volatility terms, are presented in Appendix B.

Figure A20: Robustness: Heterogeneous First-moment Controls: Heterogeneous Effect of Volatility on Workers



Notes: Figure A20 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we include controls for heterogeneous productivity effects (see text). The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A21: Robustness: Heterogeneous First-moment Controls: Effects within-Leavers and -Stayers

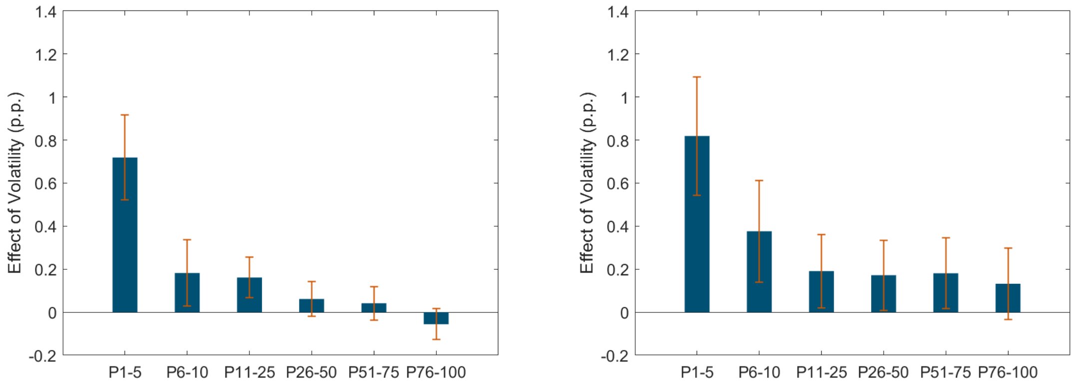


(a) Leavers

(b) Stayers

Notes: Figure A21 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we include controls for heterogeneous productivity effects (see text). The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A22: Robustness: Heterogeneous First-moment Controls: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment

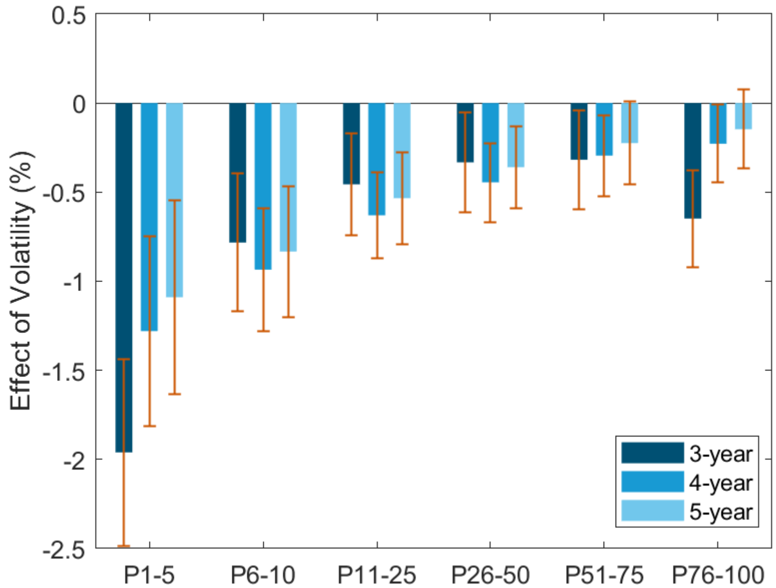
(b) Costly Separation

Notes: Figure A22 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we include controls for heterogeneous productivity effects (see text). Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.9 Robustness: Tenure Fixed Effect

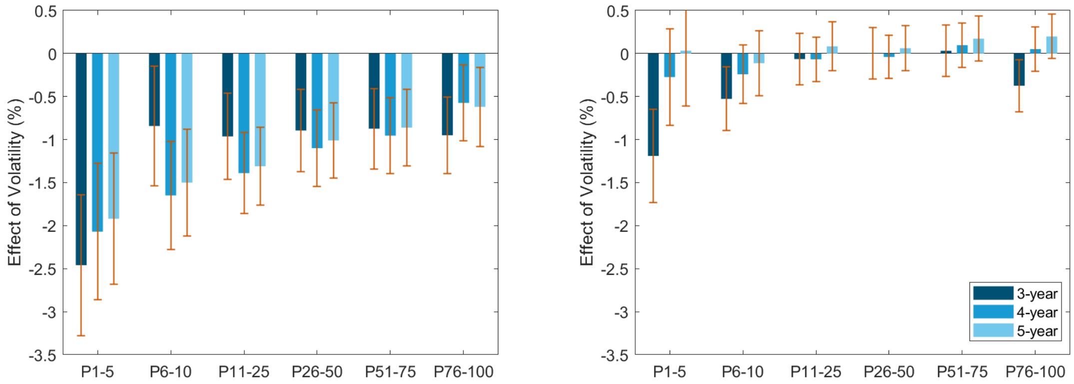
Here we present the results of our robustness exercise where we add fixed effects for worker tenure. In particulalr, we group workers by the number of consecutive observations leading into t in which their primary employer was the same employer as in t - one, two, or three and more. We stop at three or more as at this point all earnings observations in the construction of recent earnings are from the primary employer in t, although this choice is not critical. As we show in Figure A23, Figure A25, and A24, the results of this exercise are very similar to that of the results of our baseline estimates as presented in the main text.

Figure A23: Robustness: Tenure Fixed Effect: Heterogeneous Effect of Volatility on Workers



Notes: Figure A23 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we include a fixed effect for worker tenure. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

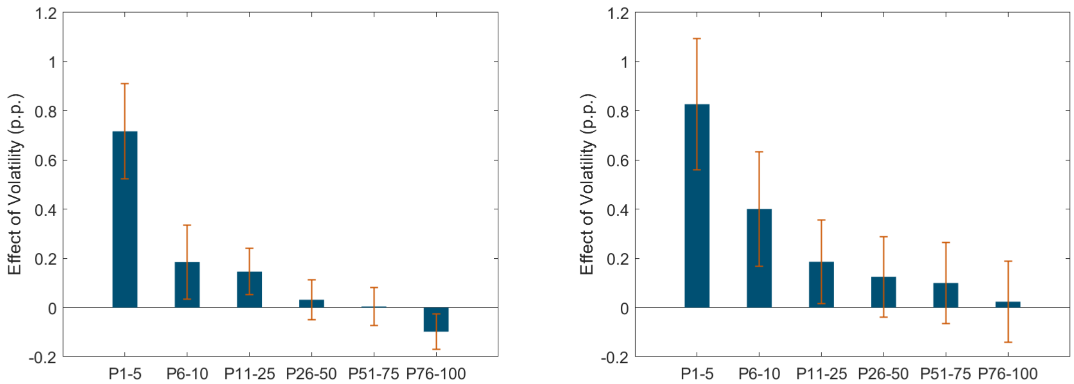
Figure A24: Robustness: Tenure Fixed Effect: Effects within-Leavers and -Stayers



(a) Leavers (b) Stayers

Notes: Figure A24 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we include a fixed effect for worker tenure. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A25: Robustness: Tenure Fixed Effect: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment

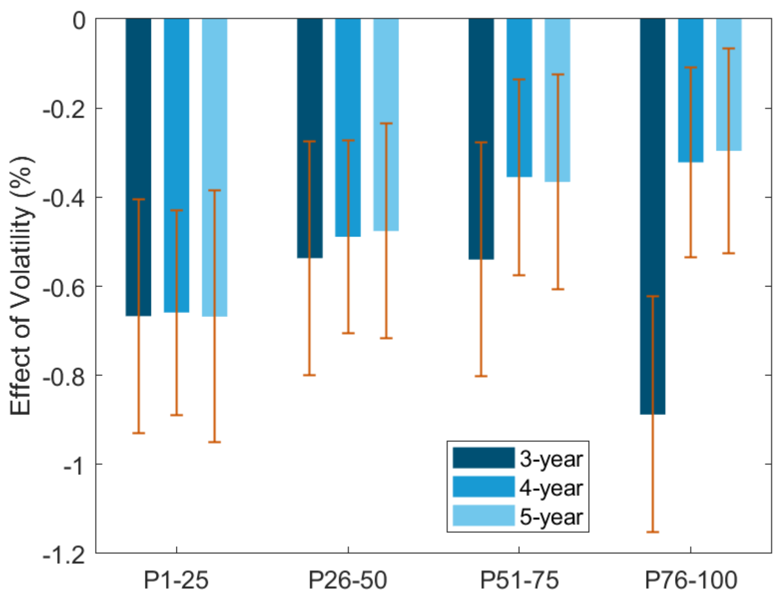
(b) Costly Separation

Notes: Figure A25 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we include a fixed effect for worker tenure. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

A.10 Robustness: Stricter Attachment Requirement

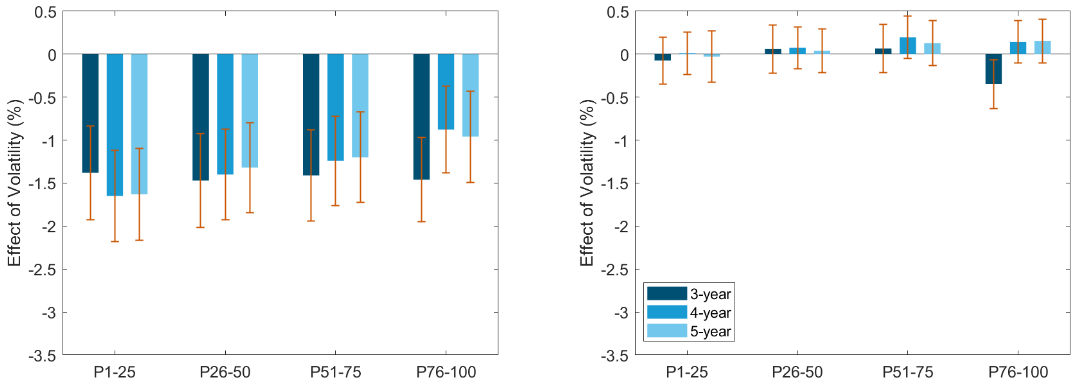
Here we present the results of requiring stricter firm attachment requirements to be included in our sample. Specifically, relative to our baseline specification, we additionally require that workers receive a nonzero amount of earnings from their firm in $t+1$ to be includeed in the regression. This requirement removes a non-uniform fraction of workers from our sample, so instead of breaking the recent earnings percentiles into $p \in \{1-5, 6-10, 11-25, 26-50, 51-75, 76-100\}$, we instead break into four groups, $p \in \{1-25, 26-50, 51-75, 76-100\}$. We then report the results in Figure A26, A28, and A27. Our results are both qualitatively and quantitatively similar with this added sample restriction.

