Time-Varying Risk Premia and Heterogeneous Labor Market Dynamics*

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Abstract

Using U.S. administrative data on worker earnings, we show that increases in risk premia lead to lower labor earnings, particularly for lower-paid workers. These declines are primarily driven by job separations. We build an equilibrium model of labor market search that quantitatively replicates the observed heterogeneity in labor market dynamics across worker earnings levels. Our findings underscore the role of time-varying risk premia as a key driver of labor market fluctuations and highlight the importance of both the job creation and the job destruction margins in understanding the heterogeneity in worker outcomes over the business cycle.

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Why does unemployment rise in recessions? The textbook answer, rooted in the Diamond, Mortensen, and Pissarides (DMP) search-and-matching paradigm, is that labor productivity is lower in recessions and therefore firms reduce their demand for workers. However, recent attempts to accurately measure productivity shocks find that they are, if anything, negatively related to hours and employment (Basu, Fernald, and Kimball, 2006). In addition, in realistic calibrations of the canonical DMP model, even large productivity shocks have small effects on unemployment (Shimer, 2005). An emerging literature, starting from the seminal work of Hall (2017), argues that countercyclical increases in discount rates (risk premia) can generate rises in unemployment and declines in output.[1] The key idea in Hall (2017) is that firms' hiring decisions have upfront costs but long-term benefits—they are an investment decision—and therefore firms hire fewer workers when discount rates rise. Subsequent work has proposed quantitative equilibrium labor market models that incorporate this idea and deliver realistic unemployment fluctuations (see, e.g. Kehoe, Lopez, Midrigan, and Pastorino, 2023). However, direct empirical support for this mechanism has been scarce.

In this paper, we provide empirical evidence that fluctuations in risk premia are a significant driver of both employment fluctuations and worker earnings. To do so, we employ administrative data on workers' wage earnings in the United States combined with a composite index of existing measures of risk premium shocks. We then interpret the resulting estimates through the lens of a structural model of labor market search. A key insight that emerges from our analysis is that heterogeneity in the dynamics of the separation rate is crucial for understanding the observed heterogeneity in earnings exposures across workers, even though the time-series variation in the separation rate plays a secondary role in driving fluctuations in the unemployment rate (Shimer, 2012).

We begin by documenting a new stylized fact: an increase in risk premia is followed by a decline in worker earnings that is heterogeneous across workers. The decline in earnings is significantly larger and more persistent for workers with lower earnings relative to those of other workers in the same firm. Importantly, increases in risk premia are associated with both an increase in the likelihood of job loss for lower-paid workers and larger earnings losses conditional on separation.[2] These patterns are in sharp contrast to the exposure of worker earnings to firm productivity shocks, which is higher for higher-paid workers (a pattern consistent with the evidence in Friedrich, Laun, Meghir, and Pistaferri, 2019) and primarily affects worker earnings through the intensive margin. We show these results are not driven by standard business cycle channels. First, ranking workers based on their earnings relative to other workers in the same firm eliminates much of the concern that firm-level differences drive the observed patterns. Second, controlling for firm performance (productivity or revenue growth) or for aggregate conditions (growth in TFP or GDP, or a recession

[1] In addition to Hall (2017), there is a long list of studies in macroeconomics and finance that have emphasized the importance of time-varying risk premia for generating significant fluctuations in aggregate quantities and prices (e.g. Campbell and Cochrane, 1999; Smets and Wouters, 2007).

[2] We proxy for involuntary job loss by a worker experiencing a nonemployment spell or leaving her current employer and simultaneously experiencing a significant decline in earnings.

indicator) leaves our estimates unchanged. Third, a shift-share design exploiting heterogeneity in firm exposure to financial conditions confirms that workers in more exposed firms suffer larger earnings losses when risk premia rise—again concentrated among the lowest-paid workers.

To understand the mechanisms through which risk premia affect worker earnings, we interpret our estimates through a model with heterogeneous workers, directed labor market search, and shocks to risk premia that builds on Kehoe, Midrigan, and Pastorino (2019); Kehoe et al. (2023). Workers are heterogeneous in their general productivity, which is stochastic and persistent over time. Importantly, matches can be endogenously terminated, and nonemployment generates long-lived consequences: worker productivity grows faster when the worker is employed than when nonemployed. Nonemployed workers endogenously choose whether to search for a job or remain outside the labor force. Workers' payoff in nonemployment is less sensitive to worker productivity than output on the job. These properties imply that the benefits from employment have high duration (are backloaded), and hence their value is fairly sensitive to risk premium shocks.

In our model, increases in risk premia lead to lower job creation and higher job destruction—and both of these channels interact in generating earnings losses for workers when risk premia rise. Lower-paid workers tend to be near the endogenous separation threshold; their expected future productivity growth is high while the outside option is close to the value of nonemployment. Since benefits are highly backloaded and opportunity costs are more frontloaded, these workers have a match surplus with an especially high duration. When risk premia rise, matches whose surplus becomes negative are endogenously destroyed, pushing affected workers into nonemployment and generating sharp earnings losses. At the same time, a decline in the value of new jobs reduces vacancy posting, job-finding rates, and entry wages, which further exacerbates earnings losses for affected workers. Thus, rising risk premia depress worker earnings through increased separations, reduced hiring, and lower wages upon rehiring.

We calibrate the model to match both asset prices and labor market dynamics. We choose parameters governing risk premia to fit key asset pricing moments, following Lettau and Wachter (2007). We set the remaining parameters to match labor market facts, with a focus on cross-sectional and time-series moments of separation and job-finding rates. Using SIPP data, we show that job-finding rates are broadly similar across workers with different prior earnings, both on average and in their cyclical fluctuations. Separations, by contrast, are highly heterogeneous: lower-paid workers face higher average separation rates, and these rates rise disproportionately in recessions. These patterns mirror heterogeneity by age, education, and wealth (Menzio, Telyukova, and Visschers, 2016; Cairó and Cajner, 2018; Krusell, Mukoyama, Rogerson, and Sahin, 2017). The model reproduces these facts, generating realistic responses of job creation and destruction to risk premium shocks. In particular, it matches the observed decline in firm hiring and the surge in separations among lower-paid workers when premia rise.

Using the calibrated model, we revisit the relative importance of the job-finding and separation margins. Consistent with Shimer (2012), fluctuations in the unemployment rate are mainly driven by the job-finding rate, which explains the literature's focus on the job-creation margin (Hall, 2017; Kehoe et al., 2023). But the separation margin is critical for heterogeneity in worker outcomes. In our calibration, roughly two-thirds of the earnings losses of lower-paid workers following a rise in risk premia come from a higher risk of separation. Without endogenous separations, the model cannot replicate the observed cross-sectional differences in earnings responses. Thus, both margins matter: job creation is the main driver of aggregate unemployment, while separations drive heterogeneity in worker outcomes.

A key advantage of our data is that it lets us test the model's mechanism directly. The model predicts that exposure to risk premium shocks depends on two forces: distance to the separation threshold and the duration of the match surplus. Holding current earnings fixed, workers with higher expected earnings growth should be more exposed—their employment value has a longer duration and is therefore more sensitive to discount rates. Consistent with this prediction, we find that workers with steeper earnings profiles experience larger earnings declines when premia rise, and that this difference is concentrated among low earners who have much higher separation rates. This empirical fact is harder to rationalize under an alternative where our results are driven by unobserved time-varying firm heterogeneity: in response to a negative firm shock, firms would need to fire workers that have higher expected earnings growth but keep workers with lower earnings growth even when both groups are paid similarly today.

The model also replicates the realized paths of key labor market variables. Feeding in our empirical risk premium shocks, we generate model-implied series that track the data closely: correlations range from 50–80% and volatilities are comparable. The model captures the slow recovery after the Great Recession, driven by persistently high premia that depress job creation and erode human capital through prolonged nonemployment. It also reproduces the observed rise in left-tail, but not right-tail, income inequality in recessions (Heathcote, Perri, and Violante, 2020), consistent with larger earnings losses for low-paid workers.

Our work speaks directly to the unemployment volatility puzzle of Shimer (2005): the canonical DMP model (Mortensen and Pissarides, 1994) cannot generate realistic unemployment volatility. Hall (2017) resolves this puzzle by emphasizing that higher discount rates in recessions reduce vacancy posting, while Kehoe et al. (2023) show that countercyclical variation in the market price of risk can reconcile asset pricing with labor market dynamics. Related work points to disaster risk (Kilic and Wachter, 2018), learning about match quality (Mitra and Xu, 2020), or constraints on stochastic discount factors (Borovička and Borovičková, 2018). We add to this literature by providing direct evidence: using administrative micro data and a new composite measure of risk premium shocks, we show that fluctuations in discount rates drive employment and worker earnings, and that a model with endogenous separations and risk premia can match both financial and labor market moments.

Finally, our work connects to a growing literature on how firm-level financial shocks shape employment outcomes (Chodorow-Reich, 2014; Caggese, Cuñat, and Metzger, 2019; Benmelech, Frydman, and Papanikolaou, 2019). Related to our paper, Caggese et al. (2019) show that exporters with weak credit ratings hit by adverse terms-of-trade shocks are more likely to lay off short-tenure workers. They interpret this as evidence of inefficiencies from financial frictions, since short-tenure workers have higher future productivity. Our model offers a complementary explanation: matches with higher expected productivity growth have longer duration and are thus more sensitive to risk premia, making them more vulnerable when discount rates rise.

1 Risk Premium Shocks and Worker Earnings

We begin by documenting a new stylized fact: low-earning workers are significantly more exposed to shocks to risk premia than workers in the middle or the top of the earnings distribution. This heterogeneity in worker exposures is in sharp contrast to that of earnings exposure to productivity shocks, which is increasing in the worker's relative earnings compared to other workers in the same firm.

1.1 Data and Methodology

We begin by describing the data that we rely on for our empirical analysis.

Worker Earnings

Our empirical analysis combines worker earnings data with firm-level information. We use a 20% random sample of earnings records from the Longitudinal Employer Household Dynamics (LEHD) database, matched to Compustat. The matched panel follows U.S. workers in public firms from 1990 to 2019. Appendix A.1 provides full details of the sample construction.

The main outcome variable is cumulative, age-adjusted earnings growth, following Autor, Dorn, Hanson, and Song (2014) and Guvenen, Ozkan, and Song (2014):

$$g_{i,t:t+h} \equiv w_{i,t+1,t+h} - w_{i,t-2,t}, \qquad w_{i,\tau_1,\tau_2} \equiv \log\left(\frac{\sum_{\tau=\tau_1}^{\tau_2} \text{real wage earnings}_{i,\tau}}{\sum_{\tau=\tau_1}^{\tau_2} D(\text{age}_{i,\tau})}\right). \tag{1}$$

This measure emphasizes persistent changes by averaging earnings over multiple years. The denominator $D(\text{age}_{i,\tau})$ adjusts for the average life-cycle earnings profile. To be included in year t, a worker must be employed by a Compustat firm in that year. We follow individuals over time regardless of subsequent employment status. Thus, the growth measure includes earnings from private firms and nonemployment spells (zero wage income). We winsorize growth rates at the 1st and 99th percentiles each year.

Appendix Table A.1 provides descriptive statistics. The average worker is 42 years old and 58% are male. Earnings growth is highly volatile and negatively skewed. Since worker heterogeneity plays an important role in our analysis, we also report these moments separately across the earnings distribution. To do so, we rank workers by their last three years of total age-adjusted wage earnings, $w_{i,t-2,t}$, relative to other workers in the same firm. Panel B shows that the volatility and negative skewness of worker earnings growth vary systematically by workers' labor income level, consistent with Guvenen, Karahan, Ozkan, and Song (2021).

Risk Premium Shocks

We construct an index of risk premium shocks that captures fluctuations in either the level of risk or investors' risk-bearing capacity. We draw on a broad set of existing measures: the excess bond premium of Gilchrist and Zakrajšek (2012); Shiller's CAPE ratio; the Chicago Fed's National Financial Conditions Index (NFCI); the financial uncertainty index of Jurado, Ludvigson, and Ng (2015); the risk appetite index of Bauer, Bernanke, and Milstein (2023); the risk aversion index of Bekaert, Engstrom, and Xu (2022); the variance risk premium of Bekaert and Hoerova (2014); the CBOE VIX; and the SVIX of Martin (2016). Each series is monthly, with signs oriented so that higher values indicate higher risk premia. Appendix A.2 provides additional detail. Because each series is a noisy proxy, we focus on their common component. For each, we remove persistence by estimating AR(1) residuals. We then extract the first principal component across these residuals. We denote the resulting series of risk premium shocks as ϵ_t^{rp}. This factor captures the dominant source of variation: it explains 60% of total variance, with correlations with individual series residuals ranging from 51% to 75%. We recover the level of risk premia from shocks by applying an exponentially weighted moving average with a monthly decay parameter of 0.0068, matching our calibration of the log price–earnings ratio in Section 2.

Figure 1 shows the resulting series. The shocks are tightly linked to financial market conditions: the contemporaneous correlation with stock returns is -77% at the monthly horizon. More importantly, ϵ_t^{rp} predicts higher excess returns at medium horizons (Figure 2), consistent with our interpretation of these shocks as risk premium shocks. To translate magnitudes into familiar terms, we scale the series so that a 1% risk premium shock corresponds to a 1% contemporaneous decline in the stock market.

The risk premium shocks are strongly countercyclical. At an annual frequency, their correlation with output growth is -39%. But the series also spikes outside of recessions: Black Monday (1987), the Asian financial crisis (1997–98), WorldCom's bankruptcy (2002), the European sovereign debt crisis (2010–12), the U.S. credit downgrade (2011), and the U.S.–China tariff dispute (2018). These episodes show that risk premia vary not only with business cycles but also with financial and geopolitical disruptions. In this sense, our series captures shifts in uncertainty, risk aversion, or both, often with origins in financial markets.

1.2 Worker Earnings Exposure to Risk Premium Shocks

We estimate the following regression:

$$g_{i,t:t+h} = \beta\, \epsilon^{rp}_{t+1} + \gamma\, \epsilon^{tfp}_{f(i,t),t+1} + c'\mathbf{Z}_{i,t} + \eta_{i,t+h}. \tag{2}$$

Here, $g_{i,t:t+h}$ is worker i's cumulative earnings growth over horizon h defined in equation (1) and $f(i,t)$ denotes the employer of worker i at time t. The controls $\mathbf{Z}_{i,t}$ include a third-order polynomial in the log of average earnings over the past three years; the lagged risk premium index interacted with labor income group dummies; fixed effects for the worker's industry, defined at the 2-digit NAICS level, interacted with her labor income bin; and worker industry $\times$ age $\times$ gender fixed effects. We cluster standard errors by worker and year. The coefficient of interest, β, captures worker exposure to risk premium shocks. Since earnings are annual, we construct annual risk premium shocks ϵ^{rp}_{t+1} by cumulating monthly shocks from mid–year t to mid–year $t+1$.

In our baseline specifications, we control for firm productivity growth, $\epsilon^{tfp}_{f,t+1}$. To do so, we build on İmrohoroğlu and Tüzel (2014) to obtain estimates of annual revenue-based total factor productivity (TFPR)—Appendix A.3 contains further details. Importantly, we allow β and γ to vary across workers, by interacting the shocks with indicators for the worker's prior earnings rank relative to that of other workers in the same firm. Doing so allows us to primarily focus on worker heterogeneity, rather than firm heterogeneity arising from some firms employing higher- or lower-paid workers compared to others.

Table 1, column (1), reports the baseline estimates of β for $h = 3$. These estimates reveal the central finding of this paper: lower-paid workers are substantially more exposed to risk premium shocks than higher-paid workers. A 10% increase in ϵ^{rp}—equivalent to a 10% stock market decline—lowers earnings of bottom-rank workers by about 2.2 percentage points. In contrast, workers between the median and 75th percentile see only a 0.7–1.1 percentage point decline. Panel A of Appendix Table A.3 reports the full set of estimated coefficients β and γ from equation (2) over horizons h of two to five years. Earnings exposures are quantitatively similar across horizons, suggesting that these are indeed persistent shocks to worker earnings. Contrasting the estimated coefficients β and γ, we see that the patterns by prior worker earnings are sharply different: unlike risk premium exposures, lower-paid workers are not more exposed to firm productivity shocks ϵ^{tfp} than middle earners; top workers are most exposed to productivity shocks—a pattern that is consistent with the existing literature (Friedrich et al., 2019). Panel B shows that our findings are not driven by restricting the sample to public firms; if anything, exposures to risk premium shocks are slightly larger when we include all workers.

1.3 Controlling for the Business Cycle

Because fluctuations in risk premia are strongly countercyclical, an important concern is that our results may simply reflect broader business cycle dynamics, with risk premia playing only a secondary role. One possibility is that lower-paid workers are disproportionately employed at firms that are systematically more exposed to the business cycle. This concern is partly addressed by our baseline design: workers are ranked by their earnings relative to other workers *within the same firm*, which substantially mitigates differences in firm-level exposures to the business cycle.

To further absorb firm-specific heterogeneity in business cycle exposure, we augment our estimating equation (2) with firm × year fixed effects. These dummies capture all time-varying shocks common to a firm in a given year. As we see in columns (1) and (2) of Table 1, this adjustment leaves our findings essentially unchanged: lower-paid workers remain significantly more exposed to risk premium shocks than their higher-paid colleagues in the same firm. A 10% increase in risk premia is followed by a 1.1 percentage point relative earnings decline for the lowest-paid workers compared to the middle bin (the omitted category).

Including firm–year effects in our specification ameliorates, but does not fully eliminate, the main concern. In particular, firm labor demand may still vary over the cycle in ways not fully captured by the TFPR measure, and this variation might differentially affect lower-paid workers. Such variation could stem either from common shocks (e.g., aggregate demand fluctuations) or from idiosyncratic firm shocks whose volatility is correlated with the cycle.

We address these concerns in two additional ways. First, we replace firm TFP with annual revenue growth, a measure that is more responsive to demand fluctuations than measured productivity. Columns (3) and (4) show that this substitution has little impact on our results. Second, we add direct controls for the aggregate business cycle, interacted with prior worker earnings ranks: aggregate productivity growth (columns (5)–(6)), aggregate output growth (columns (7)–(8)), and the fraction of the year spent in NBER recessions (columns (9)–(10)). Across all specifications, the estimated coefficients β remain stable, indicating that our main findings are not mechanically driven by the business cycle.

Taken together, these results further support our view that the differential exposure of lower-paid workers reflects genuine sensitivity to risk premia, rather than a spurious correlation due to general business cycle fluctuations.

1.4 Exploiting Heterogeneity in Firm Exposure to Risk Premia

So far, we have shown that the earnings of workers with different levels of labor income respond differently to our measure of risk premium shocks—both in absolute terms and also relative to other workers in the same firm at the same point in time. However, it is hard to rule out an alternative interpretation in which lower-paid workers in a firm are differentially exposed to economic conditions over the business cycle—and this exposure is neither fully captured by their employer's productivity or revenue growth nor by aggregate business cycle indicators. Next, we exploit an alternative empirical strategy that exploits differences in exposure to risk premium shocks at the firm level.

Firm Exposure to Risk Premium Shocks

We implement a shift–share design that isolates the effect of risk premium shocks on workers by exploiting heterogeneity in firms' exposure to these shocks. Measuring ex-ante exposure is challenging, so we construct several proxies. Our first measure of firm exposure to risk premia uses stock returns to directly estimate the sensitivity of firm valuations to risk premia. We use the CRSP/Compustat merged database to link historical firm equity returns to the employers in our sample and compute firm-level risk premium betas at the end of each year by regressing monthly firm equity returns on our measure of risk premium shocks using a ten-year rolling window. The advantage of this measure is that it gets at our object of interest directly. The disadvantage is that firm-level betas are typically measured with significant measurement error (Cochrane, 2009).

Constructing additional measures of firms' exposure to risk premium shocks requires us to take a broader view of what these shocks represent. For instance, risk premium shocks can also capture fluctuations in financial conditions or in the cost of external finance. Indeed, Whited (1992) shows how models with financial frictions can be isomorphic to one in which firms face a higher effective discount rate in their investment decisions. With this interpretation in mind, we consider several additional proxies for firms' exposure to aggregate financial conditions that are commonly used in the literature: (minus) the logarithm of firm size (Gertler and Gilchrist, 1994), since smaller firms are riskier; (minus) the level of cash holdings relative to assets (Jeenas, 2019), since it is related to firms' dependence on financial markets; and (minus) the distance to default (Ottonello and Winberry, 2020), since firms closer to default are riskier and therefore more exposed to fluctuations in risk premia. Last, we follow Almeida, Campello, Laranjeira, and Weisbenner (2011) and compute the amount of long-term debt that is maturing at years $t+1$ and $t+2$ (as of year $t-1$) relative to total assets, since firms that need to refinance a significant amount of debt are more sensitive to financial conditions.

Each proxy is noisy, so we extract their common component by taking the first principal component across the five measures. We denote this factor by $\chi_{f,t}$, scaled to have a cross-sectional standard deviation of one. On average, the first principal component explains 31% of the total variation in the exposure measures. Appendix A.4 provides further details.

To validate whether $\chi_{f,t}$ indeed captures meaningful heterogeneity in firms' exposure to risk premium shocks, we next explore its link with cross-sectional differences in firm employment growth as risk premia rise by estimating the following specification,

$$\Delta \log N_{f,t:t+1} = (b_0 + b_1\, \chi_{f,t})\; \epsilon^{rp}_{t+1} + c\, \epsilon^{tfp}_{f,t+1} + d'\mathbf{Z}_{f,t} + \eta_{f,t+1}. \tag{3}$$

Here, the outcome variable is employment growth of firm f between years t and $t+1$. Importantly, we now interact our risk premium shocks with the firm-level exposure measure $\chi_{f,t}$. The vector of controls $\mathbf{Z}$ includes lagged employment; the lagged risk premium index; and industry fixed effects (at the two-digit NAICS level) or firm fixed effects and industry $\times$ year fixed effects. Since different states enter the LEHD at different years, we estimate (3) at the firm by state level, with standard errors clustered by firm and year.

Panel A of Table 2 shows the corresponding estimates from equation (3). Column (1) first confirms that our risk premium shocks are negatively related to firm employment in the time series: a 10 percentage point increase in discount rates is associated with a 1.2 percentage point decline in employment growth. Column (2) verifies that extending the sample to all firms yields quantitatively similar estimates on firm employment growth in the time series. More importantly, column (3) shows that our firm-level exposure measure $\chi_{f,t}$ captures meaningful heterogeneity in firm responses to risk premia shocks: a 10% increase in discount rates is associated with a 0.35 percentage point greater decline in employment for firms that are one standard deviation more exposed to risk premia than the average firm.

To address the concern that our exposure measure $\chi_{f,t}$ may also capture firms' heterogeneous exposure to economic conditions over the business cycle, we also interact $\chi_{f,t}$ with aggregate productivity growth, output growth, or the fraction of the year spent in a recession. As we see in columns (6), (9), and (12) of Table 2, doing so does not materially affect our estimates of b_1, and the interaction of $\chi_{f,t}$ with these business cycle indicators is not statistically significantly related to firm employment. We conclude that $\chi_{f,t}$ indeed primarily captures firms' exposure to risk premium shocks rather than the cycle itself.

In labor search models of employment fluctuations, the job creation margin plays an important role. Thus, in Panel B of Table 2, we re-estimate equation (3), but now the main outcome variable is the firm's hiring rate. We measure a firm's hiring intensity as the number of new employees in a year scaled by lagged total employment. Consistent with Hall (2017), we expect to see that an increase in discount rates leads to a decline in job creation. The estimated coefficients in columns (1) and (2) are consistent with this prediction: a 10% increase in risk premia is associated with a 1.5 to 1.6 percentage point reduction in firm hiring. Column (3) shows that our firm exposure measure $\chi_{f,t}$ is also significant in predicting cross-sectional differences across firms in the hiring rate response to risk premia. That is, a firm that is one standard deviation more exposed to risk premia than the average firm reduces hiring by 0.27 percentage point more than the average firm as risk premia increase by 10%. The remaining columns of Panel B show that these results are also robust to including controls for the business cycle.

Worker Earnings Response by Firm Exposure

Armed with a measure $\chi_{f,t}$ of heterogeneous firm exposure to risk premium shocks, we next revisit our worker-level regressions. We estimate the following specification,

$$g_{i,t:t+h} = \beta \left(\chi_{f(i,t),t}\, \epsilon^{rp}_{t+1}\right) + \gamma\, \epsilon^{tfp}_{f(i,t),t+1} + c'\mathbf{Z}_{i,t} + \eta_{i,t+h}. \tag{4}$$

Equation (4) introduces two key modifications to our previous empirical design in (2). First, we interact the risk premium shocks with $\chi_{f,t}$, capturing the exposure of firm f (that employs worker i) to risk premium shocks ϵ^{rp}_{t+1}. Second, we include industry $\times$ earnings group $\times$ year fixed effects. Doing so fully absorbs industry-level shocks that may affect workers of different earnings levels over time. Therefore, our main coefficient of interest β is now identified by comparing the risk premium exposure of two workers at the same point in time who are in the same part of the earnings distribution and are employed in the same industry but work for firms with different exposure $\chi_{f,t}$ to risk premium shocks.

The interaction of these exposure measures with our proxy for risk premium shocks can be viewed as a shift-share design (Bartik, 1991). Under the assumption that the exposure measure $\chi_{f,t}$ is orthogonal to unobserved worker heterogeneity, this design allows us to infer the causal impact of an increase in risk premia on worker outcomes (Goldsmith-Pinkham, Sorkin, and Swift, 2020). One reason why this assumption may fail is if low-skill workers, who are paid less than their peers, match to weak firms that are more exposed to changes in financial conditions. The fact that we are defining low-paid workers based on their pay relative to other workers in the same firm should partially alleviate this concern.

Table 3 reports the estimates of equation (4). Column (1) shows that lower-paid workers employed in firms more exposed to risk premia experience significantly larger earnings declines than their peers in less exposed firms. Following a 10% increase in risk premia, lower-paid workers in firms one standard deviation more exposed experience an additional 0.8 percentage point earnings decline relative to those in the average firm. Column (2) demonstrates that this finding is robust to the inclusion of firm–year fixed effects, which restrict identification to within-firm relative earnings changes. Columns (3) and (4) show that replacing firm productivity with revenue growth leaves the results essentially unchanged.

To address concerns that $\chi_{f,t}$ may be correlated with other business cycle sensitivities, we interact our firm exposure measure with aggregate productivity growth, aggregate output growth, or a recession indicator. As we see in columns (5)–(10), these additional controls do not meaningfully affect our results. This finding is consistent with Table 2, where $\chi_{f,t}$ interacted with business cycle indicators does not significantly predict employment growth, suggesting that $\chi_{f,t}$ primarily captures sensitivity to risk premia rather than to cyclical fluctuations.

In sum, our shift-share design lends further support to the view that fluctuations in risk premia are the main driving force behind our estimates by leveraging cross-sectional variation in firm exposure to risk premia that is isolated from heterogeneous exposure to the business cycle. While in our baseline analysis, the effect of risk premium shocks is identified by comparing the earnings growth of a given worker type at times when risk premia rise or fall, in the shift-share design the effect is identified by comparing similar workers at different firms at the same point in time. Specifically, we find that, when risk premia rise, lower-paid workers in firms more exposed to risk premia experience lower earnings growth than lower-paid workers in less exposed firms. By contrast, there are no significant differences for higher-paid workers.

1.5 Drivers of Earnings Losses

Worker earnings can decline because the worker remains employed with the same firm but receives lower earnings, because she becomes unemployed and receives no wage income, or because she moves to a new job that pays a lower wage. In this section, we aim to disentangle the drivers of earnings declines in response to rising risk premia.

Probability of Job Destruction

First, we focus on the role of job loss in generating the patterns in Table 1. Since we cannot observe whether job transitions are voluntary or involuntary in the data, we use two empirical proxies for job destruction. Our first proxy is a dummy variable that takes the value of one if the worker experiences at least one full quarter with zero wage earnings (a nonemployment spell) over the next h years. Our second proxy is also an indicator variable, which takes the value of one if over the next h years the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile of the unconditional distribution. Panel C of Appendix Table A.1 reports the summary statistics on these two measures; we note that, for both measures, the probability of job destruction is sharply decreasing in the worker's prior earnings, a pattern that is consistent with documented heterogeneity by age, education, and wealth (Menzio et al., 2016; Cairó and Cajner, 2018; Krusell et al., 2017). Panels A and B of Table 4 report the estimated coefficients β from modified versions of equation (2), in which the outcome variable is the first and second measure of job destruction, respectively. We consider horizons of one to three years.

Panel A of Table 4 shows that increases in risk premia are associated with an increased probability of job destruction for lower-paid workers relative to other workers in the same firm. The magnitudes are economically sizeable: focusing on the workers at the bottom of the pay distribution, we see that over the next one to three years, a 10% risk premium shock ϵ^{rp} is associated with an approximately 0.6 to 1 percentage point increase in the likelihood of a nonemployment spell (at least one quarter of zero wage earnings). This pattern represents a significant increase relative to the base rate for these workers of approximately 30%.

Panel B of the same table shows that the results are similar using our second measure of job displacement. A 10% risk premium shock ϵ^{rp} leads to a 0.5 to 0.8 percentage point increase in the likelihood of a lower-paid worker separating from her initial employer and experiencing a significant drop in labor income—a large increase compared to a baseline probability of 12%. For workers who fall under this definition of job loss, the conditional mean of earnings growth over the next three years is equal to -143 log points. Thus, these estimates imply that the increased likelihood of job loss accounts for a significant fraction of the total effect of risk premium increases on wage earnings. Appendix Table A.4 confirms that the estimated effects of risk premia on job loss are robust to controlling for total firm revenue growth and aggregate business cycle indicators.

Appendix Table A.5 shows that our shift-share design in equation (4) yields qualitatively similar results on the likelihood of job loss to those in Table 4; that is, a 10% increase in the risk premium leads to a 0.2 to 0.4 percentage point increase in the likelihood of job destruction for those low-paid workers who are employed in highly exposed firms relative to the likelihood of low-paid workers employed at the average firm.