Figure A26: Robustness: Stricter Attachment Requirement: Heterogeneous Effect of Volatility on Workers



Notes: Figure A26 presents the results of estimating our main regression specification, given by equation (8), by 2SLS IV. The volatility-bin interactions are instrumented with the volatility instruments from Alfaro et al. (2024), interacted with bin indicators. In this version, relative to our baseline estimate reported in Figure 1, we require workers to receive nonzero income in year $t+1$ from their year t primary employer. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

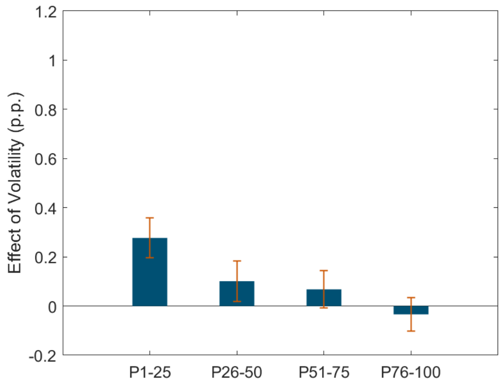
Figure A27: Robustness: Stricter Attachment Requirement: Effects within-Leavers and -Stayers



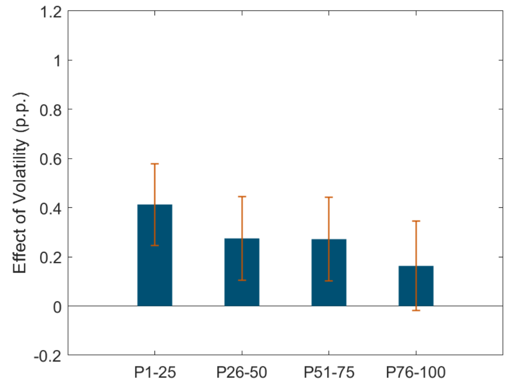
(a) Leavers (b) Stayers

Notes: Figure A27 reports the results of estimating equation (8) via 2SLS IV, where the bins B_p are defined to be over the interaction of earnings percentile bin and leaver/stayer status. The volatility terms are instrumented via the instruments from Alfaro et al. (2024) interacted with (age-adjusted) recent earnings percentile-by-leaver/stayer status indicators (see text). Panel (a) reports the effect of a 1-standard deviation increase in volatility within-leavers while panel (b) reports the effect within-stayers. In this version, relative to our baseline estimate reported in Figure 2, we require workers to receive nonzero income in year $t+1$ from their year t primary employer. The results are very similar to our baseline specification. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

Figure A28: Robustness: Stricter Attachment Requirement: Heterogeneous Effect of Volatility on Layoffs



(a) Nonemployment



(b) Costly Separation

Notes: Figure A28 reports the results of estimating equation (8) via 2SLS IV, replacing the left-hand-side variable with indicators for nonemployment and costly separations (see text for variable definitions) and instrumenting for the volatility terms with the instruments from Alfaro et al. (2024) interacted with recent earnings bins. Panel (a) reports the effect of volatility on nonemployment while panel (b) reports the effect of volatility on costly separations. In this version, relative to our baseline estimate reported in Figure 2, we require workers to receive nonzero income in year $t+1$ from their year t primary employer. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

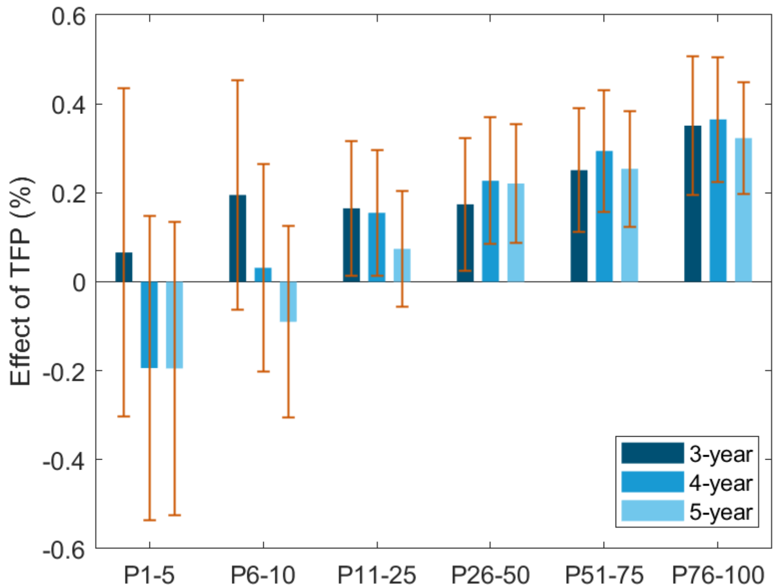
B First-moment Effect on Workers

Here we present the heterogeneous effects of first-moment firm fluctuations on workers' recent earnings. The related literature has shown that firms' first-moment fluctuations pass-through at the top of the firms' recent earnings distribution; here we show that this holds true for our sample as well. As in Appendix A.8, we take as a proxy for firm TFP the residual from a production function estimated by OLS:

$$\Delta \log(\text{ValueAdded}_{j,t}) = \alpha^{VA} + \beta^{PPENT} \log(PPENT_{j,t}) + \beta^{EMP} \log(EMP_{j,t}) + \epsilon^{tfp}_{j,t}.$$

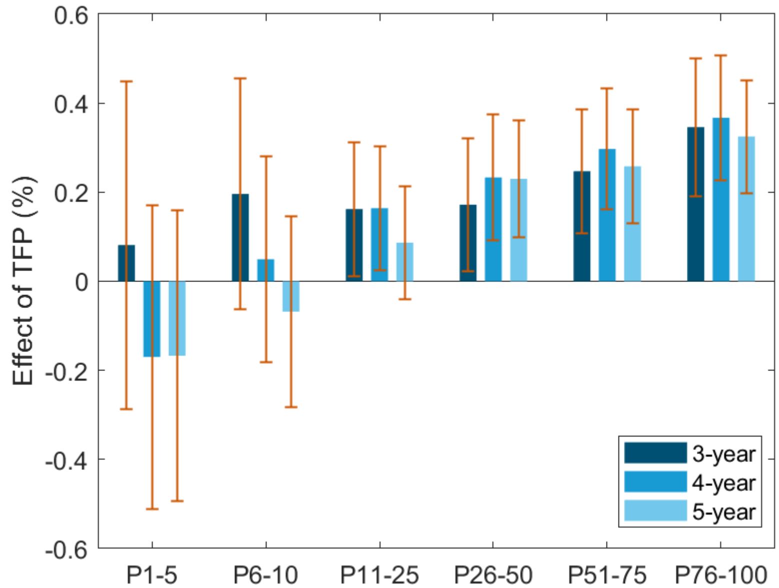
We then estimate the heterogeneous effect by interacting the TFP proxy with recent earnings bin $\epsilon^{tfp}_{j,t} \times B_{p,i,t}$. We estimate the heterogeneous effect in our baseline specification in terms of controls and fixed effects, both including and not including the volatility terms from 8. The results of this are presented in Figure A30 and Figure A29, respectively. As in the related literature, the first-moment pass-through is more incident on the top of the earnings distribution than the bottom.

Figure A29: First-moment Effect on Workers (No Het Vol Terms)



Notes: Figure A29 presents the results of estimating our main regression specification, given by equation (8), adding heterogeneous exposures to first-moment fluctuations as proxied by $\epsilon_{j,t}^{tfp}$ (see text) as exogenous controls. The volatility terms are instrumented as in our baseline specification. Similar to previous work from the literature, we find a larger pass-through at the top of the within-firm earnings distribution. Standard errors are clustered at the firm-by-year level and confidence intervals are 95 percent.

Figure A30: First-moment Effect on Workers (No Het Vol Terms)



Notes: Figure A30 presents the results of estimating our main regression specification, given by equation (8), replacing the volatility terms with heterogeneous exposures to first-moment fluctuations as proxied by $\epsilon_{j,t}^{tfp}$ (see text) and estimated by OLS. Similar to previous work from the literature, we find a larger pass-through at the top of the within-firm earnings distribution. Standard errors are clustered at the establishment level and confidence intervals are 95 percent.

C Model Characterization

Our model so closely follows the model of Balke and Lamadon (2022) that their Proposition 1 and Proposition 2 apply to our setting as well, which we will show by demonstrating that our model is nested by theirs. A necessary first step is to add randomizations choices by the firms to convexify their problem. This detail is omitted from the text for expositional reasons, but we write the problem with these randomizations here and this is the version of the model for which the proofs of Balke and Lamadon (2022) are valid.

We first set up the problem, no longer abstracting from randomizations from the firm's problem. The firm problem becomes:

$$J(V,h,z,\sigma) = \max_{w_i, W_i, \{W_i(h',z',\sigma')\}, \pi_i} \sum_{i=1,2} \pi_i \Big(f(z,h) - w_i + \lambda\beta\tilde{p}(W,h)\mathbb{E}[J(W(h',z',\sigma'),h',z',\sigma')] \Big) \tag{21}$$

subject to productivity, volatility, and human capital LOM, as well as:

$$V \leq \sum \pi_i \left(u(w) + \hat{r}(W,h)\right) \qquad \text{(promise-keeping)}$$
$$W_i = \mathbb{E}[W_i(h', z', \sigma')] \qquad \text{(rational expectations)}$$
$$\sum_{i=1,2} \pi_i = 1$$

After introducing randomizations for the firms, it is necessary to redefine the transition operators and vacancy postings to reflect this change. We begin by redefining $T^{*,e}$:

$$\begin{aligned}(T^{*,e}(\mathcal{W},\mu))(V',h',z',\sigma') = &\underbrace{\lambda \int \sum_{i=1,2} \pi_i(s) \mathbb{1}_{\{V'=(W_i(h',z',\sigma'))(s)\}} \tilde{p}(W_i(s),h) Pr(h'|h,\text{employed}) \zeta(z'|z,\sigma)\Pi(\sigma'|\sigma) d\mathcal{W}(s)}_{\text{Retention by current firm}} \\ &+ \underbrace{\lambda \int \sum_{i=1,2} \pi_i(s) \mathbb{1}_{\{V'=(W^e(h',z',\sigma'))(V^e(h,W_i(s)),h)\}} \iota p(\theta(h, V^e(h, W_i(s)))) Q(z',\sigma') Pr(h'|h,\text{employed}) d\mathcal{W}(s)}_{\text{New OTJS matches}} \\ &+ \underbrace{\lambda \int \mathbb{1}_{\{V'=(W^e(h',z',\sigma'))(V^u(h),h))\}} p(\theta(h,V^u(h))) Q(z',\sigma') Pr(h'|h,\text{unemployed}) d\mu(h)}_{\text{New matches from unemployment}}\end{aligned}$$

We then redefine $T^{*,u}$:

$$\begin{aligned}(T^{*,u}(\mathcal{W},\mu))(h') = &\underbrace{\lambda \int \sum_{i=1,2} \pi_i(s) \delta(e(W_i(s)),h) Pr(h'|h,\text{employed}) d\mathcal{W}(s)}_{\text{job separations}} \\ &+ \underbrace{\lambda \int (1 - p(\theta(h,V^u(h)))) Pr(h'|h,\text{unemployed}) d\mu(h)}_{\text{Unsuccessful job search of unemployed}} \\ &+ \underbrace{(1-\lambda)\mathbb{1}_{\{h'=\underline{h}\}}}_{\text{newborns}}\end{aligned}$$

Finally, the mass of vacancies posted in a submarket $\phi(h,V)$ is redefined as:

$$\begin{aligned}\phi(\tilde{h},V) = \theta(\tilde{h},V) \Bigg[&\mathbb{1}_{\{V=V^{*,u}(\tilde{h})\}} \mu(\tilde{h}) \\ &+ \iota \int \sum_{i=1,2} \pi_i(s) \mathbb{1}_{\tilde{h}=h} \mathbb{1}_{V=V^{*,e}(h,W_i(s))} d\mathcal{W}(s) \Bigg]\end{aligned} \tag{22}$$

We then redefine our concept of equilibrium to account for the firm randomizations:

Definition 2. *A* ***stationary recursive search equilibrium*** *consists of firm value func-*

tions $J(V,h,z,\sigma)$ and $J^e(V,h)$, an unemployed worker value $U(h)$, a job retention probability $\tilde{p}(h,V)$, a worker return function $\tilde{r}(W,h)$, optimal contract policy functions $\mathcal{C} = \{w_i^*, e_i^*, V_i^{e,*}, W_i^*, W_i^*(h',z',\sigma'), W^{e,*}(h',z',\sigma')\}_{i=1,2}$, worker submarket choice when unemployed $V^{u*}(h)$, market tightness function $\theta(h,V)$, distribution of employed workers $\mathcal{W}$, measure of unemployed workers μ and measure of vacancies in each submarket $\phi(h,V)$ such that:

i. $J(V,h,z,\sigma)$, $J^e(V,h)$, and $U(h)$ satisfy (21), (15), and (10).

ii. $\tilde{p}(h,V)$ and $\tilde{r}(W,h)$, given by (12) and (13) satisfy (11).

iii. $\mathcal{C}$ and $V^{u*}(h)$ contain the associated policies implied by the solution to these problems.

iv. $\theta(h,V)$ and $\phi(h,V)$ satisfy the free entry condition (16).

v. The distribution of employed $\mathcal{W}$ and unemployed μ workers are stationary (17), (18).

vi. $\mathcal{W}$, μ, and $\phi(h,V)$ clear the market (22).

Then, noting that the state variables in Balke and Lamadon (2022) correspond to the following state variables here: $x^{BL} = h$, $z^{BL} = (z,\sigma)'$, and the discount rate $\beta^{BL} = \tilde{\beta} = \lambda\beta$, we will prove that the following equations from this paper map directly into equations from Balke and Lamadon (2022):

1) Equation (9) maps directly into Balke and Lamadon (2022) equation (1)

2) Equation (10) maps directly into Balke and Lamadon (2022) equation (BE-U)

3) Equation (11) maps directly into Balke and Lamadon (2022) equation (EQ-W)

4) Equations (12) and (13) maps directly into the definitions of $\tilde{p}(x,W)$ and $\tilde{r}(x,W)$ from Balke and Lamadon (2022)

5) Equation (21) maps directly into Balke and Lamadon (2022) equation (BE-F)

6) Equation (15) maps directly into Balke and Lamadon (2022) equation (BE-V)

7) Equation (16) maps directly into Balke and Lamadon (2022) (EQ1)

After showing this, we tidy up a few remaining details and apply Balke and Lamadon (2022) Proposition 1 to prove existence of the equilibrium, while Balke and Lamadon (2022) Proposition 2 is immediately applicable.

C.1 Equation (9) maps directly into Balke and Lamadon (2022) equation (1)

Equation 9 gives us:

$$\begin{aligned}
Y_{j,t} &= \sum_h l_{j,t}(h) f(z_{j,t}, h) \\
&= \sum_h \sum_{(z,\sigma)} \tilde{l}_{j,t}(h,(z,\sigma)) f(z,h) \\
&= \sum_h \sum_{(z,\sigma)} \tilde{l}_{j,t}(h,(z,\sigma)) \tilde{f}(h,(z,\sigma)) \\
&= \sum_{x^{BL}} \sum_{z^{BL}} \tilde{l}_{j,t}(x^{BL}, z^{BL}) \tilde{f}(x^{BL}, z^{BL}),
\end{aligned}$$

where $\tilde{f}(h,(z,\sigma)) = f(h,z)$ and $\tilde{l}_{j,t}(h,(z,\sigma))$ is the mass of workers at firm j in period t with human capital h, matched with a firm of productivity z and volatility σ. Note that, by construction, $\tilde{l}_{j,t}(h,(z_{j,t},\sigma_{j,t})) = l_{j,t}(h)$ and $\tilde{l}_{j,t}(h,(z,\sigma)) = 0 \ \forall (z,\sigma) \neq (z_{j,t},\sigma_{j,t})$. This then matches Balke and Lamadon (2022) equation (1).

C.2 Equation (10) maps directly into Balke and Lamadon (2022) equation (BE-U)

Equation (10) gives us:

$$U(h) = u(b) + \lambda\beta \left[\max_{V^u} \left\{ p(\theta(h, V^u))V^u + (1 - p(\theta(h, V^u)))\mathbb{E}[U(h')] \right\} \right]$$

Substituting x^{BL} for h and $\tilde{\beta}$ for $\lambda\beta$, this immediately gives us:

$$U(x^{BL}) = u(b) + \tilde{\beta} \left[\max_{V^u} \left\{ p(\theta(x^{BL}, V^u))V^u + (1 - p(\theta(x^{BL}, V^u)))\mathbb{E}[U(x^{BL\prime})] \right\} \right],$$

which gives us Balke and Lamadon (2022) equation (BE-U).

C.3 Equation (11) maps directly into Balke and Lamadon (2022) equation (EQ-W)

Equation (11) gives us:

$$\max_{e,V^e} u(w) - c(e) + \lambda\beta\Big[\delta(e)\mathbb{E}[U(h')] + (1-\delta(e))[\iota p(\theta(h,V^e))V^e + (1-\iota p(\theta(h,V^e))W]\Big].$$

Substituting $\tilde{\beta} = \lambda\beta$ and $x^{BL} = h$ and writing out the terms, we recover the following:

$$\begin{aligned}&\max_{e,V^e} u(w) - c(e) + \tilde{\beta}\delta(e)\mathbb{E}[U(x^{BL\prime})] + \tilde{\beta}(1-\delta(e))\iota p(\theta(x^{BL},V^e))V^e \\ &\quad + \tilde{\beta}(1-\delta(e))(1-\iota p(\theta(x^{BL},V^e))W.\end{aligned}$$

This matches Balke and Lamadon (2022) equation (EQ-W).