Variation in Earnings Growth Conditional on Job Transition Status

Next, we examine whether fluctuations in risk premia are associated with fluctuations in worker earnings conditional on job transition status. In particular, we re-estimate equation (2) separately for workers who leave their original employer (movers) or not (stayers). Workers are characterized as a stayer at horizon h if they continue to receive a positive amount of labor income from their initial time-t employer in year $t + h + 1$, and as a mover in all other cases.

Panels A and B of Table 5 report the estimated coefficients β for movers and stayers, respectively. Examining Panel A, we see that increases in risk premia are associated with significant earnings declines for lower-paid workers that separate from their employer. Here, keep in mind that we are focusing on variation in earnings among movers, so our estimates imply that low-earning workers experience larger average earnings losses conditional on moving when risk premia are high relative to low-earning workers that move when risk premia are low. To some extent the same pattern is present for all movers, though as before, the magnitude of these earnings losses are decreasing in the worker's relative earnings within the firm. Panel B shows that there is some relation between fluctuations in risk premia and the earnings growth of stayers, though the magnitudes are significantly smaller and do not vary strongly with the worker's relative prior earnings. In other words, the earnings losses due to rising risk premia are concentrated on workers that end up separating from their initial employer. These results again point to the importance of the extensive margin as a driver of earnings exposures to risk premia.

1.6 Robustness

Our results are robust to various changes in the empirical design. We briefly summarize these here and refer the reader to Section A.5 in the Online Appendix for details. First, our results are not sensitive to the exact measurement of risk premium shocks (Appendix Table A.6). Second, our findings are robust to different measurement of firm-level exposure to risk premium shocks (Appendix Table A.7). Last, differentiating between workers on the basis of their earnings relative to those of their industry peers (as opposed to those of other workers in the same firm) leads to similar conclusions (Appendix Table A.8).

2 Model

Our empirical results indicate that lower-paid workers experience larger and more persistent declines in earnings in response to the same risk premium shock than workers in the middle or the top of the (within-firm) earnings distribution. These patterns are in sharp contrast to the exposure of worker earnings to productivity shocks, where higher-paid workers are significantly more exposed than the average worker. Importantly, job loss plays a significant role in driving the earnings declines following risk premium increases. Lower-paid workers are significantly more likely to lose their job than higher-paid workers, and conditional on separating from their initial employer they experience larger earnings declines than higher-paid workers who separated at the same point in time.

What type of model can quantitatively rationalize these facts? A natural starting point is a model with search frictions (Diamond, 1982; Mortensen, 1982; Pissarides, 1985). We model a directed search process in which firms search for workers with different levels of productivity (Montgomery, 1991; Moen, 1997). Worker productivity is stochastic and persistent. Similar to Kehoe et al. (2019, 2023), worker productivity grows faster, on average, during employment than during nonemployment. Importantly, the model features endogenous worker separations.

We model risk premium shocks as shocks to the effective discount rate that agents use to value risky future cashflows, in the spirit of Lettau and Wachter (2007). A positive risk premium shock leads to a lower valuation of a stream of risky future cashflows. Since the decisions to hire a worker and to maintain an existing worker–firm match involve calculating the present value of the relative benefits of keeping the worker in the job or not and these benefits are uncertain, fluctuations in discount rates directly affect labor allocations.

2.1 Environment

The model is set in discrete time. There is a unit measure of ex-ante identical workers who can be employed by a large number of firms. The workers are indexed by i, have heterogeneous productivity, and can be employed by a firm, be unemployed and searching for a job, or be nonparticipants in labor markets. Firms employ workers to produce output and post vacancies to attract new workers, targeting workers with a specific productivity level. Firms are competitive and make zero profits net of vacancy posting costs.

Each period in the model consists of three subperiods. First, a fraction ζ of workers die and are replaced by new (nonemployed) workers, and shocks to aggregate productivity, discount rates, and idiosyncratic productivity are realized. In the second subperiod, firms post vacancies to attract new workers, workers in the unemployment pool search for new jobs, and new matches are formed. In addition, some of the existing matches are destroyed either because the surplus generated by the match is now negative or for exogenous reasons. The rate of endogenous job destruction depends on the aggregate state of the economy, while the rate of exogenous job destruction is s. In the third subperiod, for continuing and new matches, production is realized, and wages are paid. Workers that are out of a job receive their nonemployment benefits and decide whether to pay the cost to enter the search pool for the subsequent period.

Production

Employed workers produce output at a rate that depends on the aggregate productivity level A and their individual productivity z:

$$y_{i,t} = A_t \, z_{i,t}. \tag{5}$$

Idiosyncratic worker productivity evolves according to the following mean-reverting process:

$$\log z_{i,t+1} = \psi_z \log z_{i,t} + (1 - \psi_z) \log \bar{z}_{i,t} + \sigma_z \, \varepsilon_{z,i,t+1}, \tag{6}$$

where $\varepsilon_{z,i,t+1}$ is an i.i.d. standard normal random variable. Following Kehoe et al. (2019), the long-run mean level of productivity depends on the worker's current employment status, $\bar{z}_{i,t} \in \{\bar{z}_E, \bar{z}_O\}$. As in Ljungqvist and Sargent (1998), human capital grows with work experience, and workers experience long-term costs from being out of a job; therefore, $\bar{z}_E > \bar{z}_O$. Newly born workers at time $t_0(i)$ enter the economy without a job and with initial idiosyncratic productivity equal to

$$\log z_{i,t_0(i)} = \log \bar{z}_O + \sigma_{z0} \, \varepsilon_{z,i,t_0(i)}. \tag{7}$$

Aggregate productivity A_t follows a random walk:

$$\Delta \log A_{t+1} = \mu_A + \sigma_A \, \varepsilon_{A,t+1}, \tag{8}$$

where $\varepsilon_{A,t+1} \sim N(0,1)$. We note that, given (8), output has a stochastic trend, however the economy is stationary in growth rates.

Financial Markets

Financial markets are complete: households have access to a complete set of state-contingent securities and there is a unique stochastic discount factor. The time t value of a claim to a stream of future cashflows X_τ is

$$P_t = \mathbb{E}_t \left\{ \sum_{\tau=t+1}^{\infty} \left(\prod_{k=t+1}^{\tau} \Lambda_k \right) X_\tau \right\}, \tag{9}$$

where Λ_k is the one-period stochastic discount factor (SDF) between periods k and $k+1$. Our assumption of complete markets implies that all agents in the economy, both firms and workers, use (9) to value future cashflows.

Our goal is to understand the implications of fluctuations in risk premia for worker outcomes, which does not require us to take a strong stance on the underlying economic drivers of these fluctuations. Thus, we directly specify the stochastic discount factor as in Lettau and Wachter (2007), assuming that the market price of risk (the level of risk premia) evolves according to

$$x_{t+1} = \psi_x x_t + (1-\psi_x)\bar{x} + \sigma_x \, \varepsilon_{x,t+1}, \tag{10}$$

with $\varepsilon_{x,t} \sim N(0,1)$ corresponding to the risk premium shock in the model. The correlation between shocks to productivity $\varepsilon_{A,t}$ and risk premia $\varepsilon_{x,t}$ is $\rho_{A,x}$. The one-period stochastic discount factor is given by

$$\Lambda_{t+1} = \exp\left\{ -r_f - \frac{1}{2} x_t^2 \left(1 + \delta^2 + 2\,\delta\,\rho_{A,x}\right) - x_t\,\varepsilon_{A,t+1} - \delta\, x_t\,\varepsilon_{x,t+1} \right\}. \tag{11}$$

The stochastic discount factor (11) follows Lettau and Wachter (2007), except for two modifications: first, we allow for a correlation between shocks to risk premia and productivity shocks, and second, we allow the risk premium shocks to be priced directly, captured by the parameter δ. Equation (11) implies that the risk-free rate is constant and equal to r_f.

Directed Search and Matching

Unemployed workers search for jobs in the labor market for their productivity type z. Firms post vacancies that are directed at workers of a particular type. Labor markets are competitive—all firms can freely enter any submarket for type-z workers in each period. The per-period cost to post a vacancy directed at a worker of productivity z is

$$\kappa_t(z) = \bar{\kappa}_0 \, A_t \, z^{\bar{\kappa}_1}. \tag{12}$$

The cost of posting a vacancy targeting a specific type of worker is increasing in the worker's productivity z, with the parameter $\bar{\kappa}_1 > 0$ determining the elasticity with respect to z. The assumption that vacancy costs are proportional to A ensures that the limiting employment distribution is not degenerate, while the assumption that they increase with z ensures that job-finding rates are fairly similar across workers with different prior earnings levels, as is the case in the data.

The likelihood of a vacancy being filled is a function of the current tightness $\theta_t(z) \equiv v_t(z)/u_t(z)$ of the labor market, where $u_t(z)$ is the unemployment rate and $v_t(z)$ is the number of vacancies posted by firms for worker type z. Following den Haan, Ramey, and Watson (2000), the number of matches in a labor market with unemployment rate u and vacancies v is given by

$$m(u,v) \equiv \frac{u\,v}{(u^\alpha + v^\alpha)^{\frac{1}{\alpha}}}. \tag{13}$$

This matching function ensures that job-finding and vacancy-filling rates are bounded between zero and one. Specifically, equation (13) implies that the probability that a vacancy is filled in a market with tightness θ is $q(\theta) = (1 + \theta^{\alpha})^{-1/\alpha}$ and the probability that a job searcher obtains a new match is $p(\theta) = \theta(1 + \theta^{\alpha})^{-1/\alpha}$.

Worker Labor Supply

All workers who are out of a job receive a flow benefit from being nonemployed:

$$b_t(z) = \left(\bar{b}_0 + \bar{b}_1\, z\right) A_t. \tag{14}$$

The flow benefits of being out of employment include not only unemployment benefits but also the value of leisure and the value of home production. Following Hall (2017) and Kehoe et al. (2023), the opportunity cost of employment has a unit elasticity to aggregate productivity, which is consistent with Chodorow-Reich and Karabarbounis (2016). As in Kehoe et al. (2019), we also allow for the worker opportunity cost to depend on worker productivity z to match the dynamics of labor market flows across the earnings distribution.

Newly born workers and workers who have just separated from a previous job enter the pool of nonemployed workers. Searching for a job is costly: nonemployed workers decide each period whether to participate in the labor market by entering the unemployment pool at a cost and actively looking for a job, or to stay out of the workforce. To be in the search pool for that period, a worker needs to pay an upfront search cost c_t, which is a stand-in for the costs of updating a resume and finding and applying for new jobs. This simplifying assumption implies that all workers make labor supply decisions that maximize the net present value (NPV) of labor earnings net of the NPV of nonemployment benefits and search costs.

We allow the cost of search to depend on the aggregate level of labor market tightness:

$$c_t = A_t\, f(\theta_t(\bar{z}_O)). \tag{15}$$

As in Mukoyama, Patterson, and Şahin (2018), we assume that $f(\cdot)$ is an increasing function: the cost of search increases with aggregate tightness in the labor market. We index the search cost to the tightness of the labor market corresponding to workers with a particular level of productivity ($\bar{z}_O$), rather than a cross-sectional average of z, in order to keep the model tractable. This assumption implies that search intensity increases when the labor market is slack, consistent with the data (Mukoyama et al., 2018; Faberman and Kudlyak, 2019), and thereby dampens the cyclicality of labor market participation. See Appendix B.4 for further details.

2.2 Model Solution

In this section, we outline the conditions that determine the equilibrium labor market allocations: job-finding rates, job destruction rates, and the present value of compensation promised to a worker by her firm at the initiation of a match. We construct a competitive search equilibrium in the spirit of Montgomery (1991) and Moen (1997). Firms decide on the number of vacancies to post for each type of worker, and on the associated value of employment that is offered to the worker in each vacancy. Workers choose the type of vacancy to which they will direct their search effort, leading to a block recursive equilibrium in which only the aggregate state variables A_t and x_t matter for firm and worker decision rules, similar to the setting in Menzio and Shi (2011).

Worker Search

Labor markets are characterized by a worker type z and a corresponding value of employment that is offered to a worker of this type when the match is created. Due to symmetry of the equilibrium (see Kehoe et al., 2023), each worker of type z searching for a job at time t is offered the same continuation value, which we denote by $W_t(z)$.

Consider first the problem of a worker who begins the third subperiod in the nonemployment pool with continuation value $J_t^O(z)$. She has a choice of whether to enter the next period as a nonparticipant (which yields a continuation value $J_t^N(z)$) or to pay the cost c_t now to enter the search pool for the next period (obtaining a continuation value $J_t^U(z)$). Thus, her continuation value equals

$$J_t^O(z) = \max\{J_t^N(z),\, J_t^U(z)\}. \tag{16}$$

A nonparticipating worker simply collects the nonemployment benefit specified in (14) at time t and, conditional on surviving to $t+1$, begins the next period as a nonemployed worker. Her continuation value is equal to

$$J_t^N(z) = b_t + (1-\zeta)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1} J_{t+1}^O(z')\right]. \tag{17}$$

Next, consider a worker of type z who is unemployed in period t and thus actively searches for a job in the beginning of the next period. Her continuation value is

$$J_t^U(z) = b_t - c_t + (1-\zeta)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1}\left\{J_{t+1}^O(z') + p(\theta_{t+1}(z'))\left(W_{t+1}(z') - J_{t+1}^O(z')\right)\right\}\right], \tag{18}$$

which combines the flow nonemployment benefit net of the search cost with the discounted value of the outside option in nonemployment $J_{t+1}^O(z')$ plus the job-finding rate $p(\theta_{t+1}(z'))$ times the surplus the worker gains above her outside option from entering a new match.

Firm Search

Consider a firm and a worker who are in a match that is continued in the current period t. The sum $J_t^{MC}(z)$ of the worker's lifetime value and the present value of the firm's profits from this match satisfies

$$J_t^{MC}(z) = A_t\, z + (1-\zeta)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1}\left\{sJ_{t+1}^O(z') + (1-s)J_{t+1}^M(z')\right\}\right], \tag{19}$$

where

$$J_t^M(z) = \max\left\{J_t^{MC}(z),\ J_t^O(z)\right\} \tag{20}$$

is the current total value of a match. The match value (20) reflects that a match is continued at time t if the continuation value of the match exceeds the value at nonemployment:

$$\mathbb{1}_t^C(z) = 1 \quad \Leftrightarrow \quad J_t^{MC}(z) \geq J_t^O(z). \tag{21}$$

When a match is terminated, the firm has no more future profits from this match, while the worker's continuation value is equal to the value of nonemployment from (16). As a result, the present value of a continuing match specified in (19) consists of the current output that is produced, the present value of output in future times when it is optimal to keep the current match intact, and the present value of the outside option to the worker that comes from the value of nonemployment after separation.

Firms post vacancies with wage offers to attract workers of a given type. Specifically, firms target a worker with productivity z by posting a vacancy and offering a continuation value to the worker equal to $W_t(z)$ at the moment the worker is hired. The equilibrium values of $\theta_t(z)$ and $W_t(z)$ are pinned down by the firm's first-order conditions in its vacancy posting problem together with the free-entry condition,

$$q(\theta_t(z))\left(J_t^{MC}(z) - W_t(z)\right) \leq \kappa_t(z), \tag{22}$$

which says that the expected value of a vacancy—the probability that the vacancy is filled times the present value to the firm upon filling the vacancy—is not greater than the cost of creating a vacancy. When the labor market for type z is active, $\theta_t(z) > 0$, and (22) holds with equality.

In equilibrium, the continuation value offered to a newly-employed worker of type z is

$$W_t(z) = J_t^O(z) + \eta(\theta_t(z))\left(J_t^{MC}(z) - J_t^O(z)\right). \tag{23}$$

Equation (23) states that the continuation value $W_t(z)$ when the worker is hired is equal to the unemployed worker's outside option plus a share of the surplus created by a continuing match. The endogenous share of the surplus that goes to the worker depends on the elasticity of the vacancy-filling rate, $\eta(\theta) \equiv -\theta\, q'(\theta)/q(\theta)$, which is a function of current labor market conditions. Appendix B.1 provides a derivation of this result.

Equilibrium

An equilibrium consists of value functions $J_t^O(z)$, $J_t^N(z)$, and $J_t^U(z)$ for nonemployed workers (with an associated search policy), value functions $J_t^{MC}(z)$ and $J_t^M(z)$ for continuing matches (with an associated separation policy), a market tightness function $\theta_t(z)$, and an employment offer function $W_t(z)$. These objects satisfy three conditions: (i) the value functions solve equations (16)–(20);

(ii) the free-entry condition (22) holds; and (iii) the offered employment value and corresponding tightness satisfy firm optimality (23).

The competitive search equilibrium is efficient: equation (23) is equivalent to the Nash bargaining outcome under the Hosios condition. In equilibrium, all value functions scale proportionally with A_t, and $\theta_t(z)$ is independent of A_t. Appendix B.2 provides further details.

Per-Period Wages

Equation (23) pins down the present value of wages at the time of hiring, but not the full path of realized wages. To generate explicit predictions for wage earnings—and to map model productivity z to observed earnings—we impose an additional assumption on how period-by-period wages are set. Under full commitment, the evolution of the present value of promised wages throughout the match does not affect equilibrium allocations: all that matters is that the stream of flow wages delivers the present value in (23) promised to the worker at hiring.

Specifically, consider the continuation value at time t of worker i who is in an existing match m with the firm; this value can be decomposed as

$$\widehat{W}(\Omega_{i,m,t}) \equiv \widehat{W}^M(\Omega_{i,m,t}) + W_t^S(z_{i,t}). \tag{24}$$

Here, $\Omega_{i,m,t}$ represents the set of variables that summarize the current state of the promised continuation value, which in principle could include the full history of aggregate and idiosyncratic shocks.

The first component in (24) corresponds to the present value to the worker of the flow wages paid by the employer in the current match. This value, which is also equal to the cost to the firm of retaining the worker, can be represented as

$$\widehat{W}^M(\Omega_{i,m,t}) = w(\Omega_{i,m,t}) + (1-\zeta)\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1}(1-s)\,\mathbb{1}_{t+1}^C(z_{i,t+1})\,\widehat{W}^M(\Omega_{i,m,t+1})\Big], \tag{25}$$

where $w(\Omega_{i,m,t})$ is the flow wage at t and the indicator $\mathbb{1}_t^C$ is equal to one if the match is preserved at time t. The second component of (24) equals the present value of payoffs to the worker after the current match is terminated—nonemployment benefits plus the expected benefits of her new job. This value W^S is a function only of the worker's current productivity z and the aggregate state (A_t, x_t) and solves

$$W_t^S(z) = (1-\zeta)\,\mathbb{E}_{t,z}\Big\{\Lambda_{t+1}\left[J_{t+1}^O(z') + (1-s)\mathbb{1}_{t+1}^C(z')\left(W_{t+1}^S(z') - J_{t+1}^O(z')\right)\right]\Big\}. \tag{26}$$

The only restriction imposed by the equilibrium is that the continuation value of the wage contract for a new hire at time τ is equal to the promised continuation value in (23) offered to the worker when she is hired:

$$\widehat{W}^M(\Omega_{i,m,\tau}) = W_\tau(z_{i,\tau}) - W_\tau^S(z_{i,\tau}). \tag{27}$$

The conventional view is that firms partially insure (continuing) workers against fluctuations in productivity (Guiso, Pistaferri, and Schivardi, 2005). Given the above, we assume that per-period wages are set according to

$$\log w(\Omega_{i,m,t}) = \log w_\tau(z_{i,\tau}) + (1-\phi)\ \mu_A(t-\tau) + \phi\left(\log \frac{A_t}{A_\tau} + \log \frac{z_{i,t}}{z_{i,\tau}}\right). \tag{28}$$

The level of the initial wage $w_\tau(z_{i,\tau})$ is determined so that, at the time the worker is fired, the present value of flow wages (28) is equal to the worker's promised value (27). Subsequently, per-period wage growth is a weighted average of a deterministic component equal to the rate of aggregate productivity growth μ_A, and a stochastic component directly tied to the worker's current productivity growth. The degree of wage smoothing is captured by ϕ.

2.3 Calibration

We next discuss the calibration of the model.

Parameters Calibrated a Priori

We calibrate a subset of parameters using a priori information, summarized in Panel A of Appendix Table A.9. The mean of the productivity process, μ_A, is set to the average BLS labor productivity growth rate between 1947 and 2019 (2.2% per year). The volatility, σ_A, is chosen to match the volatility of aggregate TFP growth (3.5% per year), obtained by aggregating firm-level TFP growth across all public firms in the sample. We set $\rho = -0.39$ to match the correlation between aggregate TFP growth and risk premium shocks. The real risk-free rate is 1.91% per year, following Lettau and Wachter (2007). The model is calibrated at a monthly frequency, and all values are converted accordingly.

We normalize the long-run mean of productivity in employment to $\bar{z}_E = 1$. The persistence of the worker productivity process is set to $\psi_z = 0.991$ at a monthly frequency, following Menzio et al. (2016), which implies a half-life of about six years for idiosyncratic shocks. The dispersion of initial human capital, $\sigma_{z0} = 0.666$, is chosen to match the average interquartile range of earnings at age 25 from Guvenen, Kaplan, Song, and Weidner (2022). We set the mortality rate ζ so that the average model lifespan of a worker is 30 years. The curvature of the matching function is set to $\alpha = 0.407$, following Hagedorn and Manovskii (2008). Recognizing that aggregate and idiosyncratic shocks affect both the current match and workers' outside options, we calibrate the wage-smoothing parameter ϕ to 0.149 to match the average pass-through of industry-level productivity shocks to wages estimated by Carlsson, Messina, and Skans (2015).

Parameters Calibrated to Asset Markets

Fluctuations in risk premia are the central driving force in our model, so we calibrate their dynamics to match key asset price moments. Because the mechanism works through valuation changes in long-duration employment surplus, we target both aggregate stock market moments and those of a portfolio of long-duration stocks following Gormsen and Lazarus (2023). Specifically, we set $\bar{x} = 0.386$, $\psi_x = 0.993$, $\sigma_x = 0.037$, and $\delta = 0.364$. This calibration reproduces the moments of the aggregate stock market, the predictability of excess returns across horizons by our composite risk premium proxy, and the decline in Sharpe ratios with cashflow duration. Panel B of Table A.9 summarizes the fit; Appendix B.3 and Figures A.2–A.3 provide further detail.[3]

Parameters Calibrated to Labor Markets

We calibrate the remaining parameters—worker productivity dynamics z, vacancy cost $\kappa_t(z)$, nonemployment benefits $b_t(z)$, search cost c_t, and exogenous separation s—to match a set of aggregate and cross-sectional labor market moments (see Appendix B.4 for details).

We target five sets of moments. First, the mean (6.5%) and volatility (1.4%) of the HP-filtered unemployment rate. Second, the cyclicality of the labor force participation rate, defined by its regression beta on the unemployment rate. Third, the mean and cyclicality of aggregate job-finding and separation rates, measured from CPS microdata (1978–2019) using Abowd–Zellner corrected transitions following Elsby, Hobijn, and Şahin (2015); Krusell et al. (2017) (see Appendix A.6). Fourth, the mean and cyclicality of relative job-finding and separation rates by prior earnings levels, using the Survey of Income and Program Participation (SIPP) between 1990 and 2019 (see Appendix A.7). In the data, job-finding rates are broadly similar across earnings levels, while separation rates are higher and more cyclical for lower-paid workers. Fifth, the average earnings growth of continuing incumbents by prior earnings level: lower-paid workers exhibit higher conditional growth rates (see Appendix Figure A.5).

Panel C of Table A.9 summarizes our parameter choices. We set the exogenous separation rate $s = 0.82\%$ to match the average separation rate of higher-wage workers into unemployment. The nonemployment benefit parameters $\bar{b}_0 = 0.41$ and $\bar{b}_1 = 0.58$ determine the level of employment surplus across z types and help pin down the separation threshold $z^*(x)$ and the rate of endogenous separations. The implied ratio of average benefits to average wages is 0.56, well within the $[0.4, 0.96]$ range used in the literature (Shimer, 2005; Hagedorn and Manovskii, 2008; Chodorow-Reich and Karabarbounis, 2016).

The vacancy cost parameters $\bar{\kappa}_0 = 0.036$ and $\bar{\kappa}_1 = 1.48$ allow us to match the average job-finding rates for higher-wage workers. The search cost parameters $\bar{c}_0 = 0.0036$ and $\bar{c}_1 = 6.05$ help match the job-finding rate of low-wage workers, the unemployment rate, and the cyclicality of participation. Both costs are modest in magnitude: when $x_t = \bar{x}$, the vacancy cost is 2.5% of monthly output at $z = \bar{z}_O$ and 3.6% at $z = \bar{z}_E$, while the search cost is 0.8% and 0.4% of monthly output, respectively.

[3] The calibrated persistence of risk premium shocks is higher than that of individual empirical proxies, which is likely driven by measurement error in the latter but may also reflect conceptual differences between empirical measures of risk premia and drivers of stock market valuations. Calibrating the stochastic discount factor (11) to the average persistence of the proxies would imply counterfactually high predictability of excess returns at short horizons (Appendix Figure A.3).

The parameter $\bar{z}_O$ governs the human capital loss during nonemployment. The sensitivity of the surplus of employment to discount rates decreases in $\bar{z}_O$; hence, we set $\bar{z}_O = 0.47$ to match the cyclicality of job-finding and separation rates, implying an 8.0% annual productivity decline during nonemployment. This aligns with Kehoe et al. (2019, 2023) and with micro estimates of human capital depreciation (Couch and Placzek, 2010). Last, given the level of mean reversion in z and the passthrough parameter ϕ, the volatility σ_z of idiosyncratic productivity shocks is pinned down by the heterogeneity in average earnings growth rates of continuing workers as a function of their prior earnings. The value $\sigma_z = 10.9\%$ is consistent with typical values in the literature (Krusell et al., 2017). Combined with a pass-through parameter of $\phi = 0.149$, this choice implies a monthly standard deviation of wage growth of approximately 1.6% for continuing workers.

2.4 Model Fit

The model matches the data well, both on targeted and untargeted moments.

Labor Market Dynamics. Panel A of Appendix Table A.10 compares the volatility, persistence, and cyclicality of key labor market series in the model and the data. Cyclicality is measured as the slope from regressing each series on the unemployment rate. The model reproduces the volatility of unemployment. Market tightness (vacancies to unemployment) is highly volatile and procyclical, with a correlation of -0.80 with unemployment (-0.97 in the data). As in the data, the employment-to-population ratio is strongly procyclical, labor force participation is weakly procyclical, and long-term unemployment is countercyclical. The volatility and persistence of these series are broadly consistent with the data. The main deviation is that labor force participation is more volatile in the model than in the data, which is not surprising given that the model lacks reasons for nonparticipation other than (temporarily) low worker productivity.

Unemployment Flows. Panels C of Table A.9 and B of Table A.10 show that the model reproduces the mean and dynamics of aggregate job-finding and separation rates. It also matches how these flows vary with worker earnings. Figure 3, top row, compares average job-finding and separation rates across the earnings distribution. The job-finding rate is essentially flat in the data (Figure 3a), and the model approximates this pattern well. In contrast, separation rates decline steeply with earnings in both model and data (Figure 3b). The model also captures heterogeneity in cyclicality. Figure 3c shows that the cyclicality of job finding is similar across groups, while Figure 3d shows that separation rates of low earners are much more cyclical than those of high earners. The similarity in job-finding rates and the heterogeneity in separation rates across worker earnings levels are consistent with the evidence in Cairó and Cajner (2018) on more-educated versus less-educated workers.

Drivers of the Unemployment Rate. Shimer (2005, 2012) emphasizes that unemployment volatility is driven mainly by fluctuations in the job-finding rate, not the separation rate. Following Shimer (2012); Kehoe et al. (2019, 2023), we construct two counterfactual unemployment series: one with constant separations and one with a constant job-finding rate (see Appendix B.5 for details and additional analysis). Panel C of Appendix Table A.10 shows that, in both the model and the data, a larger share of the volatility of the unemployment rate can be attributed to fluctuations in the job-finding rate than to fluctuations in the separation rate. Thus, our model is consistent with the view in Shimer (2005, 2012) that fluctuations in the job-finding rate due to vacancy creation are crucial in understanding the dynamics of unemployment.

Firm Labor Demand. We next compare the job-creation and job-destruction margins in the model to the data. Table 2 shows the empirical link between risk premia and firm employment growth and hiring rates. Because hiring in the data includes job-to-job transitions, which are outside the model, we construct a modified hiring measure that excludes these transitions and re-estimate equation (3) in both the data and simulated model. Appendix Figure A.6 shows that the estimated coefficients b_0 align closely: 1.2 in both the model and the data for total employment growth, and 0.63 in the model versus 0.37 in the data for new job creation. Thus, the relative strength of the job-creation and job-destruction channels in response to risk premia is quantitatively similar in model and data.

Heterogeneous Worker Earnings Exposures. The model replicates the heterogeneity in worker exposures to risk premia documented in Section 1, even though these moments are not calibration targets. Figure 4a compares model-implied coefficients β from equation (2) to their empirical counterparts. At horizons of three to five years, the match is close: in both model and data, low-paid workers are significantly more exposed to risk premium shocks than high-paid workers. Since wages for incumbents are not directly affected by discount rates, these earnings exposures arise through the extensive margin. Figure 4b shows that the model generates realistic rates of job destruction following risk premium shocks, measured as the probability of at least one zero-earnings quarter in the next year. Last, Figure 4c shows the model can also largely replicate the differential earnings responses to risk premium shocks for movers—which depend on the length of nonemployment spells as well as the wages received in future matches.

2.5 Model Mechanisms

Here, we briefly discuss the key model mechanisms that lead to heterogeneous labor market dynamics in response to risk premium shocks. Section B.6 in the Online Appendix includes a more detailed discussion.

Response to Aggregate Shocks. Figure 5 shows the impulse response of key model variables to a risk premium shock. Higher risk premia raise discount rates (Figure 5a), which lowers employment (Figure 5b) and raises unemployment (Figure 5c). The increase in unemployment is driven both by higher separation rates—especially among low-wage workers (Figure 5d)—and by lower job-finding rates, which decline fairly uniformly across workers (Figure 5e). Market tightness declines (Figure 5f), output falls (Figure 5g), and earnings drop most for low earners (Figure 5h). In contrast to risk premium shocks, aggregate productivity shocks do not change labor allocations in the model since all value functions are scale-invariant in aggregate productivity A. Hence, TFP shocks shift output immediately and earnings gradually (see equation (28) and Appendix Figure A.7). The rest of this section unpacks the mechanisms behind the risk premium responses.