C.4 Equations (12) and (13) maps directly into the definitions of $\tilde{p}(x,W)$ and $\tilde{r}(x,W)$ from Balke and Lamadon (2022)

Equation (12) gives us:

$$\tilde{p}(W,h) = (1-\delta(e^*(W,h)))(1-\iota p(\theta(h,V^{e*}(W,h)))),$$

and equation (13) gives us:

$$\begin{aligned}\hat{r}(W,h) &= -c(e^*(W,h)) + \lambda\beta\delta(e^*(W,h))\mathbb{E}[U(h')] \\ &\quad + \lambda\beta(1-\delta(e^*(W,h)))[\iota p(\theta(h,V^{e*}(W,h)))V^{e*}(W,h) + (1-\iota p(\theta(h,V^{e*}(W,h))))W].\end{aligned}$$

Substituting $\tilde{\beta} = \lambda\beta$ and $x^{BL} = h$, and rearranging slightly, we recover:

$$\tilde{p}(x^{BL},W) = (1-\delta(e^*(x^{BL},W)))(1-\iota p(\theta(x^{BL},V^{e*}(x^{BL},W)))),$$

and:

$$\begin{aligned}\hat{r}(x^{BL},W) &= -c(e^*(x^{BL},W)) + \tilde{\beta}(1-\delta(e^*(x^{BL},W)))\iota p(\theta(x^{BL},V^{e*}(x^{BL},W)))(V^{e*}(x^{BL},W) - W) \\ &\quad + \tilde{\beta}\delta(e^*(x^{BL},W))\mathbb{E}[U(x^{BL\prime})] + \tilde{\beta}(1-\delta(e^*(x^{BL},W)))W.\end{aligned}$$

These match the definitions of $\tilde{p}(x, W)$ and $\tilde{r}(x, W)$ from Balke and Lamadon (2022).

C.5 Equation (21) maps directly into Balke and Lamadon (2022) equation (BE-F)

Equation (21) gives us:

$$J(V, h, z, \sigma) = \max_{w_i, W_i, \{W_i(h', z', \sigma')\}, \pi_i} \sum_{i=1,2} \pi_i \Big(f(z, h) - w_i + \tilde{\beta}\tilde{p}(W, h)\mathbb{E}[J(W(h', z', \sigma'), h', z', \sigma')] \Big)$$

subject to:

$$\begin{aligned} V &\leq \sum \pi_i \left(u(w) + \hat{r}(W, h) \right) \\ W_i &= \mathbb{E}[W_i(h', z', \sigma')] \\ \sum_{i=1,2} \pi_i &= 1 \end{aligned}$$

Substituting $\tilde{\beta} = \lambda\beta$, $x^{BL} = h$, and $z^{BL} = (z, \sigma)$, we can very simply rewrite this as:

$$\begin{aligned} J(x^{BL}, z^{BL}, V) = \max_{w_i, W_i, \{W_i(x^{BL\prime}, z^{BL\prime})\}, \pi_i} \sum_{i=1,2} \pi_i \Big(& \tilde{f}(x^{BL}, z^{BL}) - w_i \\ & + \tilde{\beta}\tilde{p}(x^{BL}, W)\mathbb{E}[J(W(x^{BL\prime}, z^{BL\prime}), x^{BL\prime}, z^{BL\prime})] \Big) \end{aligned}$$

subject to:

$$\begin{aligned} V &\leq \sum \pi_i \left(u(w) + \hat{r}(x^{BL\prime}, W) \right) \\ W_i &= \mathbb{E}[W_i(x^{BL\prime}, z^{BL\prime})] \\ \sum_{i=1,2} \pi_i &= 1 \end{aligned}$$

This matches Balke and Lamadon (2022) equation (BE-F).

C.6 Equation (15) maps directly into Balke and Lamadon (2022) equation (BE-V)

Equation (15) gives us:

$$J^e(V,h) = \max_{\{W(h',z',\sigma')\}} \beta\lambda q(V,h)\mathbb{E}[J(W(h',z',\sigma'),h',z',\sigma')] - \kappa \text{ s.t. } V = \mathbb{E}[W(h',z',\sigma')]$$

Now define $\tilde{J}^e(\cdot) = J(\cdot)/(\beta\lambda)$ and $\tilde{\kappa} = \kappa/(\beta\lambda)$. Noting that $\beta\lambda > 0$, dividing equation (15) by $\beta\lambda$, and substituting $x^{BL} = h$ and $z^{BL} = (z,\sigma)$, we can rewrite this as:

$$\tilde{J}^e(x^{BL},V) = \max_{\{W(x^{BL\prime},z^{BL\prime})\}} q(x^{BL},V)\mathbb{E}[J(W(x^{BL\prime},z^{BL\prime}),x^{BL\prime},z^{BL\prime})] - \tilde{\kappa} \text{ s.t. } V = \mathbb{E}[W(x^{BL\prime},z^{BL\prime})].$$

This matches Balke and Lamadon (2022) equation (BE-V).

C.7 Equation (16) maps directly into Balke and Lamadon (2022) (EQ1)

Equation (16) gives us:

$$0 \geq J^e(V,h)$$

It is immediate that, by substituting $x^{BL} = h$ and dividing by $\beta\lambda$, this gives us

$$\tilde{J}^e(x^{BL},V) \leq 0.$$

This is Balke and Lamadon (2022) (EQ1).

C.8 Applying Theorems from Balke and Lamadon (2022)

We have now shown that the optimization problems and definitions of value functions from our paper (after adding the firm randomizations back in) are nested by the model of Balke and Lamadon (2022). What remains are the distributions and market clearing of vacancies. While Balke and Lamadon (2022) notate their measure transitions from the perspective of a firm, we make slightly different assumptions on the definition of a firm, which is not critical for the theory to go through due to the arbitrary nature of the definition of a firm in this context. We instead define the distributions as over the distribution of workers itself which is sufficient to characterize the equilibrium given the block-recursive nature of the model. Hence, while the way in which we define the distributions are different, the stationary distribution of worker over states is equivalent between our model and the model of Balke and Lamadon (2022).

The final step in showing equivalence in the model is then to show equivalence of the definition of the vacancy mass. Equation 22 gives us:

$$
\begin{aligned}
\phi(\tilde{h}, V) = \theta(\tilde{h}, V) \Bigg[& \mathbb{1}_{\{V = V^{*,u}(\tilde{h})\}} \mu(\tilde{h}) \\
& + \iota \int \sum_{i=1,2} \pi_i(s) \mathbb{1}_{\tilde{h}=h} \mathbb{1}_{V = V^{*,e}(h, W_i(s))} d\mathcal{W}(s) \Bigg].
\end{aligned}
$$

We write out the states explicitly and simplify the integral (using that z is explicitly discretized in the main text):

$$
\begin{aligned}
\phi(\tilde{h}, V) &= \theta(\tilde{h}, V) \Bigg[\mathbb{1}_{\{V = V^{*,u}(\tilde{h})\}} \mu(\tilde{h}) \\
&\quad + \iota \int_s \sum_{i=1,2} \pi_i(s) \mathbb{1}_{\tilde{h}=h} \mathbb{1}_{V = V^{*,e}(h, W_i(s))} d\mathcal{W}(s) \Bigg] \\
&= \theta(\tilde{h}, V) \Bigg[\mathbb{1}_{\{V = V^{*,u}(\tilde{h})\}} \mu(\tilde{h}) \\
&\quad + \iota \int_V \sum_{(z,\sigma)} \sum_{i=1,2} \pi_i(V, \tilde{h}, z, \sigma) \mathbb{1}_{V = V^{*,e}(\tilde{h}, W_i(V, \tilde{h}, z, \sigma))} \mathcal{W}(V, \tilde{h}, z, \sigma) dV \Bigg]
\end{aligned}
$$

Now we substitute in the variables of Balke and Lamadon (2022) and recover:

$$
\begin{aligned}
\phi(x^{BL}, V) = \theta(x^{BL}, V) \Bigg[& \mathbb{1}_{\{V = V^{*,u}(x^{BL})\}} \mu(x^{BL}) \\
& + \iota \int_V \sum_{z^{BL}} \sum_{i=1,2} \pi_i(V, x^{BL}, z^{BL}) \mathbb{1}_{V = V^{*,e}(x^{BL}, W_i(V, x^{BL}, z^{BL}))} \mathcal{W}(V, x^{BL}, z^{BL}) dV \Bigg].
\end{aligned}
$$

This matches Balke and Lamadon (2022) equation (EQ4).

To summarize what we have shown: the optimization problems and value functions in our model are nested by those in Balke and Lamadon (2022). The block recursive nature of the model ensures that the stationary distribution of workers over states is equivalent, and the vacancy posting is equivalent. Our model is then nested entirely within Balke and Lamadon (2022), and their Proposition 1 and Proposition 2 apply to our model. □

D Model Computation

Here we describe the computation of our quantitative model. We solve the model by discretizing the productivity distribution on 21 grid points, spaced linearly in $\log(z)$-space from 3 standard deviations above and below the ergodic distribution of the AR(1) process with the volatility fixed at the higher level $\sigma = \sigma_h$. Conditional expectations over z are similar to the Tauchen approximation, conditional on the current σ variable. We discretize the promised-value space V using linear grids with a large number of grid points (150), from the value of staying unemployed in all periods to the value of receiving the entire surplus of production at the highest level of productivity and human capital in all periods.

Given a firm's states (V, h, z, σ), firms choose both the wage to deliver to the employee today and a set of promises tomorrow, subject to promise keeping and rational expectations. Given the large number of states tomorrow, solving for all optimal state-contingent promises without more insight into the optimal policy is intractible. However, the optimality condition given by equation (20) provides an insight that a firm will always choose a single wage tomorrow to deliver to the worker, regardless of the state realization. We hence simplify the optimization problem by allowing a firm to choose a wage today and wage tomorrow to deliver to the worker, subject to promise-keeping and rational expectations, which we will now describe.

We begin by guessing the firm value $\hat{J}^0(V, h, z, \sigma)$ and the firm's wage policy function $\hat{w}^0(V, h, z, \sigma)$. A reasonable guess for each are the value and policy functions implied by the frictionless full-insurance problem. Then, given guesses of iteration n we invert the wage policy function which gives us the promised value in each state tomorrow (h', z', σ') which is consistent with that wage tomorrow $W^n(w', h', z', \sigma')$. We then plug the promise-keeping and rational expectations constraints into the objective and solve the following numerically using linear interpolation and a nonlinear optimizer (in practice, with appropriate upper and lower bounds this optimization is well-behaved so we use BFGS):

$$
\begin{aligned}
J^{n+1}(V, h, z, \sigma) = \max_{w' \geq 0} & f(z, h) - u^{-1}(V - \hat{r}^n(\mathbb{E}[W^n(w', h', z', \sigma')], h) \\
& + \lambda\beta\tilde{p}^n(\mathbb{E}[W^n(w', h', z', \sigma')], h)\mathbb{E}[J^n(W^n(w', h', z', \sigma'), h', z', \sigma')],
\end{aligned}
$$

where the wage policy function for iteration $n{+}1$ is given by $u^{-1}(V - \hat{r}(\mathbb{E}[W^n(w', h', z', \sigma')], h)$. Similarly, search markets are then indexed by an initial wage (as implied by the optimality condition from equation (15)) with worker values of submarkets formed by taking appropriate expectations over the promised value functions $W^n(w', h', z', \sigma')$. Worker searches are performed using a nonlinear optimizer over initial wages, and effort choices are in closed form given these optimal search decisions. In a given loop of the value function iteration, we solve for the worker policies and unemployed values, then firm policies and values. Because of the block recursive nature of the problem, as mentioned in the main text, the value function can be iterated upon until convergence, without solving for the stationary distrubution until convergence.

After the value functions converge, we can then simulate the workers forward in a straightforward fashion. For the SMM moments, we simulate 10,000 workers for 500 periods with a burn-in of 500 periods (so 1,000 periods in total, of which we drop the first 500 burn-in periods), and only consider one-worker one-firm. After calibrating the model, we consider multi-worker firms by first drawing a path of firm states, then drawing an initial distribution of workers for each firm from the distribution of workers, from our original (post burn-in simulation), that found a job. Hence, we capture both workers that transitioned into the new job from employment and from unemployment. We then simulate the workers in the firm forward until all workers have stochastically died or left. We then collect all observations that align with our empirical sample selection (i.e., have all necessary variables including individual and firm controls, as well as outcomes defined) and proceed to simulate the next firm. For these regressions, we simulate 500 firms with 1,000 workers per firm.

E Validation Appendix

E.1 Recalibration: No Fixed Costs

Here we report the calibration table for the version of the model without fixed costs ($c_f = 0$), where we recalibrate to match the moments from our baseline calibration except for the layoff rate which is dropped (cannot be matched without fixed costs).

E.2 Recalibration: No Human Capital Scarring

Here we report the calibration table for the version of the model without human capital scarring ($p_u = 0$, human capital process $\perp$ employment status), where we recalibrate to match the moments from our baseline calibration except for the earnings loss after layoff which is dropped (cannot be matched without human capital scarring).

Table A1: Calibration Fit, absent Fixed Costs

Parameter	Value	Moment	Model	Data	Source
ι	0.7011	J2J rate	0.04964	0.0495	LEHD Job-to-job
b	0.3440	UI replacement	0.3553	0.412	Braxton, Herkenhoff, Phillips (2024)
c_f	0.0	Layoff rate (dropped)	-	0.01343	Current Population Survey
p_e	0.06763	Earnings–age semielasticity	0.01030	0.0095	Braxton, Herkenhoff, Phillips (2024)
p_u	0.9245	Earnings loss after layoff	-0.08302	-0.089	Braxton, Herkenhoff, Phillips (2024)
κ	0.4036	UE rate	0.3778	0.4090	Current Population Survey
γ_0	1.186×10^3	EU rate	0.0211925	0.02012	Current Population Survey
γ_1	0.5272	Within-spell var. of $\Delta \log w$	0.02508	0.03028	Juhn, McCue, Monti, Pierce (2018)

Notes: Table A2 presents the fit of the moment matching algorithm, which identifies the parameters calibrated within the model, for the version of the model without fixed costs. See the text for more details on the moments and sources. The layoff rate is dropped as a target as the fixed cost parameter is set to 0, and the model generates no layoffs with zero fixed costs.

Table A2: Calibration Fit, absent Human Capital Scarring

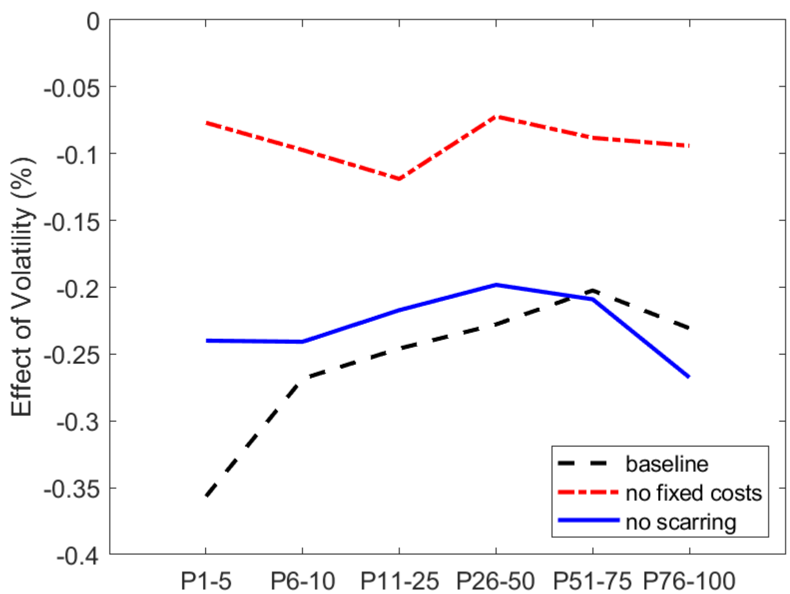
Parameter	Value	Moment	Model	Data	Source
ι	0.997	J2J rate	0.0579	0.0579	LEHD Job-to-job
b	0.449	UI replacement	0.3352	0.412	Braxton, Herkenhoff, Phillips (2024)
c_f	0.612	Layoff rate	0.01168	0.01343	Current Population Survey
p_e	0.0849	Earnings–age semielasticity	0.00803	0.0095	Braxton, Herkenhoff, Phillips (2024)
p_u	0.0	Earnings loss after layoff (dropped)	-	-0.089	Braxton, Herkenhoff, Phillips (2024)
κ	0.279	UE rate	0.4023	0.4090	Current Population Survey
γ_0	1.322×10^3	EU rate	0.01592	0.02012	Current Population Survey
γ_1	0.741	Within-spell var. of $\Delta \log w$	0.02136	0.03028	Juhn, McCue, Monti, Pierce (2018)

Notes: Table A2 presents the fit of the moment matching algorithm, which identifies the parameters calibrated within the model, for the version of the model without human capital scarring. See the text for more details on the moments and sources. The earnings loss after layoff is dropped as a target as the model cannot hit the target without human capital scarring.

E.3 Recalibration: Full Comparison Across Models

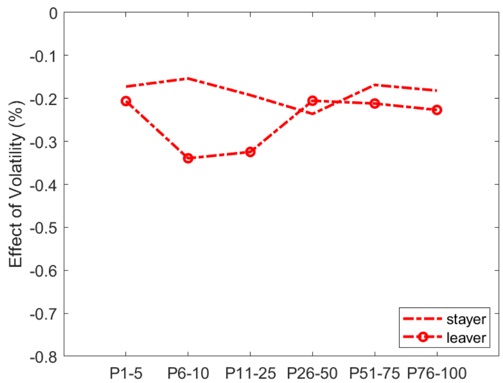
Here we present the comparison of our model validation across our baseline and alternative models without fixed costs and without human capital scarring, where the models have been recalibrated to remain consistent with the targeted moments as presented in Section E.1 and Section E.2, respectively. Figure A31 compares the heterogeneous effect of volatility on workers' earnings growth, Figure A32 compares the leaver/stayer effects within each model, and Figure A33 compares the effect of volatility on layoffs across the models.

Figure A31: Validation: Model Comparison (Recalibrated Models)

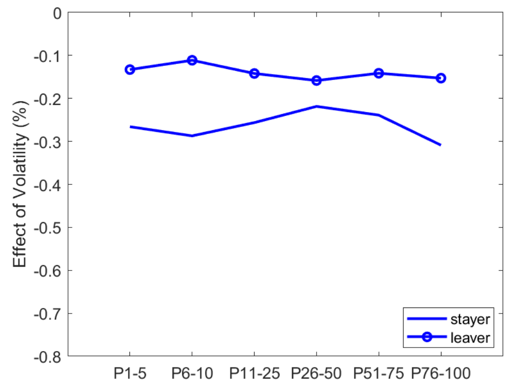


Notes: Figure A31 compares the results of estimating equation 8 on model-simulated data, between the baseline model and alternative models without fixed costs and without human capital scarring. The baseline model generates more pass-through at the bottom of the recent earnings distribution. Meanwhile, the alternative models fail to generate more pass-through at the bottom of the recent earnings distribution. The empirical results show more pass-through at the bottom of the recent earnings distribution.