Worker Heterogeneity. The main source of heterogeneity in the model is worker productivity z, which maps directly into earnings through the wage protocol in equation (28). To see why workers differ in their responses to risk premium shocks, it is informative to trace how the main channels of earnings loss—separations, duration of nonemployment, and wages in future matches—vary with the worker's current productivity z. We turn to these drivers next.

Job Separations. Endogenous job destruction is a central mechanism in the model. Separation risk is strongly linked to worker productivity z: low-z workers face higher average separation rates and more cyclical separations than high-z workers. Two features of the model drive this result. First, nonemployment benefits do not fully scale with productivity, therefore low-z workers are low-surplus matches. Employment continuation is determined by a threshold rule: workers with $z < z^*(x_t)$ are terminated. Second, productivity is mean-reverting and grows faster while employed than while nonemployed. For marginal workers (those with $z = z^*(x_t)$), employment payoffs are more backloaded than nonemployment payoffs, implying that the value of employment (19) has a higher Macaulay duration than the value of nonemployment (16)—see Appendix Figure A.9c. As a result of this duration mismatch, rising risk premia lowers the surplus value of a match, pushing the separation threshold $z^*(x_t)$ upward and generating countercyclical separations among low-z workers.

Duration of Nonemployment Spells. The length of nonemployment spells depends on vacancy posting and search decisions. On the firm side, vacancy posting follows the free-entry condition (22): market tightness is determined by the ratio of match surplus, $J_t^{MC}(z) - J_t^{O}(z)$, to posting cost $\kappa_t(z)$. This ratio is largely insensitive to z, so job-finding rates among the unemployed are relatively uniform across earnings levels. Higher risk premia x_t lower surplus values, reducing job-finding rates similarly across z. On the worker side, search is endogenous: only workers with productivity above a threshold $\underline{z}(x_t)$ choose to search. This threshold rises with risk premia, though less sharply than the separation threshold $z^*(x_t)$. Combined with the endogenous distribution of z, this means that inflows into unemployment rise more than outflows fall, raising unemployment after a risk premium shock. In short, higher risk premia reduce job-finding and raise nonparticipation, lengthening nonemployment spells—especially for low-z workers—and amplifying their earnings losses.

Wages of New Hires. Wages of new hires depend on market conditions (equation (23)) and fall when risk premia rise. For a given z, three forces drive this decline: (i) match surplus is lower, (ii) slacker labor markets reduce workers' bargaining share, and (iii) the partial insurance of flow wages against future aggregate shocks is now more valuable, a cost which is amortized into lower wages. In addition, prolonged nonemployment leads to skill depreciation, so workers typically reenter at lower z. As a result, movers hit by high risk premia suffer larger earnings losses than movers during normal times—both because they face longer spells out of work and because they earn less in their next job (recall Figure 4c).

Decomposition of Earnings Losses. In sum, risk premia affect worker earnings through three channels: job loss, the duration of nonemployment, and wages in future jobs. Figure 6 quantifies their relative contributions (details in Appendix B.7). The dominant force is endogenous separations: higher separation probabilities account for about two-thirds of the earnings decline among low-paid workers. Longer nonemployment spells also contribute, though less so. By contrast, lower reemployment wages affect all workers similarly and thus do not explain the heterogeneity in earnings responses.

2.6 Role of Specific Assumptions

Relative to Kehoe et al. (2023), our model adds two mechanisms: endogenous separations and endogenous search. Endogenous separations explain why lower-paid workers are more exposed to risk premium shocks. Search costs explain why job-finding rates are relatively flat across the earnings distribution.

Endogenous separations. In the data, job-finding rates move similarly across workers (Figure 3). Without endogenous separations, this would imply similar earnings responses to risk premium shocks across the distribution—contrary to the evidence. To show the role of separations, we shut them down, forcing matches to continue even when ex post surplus is negative. We recalibrate the model, following Kehoe et al. (2023), to match the volatility of the constant-separation unemployment rate. The model fits aggregate moments reasonably well (Appendix Table A.11, column 4), but fails to reproduce the cross-sectional pattern in earnings responses (Appendix Figure A.11a). Thus, endogenous separations may not be necessary to generate realistic fluctuations in unemployment, but they are essential for explaining heterogeneity in worker earnings responses.

Endogenous search. Since worker productivity z is persistent and job-finding rates are relatively uniform across the earnings distribution, the model needs a force to prevent low-z workers from having systematically worse job-finding outcomes than high-z workers. Search costs provide that force: some low-z workers choose not to search, which helps equalize observed job-finding rates across groups. Recalibrating the model without search costs illustrates this mechanism. As we see in column 5 of Appendix Table A.11, the model without search costs fits the heterogeneity in labor market flows poorly, while the aggregate fit and the earnings responses to risk premium shocks remain virtually unchanged (Appendix Figure A.11b).

3 Model Implications

Here, we further evaluate the connection between the model and the data.

3.1 Testable Predictions of the Risk Premium Channel

In the model, workers' exposure to risk premium shocks depends on two factors: proximity to the separation threshold and the duration of the match surplus. Both generate predictions for which workers should be most exposed.

A first prediction of our model is that high-expected growth workers are more likely to separate when risk premia rise, since their match surplus is more backloaded and hence more sensitive to discount rates x_t. To test this prediction, we estimate expected three-year earnings growth for stayers using worker characteristics (industry × age × gender bins; industry × prior earnings × tenure bins). We use the fitted values from this regression as a proxy for expected earnings growth. We perform the direct analogue in model-simulated data using worker age and the interaction of job tenure and earnings group bins as explanatory variables. We sort workers based on their expected earnings growth, and report the estimated exposure to risk premium shocks across these groups in Figure 7. We see that high-growth workers are significantly more exposed to risk premia than low-growth workers, both in the data and in the model. Appendix Table A.13 confirms that this pattern holds across horizons and is specific to risk premia, not productivity shocks.

The remaining panels of Figure 7 show that exposure depends jointly on prior earnings and expected earnings growth.[4] Workers in the bottom quartile of earnings but top quartile of growth experience the largest losses: a 10-point rise in risk premia reduces their earnings by 3.4 percentage points, compared to 1 to 1.5 points for other groups. For high-earning workers, expected growth does not materially affect exposure, consistent with the model's logic that they are far from the separation threshold.

In brief, this analysis validates a key prediction of the model: workers with higher expected growth are more exposed to risk premia, even conditional on current income, confirming that our baseline results are not simply driven by unobserved heterogeneity correlated with earnings. Still, our measure of expected growth is somewhat opaque and does not reveal which worker characteristics are its main drivers. We therefore turn to two directly observable dimensions that should correlate with surplus duration: age and tenure. Younger workers have more backloaded employment value and are thus more sensitive to discount rates x_t. Likewise, Caplin, Lee, Leth-Petersen, Sæverud, and Shapiro (2024) show that productivity grows faster for low-tenure than high-tenure workers, implying greater exposure to risk premia. Appendix Table A.14 confirms both predictions: younger and low-tenure workers are significantly more exposed than older and high-tenure workers. Last, these age and tenure patterns are distinct from the baseline earnings gradient documented in Section 1.

[4] In the model, workers' exposure to risk premium shocks is driven by the interaction of distance to the separation threshold and duration of the match surplus. Cross-sectional differences along these two dimensions go hand in hand in the model, as heterogeneity in current productivity z simultaneously reflects worker differences in distance to the separation threshold and in expected productivity growth due to mean reversion of z. However, in the data, there is significant heterogeneity in earnings growth rates after conditioning on earnings.

3.2 Can the Model Replicate Realized Fluctuations?

So far we have compared unconditional moments. We now ask whether the model can track realized fluctuations when fed actual shocks. Specifically, we take our empirical measure of risk premium shocks ϵ^{rp}_{t+1} in Section 1.1 as proxies for the model shocks $\varepsilon_{x,t+1}$, accumulate them into x using equation (10), and compute the implied series for labor market variables. Because the model is scale-invariant, these variables do not depend on A (see Appendix B.3).

Figure 8a shows that the model tracks the realized path of unemployment well. Volatility is comparable, and the correlation between the data and the model-implied series is 67%. We note that the fit is especially strong during the 2008–09 financial crisis and slow recovery—precisely when risk premia spike (Figure 1). The model also replicates the dynamics of long-term unemployment (Figure 8b) and transition rates: job-finding and separation rates have correlations of 62% and 53% with the data (Figures 8c–8d). Labor market tightness (V/U) follows the data closely (Figure 8e), offering a quantitative resolution to the Shimer (2005) puzzle. Aggregate employment paths are also realistic, though the employment-to-population ratio is somewhat more volatile than in the data (Figure 8f).

Overall, risk premia account for a large share of observed labor market fluctuations. Feeding in our empirical measure of risk premium shocks into the calibrated model allows us to quantitatively replicate the paths of key labor market variables in the data. Importantly, the model is able to account for the slow recovery in employment after the Great Recession. This slow recovery is driven by persistently elevated risk premia after the Global Financial Crisis, leading to a protracted period of depressed labor demand—the V/U ratio takes more than a decade to recover—and a decline in human capital due to protracted nonemployment spells.

Last, the model can also replicate the observed dynamics of labor income inequality over the business cycle. To do so, we now need to feed in a proxy for the TFP (A) shock since it affects the level of wages; we feed in our measure of aggregate TFP shocks constructed in Section 1.2. We use the inequality series from Heathcote et al. (2020). Figure 8g shows that the model reproduces the cyclical rise in left-tail inequality (median-to-20th percentile ratio), with a correlation of 81%. Inequality rises at the bottom because low earners face larger and more persistent earnings losses in downturns. By contrast, we see in Figure 8h that right-tail inequality (the 90/50 ratio) is essentially acyclical in both the model and the data.

Conclusion

We provide direct empirical evidence that fluctuations in risk premia give rise to heterogeneous labor market dynamics across workers. Increases in risk premia are followed by decreases in firm labor demand and increases in separation rates for incumbent workers—particularly for lower-paid workers. As a consequence, lower-paid workers experience larger earnings declines compared to higher-paid workers, which implies an increase in labor income inequality at the bottom of the earnings distribution. These patterns lie in sharp contrast to the effect of productivity shocks, which primarily affect the earnings of continuing workers, especially those at the top of the income distribution.

Our work opens up several avenues for future work. First, our work speaks to the redistributive effects of risk premia and their role in generating aggregate fluctuations in demand. Given that lower-paid workers have larger marginal propensities to consume than higher-paid workers (Patterson, 2022), our model mechanism implies that fluctuations in risk premia could have a significant impact on aggregate demand. Second, to the extent that monetary policy affects risk premia (Caballero and Simsek, 2022), our work suggests a novel channel through which monetary policy can affect aggregate demand. Third, given their impact on separations, fluctuations in risk premia can likely generate the countercyclical patterns of labor income risk documented by Guvenen et al. (2014).

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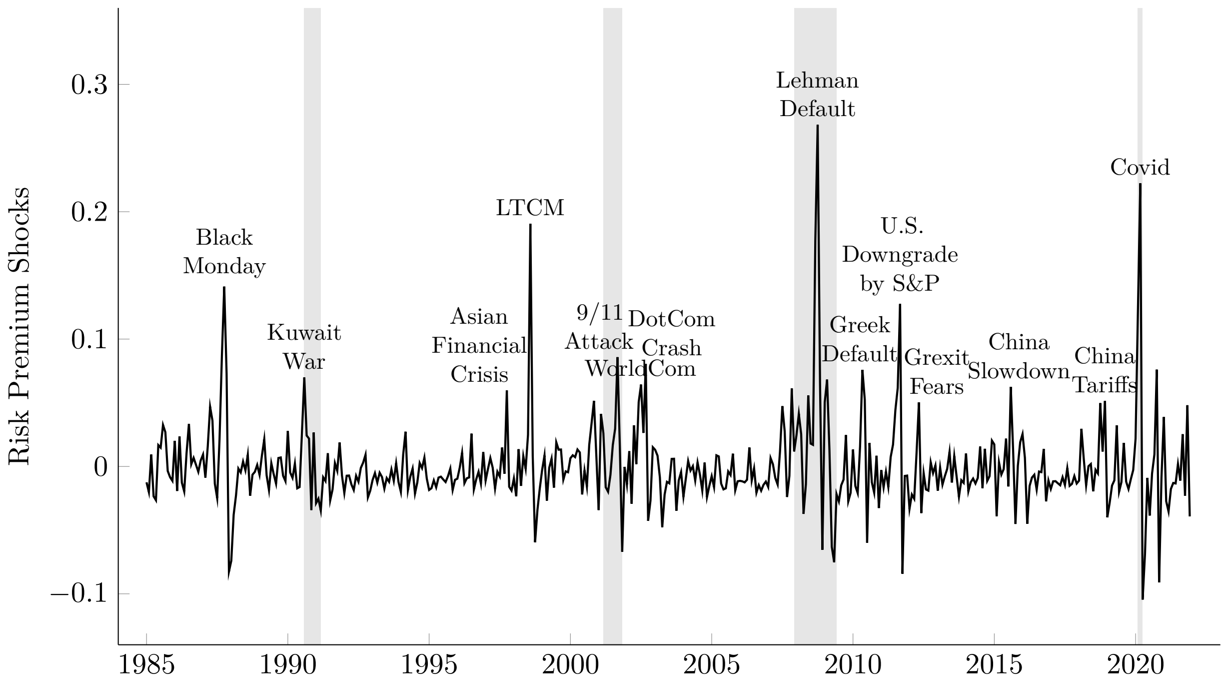
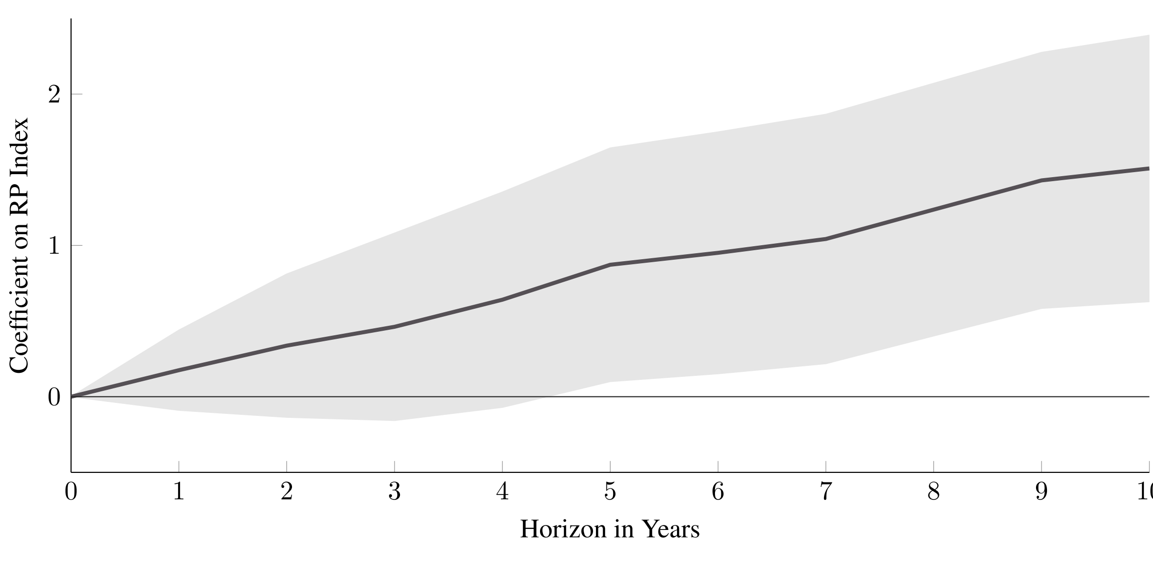
Figure 1: Risk Premium Shocks



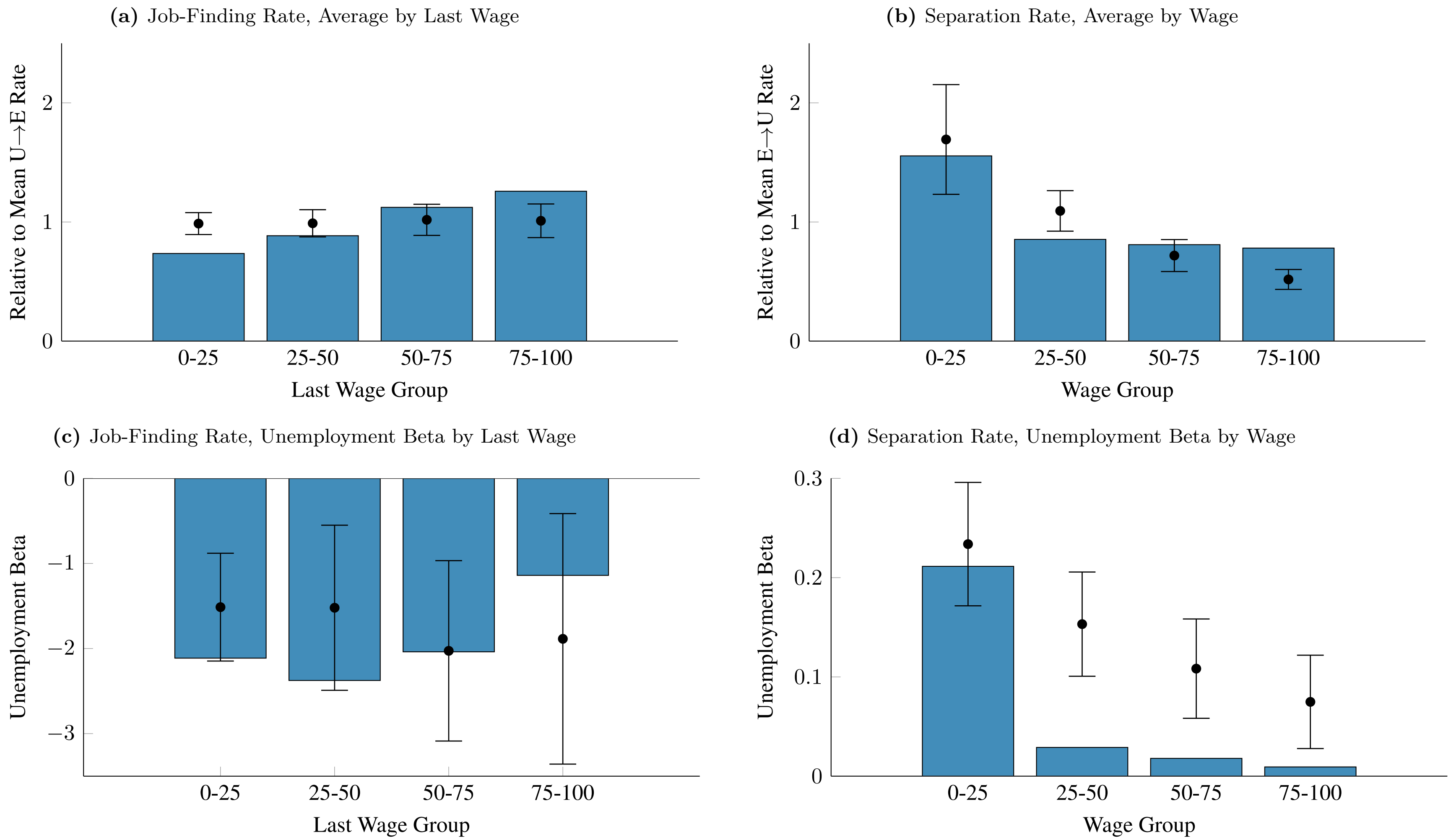
This figure plots our monthly risk premium shocks, measured as the PC1 of the AR(1) residuals of nine series from the literature (see text for details). The shocks are scaled so that a 1% positive shock corresponds to a 1% contemporaneous decline in the stock market.

Figure 2: Risk Premia and Future Stock Market Returns



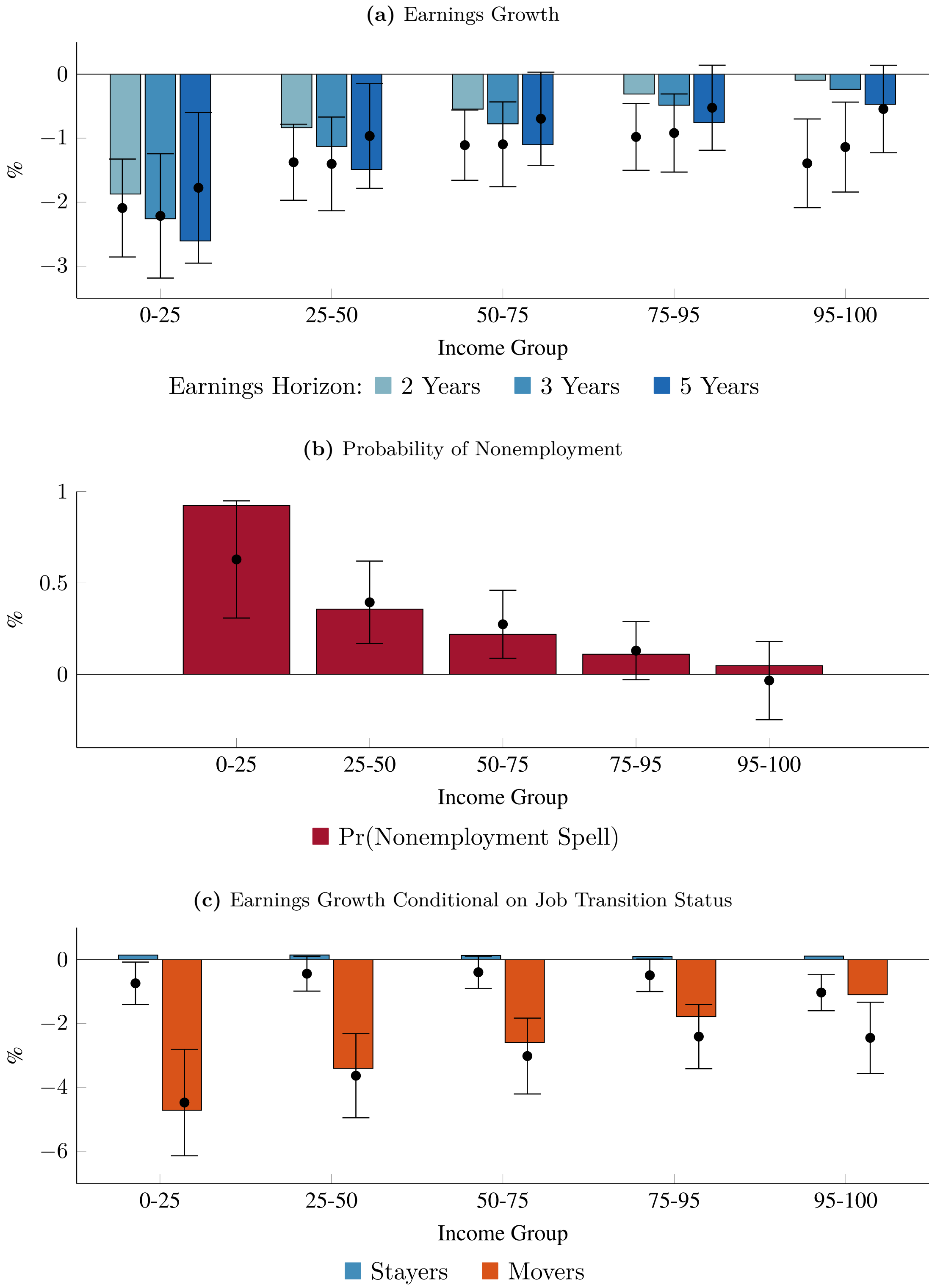
This figure reports estimates of predictive regressions where we project continuously compounded future excess stock market returns $\sum_{s=1}^{h} r_{t+s}^{e}$ at different horizons h on our risk premium index. The risk premium index is the exponentially weighted moving average of the risk premium shock, assuming a decay parameter of 0.0068 per month. The shaded area shows pointwise 95% confidence bands, calculated with Hansen–Hodrick standard errors.

Figure 3: Separation and Job-Finding Rates by Worker Income: Model vs. Data (Targeted)



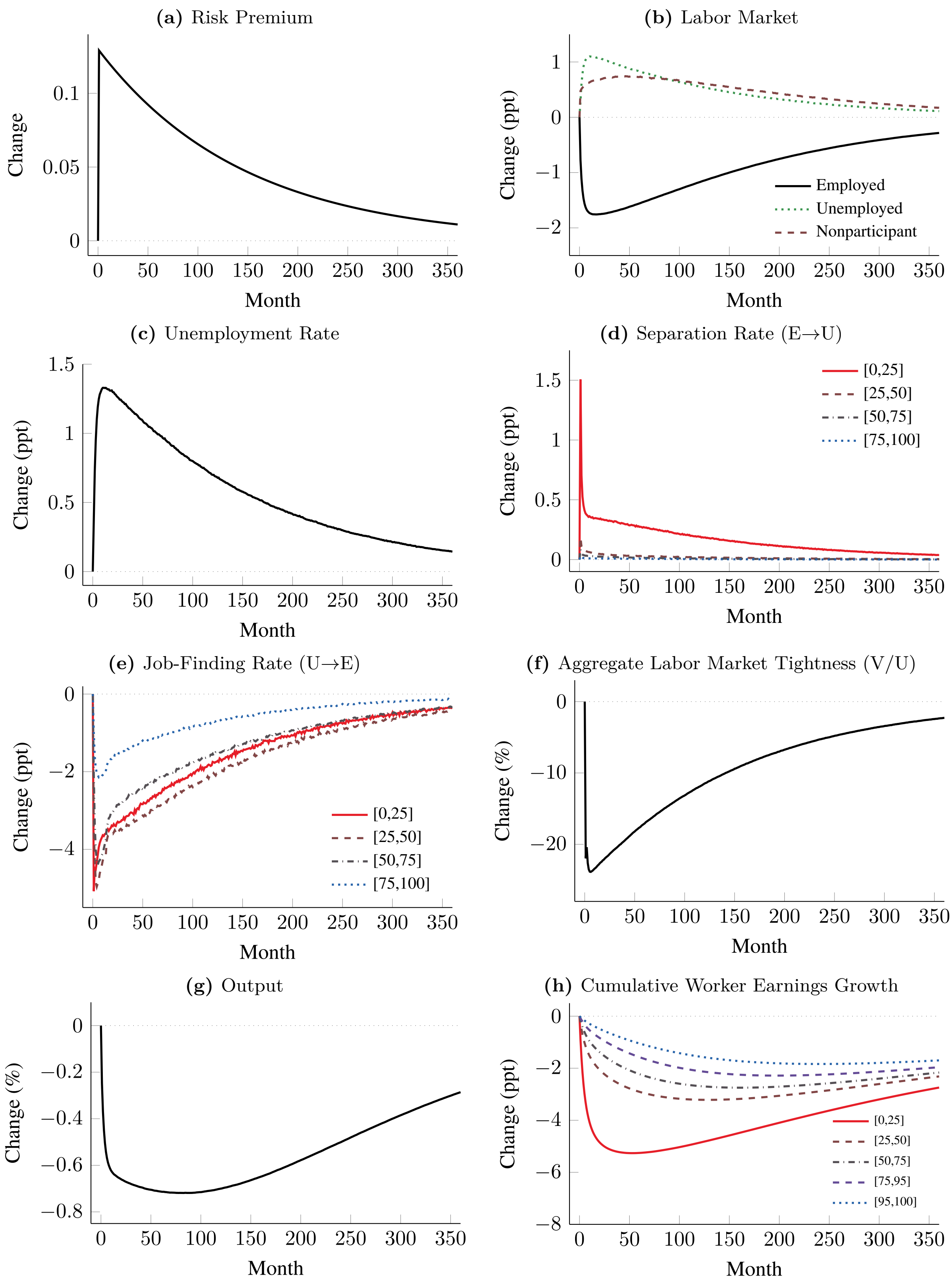
This figure compares the average and cyclicality (unemployment beta) of the job-finding rate (U→E) and the separation rate into unemployment (E→U) by income group in the model and in the data. The empirical counterparts are computed from the SIPP, adjusted for flow level differences from the CPS. Unemployed workers in Panels (a) and (c) are binned into groups based on their earnings the last time they were employed in the prior twelve months (if any). Incumbent workers in Panels (b) and (d) are binned into groups based on their current wage earnings.

Figure 4: Worker Exposure to Risk Premium Shocks: Model vs. Data (Non-Targeted)



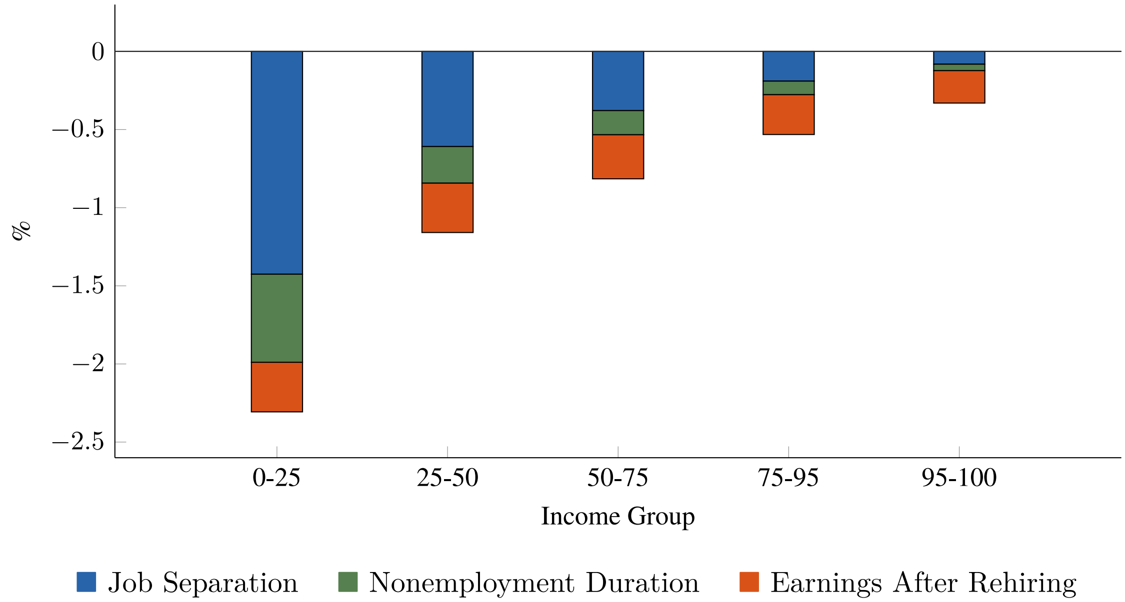
This figure reports the regression coefficients b from estimates of equation (2) by prior worker earnings. Panel (a) reports cumulative earnings exposure over different horizons h. Panel (b) reports effects on the probability of having at least one zero-earnings quarter over the next year. Panel (c) reports cumulative three-year earnings exposure separately for stayers versus movers. Model coefficients are indicated by the bars, and empirical coefficients are indicated by the black dots, with 95% confidence intervals. Coefficients are scaled so that they correspond to a 10% shock.