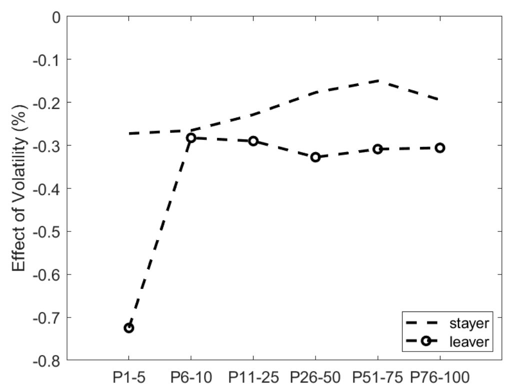
Figure A32: Validation: Model Comparison (Recalibrated Models): Leavers and Stayers



(a) No Fixed Costs



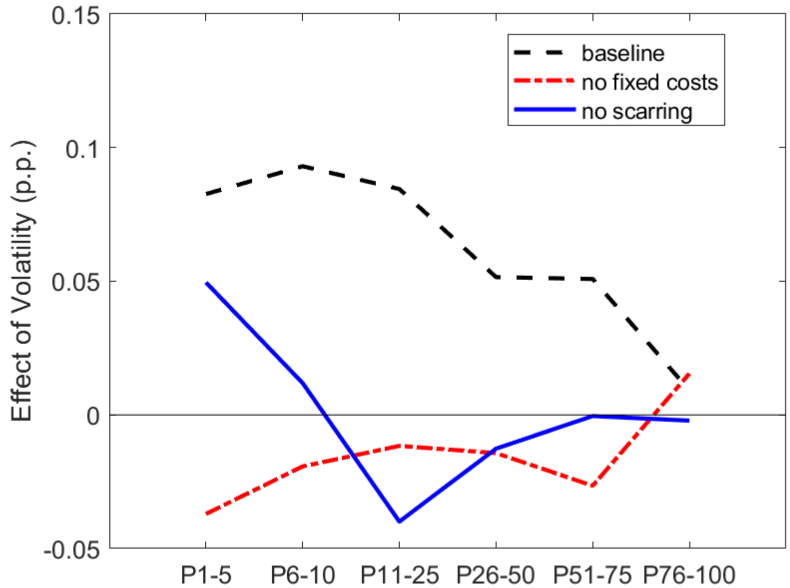
(b) No Scarring



(c) Baseline

Notes: Figure A32 compares the results of estimating equation 8 (with bins over the intersection of recent earnings bins and leaver/stayer status) on model-simulated data, between the baseline model and alternative models without fixed costs and without human capital scarring. The baseline model generates more pass-through among leavers than stayers, as does the model without fixed costs. Meanwhile, the alternative model generates more pass-through amongst stayers than leavers. The empirical results show more pass-through among leavers than stayers.

Figure A33: Validation: Model Comparison (Recalibrated Models): Nonemployment



Notes: Figure A33 compares the results of estimating equation 8 on model-simulated data, with nonemployment as the outcome variable, between the baseline model and alternative models without fixed costs and without human capital scarring. The baseline model generates nonemployment at the bottom of the earnings distribution in response to volatility fluctuations, as does the alternative model without human capital scarring. Meanwhile, the alternative model without fixed costs fails to generate layoffs at the bottom of the recent earnings distribution when volatility increases. The empirical results show that nonemployment rises in response to increases in volatility.

E.4 No Recalibration: Full Comparison Across Models

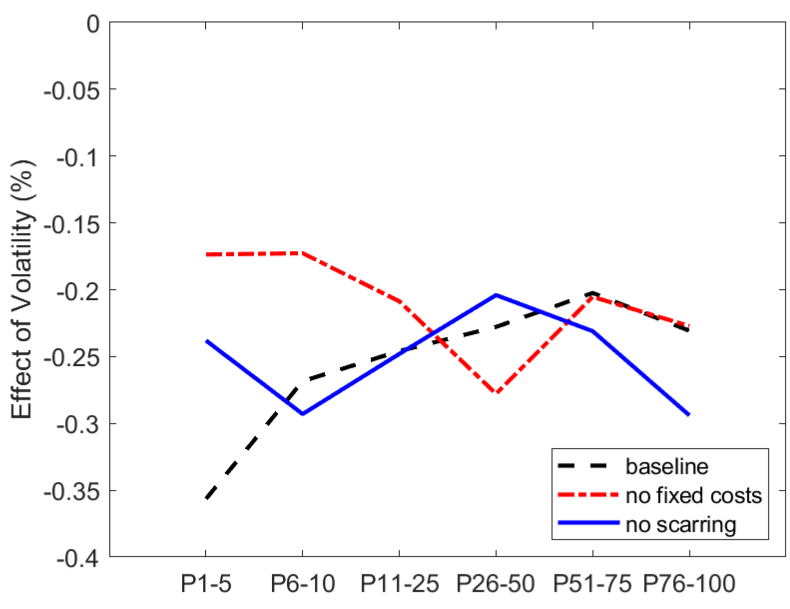
Here we present the comparison of our model validation across our baseline and alternative models without fixed costs and without human capital scarring, where the models have not been recalibrated to remain consistent with the targeted moments. Table A3 compares the average effects of firm volatility. Figure A34 compares the heterogeneous effect of volatility on workers' earnings growth, Figure A35 compares the leaver/stayer effects within each model, and Figure A36 compares the effect of volatility on layoffs across the models.

Table A3: Effect of 1 s.d. Volatility Fluctuation on Workers' Five-year Earnings Growth

	Data	Baseline	No fixed costs	No scarring
Effect (%)	-0.357	-0.233	-0.226	-0.246
Standard Error	(0.115)	-	-	-

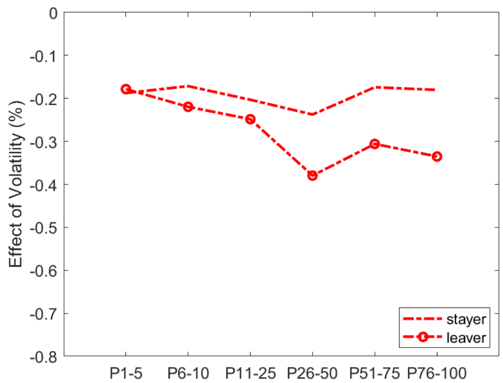
Notes: Table A3 compares the estimated average effect of a one standard deviation annual change in firm volatility on five-year real earnings growth (expressed as a percent) between the data, baseline model, and alternative models where key ingredients in the model are turned off. The model moments are untargeted in all cases. The two alternative models remove either the operating fixed costs or human capital scarring,without recalibrating the other parameters. The effect of firm volatility on workers' earnings growth is larger (closer to the data) than the alternative models.

Figure A34: Validation: Model Comparison (Non-recalibrated Models)

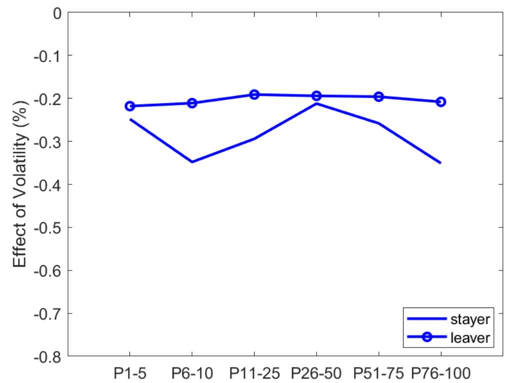


Notes: Figure A31 compares the results of estimating equation 8 on model-simulated data, between the baseline model and alternative models without fixed costs and without human capital scarring where the alternative models have not been recalibrated to remain consistent with the target moments. The baseline model generates more pass-through at the bottom of the recent earnings distribution. Meanwhile, the alternative models fail to generate more pass-through at the bottom of the recent earnings distribution. The empirical results show more pass-through at the bottom of the recent earnings distribution.

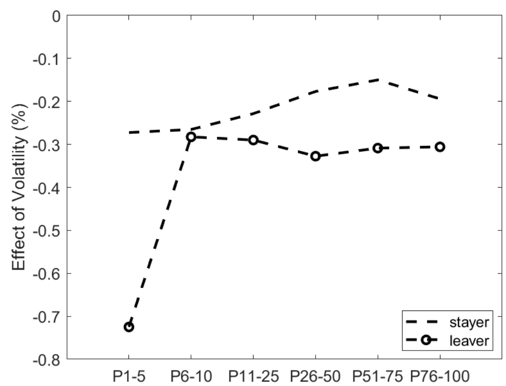
Figure A35: Validation: Model Comparison (Non-recalibrated Models): Leavers and Stayers



(a) No Fixed Costs



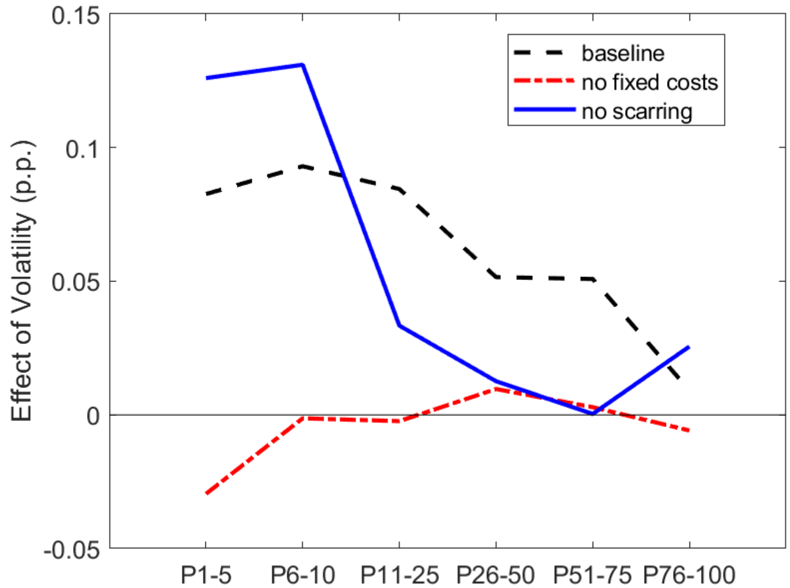
(b) No Scarring



(c) Baseline

Notes: Figure A35 compares the results of estimating equation 8 (with bins over the intersection of recent earnings bins and leaver/stayer status) on model-simulated data, between the baseline model and alternative models without fixed costs and without human capital scarring where the alternative models have not been recalibrated to remain consistent with the target moments. The baseline model generates more pass-through among leavers than stayers, as does the model without fixed costs. Meanwhile, the alternative model generates more pass-through among stayers than leavers. The empirical results show more pass-through among leavers than stayers.

Figure A36: Validation: Model Comparison (Non-recalibrated Models): Nonemployment



Notes: Figure A36 compares the results of estimating equation 8 on model-simulated data, with nonemployment as the outcome variable, between the baseline model and alternative models without fixed costs and without human capital scarring where the alternative models have not been recalibrated to remain consistent with the target moments. The baseline model generates nonemployment at the bottom of the earnings distribution in response to volatility fluctuations, as does the alternative model without human capital scarring. Meanwhile, the alternative model without fixed costs fails to generate layoffs at the bottom of the recent earnings distribution when volatility increases. The empirical results show that nonemployment rises in response to increases in volatility.

F The Firm's Role in Absorbing Risk

Our structural model of firm-worker insurance quantifies the trade-off that firms face in insuring workers' consumption stream versus providing dynamic incentives for workers, incentivizing effort. In addition to the direct effects that volatility has on workers' earnings growth that we document in Section 2, here we illustrate the effect that firm volatility has on this consumption-smoothing/dynamic incentive trade-off.

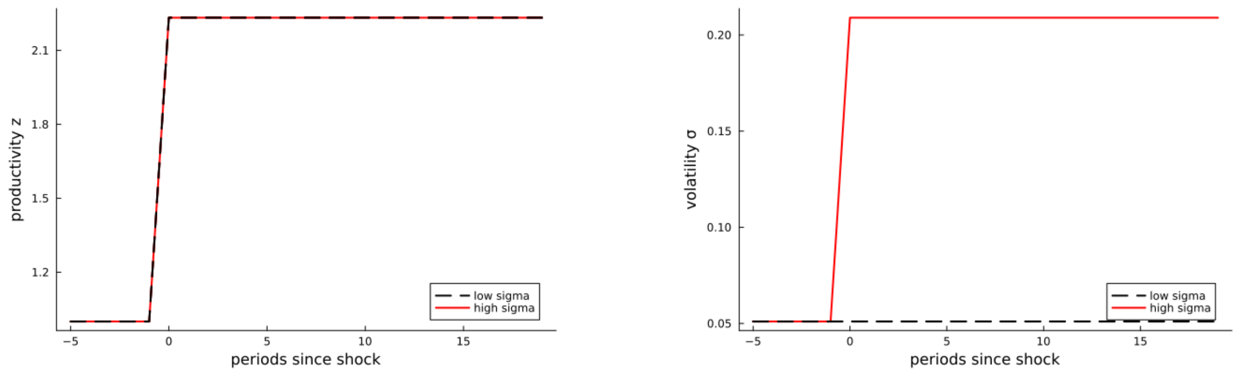
We first illustrate the effect of firm volatility on the response of a firm-worker match to a productivity shock through impulse responses, ruling out all forms of separations between workers and firms. In response to such a shock, production generates more profit in the current and, due to the persistence of productivity, future periods. Firms have more reason to want a match to continue after a positive productivity shock, and so firms use future wages as a carrot through which to incentivize workers to remain in the match, by providing higher levels of effort and by being more selective in their on-the-job-search. This forms the dynamic incentive motive. The firm trades off this incentive with a second force, the drive to smooth consumption for the worker.

When volatility is elevated, this latter force is affected. As the firm optimally perturbs worker consumption to provide dynamic incentives, as opposed to fixing consumption across periods and histories, when firm profitability becomes more volatile then, all else equal, the worker's consumption becomes more volatile. The risk-averse worker dislikes this, and hence the firm optimally responds to this increase in volatility by reducing the degree to which consumption adjusts to a given sequence of productivity shocks.

We demonstrate this effect through impulse responses under different firm volatility regimes. In particular, we consider two worker-firm matches. Both matches begin in the same states - the median level of human capital ($h = 1.5$), the steady-state level of productivity ($z = 1$), and the median level of firm volatility $\sigma = \sigma_L$. We initialize each match at the promised value consistent with the target wage at these states. At date 0, we perturb the productivity for each match by the same amount, substantially increasing productivity from $z = 1$ to $z = 2.23$. For one of the two matches, we also perturb the firm volatility from $\sigma = \sigma_L$ to $\sigma = \sigma_H$. While two states vary in this match, the productivity change is very large in both states and dominates the dynamics of the transition, however the regime over the two transitions is different due to the different volatility in the two states. We present the evolution of stochastic variables which define the impulse responses in Figure A37.

Figure A37: Impulse Response: Path of Idiosyncratic Productivity and Volatility

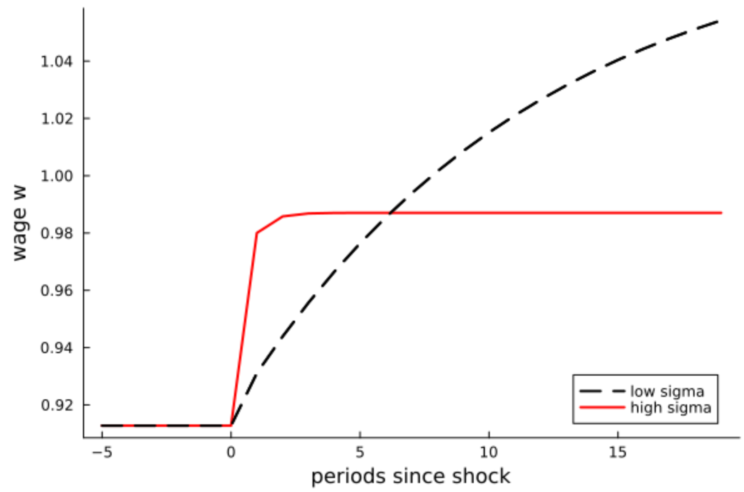
(a) Productivity (b) Volatility



Notes: Figure A37 shows the path of idiosyncratic firm productivity and idiosyncratic firm volatility for the two impulse response scenarios. In both scenarios, the match is assumed to continue for all periods (i.e., separation is ruled out) and human capital is fixed at the median level. Both scenarios are initialized at unit productivity and the low level of volatility, with the promised value at the level consistent with the target wage at the initial states. In both scenarios, productivity at period 0 jumps substantially, while in the "low sigma" response volatility stays at the lower level while in the "high sigma" response the volatility changes at period 0 to the high level of volatility. The very large shock to z ensures that the dominant driver of changes in policies are the productivity shock, while the two scenarios trace out the transition under the different volatility regimes.

In response to the shocks as presented in Figure A37, the matches respond in terms of wage. As the productivity increases substantially in both scenarios, it is straightforward that the firm will increase wages in response to this shock in order to incentivize the worker to stay and remain productive. However, how this dynamic incentive interacts with the consumption smoothing incentive of the firm-worker pair is a quantitative question which, we will show, depends on the volatility of the firm, in other words, on the quantity of risk facing the pair. We present the response of worker wages to these paths of shocks in Figure A38.

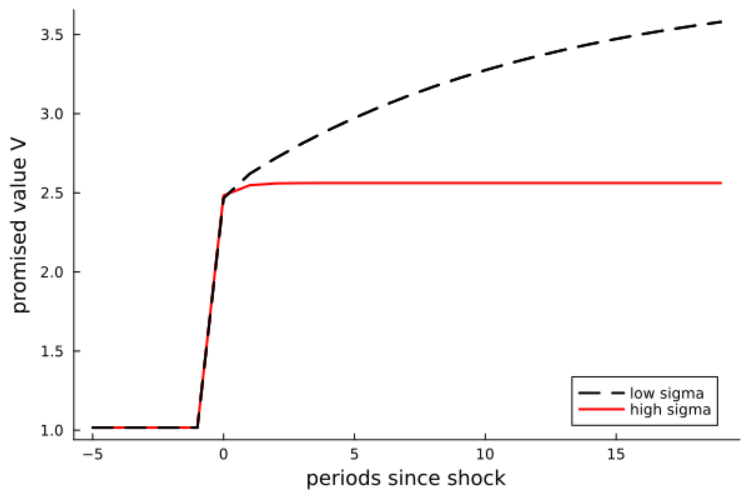
Figure A38: Impulse Response: Wage Path



Notes: Figure A38 shows the path of wages for the two impulse response scenarios. In both scenarios, the match is assumed to continue for all periods (i.e., separation is ruled out) and human capital is fixed at the median level. Both scenarios are initialized at unit productivity and the low level of volatility, with the promised value at the level consistent with the target wage at the initial states. In both scenarios, the wage does not jump at the incidence of the shock. Instead, the wages gradually adjust to new target wages, reflecting the dynamic-incentive motives for the firm's wage adjustment. Relative to the "low sigma" scenario, the target wage in the "high sigma" scenario moves less for the same productivity shock. Moreover, the wage approaches the target wage faster under the "high sigma" scenario, reflecting more consumption insurance from period 1 onwards relative to the "low sigma" scenario. In the "low sigma" scenario, the wage continues to adjust over the first 20 periods, reflecting the firm's dynamic incentive motives.

As can be seen from Figure A38, workers' wages have substantially different adjustment to productivity shocks under high- versus low-volatility regimes. Under the high volatility regime, relative to the low volatility regime, the target wage (the asymptote that wages adjust to, fixing states and assuming the match continues without end - see Balke and Lamadon (2022)) adjusts by less. This can be seen by the asymptote that the wages adjust to being different between these regimes, with the high-volatility asymptote being lower than the low-volatility asymptote. Another different feature across regimes is the speed at which the wages approach their target levels. Neither wage path adjusts instantaneously, however the higher consumption insurance granted by the path of wages under the high-volatility regime (after period 0) means that the wages in period 1 and later vary by less. In order to accomplish this, the wage in periods 1 and later approaches the target wage faster in the high-volatility regime than in the low-volatility regime. Contrasting this, in the low volatility regime consumption is allowed to vary by more across periods which results in a more gradual adjustment towards the target wage, with much more variation in wage in periods 1 and later. We will next show that the path of promised values is also different across regimes, in Figure A39.