Figure 5: Impulse Responses to Risk Premium Shocks in Model



This figure shows the impulse responses of key model quantities following a risk premium shock of one annual standard deviation.

Figure 6: Worker Exposure to Risk Premium Shocks in Baseline Model: Decomposition

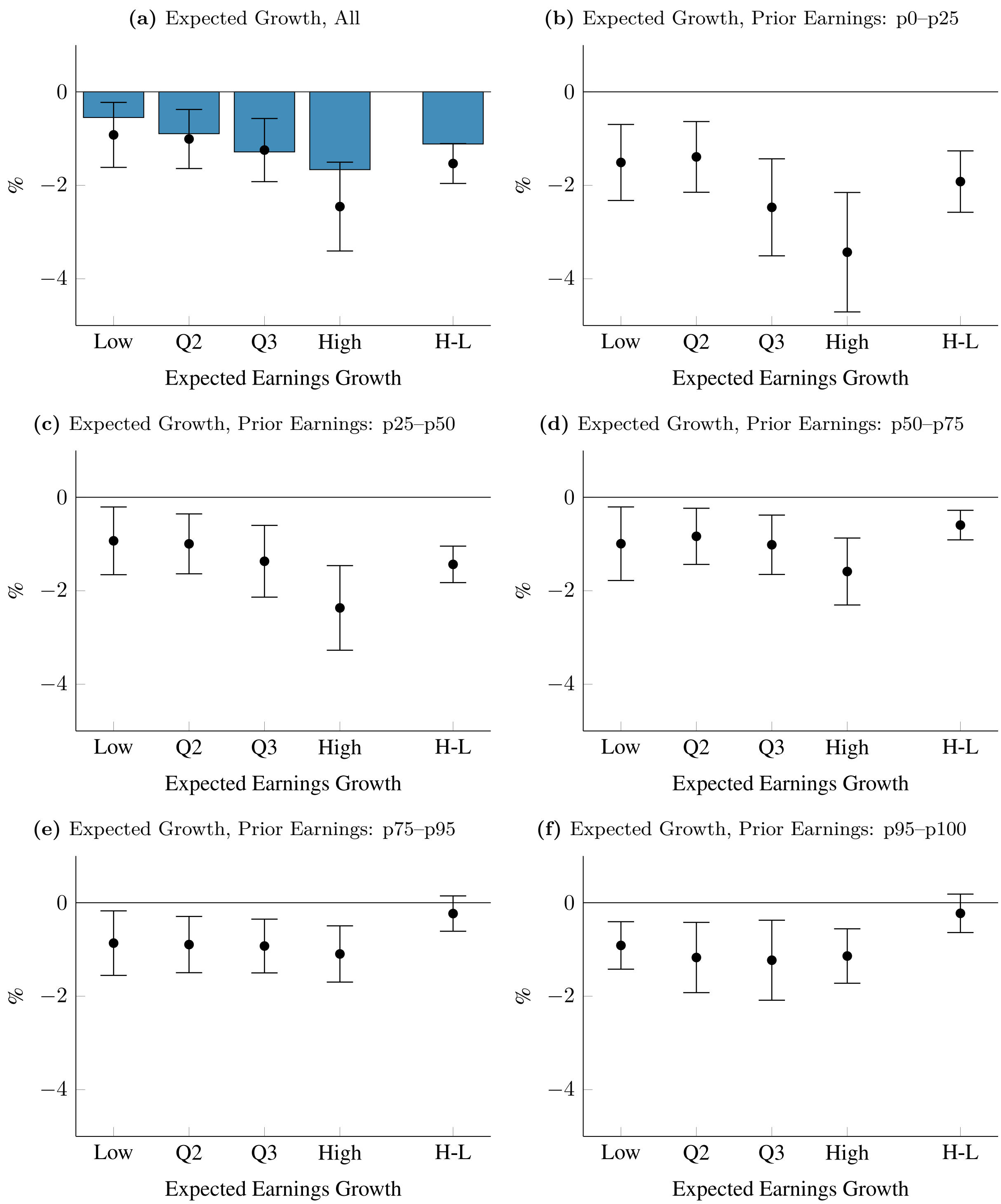


This figure presents a decomposition of the regression coefficient b from estimates of equation (2) for cumulative three-year earnings growth in the model. We decompose cumulative earnings growth as follows:

$$g_{i,t:t+h} = \underbrace{w^{stay}_{i,t+1,t+h} - w_{i,t-2,t}}_{g^{stay}_{i,t:t+h}} + \underbrace{w^{sep}_{i,t+1,t+h} - w^{stay}_{i,t+1,t+h}}_{g^{sep}_{i,t:t+h}} + \underbrace{w^{ext}_{i,t+1,t+h} - w^{sep}_{i,t+1,t+h}}_{g^{src}_{i,t:t+h}} + \underbrace{w_{i,t+1,t+h} - w^{ext}_{i,t+1,t+h}}_{g^{rehire}_{i,t:t+h}}. \quad (29)$$

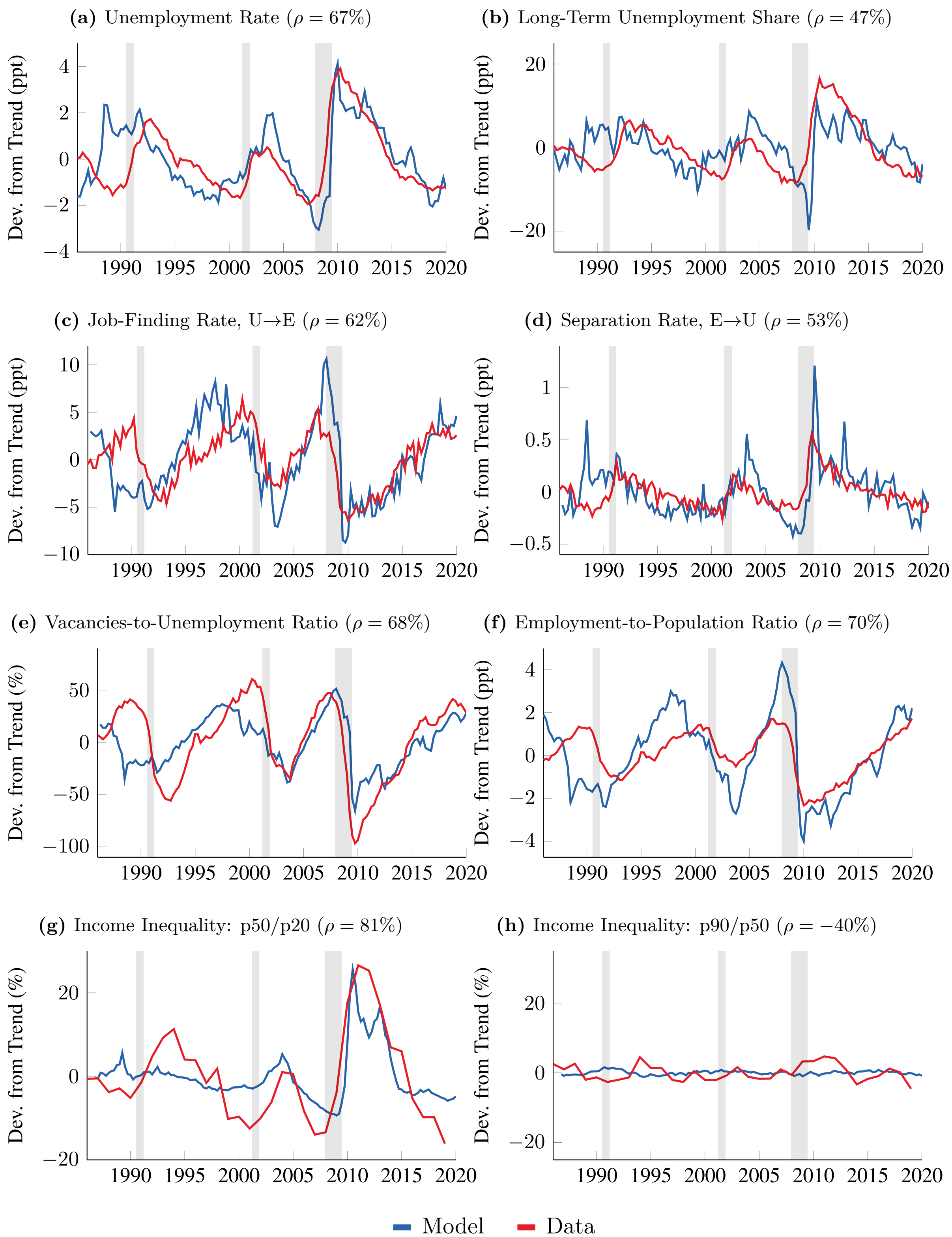
Here, $w^{stay}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker remains in her current job for the full h periods, $w^{sep}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker earns the same wage she would have received had she stayed in her initial job for all periods in which she is employed according to $\hat{e}_{i,\tau}$ and zero otherwise, and $w^{ext}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker earns the same wage she would have received had she stayed in her initial job for all periods in which she is actually employed. The employment indicator $\hat{e}_{i,\tau}$ is defined as the counterfactual employment outcome for a worker when worker search and firm vacancy posting are based on decision rules at $x_\tau = \bar{x}$ for all $\tau > t$. See Appendix B.7 for details.

Figure 7: Worker Exposure to Risk Premium Shocks: Heterogeneity by Worker Expected Earnings Growth



This table reports the regression coefficients b from estimates of equation (2) with cumulative three-year earnings growth as the dependent variable, along with 95% confidence intervals. We report worker exposure by prior earnings bin and by quartile of expected earnings growth, estimated as the average three-year earnings growth of continuing workers by industry × age × gender bin and industry × prior earnings × tenure bin. Model coefficients are indicated by the bars, and empirical coefficients are indicated by the black dots, with 95% confidence intervals. Coefficients are scaled so that they correspond to a 10% shock.

Figure 8: Realized Labor Market Fluctuations: Model vs. Data



This figure compares the realized paths of key variables between the model and the data. We directly feed into the model our (scaled) empirical measures of risk premium and productivity shocks ϵ^{rp} and ϵ^{tfp}. We detrend all series using an HP filter with quarterly smoothing parameter 10^5.

Table 1: Worker Earnings Exposure to Risk Premium Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Worker Earnings, 0–25th Percentile	-2.21	-1.12	-2.11	-1.09	-2.27	-1.11	-1.79	-0.88	-1.52	-0.78
	(-4.47)	(-6.05)	(-4.06)	(-5.87)	(-3.51)	(-5.42)	(-2.63)	(-3.69)	(-2.39)	(-3.59)
Worker Earnings, 25–50th Percentile	-1.40	-0.31	-1.34	-0.32	-1.46	-0.30	-1.15	-0.24	-0.97	-0.23
	(-3.75)	(-6.56)	(-3.33)	(-6.09)	(-2.91)	(-5.60)	(-2.23)	(-4.11)	(-2.00)	(-4.98)
Worker Earnings, 50–75th Percentile	-1.10	—	-1.03	—	-1.16	—	-0.91	—	-0.73	—
	(-3.24)		(-2.83)		(-2.53)		(-1.93)		(-1.62)	
Worker Earnings, 75–95th Percentile	-0.92	0.19	-0.82	0.22	-0.99	0.18	-0.74	0.15	-0.57	0.17
	(-2.96)	(3.58)	(-2.47)	(3.82)	(-2.30)	(2.90)	(-1.70)	(2.17)	(-1.28)	(2.39)
Worker Earnings, 95–100th Percentile	-1.14	0.01	-1.01	0.08	-1.24	-0.05	-0.95	-0.06	-0.71	0.03
	(-3.18)	(0.02)	(-2.45)	(0.27)	(-2.65)	(-0.15)	(-1.76)	(-0.16)	(-1.16)	(0.06)
Bottom (1) – Middle (3) Earners	-1.12		-1.08		-1.11		-0.89		-0.79	
	(-6.08)		(-5.90)		(-5.34)		(-3.74)		(-3.58)	
Middle (3) – Top (5) Earners	0.04		-0.02		0.07		0.04		-0.02	
	(0.14)		(-0.08)		(0.20)		(0.11)		(-0.05)	
Bottom (1) – Top (5) Earners	-1.08		-1.10		-1.03		-0.85		-0.81	
	(-2.68)		(-2.75)		(-2.06)		(-1.64)		(-1.49)	
Firm Controls:										
Earn Grp ×	ΔFirmTFP		ΔRevenue		ΔFirmTFP		ΔFirmTFP		ΔFirmTFP	
Business Cycle Controls:										
Earn Grp ×					ΔAggTFP		ΔGDP		USREC	
Fixed Effects										
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm × Year	-	✓	-	✓	-	✓	-	✓	-	✓
Observations	45.2m	45.2m	50.0m	50.0m	45.2m	45.2m	45.2m	45.2m	45.2m	45.2m

This table reports the regression coefficients b and c from estimates of equation (2) with cumulative three-year earnings growth as the dependent variable. We report exposure across the worker earnings distribution, which we estimate by interacting the two shocks with indicators for the worker's prior earnings level relative to other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, the lagged risk premium index interacted with income group dummies, and the listed fixed effects. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table 2: Firm Employment Response to Risk Premium Shocks

A. *Employment Growth*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Firm Productivity	0.63	0.38	0.48	0.61	0.38	0.48	0.62	0.38	0.48	0.62	0.38	0.48
	(8.73)	(23.71)	(7.16)	(9.03)	(24.58)	(7.17)	(8.75)	(24.06)	(7.15)	(8.86)	(23.39)	(7.15)
Risk Premium	-1.21	-1.09		-1.12	-1.02		-1.11	-0.90		-1.05	-0.79	
	(-9.90)	(-7.42)		(-8.16)	(-6.98)		(-6.47)	(-5.11)		(-5.36)	(-4.09)	
Firm RP Exposure × Risk Premium			-0.35			-0.36			-0.36			-0.33
			(-7.36)			(-7.38)			(-6.31)			(-5.15)
Business Cycle				0.74	0.57		1.67	3.10		-0.15	-0.26	
				(1.34)	(0.92)		(1.07)	(3.15)		(-1.29)	(-4.44)	
Firm RP Exposure × Business Cycle						-0.09			-0.16			-0.02
						(-0.35)			(-0.27)			(-0.39)
B. *Hiring Rate*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Firm Productivity	0.32	0.06	0.31	0.29	0.06	0.31	0.29	0.06	0.31	0.31	0.06	0.31
	(6.86)	(3.41)	(6.57)	(6.43)	(3.42)	(6.56)	(6.34)	(3.37)	(6.55)	(6.81)	(3.34)	(6.57)
Risk Premium	-1.60	-1.47		-1.39	-1.35		-1.24	-1.13		-1.28	-1.11	
	(-6.61)	(-5.61)		(-5.66)	(-5.26)		(-4.00)	(-3.68)		(-3.89)	(-3.32)	
Firm RP Exposure × Risk Premium			-0.27			-0.27			-0.25			-0.23
			(-6.52)			(-5.27)			(-4.82)			(-3.43)
Business Cycle				1.78	1.01		5.68	5.43		-0.29	-0.31	
				(1.97)	(0.98)		(3.14)	(3.66)		(-2.04)	(-2.14)	
Firm RP Exposure × Business Cycle						-0.01			0.19			-0.04
						(-0.03)			(0.30)			(-0.86)
Business Cycle Controls:					ΔAggTFP			ΔGDP			USREC	
Sample	Public	All	Public	Public	All	Public	Public	All	Public	Public	All	Public
Fixed Effects												
NAICS2	✓	✓	-	✓	✓	-	✓	✓	-	✓	✓	-
NAICS2 × Year	-	-	✓	-	-	✓	-	-	✓	-	-	✓
Firm	-	-	✓	-	-	✓	-	-	✓	-	-	✓
Observations	486,000	8,898,000	290,000	486,000	8,898,000	290,000	486,000	8,898,000	290,000	486,000	8,898,000	290,000

The table reports the estimated coefficients from equation (3). In Panel A the dependent variable is the change in log employment. In Panel B the dependent variable is the firm's hiring intensity, defined as the number of new employees scaled by lagged total employment. Observations are at the firm by state level. The sample is either all matched firms in Compustat (public) or all matched firms in the revenue-enhanced LBD (all). The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by firm and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table 3: Worker Earnings Exposure to Risk Premium Shocks: Shift-Share Design

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Worker Earn. (0–25) × Firm RP Exp.	-0.82	-0.37	-0.72	-0.31	-0.88	-0.37	-0.83	-0.34	-0.73	-0.32
	(-6.47)	(-4.58)	(-6.96)	(-3.91)	(-7.67)	(-4.03)	(-5.62)	(-3.72)	(-4.03)	(-3.10)
Worker Earn. (25–50) × Firm RP Exp.	-0.56	-0.10	-0.48	-0.06	-0.60	-0.09	-0.54	-0.05	-0.45	-0.04
	(-4.57)	(-2.72)	(-4.57)	(-1.81)	(-5.43)	(-2.42)	(-3.66)	(-1.35)	(-2.85)	(-0.85)
Worker Earn. (50–75) × Firm RP Exp.	-0.46	—	-0.42	—	-0.51	—	-0.49	—	-0.41	—
	(-4.03)		(-3.99)		(-4.46)		(-3.23)		(-2.77)	
Worker Earn. (75–95) × Firm RP Exp.	-0.31	0.15	-0.28	0.14	-0.37	0.14	-0.35	0.14	-0.29	0.13
	(-3.25)	(3.34)	(-3.05)	(3.44)	(-3.84)	(3.08)	(-2.77)	(2.49)	(-2.17)	(2.03)
Worker Earn. (95–100) × Firm RP Exp.	-0.18	0.29	-0.14	0.28	-0.28	0.23	-0.21	0.28	-0.28	0.12
	(-0.90)	(1.74)	(-0.71)	(1.77)	(-1.51)	(1.34)	(-0.87)	(1.40)	(-0.94)	(0.45)
[Bottom (1) – Middle (3)] × Firm RP Exp.	-0.36		-0.31		-0.36		-0.34		-0.32	
	(-4.48)		(-3.91)		(-3.93)		(-3.65)		(-3.02)	
[Middle (3) – Top (5)] × Firm RP Exp.	-0.28		-0.27		-0.24		-0.28		-0.13	
	(-1.71)		(-1.66)		(-1.34)		(-1.41)		(-0.47)	
[Bottom (1) – Top (5)] × Firm RP Exp.	-0.65		-0.58		-0.60		-0.62		-0.45	
	(-3.23)		(-3.06)		(-3.16)		(-2.56)		(-1.59)	
Firm Controls:										
Earn Grp ×	ΔFirmTFP		ΔRevenue		ΔFirmTFP		ΔFirmTFP		ΔFirmTFP	
Business Cycle Controls:										
Earn Grp × Firm RP Exp. ×					ΔAggTFP		ΔGDP		USREC	
Fixed Effects										
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm	✓	-	✓	-	✓	-	✓	-	✓	-
Firm × Year	-	✓	-	✓	-	✓	-	✓	-	✓
Observations	32.5m	32.5m	34.8m	34.8m	32.5m	32.5m	32.5m	32.5m	32.5m	32.5m

This table reports the regression coefficient b from estimates of equation (4) with cumulative three-year earnings growth as the dependent variable. We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Firm risk premium exposure is standardized to have unit cross-sectional standard deviation, and coefficients are scaled so that they correspond to a 10% shock.

Table 4: Worker Exposure to Risk Premium Shocks: Extensive Margin

	A. *Pr(Nonemployment Spell)*						B. *Pr(Move + Tail Loss)*					
	1 Years		2 Years		3 Years		1 Years		2 Years		3 Years	
Worker Earnings, 0–25th Percentile	0.63	0.35	0.98	0.51	0.82	0.48	0.49	0.23	0.77	0.36	0.77	0.39
	(3.85)	(4.43)	(4.25)	(5.18)	(2.73)	(3.74)	(5.20)	(5.54)	(6.84)	(6.57)	(5.85)	(5.74)
Worker Earnings, 25–50th Percentile	0.39	0.12	0.67	0.19	0.50	0.17	0.33	0.07	0.54	0.13	0.52	0.15
	(3.43)	(4.56)	(3.58)	(5.34)	(2.03)	(3.40)	(5.12)	(6.45)	(6.61)	(8.71)	(5.80)	(6.67)
Worker Earnings, 50–75th Percentile	0.27	—	0.48	—	0.33	—	0.26	—	0.41	—	0.38	—
	(2.89)		(2.95)		(1.53)		(4.77)		(5.81)		(5.10)	
Worker Earnings, 75–95th Percentile	0.13	-0.15	0.23	-0.25	0.10	-0.23	0.17	-0.09	0.27	-0.14	0.23	-0.15
	(1.61)	(-3.61)	(1.54)	(-4.49)	(0.50)	(-3.08)	(3.98)	(-5.89)	(4.60)	(-7.29)	(3.54)	(-5.25)
Worker Earnings, 95–100th Percentile	-0.03	-0.31	-0.10	-0.57	-0.30	-0.63	0.10	-0.16	0.15	-0.27	0.11	-0.28
	(-0.30)	(-3.44)	(-0.48)	(-4.81)	(-1.09)	(-3.37)	(1.89)	(-2.78)	(1.70)	(-4.14)	(1.05)	(-3.14)
Bottom (1) − Middle (3) Earners	0.35		0.51		0.48		0.23		0.36		0.39	
	(4.43)		(5.14)		(3.71)		(5.45)		(6.50)		(5.70)	
Middle (3) − Top (5) Earners	0.31		0.57		0.63		0.16		0.26		0.27	
	(3.42)		(4.77)		(3.35)		(2.73)		(4.11)		(3.09)	
Bottom (1) − Top (5) Earners	0.66		1.08		1.12		0.39		0.62		0.67	
	(4.17)		(5.30)		(3.62)		(4.07)		(5.49)		(4.47)	
Fixed Effects												
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm × Year	-	✓	-	✓	-	✓	-	✓	-	✓	-	✓
Observations	50.0m	50.0m	47.6m	47.6m	45.2m	45.2m	47.6m	47.6m	45.2m	45.2m	42.8m	42.8m

This table reports the regression coefficient b from estimates of modified versions of equation (2), where we replace the dependent variable with two indicators for job loss over the next h years: whether the worker experiences at least one full quarter with zero wage earnings (nonemployment spell) or whether the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile (move + tail loss). We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table 5: Worker Earnings Exposure to Risk Premium Shocks: Movers vs. Stayers

	A. *Movers*						B. *Stayers*					
	2 Years		3 Years		5 Years		2 Years		3 Years		5 Years	
Worker Earnings, 0–25th Percentile	-4.91	-1.35	-4.46	-1.46	-3.37	-1.38	-0.80	-0.31	-0.74	-0.36	-0.58	-0.30
	(-6.69)	(-5.54)	(-5.26)	(-4.98)	(-3.84)	(-4.12)	(-3.00)	(-3.72)	(-2.19)	(-3.45)	(-1.60)	(-2.46)
Worker Earnings, 25–50th Percentile	-4.16	-0.57	-3.63	-0.59	-2.48	-0.49	-0.55	-0.05	-0.44	-0.06	-0.33	-0.05
	(-6.95)	(-5.67)	(-5.41)	(-5.79)	(-3.69)	(-4.17)	(-2.38)	(-1.98)	(-1.59)	(-1.64)	(-1.13)	(-1.01)
Worker Earnings, 50–75th Percentile	-3.55	—	-3.01	—	-1.98	—	-0.50	—	-0.40	—	-0.30	—
	(-6.41)		(-4.99)		(-3.29)		(-2.28)		(-1.54)		(-1.13)	
Worker Earnings, 75–95th Percentile	-2.87	0.59	-2.41	0.58	-1.52	0.47	-0.61	-0.08	-0.49	-0.07	-0.35	-0.03
	(-5.98)	(4.11)	(-4.70)	(3.80)	(-2.94)	(3.23)	(-2.70)	(-1.70)	(-1.90)	(-1.51)	(-1.30)	(-0.74)
Worker Earnings, 95–100th Percentile	-2.74	0.74	-2.44	0.60	-1.56	0.46	-1.28	-0.71	-1.03	-0.55	-0.58	-0.18
	(-5.53)	(1.68)	(-4.31)	(1.32)	(-3.13)	(1.21)	(-4.21)	(-2.48)	(-3.54)	(-1.99)	(-2.24)	(-0.86)
Bottom (1) – Middle (3) Earners	-1.37		-1.45		-1.39		-0.29		-0.35		-0.28	
	(-6.04)		(-5.36)		(-4.37)		(-3.72)		(-3.41)		(-2.49)	
Middle (3) – Top (5) Earners	-0.81		-0.57		-0.41		0.77		0.63		0.28	
	(-1.70)		(-1.16)		(-1.07)		(2.66)		(2.25)		(1.33)	
Bottom (1) – Top (5) Earners	-2.17		-2.02		-1.81		0.48		0.29		0.01	
	(-3.37)		(-2.89)		(-2.76)		(1.55)		(0.87)		(0.02)	
Fixed Effects												
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm × Year	-	✓	-	✓	-	✓	-	✓	-	✓	-	✓
Observations	11.8m	11.8m	14.8m	14.8m	18.1m	18.1m	33.4m	33.4m	28.0m	28.0m	19.9m	19.9m

This table reports the regression coefficient b from estimates of equation (2) with cumulative earnings growth over various horizons h as the dependent variable, separately estimated for job movers and job stayers. Individuals are characterized as a stayer at horizon h if they continue to receive a positive income from their initial time-t employer in year $t+h+1$, and as a mover in all other cases. We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Online Appendix

A Additional Details on the Empirical Analysis

Here, we provide further details on the data construction and empirical analysis.

A.1 Worker Earnings Data

Our main data are employer–employee linked data from the Longitudinal Employer–Household Dynamics (LEHD) database. The LEHD contains earnings and employer information for U.S. workers, collected from state unemployment insurance filings. The LEHD data start in 1990, although many states joined the sample in later years as coverage became more complete. By the mid- to late-1990s, the LEHD covers the majority of jobs. We use data for years until 2019; only a few states drop out of the sample for years before then. The LEHD data are based on firms' unemployment insurance filings to the state and contain total gross wages and other taxable forms of compensation as a measure of earnings. For the state–quarters in the LEHD, coverage of private sector jobs is nearly 100%. We link worker earnings to demographic information such as age and gender and convert all nominal earnings measures to real figures by deflating with the consumer price index (CPI).

The data allow us to track the incomes of individual workers over time and across employers. Our sample in year t covers individuals between ages 25 and 60 who live in a state in year t that is in the LEHD between years $t-2$ and $t+5$ and who have labor earnings in years t, $t-1$, and $t-2$ that exceed a minimum annual threshold as in Guvenen et al. (2014): the federal minimum wage times 20 hours times 13 weeks (1885 dollars in 2019). We merge leads and lags of individual annual labor earnings to the base year, where individuals without any earnings are assigned zero wage earnings for that year.

In addition to total earnings, we separately observe earnings and employer identity for the top three jobs (by income) of an individual in that year. We use the Employer Identification Number (EIN) of the employer associated with the highest annual earnings for the individual to assign workers to firms. In selecting the sample for year t, we require individuals to have strictly positive earnings from this employer in year $t+1$ to make sure that the employment relationship is still active by the end of year t. For workers for whom we observe a complete earnings history between years $t-5$ and t, we construct indicators for employment tenure by counting the number of consecutive years that the worker has received income from the current main employer.

A key focus of our analysis is on heterogeneity in the effects of risk premium and productivity shocks across the income distribution. We rank workers by their prior earnings relative to their peers. In particular, we sort workers by their last three years of total age-adjusted wage earnings, $w_{i,t-2,t}$, and compute the income rank of workers within their own firm. To compute these earnings ranks, we require observing at least 50 workers in the sample for a firm–year. We focus on quartiles of the initial earnings distribution, where we further separate out the top 5% from the remainder of the top quartile.

We use an internal Census table for mapping EIN to GVKEY identifiers to link firm information from Compustat to the worker earnings data. For most of our analysis, we focus on employees of publicly traded companies, for whom we have better measures of risk premium exposures and productivity shocks. We build our sample by first collecting data for all U.S. workers in the LEHD who are linked to Compustat firms in the base year t and constructing the yearly income ranks for this full sample. Then, after constructing all relevant variables, we randomly sample 20% of all workers in each year for inclusion in our final dataset to keep the analysis computationally feasible. We exclude workers employed by firms with missing industry codes or who work in the utilities sector (NAICS codes starting with 22) or financial sector (NAICS codes starting with 52 or 53) from the sample. We also build an alternative 5% sample of all employees of both public and private companies, linked to firm information from the Longitudinal Business Database (LBD).

An additional benefit of the LEHD is that it contains total earnings for each quarter in addition to the annual information. We use this information to construct a nonemployment indicator that takes the value of one if an individual has a quarter of zero earnings over a particular period. We also use worker earnings data split out per employer in future years to classify workers as stayers versus movers with respect to their initial job.

Last, when comparing the patterns of new hiring between the model and the data, we consider a modified measure of firms' hiring intensity that excludes job-to-job transitions. Specifically, we estimate the intensity of new job creation for a firm in year $t+1$ as the number of new hires at time $t+1$ that went through a nonemployment spell: workers who are employed by the firm at year $t+1$ but not at t, and who had at lease one quarter with zero wage earnings in the last quarter of t or the first three quarters of $t+1$.

A.2 Risk Premium Shocks

Table A.2 summarizes the nine existing series in the literature that capture fluctuations in risk or the risk-bearing capacity of investors and that we use to construct our measure of risk premium shocks. Since the majority of the series are available from the 1980s and for the purposes of linking these to our worker data starting from 1990, we collect data from December 1984. All series are signed so that an increase is an indication of elevated risk premia. As a consequence, innovations to all series are negatively correlated with stock market returns in the same month. Figure A.1 plots these nine series.

We construct the risk premium shock as the first principal component of the AR(1) residuals of each individual series. We follow Bauer et al. (2023) in dealing with missing observations to obtain a complete time series. The resulting series is highly positively correlated with each component, with a minimum correlation of 51% and an average correlation of 75%.

A.3 Productivity Shocks

We use the approach from İmrohoroğlu and Tüzel (2014) to estimate a revenue-based measure of total factor productivity (TFP) growth at the firm level based on the production function

$$y_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \omega_{jt} + \eta_{jt}, \tag{A.1}$$

where y_{jt} is the log of value added for firm j in year t, k_{jt} and l_{jt} are log capital and labor, respectively, ω_{jt} is log firm TFP, and η_{jt} is an error term. We estimate the parameters β_k and β_l by implementing the semiparametric methodology of Olley and Pakes (1996). From these estimates, we then compute firm-level TFP growth as

$$\Delta\omega_{jt} = \Delta y_{jt} - \hat{\beta}_k \Delta k_{jt} - \hat{\beta}_l \Delta l_{jt}. \tag{A.2}$$

In their estimation of β_k and β_l, İmrohoroğlu and Tüzel (2014) use industry–time fixed effects to separate firm productivity from industry or aggregate effects. To obtain estimates of firm-level TFP growth that are suitable for aggregation, we re-estimate firm TFP growth based on their methodology but replace the industry–year fixed effects with industry fixed effects at the 3-digit SIC level.

We apply this methodology using data from Compustat, complemented by output and investment deflators from the Bureau of Economic Analysis and wage data from the Social Security Administration. We estimate the production function parameters for every year between 1964 and 2020 using all data up until that year to avoid using any forward-looking information. We winsorize the resulting firm-level growth series at the 1% and 99% levels. To obtain measures of industry-level or aggregate TFP growth, we compute the weighted average of firm TFP growth where we weight firms by their lagged number of employees.

We use this series rather than the TFP series from the Bureau of Labor Statistics (BLS) for several reasons. First, the İmrohoroğlu and Tüzel (2014) series is a direct estimate of revenue-based total factor productivity (TFPR) at the firm level, which Guiso et al. (2005) show has some pass-through to worker wages. By contrast, the TFP series from the BLS are defined as the difference between real output and a shares-weighted combination of factor inputs at the sector or industry level. Second, the BLS series are available only at a granular level for manufacturing industries. Third, for some industries, there are some salient differences between private and public firms; our analysis is based on public firms, and the İmrohoroğlu and Tüzel (2014) measure of productivity directly applies to these firms.

For the analysis in Table A.3 in this Appendix, we analyze a different (5%) sample of workers employed in all public and private firms. Since our measure of firm productivity is only available for publicly traded firms in Compustat, when extending the analysis to workers employed in all firms we measure firm productivity as revenue per worker from the revenue-enhanced Longitudinal Business Database (LBD) (Haltiwanger, Jarmin, Kulick, and Miranda, 2017).

A.4 Measures of Firm Exposure to Risk Premium Shocks

To construct the firm-level risk premium exposure measure $\chi_{f,t}$ in (4), we use various proxies for firms' sensitivity to aggregate financial conditions as described below.

Equity Betas

We use the CRSP/Compustat merged database to link historical firm equity returns to the employers in our sample. We compute firm-level risk premium betas at the end of each year by regressing monthly firm equity returns on the risk premium shock over the past ten years, requiring at least 60 monthly observations. We also compute firm betas with respect to the aggregate stock market using the same approach. As measures of firm exposure as of year t, we use the respective beta that is computed at the end of calendar year $t-1$.

Company-Level Financial Variables

We also compute company-level exposure measures from Compustat. For measuring exposure in year t, we use annual data from fiscal year $t-1$. The amount of debt that matures in years $t+1$ and $t+2$ (as of $t-1$) relative to total assets is given by $\texttt{dd2}/\texttt{at} + \texttt{dd3}/\texttt{at}$. Cash to assets is defined as $\texttt{che}/\texttt{at}$. Firm size is measured as the log of total assets ($\texttt{at}$) in real terms. Finally, we construct the Whited–Wu index following Whited and Wu (2006) as

$$\begin{aligned} &-0.091\,\frac{\texttt{ib}+\texttt{dp}}{\texttt{at}} - 0.062 \times \mathbb{1}(\texttt{dvc}+\texttt{dvp} > 0) + 0.021 \times \frac{\texttt{dltt}}{\texttt{at}} - 0.044 \times \log(\text{real assets}) + \\ &\quad 0.102 \times \text{average SIC 3-digit industry sales growth in year} - 0.035 \times \text{sales growth}. \end{aligned} \tag{A.3}$$

See Farre-Mensa and Ljungqvist (2016) for further details. All Compustat variables (except for size) are winsorized at the 1% and 99% levels.

Distance to Default

The one-year distance to default (Merton, 1974) is defined as

$$DD = \frac{\log(V/D) + \mu_V - 0.5\,\sigma_V^2}{\sigma_V}, \tag{A.4}$$

where V is the total value of the firm, D is the face value of debt, μ_V is the expected return on assets, and σ_V is the volatility of the return on assets. We measure firm distance to default following the iterative procedure from Gilchrist and Zakrajšek (2012). The value of equity is measured as the firm's market capitalization in CRSP. The face value of debt is computed from quarterly Compustat data as $D = \texttt{dlc} + 0.5\,\texttt{dltt}$. The value V and the mean μ_V and volatility σ_V of its return are estimated using the Black–Scholes–Merton option pricing framework and daily equity return data over the past year from CRSP. See Ottonello and Winberry (2020) for further details. As a measure of firm exposure in year t, we use the firm's distance to default as of the end of calendar year $t-1$.

Principal Component

As our main measure of firm exposure $\chi_{f,t}$ to risk premium shocks, we take the first principal component of the risk premium beta, firm size, cash relative to assets, distance to default, and maturing debt in the next two years relative to total assets. On average across years, the first principal component explains 31% of the total cross-sectional variation in these measures. The average cross-sectional correlation of the exposure measure $\chi_{f,t}$ is 38% with the risk premium beta, 60% with negative size, -5% with negative cash to assets, 73% with negative distance to default, and 39% with maturing debt to assets.

A.5 Robustness to Alternative Assumptions

Our results are robust to various changes in the empirical design.

First, Table A.6 examines the extent to which our results are sensitive to the exact measurement of risk premium shocks. Columns (1) and (2) report estimates of b from equation (2) without controls for the lagged level of the risk premium index. Columns (3) to (6) explore alternative timing assumptions: contemporaneous shocks, when worker earnings are paid at the end of the year; and one-year lagged shocks, with beginning-of-the-year earnings—as in Campbell (2003). Columns (7) to (10) explore alternative versions of the risk premium shock. In Columns (7) and (8), we construct our risk premium shock only based on the four indicators for risk appetite considered in Bauer et al. (2023). In Columns (9) and (10), we construct our risk premium shocks only based on the five remaining measures of risk in financial markets. Overall, we see that our main empirical finding is largely invariant to these choices.

Second, Table A.7 examines the robustness of our findings to different measurement of firm-level exposure to risk premium shocks. In Columns (1) and (2), we replace the stock return beta with respect to risk premium shocks with the firm's beta with the aggregate stock market index—since it measures the sensitivity of its cost of capital to aggregate shocks in the Capital Asset Pricing Model (CAPM) of Sharpe (1964). We then take the first principal component of this beta and the other exposure measures. Since the two stock betas are highly correlated, given that our risk premium shock is itself highly correlated with the market portfolio, this leads to a similar exposure measure. In Columns (3) and (4), we construct an exposure index as the first principal component of only the two firm equity betas. Focusing on these two measures of firm exposure to risk premium shocks implicitly takes a narrow view of what these shocks represent—that is, that they capture fluctuations in either the market price of risk or on the quantity of systematic risk that firms are exposed to. Columns (5) and (6) use firm size alone as the measure of firm exposure, and Columns (7) and (8) use the Whited and Wu (2006) index of financial constraints, since more constrained firms are more sensitive to conditions in financial markets. Examining the table, we again note that our results are largely comparable across these choices.

Last, Table A.8 shows that differentiating between workers on the basis of their earnings relative to those of their industry peers (as opposed to those of other workers in the same firm) leads to similar conclusions.

A.6 CPS Data on Worker Flows

We measure gross flows between worker employment states using microdata from the Current Population Survey (CPS) between January 1978 and December 2019. The flows are calculated by making use of the rotating-panel sampling procedure, where households are included in the sample for four months, rotated out for eight months, and then rotated back in for another four months. We follow the algorithm of Elsby et al. (2015); Krusell et al. (2017) in estimating worker flows for all respondents and the associated monthly transition flow probabilities between employment, unemployment, and nonparticipation.

It is well known that survey-based measures of gross flows between recorded employment states are sensitive to classification errors, especially between the states of unemployment and nonparticipation. We implement the Abowd-Zellner correction for classification errors that adjusts transition probabilities for the estimates of misclassification probabilities from Abowd and Zellner (1985), which are based on resolved labor force status from follow-up CPS interviews. The literature has found that all labor market states become more persistent after correction than what is implied by the unadjusted flows. Following the prior literature, we also implement a margin-error adjustment that restricts the estimates of worker flows to be consistent with the published aggregate labor market stocks of workers in employment, unemployment, and nonparticipation.

A.7 SIPP Data on Worker Flows

Given our focus on heterogeneity in labor market dynamics across workers with different income levels, we also want to measure worker flows conditional on wage earnings in the data. Since it is not possible to compute a time series of transition rates by income in the CPS, we turn to data from the Survey of Income and Program Participation (SIPP) of the U.S. Census Bureau to assess the relation between gross worker flows and earnings.

The SIPP is a longitudinal national household survey where participants are repeatedly interviewed on their labor market participation, income, demographic characteristics, and other economically relevant dynamics over a multiyear period. The SIPP consists of multiple panels that each last for several years. The SIPP had major redesigns in 1996 and 2014. Respondents are interviewed every four months (before 2014) or year (from 2014) about monthly outcomes over the past months.

We use data from the 1990–2019 panels of the SIPP, which cover the period from November 1989 to December 2019 with some gaps. We measure monthly employment status from reports in the last week of each month. Analogous to the CPS, we classify individuals as employed if they have a job and are working, absent without pay, or on paid leave. Individuals are classified as unemployed if they have no job and are either looking for work or on layoff. We also track workers who are not participating in the labor market.

In our calibration, we separately target the dynamics of separation and job-finding rates by worker earnings levels. For separation rates, we restrict attention to incumbent workers with positive wage earnings who report having a job in all weeks of the initial month. We sort these employed workers into income groups based on their wage earnings in the current month and compute the share of workers that become unemployed in the next month by earnings quartile bin. For job-finding rates, we sort unemployed workers into income groups based on their last reported (full-month) monthly wage income during the prior 12 months, if any. We then compute the share of workers that report having a job in the next month by prior earnings quartile bin.

It is well established that there is a significant level difference in flow rates computed using the CPS versus the SIPP (Fujita, Nekarda, and Ramey, 2007). Since we calibrate the model to conventional moments of aggregate flows based on the CPS, we adjust the flow rates from the SIPP by removing the level effect. Specifically, we scale the monthly transition probabilities for each earnings group by the respective unconditional average flow rate. That is, we only use the SIPP to estimate relative differences in flows across the earnings distribution.

A.8 Cyclical Dynamics

Both in the data and in the model, we average all monthly labor market stocks and flows at the quarterly frequency. Following Shimer (2005), we apply a low-frequency HP filter with smoothing parameter 10^5 to these series to capture business-cycle fluctuations. When computing labor income inequality in the model, we follow Heathcote et al. (2020) and impose a weak attachment restriction in the simulated data by focusing on workers who have been employed for at least one month in the last 5 years.

B Model Appendix

Here, we include additional details on the solution, calibration, and mechanisms of the model.

B.1 Derivation of Labor Search Equilibrium Conditions

To pin down how the match surplus is shared between workers and firms, we need to consider how a worker's search strategy would change if a firm were to deviate by offering an employment contract with worker value $\widetilde{W}_t(z)$. Let $\widetilde{\theta}_t(z)$ be the tightness in the market for this offer. If the alternative contract has a sufficiently high value, unemployed workers of this type will flow between the two markets until the value from searching in either market is equalized, i.e., when

$$p(\widetilde{\theta}_t(z))(\widetilde{W}_t(z) - J_t^O(z)) = p(\theta_t(z))(W_t(z) - J_t^O(z)). \tag{A.5}$$

Note that when the offer is so bad that even when the probability of getting the job is equal to one, the offer is still dominated by the existing labor market, the market for this alternative offer is inactive with $\widetilde{\theta} = 0$.

Firms target a specific type of worker z by posting a vacancy and offering a continuation value to the worker equal to $W_t(z)$ at the moment the worker is hired (recall the symmetry of the equilibrium). By the one-shot deviation principle, we only need to consider a one-time deviation for a firm in period t while workers are being offered the symmetric offer $W_t(z)$ by all other firms and in all other time periods.

First, consider an active labor market where workers are being offered the symmetric value $W_t(z)$. The value $J_t^V(z)$ of a posted vacancy to a firm is given by

$$\begin{aligned} J_t^V(z) = & -\kappa_t(z) + q(\theta_t(z)) \left(J_t^{MC}(z) - W_t(z) \right) \\ & + (1 - q(\theta_t(z))) \times \mathbb{E}_t \left[\Lambda_{t+1} \max_{\tilde{z}} \left\{ J_{t+1}^V(\tilde{z}) \right\} \right]. \end{aligned} \tag{A.6}$$

Since there is free entry of firms into labor markets, the equilibrium number of vacancies is pinned down by the zero-profit condition in (22).

Second, in equilibrium, no firm can gain by deviating. Consider a firm that deviates by offering worker value $\widetilde{W}_t(z)$. The firm solves the following problem:

$$\begin{aligned} \max_{\widetilde{\theta}_t(z),\widetilde{W}_t(z)} \quad & -\kappa_t(z) + q(\widetilde{\theta}_t(z))(J_t^{MC}(z) - \widetilde{W}_t(z)) \\ \text{s.t.} \quad & p(\widetilde{\theta}_t(z))(\widetilde{W}_t(z) - J_t^O(z)) = p(\theta_t(z))(W_t(z) - J_t^O(z)). \end{aligned} \tag{A.7}$$

It is without loss of generality to consider only serious offers, those for which $\widetilde{W}_t(z) - J_t^O(z) \geq p(\theta_t(z))(W_t(z) - J_t^O(z))$, because there is no point for the firm to offer a wage contract that will be ignored by all workers. The first-order conditions for the firm's problem are

$$-q(\widetilde{\theta}_t(z)) = \zeta_t(z) \cdot p(\widetilde{\theta}_t(z)) \tag{A.8}$$

$$q'(\widetilde{\theta}_t(z))(J_t^{MC}(z) - \widetilde{W}_t(z)) = \zeta_t(z) \cdot p'(\widetilde{\theta}_t(z))(\widetilde{W}_t(z) - J_t^O(z)), \tag{A.9}$$

with Lagrange multiplier $\zeta_t(z)$. By combining these two conditions and imposing symmetry of the equilibrium, we obtain the equilibrium condition

$$-\frac{q'(\theta_t(z))}{q(\theta_t(z))}(J_t^{MC}(z) - W_t(z)) = \frac{p'(\theta_t(z))}{p(\theta_t(z))}(W_t(z) - J_t^O(z)). \tag{A.10}$$

Defining the elasticity of the vacancy filling rate by $\eta(\theta) \equiv -\theta q'(\theta)/q(\theta)$ and noting that $1 - \eta(\theta) = \theta p'(\theta)/p(\theta)$, we can rearrange to solve for the worker value in a new match that is given by equation (23).

B.2 Model Solution

Our model is solved in two steps. First, we solve for the labor search equilibrium in the model. We define the normalized values $\overline{J}_t^N(z) = J_t^N(z)/A_t$, $\overline{J}_t^U(z) = J_t^U(z)/A_t$, $\overline{J}_t^O(z) = J_t^O(z)/A_t$, $\overline{J}_t^{MC}(z) = J_t^{MC}(z)/A_t$, $\overline{J}_t^M(z) = J_t^M(z)/A_t$, and $\overline{W}_t(z) = W_t(z)/A_t$. Rewriting the equilibrium conditions, labor market allocations in this model are pinned down by the solution to the following system of equations:

$$\overline{J}_t^N(z) = \bar{b}_0 + \bar{b}_1\, z + (1-\zeta)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1} e^{\mu_A + \sigma_A \varepsilon_{A,t+1}} \overline{J}_{t+1}^O(z')\right] \tag{A.11}$$

$$\begin{aligned} \overline{J}_t^U(z) = {} & \bar{b}_0 + \bar{b}_1\, z - f(\theta_t(\bar{z}_O)) + (1-\zeta)\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1} e^{\mu_A + \sigma_A \varepsilon_{A,t+1}} \Big\{\overline{J}_{t+1}^O(z') \\ & + p(\theta_{t+1}(z'))\left(\overline{W}_{t+1}(z') - \overline{J}_{t+1}^O(z')\right)\Big\}\Big] \end{aligned} \tag{A.12}$$

$$\overline{J}_t^O(z) = \max\{\overline{J}_t^N(z), \overline{J}_t^U(z)\} \tag{A.13}$$

$$\overline{J}_t^{MC}(z) = z + (1-\zeta)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1} e^{\mu_A + \sigma_A \varepsilon_{A,t+1}} \left\{s\overline{J}_{t+1}^O(z') + (1-s)\overline{J}_{t+1}^M(z')\right\}\right] \tag{A.14}$$

$$\overline{J}_t^M(z) = \max\{\overline{J}_t^{MC}(z), \overline{J}_t^O(z)\} \tag{A.15}$$

$$\begin{aligned} \bar{\kappa}_0\, z^{\bar{\kappa}_1} & \geq q(\theta_t(z))\left(\overline{J}_t^{MC}(z) - \overline{W}_t(z)\right) \\ & = \ \text{if } \theta_t(z) > 0 \end{aligned} \tag{A.16}$$

$$\overline{W}_t(z) = \overline{J}_t^O(z) + \eta(\theta_t(z)) \left(\overline{J}_t^{MC}(z) - \overline{J}_t^O(z) \right). \tag{A.17}$$

From these equations, it follows that the functions $\theta_t(z)$, $\overline{J}_t^N(z)$, $\overline{J}_t^U(z)$, $\overline{J}_t^O(z)$, $\overline{J}_t^{MC}(z)$, $\overline{J}_t^M(z)$, and $\overline{W}_t(z)$ depend only on the aggregate state through the stationary price-of-risk process x_t. Thus, in the competitive search equilibrium, labor market tightness $\theta_t(z)$ does not depend on A_t, and the value functions $J_t^N(z)$, $J_t^U(z)$, $J_t^O(z)$, $J_t^{MC}(z)$, $J_t^M(z)$, and $W_t(z)$ are linear in A_t. The equilibrium continuation policy in (21) is given by

$$\mathbb{1}_t^C(z) = 1 \quad \Leftrightarrow \quad \overline{J}_t^{MC}(z) \geq \overline{J}_t^O(z). \tag{A.18}$$

After solving for the equilibrium allocations, the second step is to find per-period wages based on the imposed wage contract. Similar to above, the normalized value $\overline{W}_t^S(z) = W_t^S(z)/A_t$ derived from payoffs after the current match ends is given by

$$\overline{W}_t^S(z) = (1-\zeta)\,\mathbb{E}_{t,z}\Big\{\Lambda_{t+1}\, e^{\mu_A + \sigma_A \varepsilon_{A,t+1}} \left[\overline{J}_{t+1}^O(z') + (1-s)\,\mathbb{1}_{t+1}^C(z') \left(\overline{W}_{t+1}^S(z') - \overline{J}_{t+1}^O(z')\right)\right]\Big\}. \tag{A.19}$$

Under the wage protocol (28), the present value of wages is

$$\widehat{W}^M(\Omega_{i,m,t}) = w_{i,\tau}\, e^{\mu_A (t-\tau)(1-\phi)} \left(\frac{A_t\, z_{i,t}}{A_\tau\, z_{i,\tau}}\right)^{\phi} + (1-\zeta)\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1}\,(1-s)\,\mathbb{1}_{t+1}^C(z_{i,t+1})\,\widehat{W}^M(\Omega_{i,m,t+1})\Big]. \tag{A.20}$$

Let $\widetilde{W}^M(\Omega_{i,m,t}) = \frac{\widehat{W}^M(\Omega_{i,m,t})}{A_\tau\, e^{\mu_A (t-\tau)(1-\phi)} \left(\frac{A_t}{A_\tau}\right)^{\phi}}$ and $\widetilde{w}_{i,\tau} = \frac{w_{i,\tau}}{A_\tau\, z_{i,\tau}^{\phi}}$. We obtain the following recursive expression for the normalized wage contract value:

$$\widetilde{W}_t^M(\widetilde{w}, z) = \widetilde{w}\, z^{\phi} + (1-\zeta)\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1}\, e^{\mu_A + \phi\, \sigma_A \varepsilon_{A,t+1}}\,(1-s)\,\mathbb{1}_{t+1}^C(z')\,\widetilde{W}_{t+1}^M(\widetilde{w}, z')\Big]. \tag{A.21}$$

Finally, the wages of new hires can be pinned down by solving (27) in terms of normalized values:

$$\widetilde{W}_\tau^M(\widetilde{w}_\tau(z), z) = \overline{W}_\tau(z) - \overline{W}_\tau^S(z). \tag{A.22}$$

B.3 Calibration of the Stochastic Discount Factor

We calibrate the parameters of the stochastic discount factor (SDF) to match moments of asset prices. To do so, we make the common assumption that corporate earnings E_t represent a levered claim on aggregate productivity,

$$\Delta E_{t+1} = \mu_E + \lambda\, \sigma_A\, \varepsilon_{A,t+1}, \tag{A.23}$$

where μ_E is expected earnings growth and λ is the leverage parameter. Based on the average value of nonfinancial corporate business debt as a percentage of the market value of corporate equity between 1952 and 2019 from the Flow of Funds, which is 49%, we assume a leverage parameter

λ equal to 1.49. The total value of the stock market is given by the present value of aggregate earnings as specified in (9).

To calibrate the price of risk process x_t in (10), we follow a strategy similar to that of Lettau and Wachter (2007), with one important distinction: we allow for a negative correlation between productivity shocks and risk premium shocks. In particular, we set $\rho_{A,x}$ to -0.39 to match the correlation between our measures of annual aggregate TFP growth and risk premium shocks. To accommodate this negative correlation in a model with realistic asset pricing implications, we also allow risk premium shocks to be priced (i.e., $\delta \neq 0$).

Given that the model's mechanism operates through changes in employment values at relatively long maturities, we target both the moments of the stock market as a whole and the moments of a risky long-duration claim. Specifically, we consider the returns on the long-duration portfolio from Gormsen and Lazarus (2023), who sort stocks into decile portfolios based on ex ante duration. The realized duration of the long-duration portfolio is 59 years. We mimic this long-duration portfolio in our model by computing the returns on a long-run dividend strip (zero-coupon equity) with an equivalent maturity of 59 years. We assume that the duration of the market is 20 years, which is the realized duration of the median portfolio.

We simulate the model at a monthly frequency and aggregate all financial variables to an annual frequency to compute annual moments. We choose μ_E, $\bar{x}$, ψ_x, σ_x, and δ to target the average price–earnings ratio, the autocorrelation of the log price–earnings ratio, the duration of the market, the mean and volatility of aggregate stock market returns, and the mean and volatility of the return on the long-duration claim. Panel B of Table **??** shows that our calibration (with $\mu_E = 0.16\%$ per year) matches the average and persistence of the price–earnings ratio and the distribution of aggregate stock market returns. The volatility of the log price–earnings ratio is 0.39, which is close to the empirical value of 0.41. In addition, as Figure A.2 illustrates, the calibrated SDF captures the stylized fact that the Sharpe ratios of risky assets decline with the duration of their cashflows (Lettau and Wachter, 2007; van Binsbergen, Brandt, and Koijen, 2012; Gormsen and Lazarus, 2023). The value of $\delta > 0$ implies that shocks to risk premia that are orthogonal to productivity are viewed as low-marginal-utility states by households, potentially because of improved investment opportunities. The maximum monthly Sharpe ratio that can be attained in financial markets is

$$\frac{\sqrt{\mathrm{Var}_t[\Lambda_{t+1}]}}{\mathbb{E}_t[\Lambda_{t+1}]} = \sqrt{\exp\left\{x_t^2\ (1 + \delta^2 + 2\,\delta\,\rho_{A,x})\right\} - 1}. \tag{A.24}$$

When x_t is at its long-run mean $\bar{x}$, the maximum Sharpe ratio is 0.37.

We assume that our empirical measure of risk premium shocks ϵ^{rp}_{t+1} corresponds to the price-of-risk shock $\varepsilon_{x,t+1}$ in the model. Therefore, in quantitative comparisons of the model with the data, we assume that the model-equivalent risk premium shock ϵ^{rp}_{t+1} is proportional to $\varepsilon_{x,t+1}$. Given that the empirical distribution of ϵ^{rp}_{t+1} is positively skewed and leptokurtic, we calibrate the proportionality coefficient such that the interpercentile range (p99–p1) of monthly risk premium shocks matches between the model and the data: $\epsilon^{rp}_{t+1} = 0.045 \times \varepsilon_{x,t+1}$. Under this assumption, the sample moments of model-implied quantities given the realized risk premium shock series are similar to the unconditional moments. We maintain the timing assumption from Section 1.2 in linking financial shocks to labor market outcomes.

Figure A.3 shows that our model has realistic implications for return predictability. First, in Figure A.3a, we run a predictive regression of future stock market returns on the level of risk premia analogous to Figure 2, comparing the results in model-simulated data to the empirical results. A high value of x_t predicts positive future stock market returns, with a magnitude close to the empirical counterpart. Second, Figure A.3b shows that the model also has realistic implications for the predictability of long-horizon returns by the level of the price–earnings ratio.

In our calibration, x is highly persistent ($\psi_x = 0.993$ monthly) to match the empirical persistence of market prices. Notably, as Figure A.1 shows, some of the empirical series we use as proxies for time-varying financial conditions are less persistent. We therefore consider an alternative calibration where we do not target the persistence of the price–earnings ratio, but instead set $\psi_x = 0.883$ as the average monthly persistence of the nine series. While this calibration can match the remaining target financial moments reasonably well, this model has counterfactual implications for valuations. Figure A.3 shows that there is way too much predictability of market returns at short horizons. The resulting autocorrelation of monthly returns is -0.35, while this autocorrelation is close to zero both in the data and in the baseline model.

B.4 Calibration of the Labor Search Model

After calibrating a subset of the parameters based on ex-ante information and to match asset pricing moments, the other parameters are chosen so that the labor search model equilibrium matches key labor market target moments. These remaining parameters include the exogenous separation rate (s), the long-run mean of z in nonemployment ($\bar{z}_O$), the volatility of z (σ_z), and the parameters governing the vacancy cost function, the nonemployment benefit function, and the worker search cost function.

Equations (12) and (14) make functional form assumptions on vacancy costs and nonemployment benefits as a function of the aggregate state and worker productivity. It remains to parameterize the worker search cost function (15). In any reasonable calibration of our model, labor market tightness $\theta_t(\bar{z}_O)$ is a monotonically decreasing function of x_t (see Figure A.4a). To simplify the calibration, we directly parameterize search costs as a function of x:

$$c_t = A_t\, \bar{c}_0\, e^{-\bar{c}_1\,(x_t - \bar{x})}. \tag{A.25}$$

This reduced-form assumption is consistent with the model of Krusell et al. (2017), which features a wealth effect that increases the desire to participate in bad times, nearly offsetting the substitution effect caused by worsened labor market opportunities. Figure A.4b plots the resulting search cost function $f(\theta)$ implied by our model calibration.

After solving the model, we simulate a monthly panel of 10,000 workers over 75 years, starting from the steady-state distribution of worker states along the balanced growth path. Based on this model-simulated data, we compute the moments of the unemployment rate, job-finding and separation rates (overall and by income), and earnings growth for continuing workers by prior earnings, constructed directly analogously to their empirical counterparts. We repeat this simulation 20 times and average the results to obtain the model moments. We select the parameters $(s, \bar{z}_O, \sigma_z, \bar{\kappa}_0, \bar{\kappa}_1, \bar{b}_0, \bar{b}_1, \bar{c}_0, \bar{c}_1)$ to minimize the distance between the 28 model moments and the empirical targets.

B.5 Decomposition of Unemployment Rate Fluctuations

Section 2.4 considers two counterfactual unemployment rates to assess the relative importance of the job separation and job-finding margins. The first series assumes that the separation rate is constant:

$$u^1_{t+1} = \bar{p}^{EU}\,(1 - u^1_t) + p^{UE}_{t+1}\,u^1_t, \tag{A.26}$$

where p^{ij}_t is the probability of transitioning from state i to state j and $\bar{p}^{ij}$ is the average flow rate. The second series assumes that the job-finding rate is constant:

$$u^2_{t+1} = p^{EU}_{t+1}\,(1 - u^2_t) + \bar{p}^{UE}\,u^2_t. \tag{A.27}$$

As we see in Panel C of Table A.10, in both the model and the data, a larger share of the volatility of the unemployment rate can be attributed to fluctuations in the job-finding rate than to fluctuations in the separation rate. In this regard, our model is consistent with the view in Shimer (2005, 2012) that fluctuations in the job-finding rate due to vacancy creation are crucial in understanding the dynamics of unemployment.

The above two counterfactual series do not account for dynamic interactions of the flows and ignore the nonparticipation margin. Therefore, as an additional test of the model's implications for the dynamics of labor market flows, we implement the approach from Elsby et al. (2015) to conduct a more formal decomposition of unemployment fluctuations into the individual contributions of flows between labor market states. This decomposition also accounts for the participation margin.