Figure A39: Impulse Response: Value Path

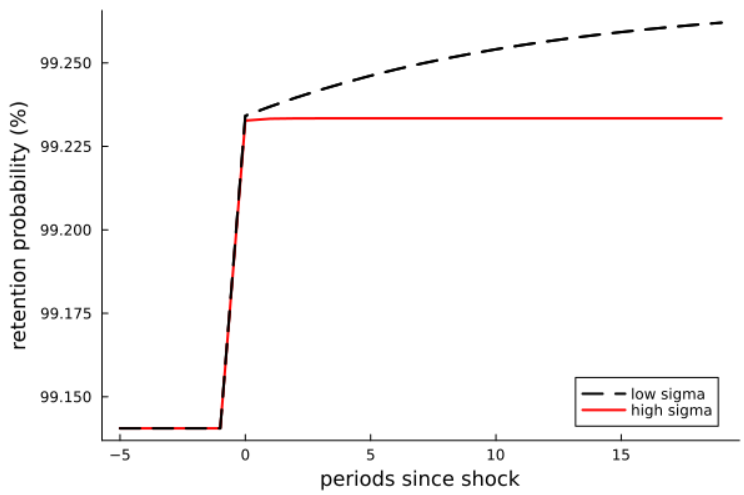


Notes: Figure A39 shows the path of promised value for the two impulse response scenarios. In both scenarios, the match is assumed to continue for all periods (i.e., separation is ruled out) and human capital is fixed at the median level. Both scenarios are initialized at unit productivity and the low level of volatility, with the promised value at the level consistent with the target wage at the initial states. Unlike the wage, the promised value jumps upon the realization of the productivity shock. The very similar jump in promised value between the two scenarios reflects the fact that the scenarios were designed such that the productivity shock, common to both scenarios, was the dominant shock for which both firm-worker matches respond to. In the"high sigma" scenario, the promised value does not change much after the incidence of the shock, reflecting the fact that the wage quickly approaches the new target wage, as demonstrated in Figure A38. In the "low sigma" scenario, however, the promised value continues to adjust, reflecting the firm's dynamic incentive motive.

The impact of the heterogeneous wage paths in the different productivity regimes on promised values for workers is presented in Figure A39. Under the high-volatility regime, the wages in periods 1 and later are almost constant which is reflected by the promised values being almost constant after the shocks. It does increase at the instant of the shock, which reflects the wages increasing in response to the shocks. In the low-volatility regime, however, the gradual wage adjustment reflects in a gradual promised-value adjustment for the worker. We will next show that this promised value adjustment has an impact on the firm's probability of retaining the worker through adjusting the dynamic incentives provided to the worker. We illustrate this in Figure A40.

We illustrate the response of the firm's probability of retaining their worker in Figure A40. In both scenarios, when the productivity increases the higher wages provided to the worker incentivizes the workers to stay in the match. Under the high-volatility regime, this increase is immediate but the retention probability remains almost constant after period-0. Under

Figure A40: Impulse Response: Retention Probability



Notes: Figure A40 shows the path of promised value for the two impulse response scenarios. In both scenarios, the match is assumed to continue for all periods (i.e., separation is ruled out) and human capital is fixed at the median level. Both scenarios are initialized at unit productivity and the low level of volatility, with the promised value at the level consistent with the target wage at the initial states. Unlike the wage, the promised value jumps upon the realization of the productivity shock. In both scenarios, the retention probability increases after the realization of the productivity shock, reflecting that the firm promises more value to the worker in order to incentivize the worker to remain in the match. In the "high sigma" scenario, the firm tilts their compensation scheme more towards consumption insurance than dynamic incentive provision, and hence while the retention probability jumps upon the shock's impact, it quickly flattens and is lower across the entire transition than the "low sigma" scenario. In the latter scenario, the retention probability continues to rise as the worker's wage and promised value increase (see Figure A38 and Figure A39, respectively).

the low-volatility regime, however, the retention probability adjusts on impact but continues to adjust, reflecting the continuous adjustment of wages under the regime, continuing to incentivize the worker more and more to remain in the match. This adjustment is almost entirely on the effort margin as, in both cases, the promised values given to the worker after such a large productivity shock are sufficiently high so as to make it impossible for a firm, ex ante, to deliver higher promises to the worker.

We next quantify the degree of risk absorption that firms provide workers by quantifying how firm productivity shocks transmit to workers' earnings in the different volatility regimes. As is suggested by the impulse responses just presented, workers' long-run earnings growth over long horizons is differentially affected by a given productivity fluctuation across the different regimes. To measure this effect, we run regressions on model-simulated data, regressing workers' 5-year earnings growth on firm (log) productivity fluctuations, with transmission a function of the current volatility state, and the controls and fixed effects included in our baseline specifications. We describe this regression by Equation 23.

$$g_{i,t:t+h} = \beta(\sigma_{j,t}) \Delta \log z_{j,t+1} + \Xi X_{i,t} + \varepsilon_{i,t} \tag{23}$$

We present the σ-dependent transmission of firm productivity shocks to workers' earnings growth in Table A4.

As Table A4 shows, the transmission of firm productivity fluctuations to workers' earnings growth changes substantially under the two firm volatility regimes. When firms' productivity shocks themselves become more volatile, firms perturb workers' consumption by less for a given shock in order to tilt the compensation scheme more towards providing consumption insurance instead of providing dynamic incentives to workers. Using these conditional shock transmissions, as well as the levels of productivity volatility in each state, we can then measure the quantity of risk that firms absorb when firm volatility increases. In particular, we define risk absorption as the fraction of five-year earnings variance that the worker would counter-factually be exposed to if the firm did not adjust its transmission of productivity shocks, that the worker is insulated from by the firm's change in wage policies. That is, the change in five-year earnings risk from a given shock being at the high-volatility level versus the low-volatility level, without the firm adjusting its policies, is $\beta(\sigma_L)(\sigma_H^2 - \sigma_L^2)$. The quantity of risk absorbed by the firm is $(\beta(\sigma_L) - \beta(\sigma_H))\sigma_H^2$ so the fraction of risk absorbed by the firm is $\frac{(\beta^2(\sigma_L) - \beta^2(\sigma_H))\sigma_H^2}{(\sigma_H^2 - \sigma_L^2)\beta^2(\sigma_L)} = 58.9\%$. We then show how this risk absorption is heterogeneous across workers in Figure A41.

Table A4: Model effect of $\Delta \log z_{j,t+1}$ on $g_{i,t:t+5}$ (as a %)

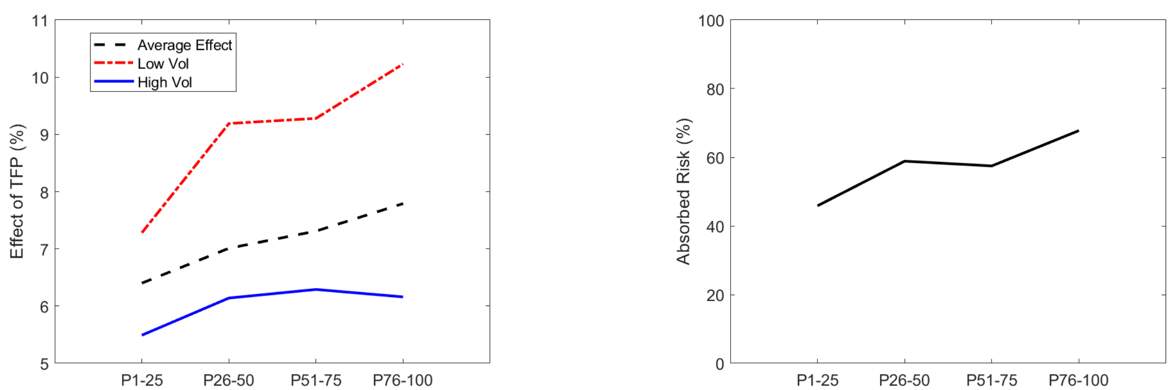
$\beta(all)$	7.13
$\beta(\sigma_L)$	8.98
$\beta(\sigma_H)$	6.02

Notes: Table A4 displays the transmission of firm productivity changes to workers' 5-year earnings growth in the structural model. Productivity is not rescaled. A unit change in firm productivity in the model thus reduces workers' 5-year earnings by about 7 percent. The table also presents the *conditional* transmission of firm productivity shocks, depending on the volatility state of the firm in period $t+1$. Consistent with the impulse response of wage to workers' wages under a high- versus low-volatility regime as displayed in Figure A38, a given firm productivity shock passes through to a larger change in wages for workers over long horizons under low volatility versus high volatility. This is due to the firm's optimal worker compensation scheme tilting more towards consumption smoothing versus dynamic incentives under the high volatility regime.

Figure A41: Impulse Response: Path of Idiosyncratic Productivity and Volatility

(a) Productivity Pass-Through

(b) Risk Absorption



Notes: Figure A41 shows the transmission of risk and risk absorption from firms across volatility states across workers within the firm. The transmission of firm risk to workers flattens when volatility increases, implying an increasing pattern of risk absorption across workers' earnings levels. See text for the explanation and definition of risk absorption.

Finally, we use the model to document the macroeconomic implications of a common increase in idiosyncratic volatility in Section 6. The model both matches the direct impacts of volatility fluctuations on workers, and endogenizes the tradeoff that firms face in insuring their workers' consumption streams and providing dynamic incentives for workers, as we have illustrated here.