Define E_t, U_t, N_t as the current stock of workers that are employed, unemployed, and nonparticipating, respectively, and denote the transition rate between states $i, j \in \{E, U, N\}$ by p^{ij}_t. The dynamics of the stocks in terms of the flows are given by the Markov chain

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_t = \begin{bmatrix} 1 - p^{EU} - p^{EN} & p^{UE} & p^{NE} \\ p^{EU} & 1 - p^{UE} - p^{UN} & p^{NU} \\ p^{EN} & p^{UN} & 1 - p^{NE} - p^{NU} \end{bmatrix}_t \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t-1}. \tag{A.28}$$

By normalizing the stocks by the size of the population so that they represent population shares, the accounting identity $E_t + U_t + N_t = 1$ holds, which means that labor market dynamics can be represented by the two-dimensional system

$$\underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_t}_{S_t} = \underbrace{\begin{bmatrix} 1 - p^{EU} - p^{EN} - p^{NE} & p^{UE} - p^{NE} \\ p^{EU} - p^{NU} & 1 - p^{UE} - p^{UN} - p^{NU} \end{bmatrix}_t}_{P_t} \underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_{t-1}}_{S_{t-1}} + \underbrace{\begin{bmatrix} p^{NE} \\ p^{NU} \end{bmatrix}_t}_{Q_t}. \tag{A.29}$$

Let $\bar{S}_t = (I - P_t)^{-1} Q_t$ be the steady state that the Markov chain is currently converging to. Elsby et al. (2015) show that the dynamics of S_t can be written as

$$\Delta S_t = A_t \, \Delta \bar{S}_t + B_t \, \Delta S_{t-1}, \tag{A.30}$$

where $A_t = I - P_t$ and $B_t = (I - P_t) P_{t-1} (I - P_{t-1})^{-1}$. Note that the first term in (A.30) captures the effect of contemporaneous changes in flow rates on long-run labor market stocks, while the second term captures the effect of past flows on the current state. Iterating this equation backwards over all periods in the sample (starting from $t = 0$) gives an expression for changes in S_t as a function of current and past changes in steady-state values $\bar{S}_t$,

$$\Delta S_t = \sum_{k=0}^{t-2} C_{k,t} \, \Delta \bar{S}_{t-k} + D_t \, \Delta S_1, \tag{A.31}$$

where $C_{k,t} = (\prod_{n=0}^{k-1} B_{t-n}) A_{t-k}$ and $D_t = \prod_{n=0}^{t-2} B_{t-n}$.

Next, to link changes in labor market stocks to underlying changes in flows, consider a first-order approximation to changes in $\bar{S}_t$:

$$\Delta \bar{S}_t \approx \sum_{i \neq j} \frac{\partial \bar{S}_t}{\partial p_t^{ij}} \, \Delta p_t^{ij}. \tag{A.32}$$

Combining the above ingredients leads to the following decomposition of the variance of changes in labor stocks:

$$\mathrm{Var}(\Delta S_t) \approx \sum_{i \neq j} \mathrm{Cov}(\Delta S_t, \Delta S_t^{ij}), \tag{A.33}$$

where

$$\Delta S_t^{ij} = \sum_{k=0}^{t-2} C_{k,t} \, \frac{\partial \bar{S}_{t-k}}{\partial p_{t-k}^{ij}} \, \Delta p_{t-k}^{ij}. \tag{A.34}$$

Note that this decomposition does not directly apply to the unemployment rate $u_t = \frac{U_t}{E_t + U_t}$, which is a nonlinear function of the stocks. However, we can derive a decomposition for unemployment rate fluctuations by using a linear approximation,

$$\Delta u_t \approx (1 - u_{t-1}) \, \frac{\Delta U_t}{E_{t-1} + U_{t-1}} - u_{t-1} \, \frac{\Delta E_t}{E_{t-1} + U_{t-1}}. \tag{A.35}$$

Plugging in the above expressions for ΔS_t, it is now straightforward to arrive at a similar decomposition for changes in u_t,

$$\mathrm{Var}(\Delta u_t) \approx \sum_{i \neq j} \mathrm{Cov}(\Delta u_t, \Delta u_t^{ij}). \tag{A.36}$$

To assess the contribution of each flow component to fluctuations in the unemployment rate, we compute

$$\rho^{ij} = \frac{\mathrm{Cov}(\Delta u_t, \Delta u_t^{ij})}{\sum_{i \neq j} \mathrm{Cov}(\Delta u_t, \Delta u_t^{ij})}. \tag{A.37}$$

Table A.12 compares the results of this decomposition between the data and the model. Consistent with Elsby et al. (2015), we find that unemployment outflows account for approximately 60 percent of unemployment fluctuations in the data and unemployment inflows account for 40 percent, with the participation margin contributing around 30 percent of the overall variation despite the labor market participation rate being nearly acyclical. We see that the model matches the contributions of the individual components quite well, with prominent roles for both countercyclical job-loss rates and procyclical job-finding rates and a negligible impact of flows between employment and nonparticipation. The model understates the importance of procyclical movements from unemployment to nonparticipation, likely because of the absence of labor supply motives other than current productivity, and therefore has a more modest—but still substantial—total contribution by the participation margin of around 20 percent.

B.6 Detailed Discussion of Model Mechanisms

Here, we discuss the key model mechanisms that lead to heterogeneous labor market dynamics in response to risk premium shocks.

Worker Heterogeneity

The key source of worker heterogeneity in the model is worker productivity z. Worker productivity maps directly into worker earnings—recall our wage protocol in equation (28) above; the parameter ϕ controls the strength of the pass-through. Figure A.8a shows that this relation is fairly strong, though not perfect, since worker productivity and labor market conditions at the time that the worker is hired determine the total value that accrues to the worker during a match, thus directly affecting earnings beyond the current level of z.

Overall, to understand why the model delivers heterogeneous worker outcomes, it is sufficient to understand how the key drivers of worker earning declines in response to risk premium shocks vary across workers with different current skills z. These key drivers include the probability of separation, the duration of nonemployment, and wages in future jobs. We discuss these next, together with a quantitative assessment of their importance in generating the results in Figure 4a.

Job Separations

A key model mechanism is endogenous job destruction in response to changes in risk premia. Since worker productivity z is persistent, the risk of future termination is strongly related to the current level of z. As Figure A.8b shows, low-productivity workers face a higher probability of termination compared to high-productivity workers. Rising risk premia increase the likelihood of termination, especially for low-productivity workers. Therefore, the separation rate of low-z workers is not only higher on average, but also substantially more countercyclical than that of high-z workers.

Why are less-productive workers more exposed to risk premium shocks? This result rests on two features of the model. First, for a given level of risk premia x_t, the surplus from employment is increasing in z. As we see in Figure A.9a, the surplus is negative for low values of z and positive for higher values of z. This pattern is due to the assumption that nonemployment benefits do not fully scale with worker productivity—equation (14). As a consequence, low-productivity workers are low-surplus workers, and job destruction depends on a simple threshold rule: existing matches in which worker productivity is below a threshold $z < z^*(x_t)$ are terminated. The separation threshold $z^*(x_t)$ is defined implicitly through the indifference condition:

$$J_t^{MC}(z^*(x_t)) = J_t^O(z^*(x_t)). \tag{A.38}$$

At $z^*(x_t)$, the worker and the firm are indifferent between continuing the match on one hand, and the worker joining the nonemployed pool with the job being destroyed on the other. Given that the model is scale-invariant with respect to A, the threshold depends solely on the current level of risk premia, x_t.

Second, the surplus from employment falls with x around $z = z^*$. From (A.38), it follows that an increase in x raises the termination threshold z^*; there are some workers for whom the total surplus that was positive before now becomes negative, leading to higher job destruction. To illustrate why the separation threshold moves with risk premia, which is an important driver of time-varying labor market dynamics in our model, we start by rewriting equation (A.38) as

$$\overline{J}^{MC}(x, z^*(x)) = \overline{J}^O(x, z^*(x)). \tag{A.39}$$

Taking the derivative with respect to x on both sides of this equation, we can write the change in the threshold as

$$z^{*\prime}(x) = -\frac{\frac{\partial}{\partial x}\overline{J}^{MC}(x, z^*(x)) - \frac{\partial}{\partial x}\overline{J}^O(x, z^*(x))}{\frac{\partial}{\partial z}\overline{J}^{MC}(x, z^*(x)) - \frac{\partial}{\partial z}\overline{J}^O(x, z^*(x))}. \tag{A.40}$$

Figure A.9a shows that, around the threshold, the continuation value of a match declines more in value when x rises than the outside option: the match surplus value is decreasing in x. Combined with the fact that the surplus is increasing in worker productivity z, we obtain the result that the separation threshold increases in x.

It is fairly straightforward to see why the denominator of (A.40) is positive: the difference between the output that is produced in a match and the nonemployment benefit is increasing in z. Where, however, does the negative numerator for the marginal worker come from? To see why this is the case, we break down the present values of continued employment and the outside option by horizon. That is, we write the present values as the sum of values of individual strips, where a strip is a claim to the total net payoff generated by the worker at a single horizon. The strip that matures at time t has the following payoff:

$$d_t(z,e) = \begin{cases} A_t\, z & \text{if } e = E \\ b_t(z) - c_t - k_t(z) & \text{if } e = U \\ b_t(z) & \text{if } e = N. \end{cases} \tag{A.41}$$

The strip payoffs in (A.41) are a function of worker productivity z and employment status $e \in \{E, U, N\}$. A worker who is matched with a firm produces output $A_t\, z$. A worker who does not participate in labor markets collects the nonemployment benefit $b_t(z)$. A worker who is unemployed collects the benefit $b_t(z)$ and pays the search cost c_t. In the labor market at time $t+1$, she is targeted by firms that post $\theta_{t+1}(z')$ vacancies per unemployed worker of type z' at a unit cost of $\kappa_{t+1}(z')$. Due to perfect competition, these firms are fairly compensated for the costs of posting vacancies by receiving a share of the surplus value of a match upon finding a worker. These costs of giving up a share of total surplus are reflected in the net payoff generated by an unemployed worker by subtracting the expected discounted hiring cost $k_t(z)$ per worker:

$$k_t(z) = \mathbb{E}_{t,z}\left[\Lambda_{t+1}\kappa_{t+1}(z')\theta_{t+1}(z')\right]. \tag{A.42}$$

The net present value at time t of a strip with maturity T can be computed with the standard valuation equation (9), given current aggregate information $\mathcal{F}_t$ and current worker status (z, e):

$$J_t^d(z,e;T) = (1-\zeta)^{T-t}\,\mathbb{E}\left[\left(\prod_{\tau=t+1}^{T}\Lambda_\tau\right) d_T(z_T, e_T)\,\middle|\,\mathcal{F}_t, z, e\right]. \tag{A.43}$$

When we combine the payoffs of the strips with the law of iterated expectations, it follows that the main worker value functions can be decomposed into the sum of values of individual strips given the current worker state:

$$J_t^{MC}(z) = \sum_{\tau=0}^{\infty} J_t^d(z, E; t+\tau) \tag{A.44}$$

$$J_t^{U}(z) = \sum_{\tau=0}^{\infty} J_t^d(z, U; t+\tau) \tag{A.45}$$

$$J_t^{N}(z) = \sum_{\tau=0}^{\infty} J_t^d(z, N; t+\tau). \tag{A.46}$$

Figure A.9c plots the valuation weight that the strip with payoff at horizon τ has in the total continuation value $J_t^{MC}(z)$ (i.e., $J_t^d(z,E;t+\tau)/J_t^{MC}(z)$) and in the outside option $J_t^O(z)$ (i.e., $J_t^d(z,U;\tau)/J_t^U(z)$ when $z \geq \underline{z}(x_t)$). The figure shows the weights by horizon for the marginal worker who is at the separation threshold when $x = \bar{x}$: $z = z^*(\bar{x})$. We see that, for this marginal worker, the value of employment is more backloaded than the value of nonemployment. This effect is driven by the assumptions that worker productivity is mean-reverting and grows relatively faster when employed than when nonemployed.

Finally, we note that the payoffs in (A.41) are linear in A_t. The semi-elasticity with respect to x_t of the present value of a claim to payoff $g(z_{i,t+\tau}, e_{i,t+\tau})A_{t+\tau}$ at horizon τ is the same for each function g and is plotted in Figure A.9d. Thus, the only reason why the left- and right-hand sides of (A.38) have different elasticities with respect to changes in x_t is differences in the timing of their cashflows. Since the values of longer-duration payoffs are more sensitive to risk premium shocks than the values of shorter-duration payoffs, it now follows that the continuation value of the marginal worker has a larger exposure to risk premium shocks than the outside option and therefore that the separation threshold is increasing in x.

Duration of Nonemployment Spells

Firms' and workers' endogenous search decisions jointly determine the likelihood that a nonemployed worker finds a new job and therefore the duration of nonemployment spells. The first determinant of the length of nonemployment spells is the firms' vacancy posting policy, which is pinned down by the free-entry condition (22). Recall that the job-finding rate $p(\theta)$ is strictly increasing in the level of labor market tightness θ. In equilibrium, for worker productivity types z that are actively searching for a job, the tightness of the labor market is equal to

$$\theta_t(z) = \left(\left(\frac{J_t^{MC}(z) - J_t^{O}(z)}{\kappa_t(z)} \right)^{\frac{\alpha}{1+\alpha}} - 1 \right)^{\frac{1}{\alpha}}. \tag{A.47}$$

Thus, how job-finding rates for workers in the unemployment pool vary over time and across worker types depends on how the ratio of the match surplus $J_t^{MC}(z) - J_t^{O}(z)$ to the vacancy posting cost $\kappa_t(z)$ changes with z and x_t.

First, recall from the discussion above that the match surplus is increasing in z. This pattern is offset by the fact that the vacancy posting cost is also increasing in z, which allows the job-finding rate $p(\theta)$ to be relatively insensitive to z, and therefore helping the model match the data by generating similar average job-finding rates across unemployed workers (Figure 3a). Second, an increase in risk premia x_t lowers the surplus value of all matches and therefore lowers job-finding rates. This decline is, with the exception of very low-productivity workers, largely homogeneous across values of z (Figure A.8c), which helps the model generate job-finding rates with similar levels of cyclicality across high- and low-paid workers to match the data (Figure 3c).

The second determinant of the length of a nonemployment spell is the endogenous decision of nonemployed workers to search for a job. When deciding whether to do so, workers trade off the benefits of finding a job against the cost of search and the benefits of staying nonemployed. The productivity threshold $\underline{z}(x_t)$ above which workers choose to enter the search pool solves

$$J_t^{U}(\underline{z}(x_t)) = J_t^{N}(\underline{z}(x_t)). \tag{A.48}$$

Workers with sufficiently low levels of productivity $z < \underline{z}(x_t)$ choose not to search for a job. To match the separation rate into unemployment in the data, the thresholds $z^*(\bar{x})$ and $\underline{z}(\bar{x})$ are fairly close to each other so that workers endogenously separate into both unemployment and nonparticipation.

The search threshold $\underline{z}(x_t)$ depends on risk premia for three reasons. First, echoing the discussion above, the benefits of finding a job for a marginal worker (those with relatively low z) are more backloaded than the benefits of nonemployment plus the search cost. Second, labor market tightness, and therefore the job-finding rate, declines with x_t. Both forces imply a lower benefit of entering the search pool when risk premia x_t are high. However, there is also an offsetting third force that mutes the increase in the threshold: the cost of searching for a job declines as the job market becomes weaker—recall equation (15).

In our calibration, the search threshold $\underline{z}(x_t)$ increases with risk premia, though relatively less than the separation threshold $z^*(x_t)$, as we see in Figure A.9b. Combined with the endogenous distributions of z conditional on employment and nonemployment, this fact implies that when x rises, outflows from the unemployment pool (workers finding a new job or switching into nonparticipation) are smaller than inflows (previously employed or nonparticipating workers entering unemployment), so that the unemployment rate increases in response to a risk premium shock (Figure 5c).

The fact that rising risk premia lead to a fall in job-finding rates and increased nonparticipation implies that the average duration of nonemployment spells increases, particularly for low-z workers (Figure A.8d). The increase in nonemployment duration in response to elevated risk premia directly affects the magnitude of earnings declines for displaced workers: workers face a lower probability of finding a new job than when risk premia are low, and therefore have longer zero-earnings spells.

Wages of New Hires

The wages of new hires are subject to market conditions—equation (23)—and therefore respond to changes in risk premia. Figure A.10 plots the effects of risk premia on both the NPV and flow value of wages for newly hired workers. For a given level of z, the wages of new hires are lower when risk premia are high for several reasons. First, the total surplus of a match is lower. Second, workers face a slacker labor market, implying that they get a smaller share of the match surplus. Third, they have to pay a larger cost of receiving (partial) insurance against aggregate shocks. Because of wage smoothing ($\phi < 1$), if wages were to remain the same, the ratio of the present value of wages to the employment surplus would rise. Holding the tightness of the labor market constant, this would imply that the level of wages would have to fall to satisfy equation (23). A slacker labor market puts further downward pressure on wages. In addition to wage declines conditional on z, workers are expected to start new jobs with lower productivity levels due to skill depreciation as a result of prolonged nonemployment spells. Thus, moving workers face larger earnings losses in response to rising risk premia (recall Figure 4c) relative to workers that move when risk premia are low, not only because they face longer unemployment spells, but also because they earn less in their subsequent job.

B.7 Decomposition of Worker Earnings Exposures

We decompose worker earnings outcomes in the model into three components: wages earned while remaining in the current match, zero earnings during nonemployment spells, and wages earned in future jobs after rehiring. Analogous to (1), cumulative worker earnings growth in the model is defined as

$$g_{i,t:t+h} \equiv w_{i,t+1,t+h} - w_{i,t-2,t}, \qquad w_{i,\tau_1,\tau_2} \equiv \log\left\{\sum_{\tau=\tau_1}^{\tau_2} w_{i,\tau}/(\tau_2-\tau_1+1)\right\}. \tag{A.49}$$

For future periods $\tau > t$, we compute two counterfactual outcome variables. First, we define $\hat{w}^c_{i,\tau}$ as the counterfactual wage that the worker would earn if she remained in her current job until time τ, given the law of motion for z (6) and the wage protocol (28). Second, we define $\hat{e}_{i,\tau}$ as the counterfactual employment outcome for a worker when worker search and firm vacancy posting are based on decision rules at $x_\tau = \bar{x}$ for all $\tau > t$. Armed with these variables, we then compute the following counterfactual cumulative earnings measures:

$$\begin{aligned} w^{stay}_{i,t+1,t+h} &\equiv \log\left\{\sum_{\tau=t+1}^{t+h} \hat{w}^c_{i,\tau}/h\right\} \\ w^{sep}_{i,t+1,t+h} &\equiv \log\left\{\sum_{\tau=t+1}^{t+h} \hat{w}^c_{i,\tau}\mathbb{1}(\hat{e}_{i,\tau}=E)/h\right\} \\ w^{ext}_{i,t+1,t+h} &\equiv \log\left\{\sum_{\tau=t+1}^{t+h} \hat{w}^c_{i,\tau}\mathbb{1}(e_{i,\tau}=E)/h\right\}. \end{aligned} \tag{A.50}$$

Here, $w^{stay}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker remains in her current job for the full h periods, $w^{sep}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker earns the same wage she would have received had she stayed in her initial job for all periods in which she is employed according to $\hat{e}_{i,\tau}$ and zero otherwise, and $w^{ext}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker earns the same wage she would have received had she stayed in her initial job for all periods in which she is actually employed.

We decompose cumulative earnings growth as follows:

$$g_{i,t:t+h} = \underbrace{w^{stay}_{i,t+1,t+h} - w_{i,t-2,t}}_{g^{stay}_{i,t:t+h}} + \underbrace{w^{sep}_{i,t+1,t+h} - w^{stay}_{i,t+1,t+h}}_{g^{sep}_{i,t:t+h}} + \underbrace{w^{ext}_{i,t+1,t+h} - w^{sep}_{i,t+1,t+h}}_{g^{src}_{i,t:t+h}} + \underbrace{w_{i,t+1,t+h} - w^{ext}_{i,t+1,t+h}}_{g^{rehire}_{i,t:t+h}}. \tag{A.51}$$

We separately estimate equation (2) with each of these components as the dependent variable. Figure 6 presents the results of this decomposition of worker earnings exposures to risk premium shocks. The first component ($g^{stay}_{i,t:t+h}$) captures the effect on earnings in the current job; since wages are not directly affected by discount rates, this effect is zero. The second component ($g^{sep}_{i,t:t+h}$) captures earnings losses as a result of time-varying job-separation rates. We see that this component is the main driver of heterogeneity in worker earnings exposures. The third component ($g^{src}_{i,t:t+h}$)

captures earnings losses as a result of reduced exit out of nonemployment. This component shows a similar pattern as the effect due to transitions into nonemployment but is less than half as large. The fourth component ($g^{rehire}_{i,t:t+h}$) captures earnings losses as a result of lower wages after rehiring, driven by worsened labor market conditions and human capital losses during nonemployment. This component is nearly homogeneous across workers; it has a modest impact on total earnings losses for low-wage workers but drives the majority of earnings losses for high-wage workers.

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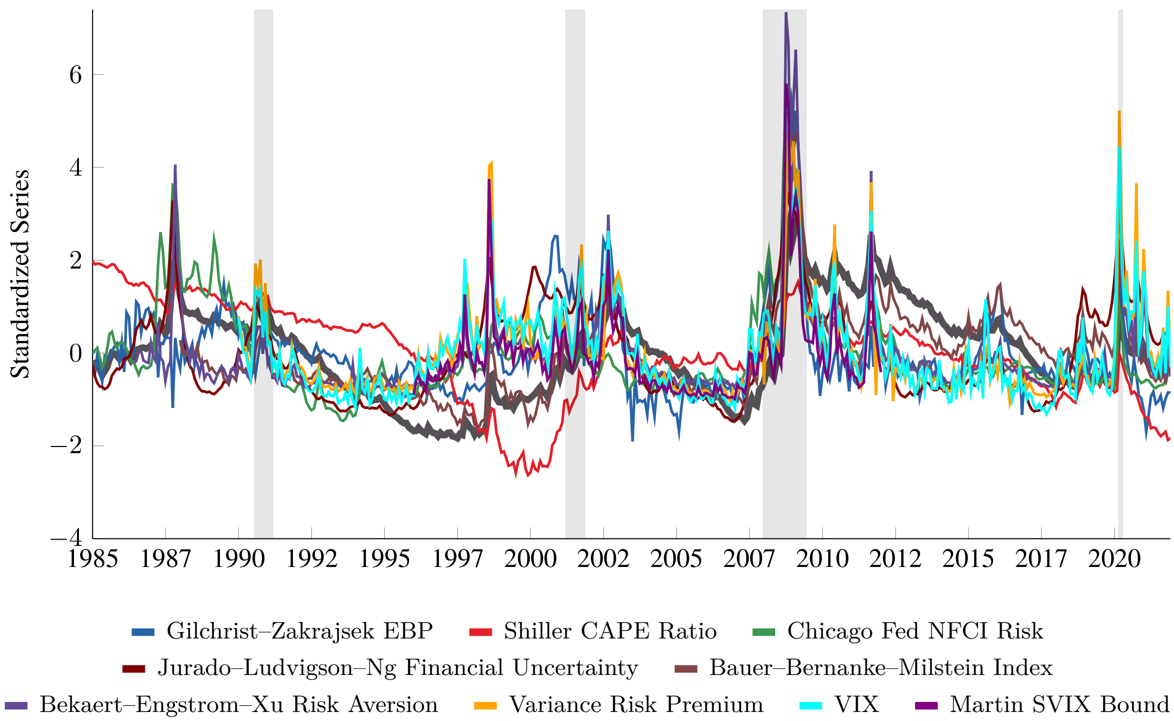
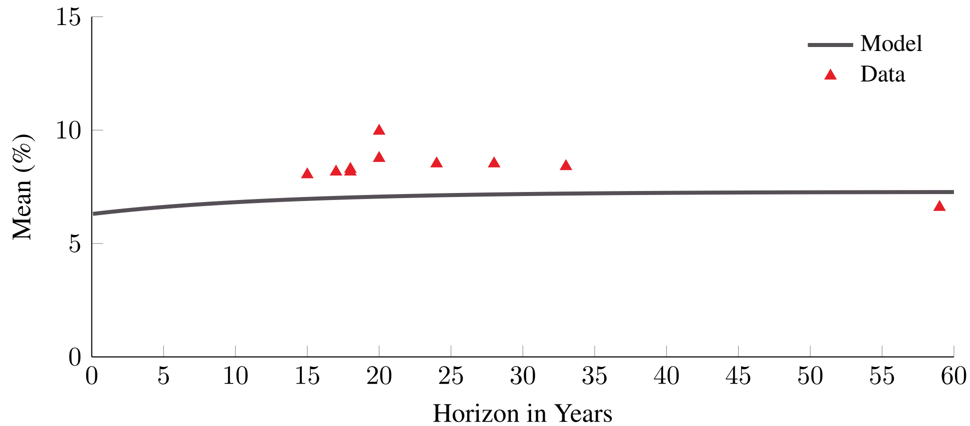
Figure A.1: Time-Varying Risk Premia in the Data



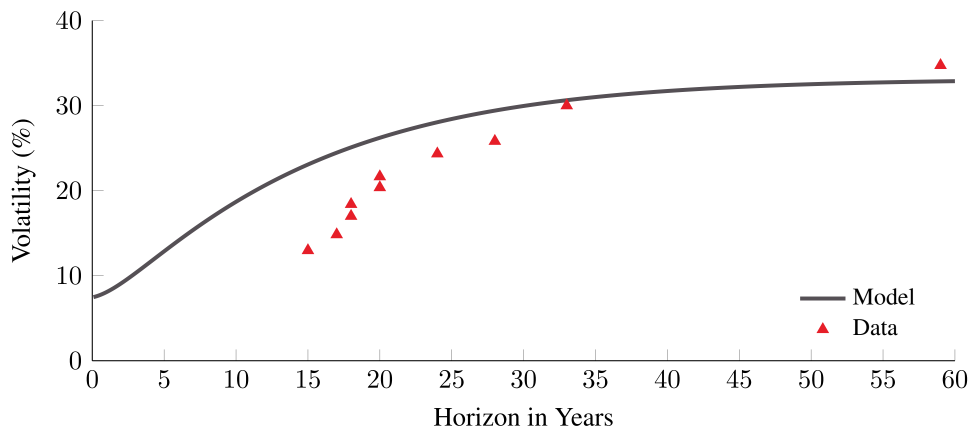
This figure plots nine series from the literature that capture fluctuations in risk premia: the excess bond premium from Gilchrist and Zakrajšek (2012); Robert Shiller's CAPE Ratio; the Chicago Fed's National Financial Conditions Index (NFCI); the financial uncertainty index of Jurado et al. (2015); the risk appetite index of Bauer et al. (2023); the risk aversion index of Bekaert et al. (2022); the variance risk premium from Bekaert and Hoerova (2014); the CBOE VIX; and the SVIX of Martin (2016). All series are standardized.

Figure A.2: Term Structure of Risk Premia in Financial Markets: Model vs. Data

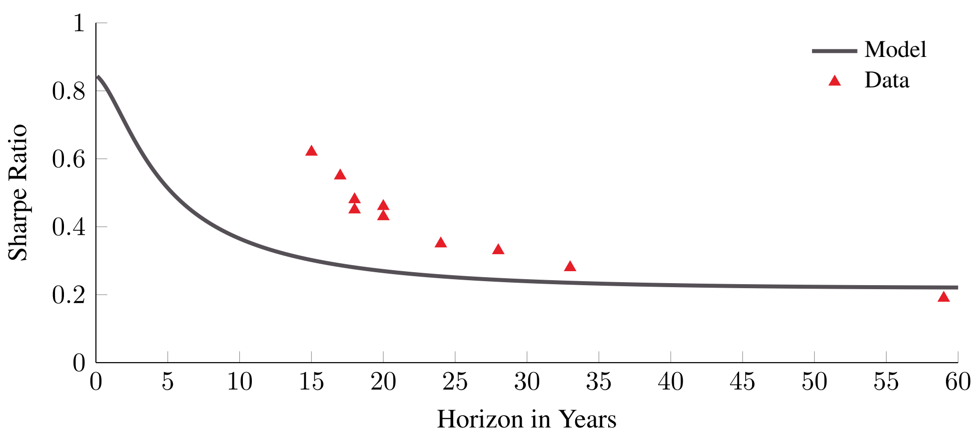
(a) Mean Return, by Cashflow Duration



(b) Return Volatility, by Cashflow Duration

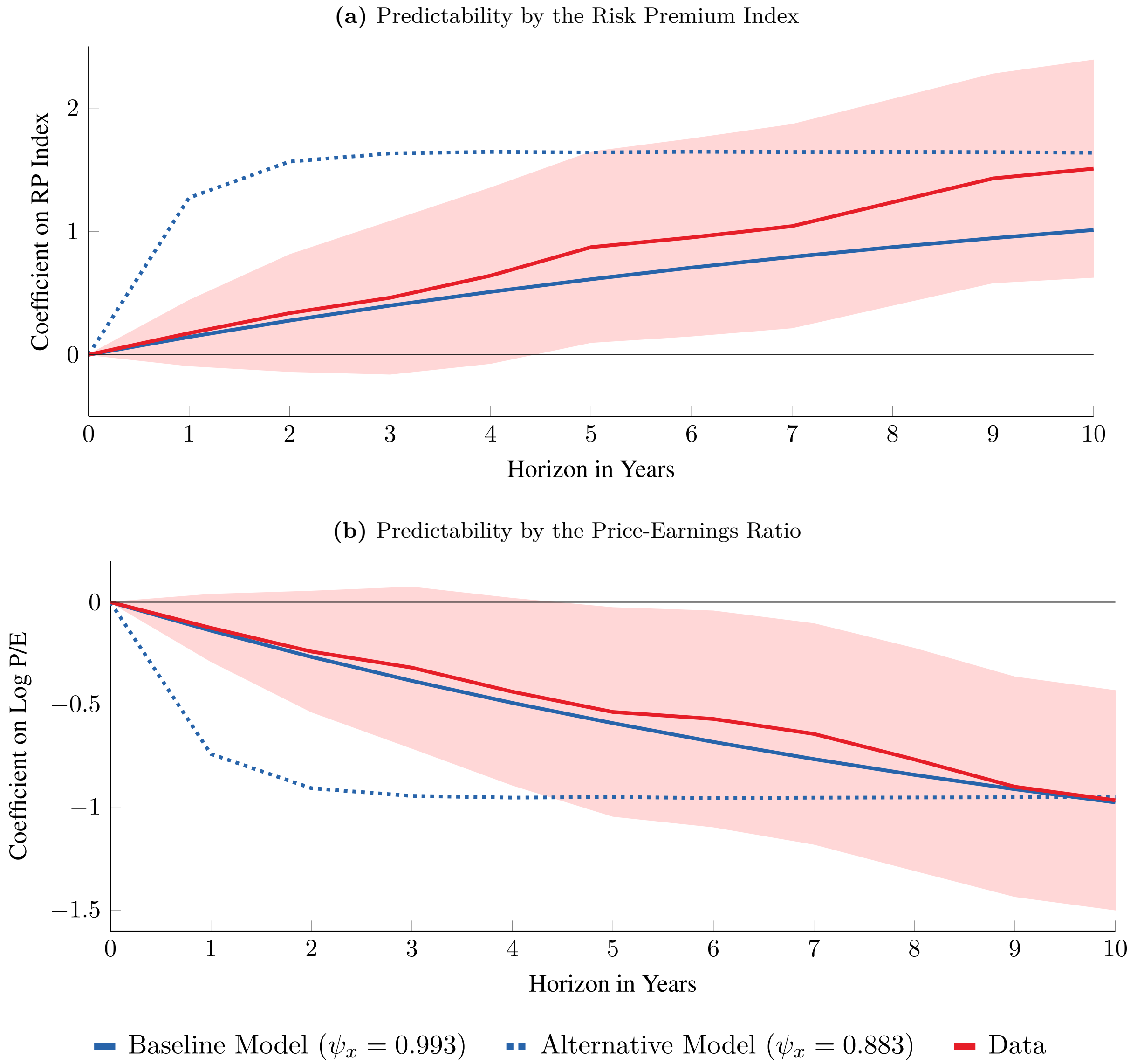


(c) Risk-Return Tradeoff (Sharpe Ratio), by Cashflow Duration



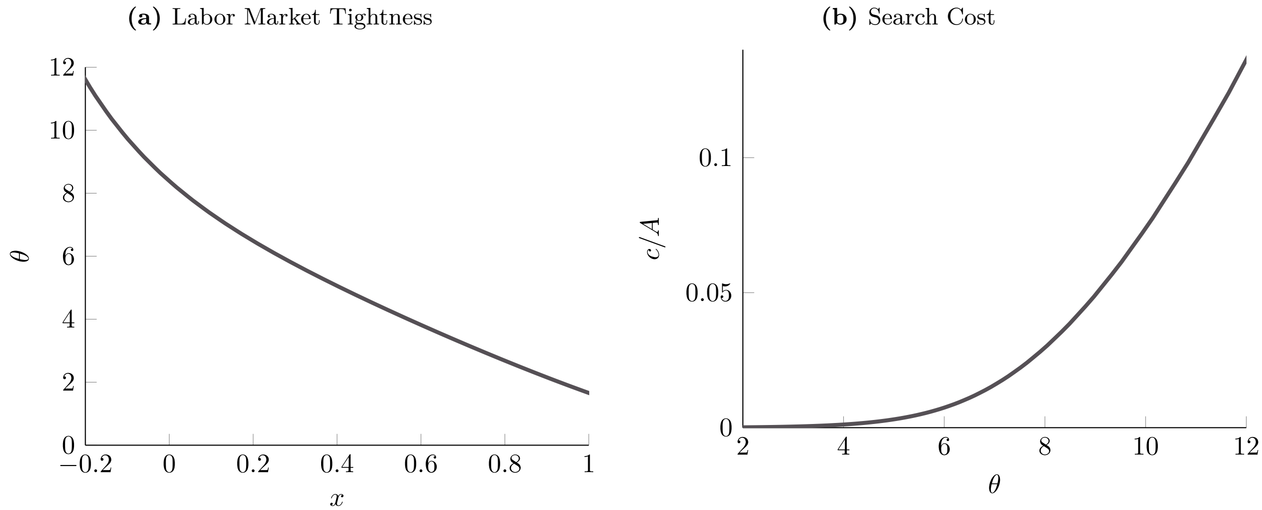
This figure plots the annualized mean (Panel (a)), volatility (Panel (b)), and Sharpe ratio (Panel (c)) of returns on a claim to firm cashflows at a fixed horizon. The data are from the ten duration-sorted portfolios of Gormsen and Lazarus (2023).

Figure A.3: Predictability of Future Stock Market Returns: Model vs. Data



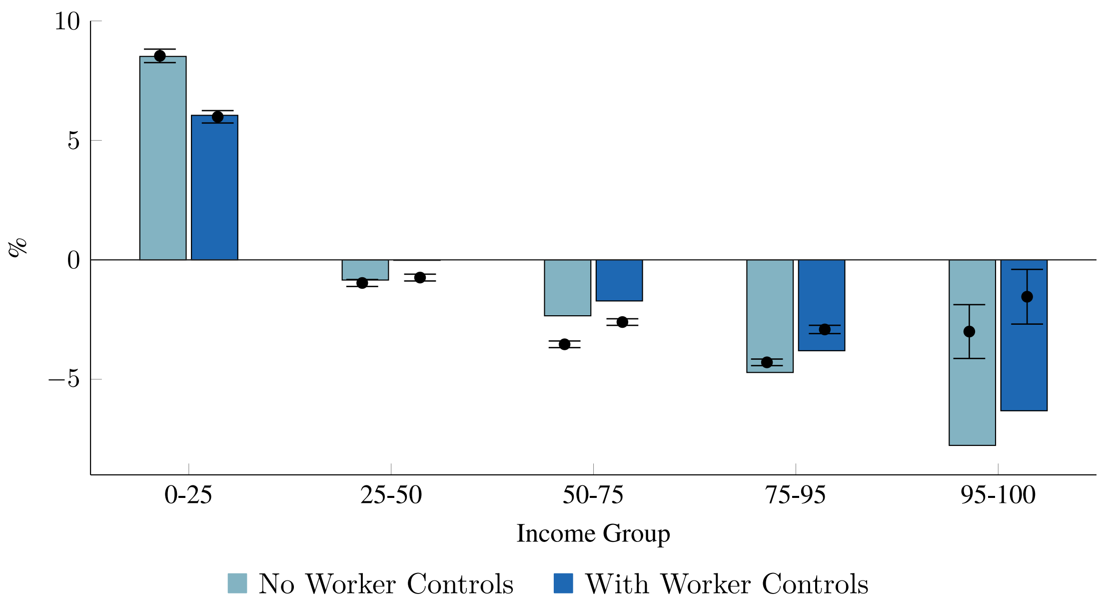
This figure reports estimates of predictive regressions where we project continuously compounded future excess stock market returns $\sum_{s=1}^{H} r_{t+s}^{e}$ on our risk premium index (Panel (a)) and on the log price-earnings ratio (Panel (b)) at different horizons H, in the model and in the data. The shaded area shows pointwise 95% confidence bands for the empirical estimates, calculated using Hansen-Hodrick standard errors.

Figure A.4: Market Tightness and Worker Search Cost



Panel (a) of this figure plots the relation between risk premia x and the labor market tightness θ for a worker with $z = \bar{z}_O$ in our calibrated model. Panel (b) plots the normalized worker search cost c_t/A_t as a function of $\theta_t(\bar{z}_O)$.

Figure A.5: Worker Expected Earnings Growth by Prior Earnings: Model vs. Data (Targeted)

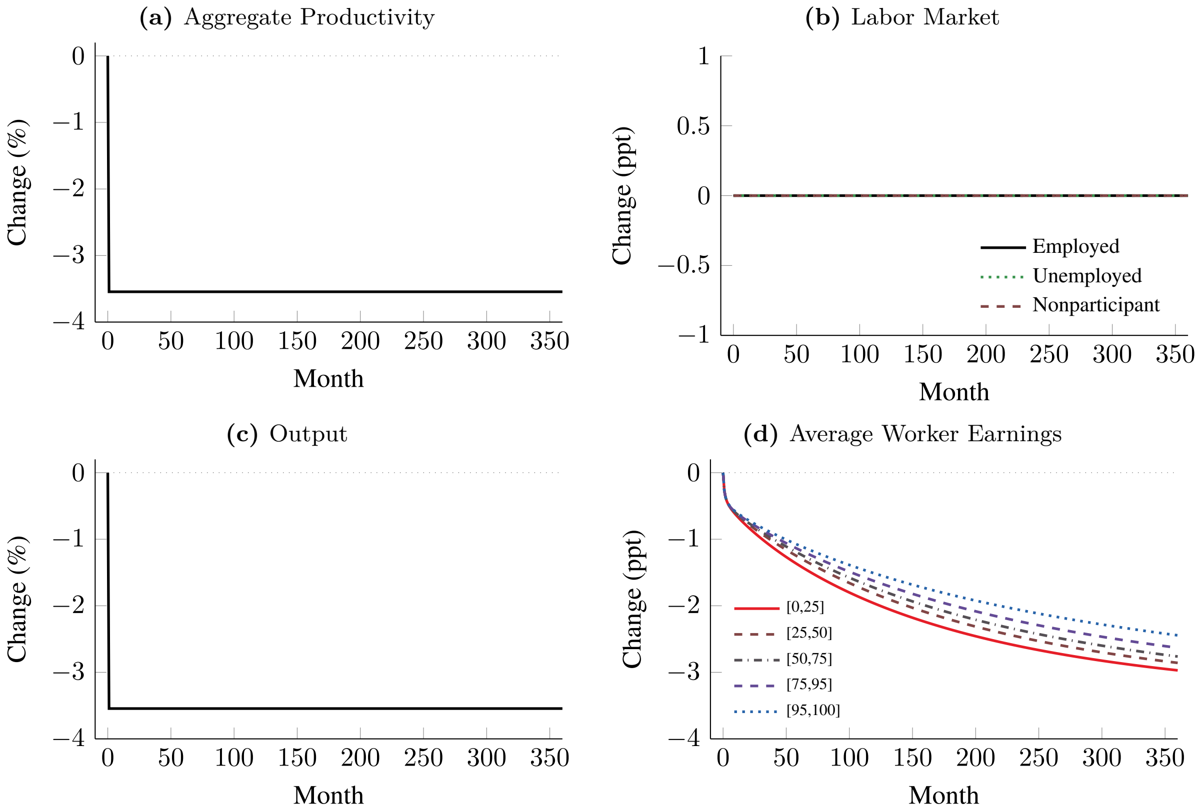


This figure reports average three-year cumulative worker earnings growth for continuing workers in the model and in the data. We report the regression coefficient of earnings growth on a dummy for a worker's relative earnings rank, restricting the sample to workers who remain employed by their initial employer over this period. We normalize the coefficients so that the average across groups is zero. We report estimates with and without worker controls. In the data, worker controls are the interaction of industry (2-digit NAICS code) with worker age and gender, and the interaction between industry and worker tenure. In the model, the analogous controls are age and tenure bins. Model coefficients are indicated by the bars, and empirical coefficients are indicated by the black dots, with 95% confidence intervals.

Figure A.6: Firm Employment and Risk Premium Shocks: Model vs. Data (Non-Targeted)

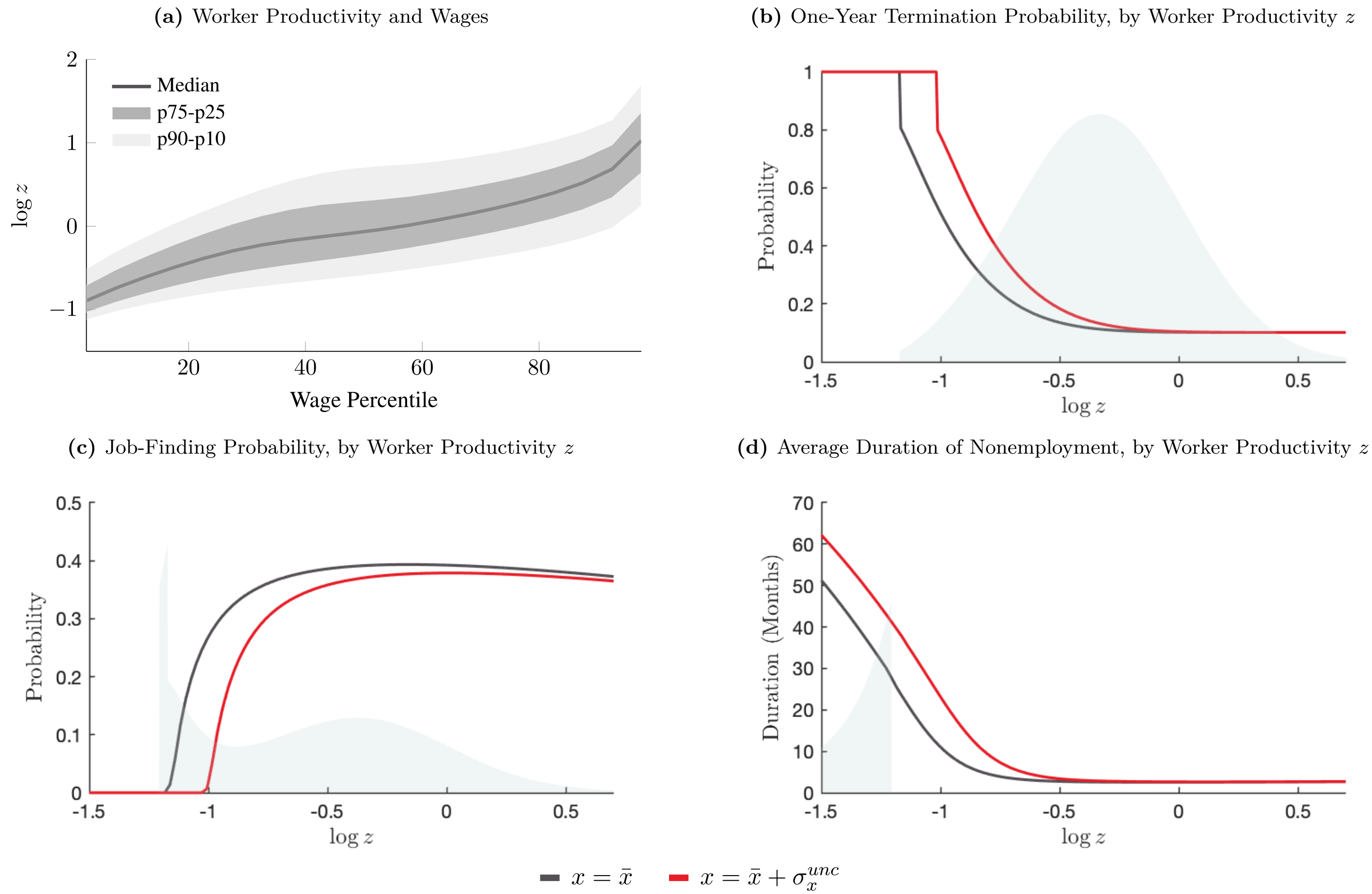
This figure reports the regression coefficients b_0 from estimates of equation (3) in the model and in the data. The outcome variables are one-year firm employment growth (left) and firm hiring of workers out of unemployment (right), defined as the ratio of new employees in year $t+1$ with at least one zero-earnings quarter in the last quarter of t or the first three quarters of $t+1$ relative to total employment in t. Model coefficients are indicated by the bars, and empirical coefficients are indicated by the black dots, with 95% confidence intervals. Coefficients are scaled so that they correspond to a 10% shock.

Figure A.7: Impulse Responses to TFP Shocks in Model



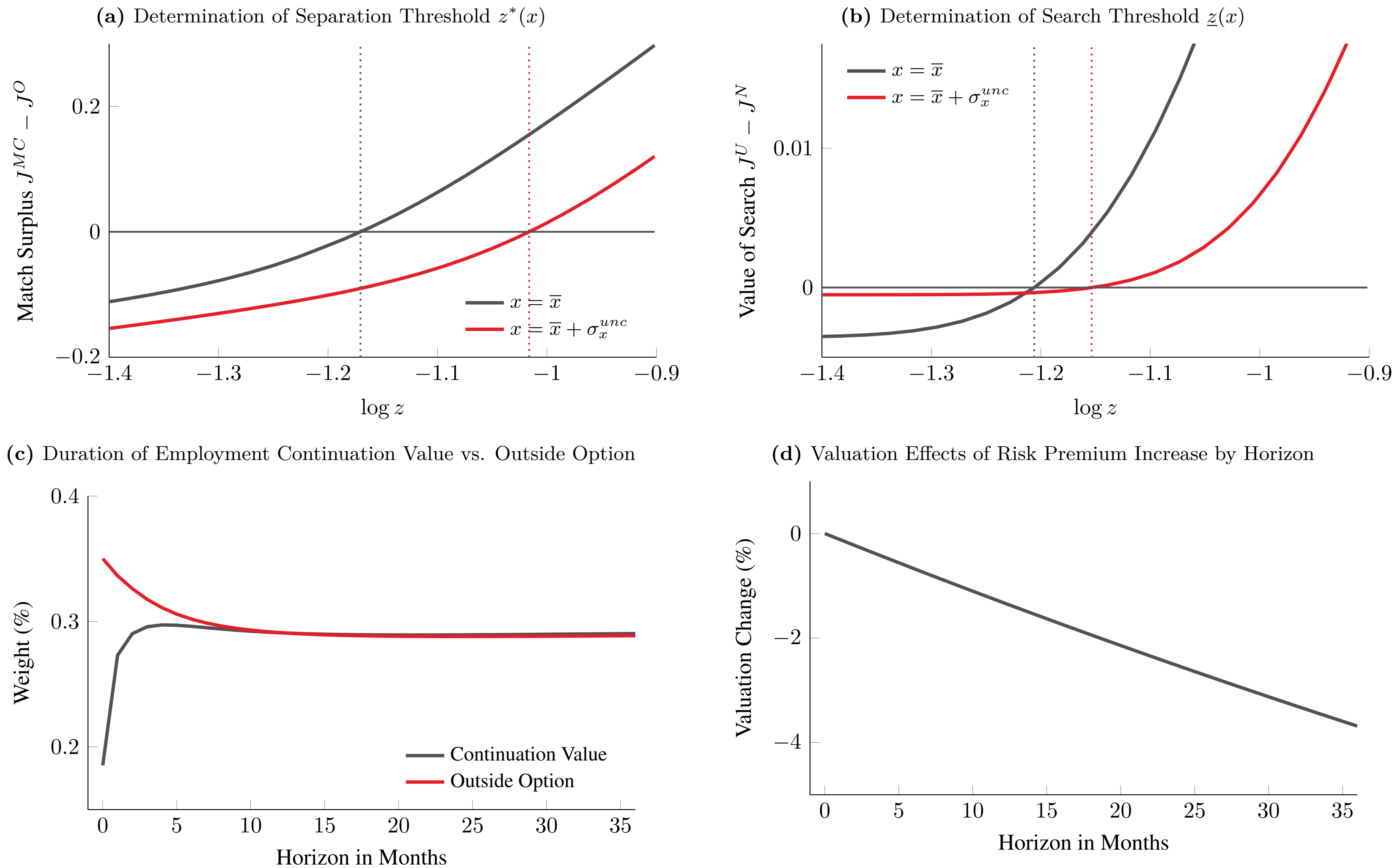
This figure shows the impulse responses of key model quantities following an aggregate TFP shock of one annual standard deviation.

Figure A.8: Model Mechanism (I)



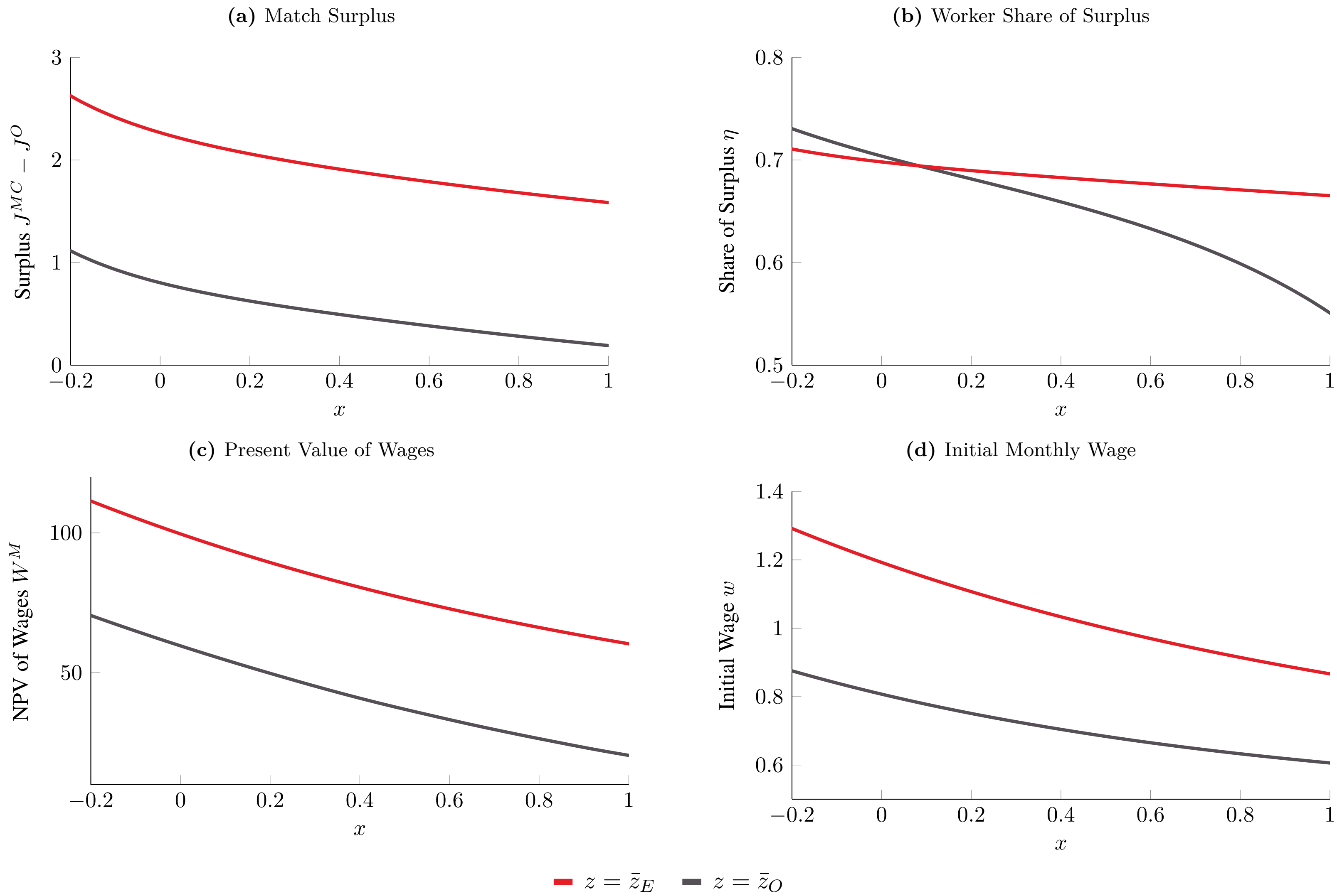
Panel (a) plots the distribution of z for incumbent workers as a function of current wage percentile. Panel (b) plots the probability of match termination over the next year by z for incumbent workers. Panel (c) plots the monthly probability of job finding by z for workers in the unemployment pool. Panel (d) plots the expected nonemployment duration (in months) by z for nonemployed workers. The shaded area represents the stationary distribution of z along the balanced growth path conditional on employment (b), unemployment (c), and nonparticipation (d).

Figure A.9: Model Mechanism (II)



Panel (a) plots the match surplus value $J_t^{MC}(z) - J_t^O(z)$ (relative to A_t) by z and x_t. Panel (b) plots the surplus from worker search $J_t^U(z) - J_t^N(z)$ (relative to A_t) by z and x_t. Panel (c) plots the valuation weight that the strip with payoff at horizon τ has in the employment continuation value J^{MC} and in the outside option J^O for the marginal worker who is at the separation threshold $z^*(\bar{x})$ when $x_t = \bar{x}$. Panel (d) shows the semi-elasticity with respect to x_t of the present value of a claim to a payoff proportional to $A_{t+\tau}$ at horizon τ.

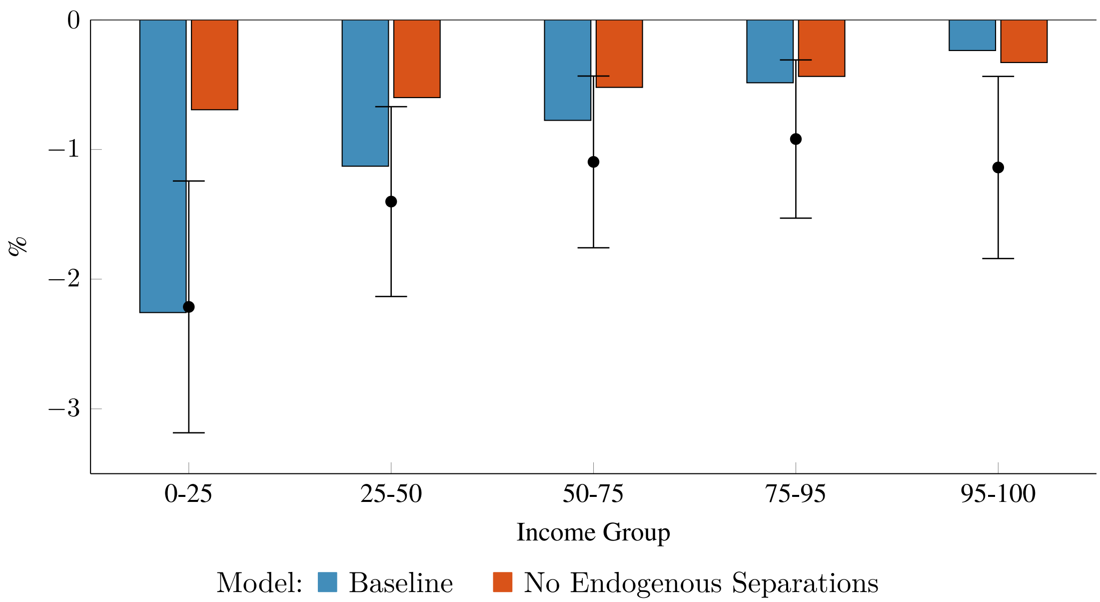
Figure A.10: Model Mechanism (III)



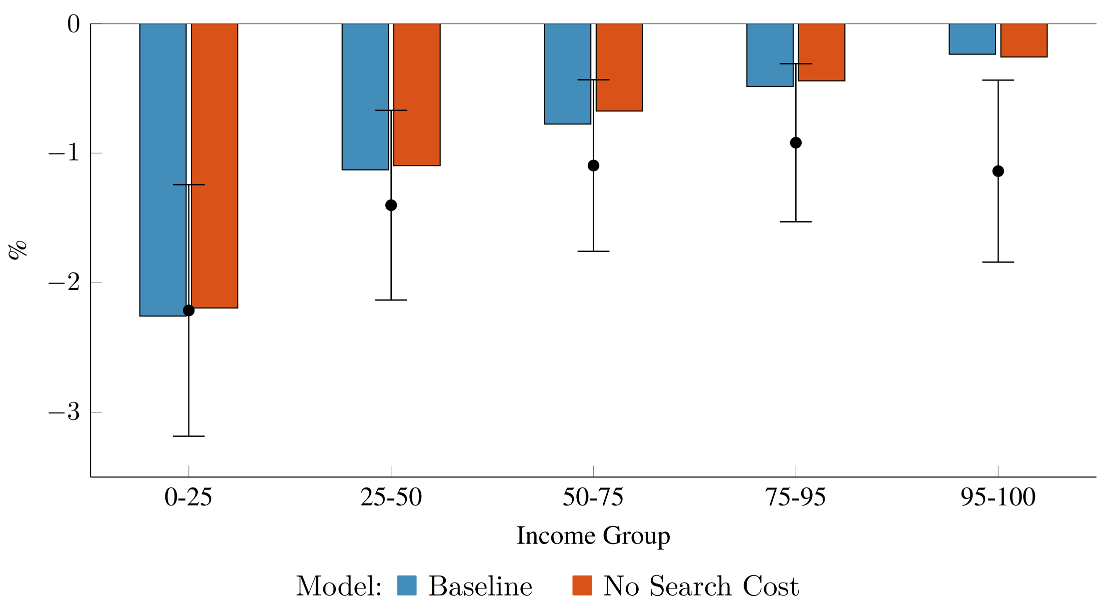
This figure plots values for newly hired workers in the model as a function of current risk premia x, for different values of z. Panel (a) plots the total surplus of the match. Panel (b) plots the share of the total surplus that goes to the worker. Panel (c) plots the value that the worker derives from wages in the current match. Panel (d) plots the initial wage of the worker under the assumed wage protocol (28).

Figure A.11: Worker Exposure to Risk Premium Shocks: Role of Model Assumptions

(a) Endogenous Separations



(b) Endogenous Worker Search



This figure reports the regression coefficient b from estimates of equation (2) with cumulative three-year earnings growth as the dependent variable, in the data and in different versions of the model. In the top panel, we compare the baseline to an alternative that shuts down the endogenous separation margin. In the bottom panel, we compare the baseline to an alternative that shuts down the endogenous worker search decision. We estimate exposure across the worker earnings distribution by interacting the shocks with indicators for the worker's prior earnings bin. Model coefficients are indicated by the bars, and empirical coefficients are indicated by the black dots, with 95% confidence intervals. Coefficients are scaled so that they correspond to a 10% shock.

Table A.1: Summary Statistics for Workers in the Baseline Sample

A. *Worker Characteristics*	Observations	Mean	SD	p10	p50	p90
Age	50.1m	42.15	9.87	28	42	56
Female	50.1m	0.42				
Tenure, < 1 Year	40.0m	0.08				
Tenure, 1–3 Years	40.0m	0.19				
Tenure, 3–5 Years	40.0m	0.15				
Tenure, > 5 Years	40.0m	0.58				
Log Earnings (Cum. Over Last Three Years)	50.1m	10.08	0.74	9.16	10.10	10.96
B. *Worker Earnings Dynamics*						
Earnings Growth $g_{i,t:t+1}$	50.1m	-0.04	0.41	-0.33	0.00	0.30
Earnings Growth $g_{i,t:t+2}$	47.7m	-0.07	0.46	-0.45	0.00	0.30
Earnings Growth $g_{i,t:t+3}$	45.2m	-0.10	0.51	-0.57	-0.01	0.30
Prior Earnings, 0–25th Percentile	11.3m	-0.09	0.65	-0.81	0.03	0.51
Prior Earnings, 25–50th Percentile	11.3m	-0.11	0.49	-0.57	-0.01	0.26
Prior Earnings, 50–75th Percentile	11.3m	-0.11	0.44	-0.48	-0.03	0.21
Prior Earnings, 75–95th Percentile	9.0m	-0.10	0.41	-0.45	-0.03	0.21
Prior Earnings, 95–100th Percentile	2.3m	-0.10	0.49	-0.56	-0.03	0.33
Earnings Growth $g_{i,t:t+5}$	40.4m	-0.17	0.59	-0.78	-0.04	0.30
C. *Measures of Job Destruction*						
Nonemployment Spell$_{i,t:t+1}$	50.1m	0.07				
Nonemployment Spell$_{i,t:t+2}$	47.7m	0.14				
Nonemployment Spell$_{i,t:t+3}$	45.2m	0.20				
Prior Earnings, 0–25th Percentile	11.3m	0.29				
Prior Earnings, 25–50th Percentile	11.3m	0.20				
Prior Earnings, 50–75th Percentile	11.3m	0.16				
Prior Earnings, 75–95th Percentile	9.0m	0.14				
Prior Earnings, 95–100th Percentile	2.3m	0.15				
Move and Tail Loss$_{i,t:t+1}$	47.7m	0.06				
Move and Tail Loss$_{i,t:t+2}$	45.2m	0.08				
Move and Tail Loss$_{i,t:t+3}$	42.8m	0.09				
Prior Earnings, 0–25th Percentile	10.7m	0.12				
Prior Earnings, 25–50th Percentile	10.7m	0.09				
Prior Earnings, 50–75th Percentile	10.7m	0.08				
Prior Earnings, 75–95th Percentile	8.6m	0.07				
Prior Earnings, 95–100th Percentile	2.1m	0.07				

This table summarizes the variables that characterize the earnings dynamics of the workers in our main sample. Earnings growth is defined in equation (1). A worker is characterized as having a nonemployment spell between t and $t+h$ if she has at least one quarter of zero earnings between the end of year t and the end of year $t+h$. Individuals are characterized as a stayer at horizon h if they continue to receive a positive income from their initial time-t employer in year $t+h+1$, and as a mover in all other cases. A tail loss is defined by having earnings growth in the bottom 10% of the unconditional distribution. The sample is a 20% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1990–2019.

Table A.2: Risk Premium Series

Series	Start Date	End Date	Sign	AR(1)	Correlation of AR(1) Residual With: RP Shock	Market
Gilchrist–Zakrajsek EBP	1984:12	2021:12	+	0.916	0.51	-0.34
Shiller CAPE ratio	1984:12	2021:12	-	0.993	0.61	-0.64
Chicago Fed NFCI risk	1984:12	2021:12	+	0.965	0.69	-0.46
Jurado–Ludvigson–Ng financial uncertainty	1984:12	2021:12	+	0.980	0.58	-0.39
Bauer–Bernanke–Milstein index	1988:01	2021:12	-	0.959	0.92	-0.84
Bekaert–Engstrom–Xu risk aversion	1986:06	2021:12	+	0.794	0.85	-0.63
Variance risk premium	1990:01	2021:12	+	0.743	0.78	-0.55
VIX	1990:01	2021:12	+	0.815	0.91	-0.73
Martin SVIX bound	1996:01	2012:01	+	0.781	0.94	-0.72

This table summarizes the nine proxies for fluctuations in risk premia that we use as inputs from the literature: the excess bond premium from Gilchrist and Zakrajšek (2012); Robert Shiller's CAPE Ratio; the Chicago Fed's National Financial Conditions Index (NFCI); the financial uncertainty index of Jurado et al. (2015); the risk appetite index of Bauer et al. (2023); the risk aversion index of Bekaert et al. (2022); the variance risk premium from Bekaert and Hoerova (2014); the CBOE VIX; and the SVIX from Martin (2016). We measure risk premium shocks as the PC(1) of the AR(1) residuals from each series.

Table A.3: Worker Earnings Exposure to Risk Premium Shocks: Alternative Horizons and Sample

	A. *Public Firms*						B. *All Firms*					
	2 Years		3 Years		5 Years		2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP	RP	TFP	RP	TFP	RP	TFP
Worker Earnings, 0–25th Percentile	-2.09	0.63	-2.21	0.69	-1.77	0.75	-2.34	0.05	-2.46	0.04	-1.98	0.04
	(-5.36)	(2.71)	(-4.47)	(2.79)	(-2.96)	(2.81)	(-5.88)	(1.61)	(-4.69)	(1.32)	(-3.07)	(1.35)
Worker Earnings, 25–50th Percentile	-1.38	0.57	-1.40	0.63	-0.97	0.73	-1.68	0.07	-1.72	0.06	-1.26	0.06
	(-4.54)	(3.52)	(-3.75)	(3.54)	(-2.32)	(3.64)	(-5.07)	(2.69)	(-4.08)	(2.27)	(-2.54)	(2.06)
Worker Earnings, 50–75th Percentile	-1.11	0.53	-1.10	0.59	-0.70	0.67	-1.38	0.08	-1.40	0.07	-0.96	0.08
	(-3.96)	(3.82)	(-3.24)	(3.88)	(-1.88)	(3.96)	(-4.63)	(4.13)	(-3.73)	(3.54)	(-2.24)	(3.46)
Worker Earnings, 75–95th Percentile	-0.98	0.61	-0.92	0.66	-0.53	0.75	-1.17	0.10	-1.15	0.11	-0.76	0.13
	(-3.69)	(4.23)	(-2.96)	(4.02)	(-1.55)	(4.16)	(-4.41)	(4.92)	(-3.53)	(4.67)	(-2.06)	(5.72)
Worker Earnings, 95–100th Percentile	-1.39	1.25	-1.14	1.28	-0.54	1.36	-1.37	0.21	-1.25	0.24	-0.73	0.29
	(-3.94)	(5.45)	(-3.18)	(4.93)	(-1.56)	(4.72)	(-5.18)	(7.85)	(-4.19)	(8.45)	(-2.54)	(12.39)
Bottom (1) – Middle (3) Earners	-0.98	0.10	-1.12	0.11	-1.08	0.08	-0.96	-0.03	-1.06	-0.03	-1.01	-0.03
	(-7.19)	(0.90)	(-6.08)	(0.92)	(-4.02)	(0.66)	(-7.92)	(-1.86)	(-6.28)	(-1.77)	(-4.39)	(-1.43)
Middle (3) – Top (5) Earners	0.28	-0.72	0.04	-0.70	-0.15	-0.69	-0.01	-0.13	-0.15	-0.16	-0.23	-0.21
	(0.94)	(-4.52)	(0.14)	(-3.96)	(-0.48)	(-3.45)	(-0.05)	(-6.44)	(-0.74)	(-7.85)	(-1.00)	(-9.54)
Bottom (1) – Top (5) Earners	-0.70	-0.62	-1.08	-0.59	-1.23	-0.61	-0.97	-0.16	-1.21	-0.20	-1.24	-0.24
	(-1.91)	(-3.36)	(-2.68)	(-2.93)	(-2.31)	(-2.58)	(-4.03)	(-6.81)	(-3.98)	(-8.27)	(-2.97)	(-7.88)
Fixed Effects												
NAICS2 × Age × Gender	✓		✓		✓		✓		✓		✓	
NAICS2 × Earn Grp	✓		✓		✓		✓		✓		✓	
Observations	47.6m		45.2m		40.4m		28.1m		26.4m		23.1m	

This table reports the regression coefficients b and c from estimates of equation (2) with cumulative earnings growth over various horizons h as the dependent variable. We report exposure across the worker earnings distribution, which we estimate by interacting the two shocks with indicators for the worker's prior earnings level relative to other workers in the same firm. Panel A reports results for our main sample of workers employed by public firms in Compustat (using a 20% random subsample). Panel B reports results for workers in all firms in the revenue-enhanced LBD (using a 5% random subsample), with revenue per worker as the productivity measure. The controls include a third-order polynomial in the log of average income over the past three years, the lagged risk premium index interacted with income group dummies, and the listed fixed effects. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.4: Worker Exposure to Risk Premium Shocks: Extensive Margin (Additional Controls)

	A. *Pr(Nonemployment Spell)*				B. *Pr(Move + Tail Loss)*			
Worker Earnings, 0–25th Percentile	0.62	0.86	0.87	0.72	0.46	0.57	0.58	0.50
	(3.95)	(4.94)	(4.60)	(3.48)	(5.23)	(5.19)	(4.86)	(3.74)
Worker Earnings, 25–50th Percentile	0.38	0.58	0.60	0.51	0.31	0.39	0.40	0.35
	(3.35)	(4.97)	(4.86)	(3.56)	(4.77)	(5.11)	(4.77)	(3.69)
Worker Earnings, 50–75th Percentile	0.27	0.43	0.47	0.39	0.24	0.32	0.32	0.28
	(2.83)	(4.66)	(4.76)	(3.29)	(4.26)	(4.93)	(4.68)	(3.54)
Worker Earnings, 75–95th Percentile	0.14	0.26	0.32	0.27	0.15	0.22	0.23	0.19
	(1.59)	(3.70)	(4.08)	(2.61)	(3.35)	(4.33)	(4.09)	(2.84)
Worker Earnings, 95–100th Percentile	-0.04	0.10	0.20	0.13	0.07	0.14	0.17	0.12
	(-0.33)	(1.04)	(1.67)	(0.87)	(1.02)	(2.35)	(2.40)	(1.40)
Bottom (1) − Middle (3) Earners	0.35	0.43	0.40	0.34	0.22	0.25	0.26	0.22
	(4.80)	(4.53)	(4.00)	(3.26)	(6.10)	(5.22)	(4.81)	(3.76)
Middle (3) − Top (5) Earners	0.31	0.33	0.27	0.26	0.17	0.18	0.15	0.16
	(3.51)	(3.71)	(2.37)	(2.39)	(2.73)	(2.80)	(2.17)	(2.29)
Bottom (1) − Top (5) Earners	0.66	0.76	0.67	0.60	0.39	0.43	0.41	0.38
	(4.44)	(4.47)	(3.36)	(3.10)	(4.24)	(4.12)	(3.50)	(3.24)
Firm Controls:								
Earn Grp × ΔRevenue	✓	-	-	-	✓	-	-	-
Earn Grp × ΔFirmTFP	-	✓	✓	✓	-	✓	✓	✓
Business Cycle Controls:								
Earn Grp × ΔAggTFP	-	✓	-	-	-	✓	-	-
Earn Grp × ΔGDP	-	-	✓	-	-	-	✓	-
Earn Grp × USREC	-	-	-	✓	-	-	-	✓
Fixed Effects								
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp	✓	✓	✓	✓	✓	✓	✓	✓
Observations	55.2m	50.0m	50.0m	50.0m	52.6m	47.6m	47.6m	47.6m

This table reports the regression coefficient b from estimates of modified versions of equation (2), where we replace the dependent variable with two indicators for job loss over the next year: whether the worker experiences at least one full quarter with zero wage earnings (nonemployment spell) or whether the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile (move + tail loss). We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.5: Worker Exposure to Risk Premium Shocks: Extensive Margin (Shift-Share Design)

	A. *Pr(Nonemployment Spell)*			B. *Pr(Move + Tail Loss)*		
	1 Years	2 Years	3 Years	1 Years	2 Years	3 Years
Worker Earn. (0–25) × Firm RP Exp.	0.33	0.35	0.23	0.30	0.35	0.31
	(3.95)	(5.79)	(3.53)	(4.75)	(8.38)	(6.93)
Worker Earn. (25-50) × Firm RP Exp.	0.27	0.31	0.19	0.24	0.26	0.21
	(4.19)	(4.18)	(1.90)	(4.99)	(7.78)	(4.94)
Worker Earn. (50-75) × Firm RP Exp.	0.20	0.24	0.12	0.21	0.24	0.18
	(3.52)	(4.09)	(1.59)	(4.86)	(8.35)	(5.52)
Worker Earn. (75-95) × Firm RP Exp.	0.14	0.15	0.09	0.16	0.18	0.13
	(3.33)	(3.02)	(1.39)	(4.97)	(6.36)	(4.65)
Worker Earn. (95-100) × Firm RP Exp.	0.05	0.02	-0.06	0.07	0.11	0.08
	(1.43)	(0.55)	(-0.98)	(1.79)	(2.57)	(1.71)
[Bottom (1) − Middle (3)] × Firm RP Exp.	0.13	0.11	0.11	0.10	0.11	0.13
	(3.50)	(3.48)	(2.71)	(3.02)	(3.16)	(3.02)
[Middle (3) − Top (5)] × Firm RP Exp.	0.15	0.21	0.18	0.14	0.13	0.10
	(3.26)	(5.36)	(3.74)	(8.90)	(4.80)	(2.87)
[Bottom (1) − Top (5)] × Firm RP Exp.	0.28	0.33	0.29	0.23	0.24	0.22
	(3.94)	(6.60)	(5.81)	(6.71)	(4.94)	(3.51)
Fixed Effects						
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp × Year	✓	✓	✓	✓	✓	✓
Firm	✓	✓	✓	✓	✓	✓
Observations	36.3m	34.4m	32.5m	34.4m	32.5m	30.6m

This table reports the regression coefficient b from estimates of modified versions of equation (4), where we replace the dependent variable with two indicators for job loss over the next h years: whether the worker experiences at least one full quarter with zero wage earnings (nonemployment spell) or whether the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile (move + tail loss). We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Firm risk premium exposure is standardized to have unit cross-sectional standard deviation, and coefficients are scaled so that they correspond to a 10% shock.

Table A.6: Worker Earnings Exposure to Risk Premium Shocks: Robustness to Alternative Assumptions

	No Lagged RP Index		Alternative Timing				Alternative RP Shock			
			End of Period		Begin of Period		Risk Appetite		Risk	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Worker Earnings, 0–25th Percentile	-2.13	-0.96	-1.48	-0.68	-1.53	-0.86	-1.85	-1.06	-3.04	-1.34
	(-4.89)	(-5.83)	(-4.06)	(-6.38)	(-3.89)	(-5.10)	(-3.70)	(-5.32)	(-5.43)	(-6.38)
Worker Earnings, 25–50th Percentile	-1.43	-0.26	-0.99	-0.20	-0.91	-0.25	-1.10	-0.31	-2.04	-0.36
	(-4.09)	(-5.94)	(-3.40)	(-8.50)	(-3.30)	(-6.22)	(-3.15)	(-6.79)	(-4.45)	(-6.44)
Worker Earnings, 50–75th Percentile	-1.16	—	-0.80	—	-0.67	—	-0.81	—	-1.68	—
	(-3.55)		(-2.92)		(-2.72)		(-2.54)		(-3.88)	
Worker Earnings, 75–95th Percentile	-1.00	0.16	-0.67	0.13	-0.54	0.15	-0.64	0.18	-1.45	0.23
	(-3.23)	(3.11)	(-2.55)	(3.66)	(-2.31)	(3.38)	(-2.18)	(3.78)	(-3.55)	(3.54)
Worker Earnings, 95–100th Percentile	-1.39	-0.22	-0.86	-0.03	-0.57	0.17	-0.89	-0.00	-1.74	-0.06
	(-3.23)	(-0.63)	(-2.83)	(-0.12)	(-2.03)	(0.69)	(-3.52)	(-0.00)	(-3.53)	(-0.17)
Bottom (1) – Middle (3) Earners	-0.97		-0.68		-0.85		-1.05		-1.35	
	(-5.92)		(-6.31)		(-5.09)		(-5.27)		(-6.63)	
Middle (3) – Top (5) Earners	0.22		0.06		-0.11		0.08		0.06	
	(0.66)		(0.26)		(-0.44)		(0.28)		(0.17)	
Bottom (1) – Top (5) Earners	-0.75		-0.62		-0.96		-0.96		-1.29	
	(-1.62)		(-2.24)		(-2.83)		(-2.26)		(-2.70)	
Fixed Effects										
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm × Year	-	✓	-	✓	-	✓	-	✓	-	✓
Observations	45.2m	45.2m	45.2m	45.2m	45.2m	45.2m	45.2m	45.2m	45.2m	45.2m

This table reports the regression coefficient b from estimates of equation (2) with cumulative three-year earnings growth as the dependent variable. In (1)–(2), we remove the lagged risk premium index from the controls. In (3)–(6), we consider two variations to the timing of risk premium shocks: measured over calendar year $t+1$ (end-of-period earnings) or over calendar year t (beginning-of-period earnings). In (7)–(10), we consider alternative measures of risk premium shocks: the PC1 of the four indicators for risk appetite considered in Bauer et al. (2023), and the five remaining measures of risk in financial markets. We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.7: Worker Earnings Exposure to Risk Premium Shocks: Shift-Share Design (Alternative Exposure Measures)

	Alternative Exposure Measure							
	PC1 Market		Betas		Firm Size		Whited–Wu	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Worker Earn. (0–25) × Firm RP Exp.	-0.75	-0.34	-0.35	-0.08	-0.59	-0.22	-0.67	-0.24
	(-4.68)	(-3.36)	(-4.05)	(-2.00)	(-6.65)	(-2.90)	(-8.22)	(-3.29)
Worker Earn. (25–50) × Firm RP Exp.	-0.51	-0.10	-0.30	-0.03	-0.52	-0.15	-0.56	-0.13
	(-3.57)	(-2.22)	(-3.43)	(-1.38)	(-9.19)	(-5.13)	(-9.67)	(-4.19)
Worker Earn. (50–75) × Firm RP Exp.	-0.41	—	-0.28	—	-0.37	—	-0.43	—
	(-2.88)		(-3.61)		(-7.07)		(-7.34)	
Worker Earn. (75–95) × Firm RP Exp.	-0.23	0.18	-0.27	0.01	-0.21	0.16	-0.28	0.15
	(-1.78)	(6.47)	(-3.07)	(0.15)	(-4.26)	(7.70)	(-4.27)	(5.51)
Worker Earn. (95–100) × Firm RP Exp.	0.10	0.51	-0.25	0.02	-0.02	0.36	-0.08	0.35
	(0.34)	(2.82)	(-1.18)	(0.12)	(-0.18)	(3.48)	(-0.85)	(3.50)
[Bottom (1) – Middle (3)] × Firm RP Exp.	-0.34		-0.07		-0.22		-0.24	
	(-3.28)		(-1.85)		(-2.98)		(-3.29)	
[Middle (3) – Top (5)] × Firm RP Exp.	-0.51		-0.02		-0.35		-0.35	
	(-2.81)		(-0.13)		(-3.45)		(-3.45)	
[Bottom (1) – Top (5)] × Firm RP Exp.	-0.85		-0.10		-0.57		-0.58	
	(-3.64)		(-0.54)		(-4.42)		(-4.83)	
Fixed Effects								
NAICS2 × Age × Gender	✓	✓	✓	✓	✓	✓	✓	✓
NAICS2 × Earn Grp × Year	✓	✓	✓	✓	✓	✓	✓	✓
Firm	✓	-	✓	-	✓	-	✓	-
Firm × Year	-	✓	-	✓	-	✓	-	✓
Observations	32.5m	32.5m	39.2m	39.2m	45.2m	45.2m	44.8m	44.8m

This table reports the regression coefficient b from estimates of equation (4) with cumulative three-year earnings growth as the dependent variable, for alternative measures of firm-level risk premium exposure. In (1)–(2), we take the PC1 of the exposure measures after replacing the risk premium beta with the market beta. In (3)–(4), we take the PC1 of just the two firm equity betas. In (5)–(6), we use firm size (negative log assets). In (7)–(8), we use the Whited-Wu (2006) index of financial constraints. We report exposure across the worker earnings distribution within firms. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Firm risk premium exposure is standardized to have unit cross-sectional standard deviation, and coefficients are scaled so that they correspond to a 10% shock.

Table A.8: Worker Earnings Exposure to Risk Premium and Productivity Shocks: By Rank Within Industry

	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Worker Earnings, 0–25th Percentile	-2.28	0.56	-2.43	0.60	-2.01	0.66
	(-5.76)	(3.02)	(-4.74)	(3.17)	(-3.17)	(3.47)
Worker Earnings, 25–50th Percentile	-1.37	0.59	-1.40	0.65	-0.98	0.73
	(-4.64)	(2.87)	(-3.88)	(2.93)	(-2.46)	(2.99)
Worker Earnings, 50–75th Percentile	-1.02	0.58	-0.99	0.65	-0.55	0.77
	(-3.67)	(3.27)	(-2.96)	(3.27)	(-1.52)	(3.26)
Worker Earnings, 75–95th Percentile	-0.87	0.56	-0.78	0.60	-0.35	0.69
	(-3.06)	(4.23)	(-2.40)	(3.94)	(-1.03)	(3.90)
Worker Earnings, 95–100th Percentile	-1.69	1.19	-1.40	1.24	-0.73	1.37
	(-3.51)	(4.62)	(-2.84)	(4.07)	(-1.49)	(4.10)
Bottom (1) − Middle (3) Earners	-1.26	-0.03	-1.44	-0.06	-1.46	-0.11
	(-7.49)	(-0.31)	(-6.01)	(-0.60)	(-4.21)	(-0.78)
Middle (3) − Top (5) Earners	0.67	-0.61	0.41	-0.59	0.18	-0.60
	(1.86)	(-2.63)	(1.21)	(-2.29)	(0.51)	(-2.12)
Bottom (1) − Top (5) Earners	-0.59	-0.63	-1.03	-0.65	-1.28	-0.71
	(-1.42)	(-2.74)	(-2.33)	(-2.48)	(-2.15)	(-2.55)
Fixed Effects						
NAICS2 × Age × Gender	✓		✓		✓	
NAICS2 × Earn Grp	✓		✓		✓	
Observations	47.6m		45.2m		40.4m	

This table reports the regression coefficients b and c from estimates of equation (2) with cumulative earnings growth over various horizons h as the dependent variable. We report exposure across the worker earnings distribution that we estimate by interacting the two shocks with indicators for the worker's prior earnings level relative to the levels of other workers in the same industry (instead of the same firm). The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.9: Calibrated Parameters

A. *Parameters Calibrated a Priori*	Symbol	Value	Source		
Average TFP growth (%)	μ_A	0.18	Bureau of Labor Statistics (BLS)		
Volatility of TFP growth (%)	σ_A	1.02	Section A.3		
Correlation between TFP and RP shock	$\rho_{A,x}$	-0.39	Sections 1.1 and A.3		
Interest rate (%)	r	0.16	Lettau and Wachter (2007)		
Mortality rate (%)	ζ	0.28	Average working life span of 30 years		
Matching function elasticity	α	0.41	Hagedorn and Manovskii (2008)		
Wage pass-through (%)	ϕ	14.9	Carlsson et al. (2015)		
Persistence of z	ψ_z	0.99	Menzio et al. (2016)		
Long-run mean of z in employment	$\bar{z}_E$	1	Normalization		
Volatility of initial z (%)	σ_{z0}	66.6	Guvenen et al. (2022)		
B. *Parameters Calibrated to Asset Returns*	**Symbol**	**Value**	**Moment**	**Model**	**Data**
Persistence of price of risk	ψ_x	0.99	Autocorrelation of log P/E	0.90	0.90
Average price of risk	$\bar{x}$	0.39	Average excess market return (%)	6.80	7.93
Volatility of price of risk (%)	σ_x	3.72	Volatility of excess market return (%)	20.2	20.0
Price of risk premium shock	δ	0.36	Average excess long-run strip return (%)	7.27	6.60
			Volatility of excess long-run strip return (%)	32.9	34.7
			Duration of market portfolio (years)	20.0	20.0
			Average P/E	18.1	18.2
C. *Parameters Calibrated to Job Flows*	**Symbol**	**Value**	**Moment**	**Model**	**Data**
Vacancy posting cost, scale ($\times 100$)	$\bar{\kappa}_0$	3.61	Job-finding rate, mean (%)	26.5	22.5
Vacancy posting cost, elasticity to z	$\bar{\kappa}_1$	1.48	Job-finding rate, mean by last wage	(Figure 3a)	
Exogenous separation rate (%)	s	0.82	Separation rate, mean (%)	1.09	1.34
Nonemployment flow, intercept	$\bar{b}_0$	0.41	Separation rate, mean by wage	(Figure 3b)	
Job search cost at $x = \bar{x}$ ($\times 100$)	$\bar{c}_0$	0.36	Unemployment rate, mean (%)	6.89	6.53
Long-run mean of z in nonemployment	$\bar{z}_O$	0.47	Unemployment rate, volatility (%)	1.49	1.44
Volatility of z (%)	σ_z	10.9	Earnings growth for continuing workers, mean by prior earnings	(Figure A.5)	
Job search cost, dependence on x	$\bar{c}_1$	6.05	Labor force participation rate, unemployment beta	-0.13	-0.07
Nonemployment flow, dependence on z	$\bar{b}_1$	0.58	Job-finding rate, unemployment beta	-2.04	-1.91
			Job-finding rate, unemployment beta by last wage	(Figure 3c)	
			Separation rate, unemployment beta	0.07	0.10
			Separation rate, unemployment beta by wage	(Figure 3d)	

This table reports the parameter values in our baseline calibration of the model. Model is calibrated at a monthly frequency. See Section 2.3 in the main text for details.

Table A.10: Labor Market Dynamics: Model vs. Data

	Volatility		Autocorrelation		Cyclicality	
A. *Labor Market Indicators*	Model	Data	Model	Data	Model	Data
Unemployment rate (%)	1.49	1.44	0.93	0.97	1.00	1.00
Long-term unemployment share (%)	5.41	5.78	0.83	0.97	2.11	3.45
Employment-to-population ratio (%)	1.92	1.08	0.95	0.97	-1.04	-0.72
Labor force participation rate (%)	1.34	0.35	0.93	0.91	-0.13	-0.07
Labor market tightness (log V/U ratio, %)	25.22	37.71	0.92	0.97	-13.48	-25.32
B. *Job Flows*						
Job-finding rate (%)	4.30	2.93	0.85	0.92	-2.04	-1.91
Separation rate into unemployment (%)	0.17	0.17	0.62	0.83	0.07	0.10
C. *Decomposition of Unemployment Rate*						
Unemployment rate assuming constant separations (%)	0.87	0.79	0.96	0.97	0.55	0.51
Unemployment rate assuming constant job finding (%)	0.56	0.61	0.88	0.94	0.27	0.40

This table reports key labor market moments in the model and in the data. We report the volatility and persistence (autocorrelation) of these series, together with their cyclicality—the slope coefficient (beta) of a regression of each series on the unemployment rate. Panel C reports the moments of counterfactual unemployment rate series that hold either the separation rate or the job-finding rate constant.

Table A.11: Model Calibration: Baseline vs. Alternatives

	Data		Model		
	Overall	Constant Separations	Baseline	No Endog. Separations	No Search Cost
Unemployment rate, mean (%)	6.53		6.89	6.61	6.96
Unemployment rate, volatility (%)	1.44	0.79	1.49	0.74	1.52
Participation rate, unemployment beta	-0.07	-0.07	-0.13	0.00	0.00
Separation rate, mean					
Aggregate (%)	1.34		1.09	1.22	1.06
Q1 (relative to mean of aggregate rate)	1.69		1.55	0.94	2.09
Q2 (relative to mean of aggregate rate)	1.09		0.85	1.02	0.68
Q3 (relative to mean of aggregate rate)	0.72		0.81	1.02	0.62
Q4 (relative to mean of aggregate rate)	0.52		0.78	1.02	0.60
Separation rate, unemployment beta					
Aggregate	0.10		0.07	0.02	0.07
Q1	0.23		0.21	0.04	0.22
Q2	0.15		0.03	0.03	0.03
Q3	0.11		0.02	0.02	0.01
Q4	0.07		0.01	0.02	0.01
Job-finding rate, mean					
Aggregate (%)	22.5		26.5	22.7	21.8
Q1 (relative to mean of aggregate rate)	0.99		0.74	0.97	0.58
Q2 (relative to mean of aggregate rate)	0.99		0.88	0.99	0.90
Q3 (relative to mean of aggregate rate)	1.02		1.12	1.00	1.29
Q4 (relative to mean of aggregate rate)	1.01		1.26	1.03	1.23
Job-finding rate, unemployment beta					
Aggregate	-1.91	-3.42	-2.04	-2.53	-1.85
Q1	-1.51	-2.25	-2.11	-2.61	-1.12
Q2	-1.52	-1.81	-2.38	-2.31	-2.34
Q3	-2.03	-2.57	-2.04	-2.17	-2.78
Q4	-1.89	-2.17	-1.14	-1.85	-0.70
Earnings growth for stayers, mean (%)					
Q1	8.54		8.51	6.27	8.18
Q2	-0.97		-0.85	1.56	0.02
Q3	-3.54		-2.34	-1.72	-2.25
P75-95	-4.29		-4.72	-5.32	-4.93
P95-100	-3.00		-7.77	-9.23	-10.10

This table compares targeted moments between the data and alternative calibrations of the model. In the first alternative, we rule out endogenous separations (using the constant-separation unemployment rate for the empirical targets). In the second alternative, we set the worker search cost to zero ($c_t = 0$).

Table A.12: Decomposition of Unemployment Fluctuations

	Share of Variance (%)						Total Share	
	E→U	E→N	U→E	U→N	N→E	N→U	→U	U→
Data	33.1	-3.0	35.6	23.2	4.2	6.8	39.9	58.8
Model	35.3	-1.4	47.0	4.8	0	14.3	49.6	51.8

This table presents the results from a decomposition of quarterly unemployment rate fluctuations into the contribution of each individual flow. See Section B.5 for details.

Table A.13: Worker Exposure to Risk Premium and Productivity Shocks: By Expected Earnings Growth

	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Low Expected Earnings Growth (Q1)	-0.91	0.50	-0.92	0.57	-0.49	0.66
	(-3.07)	(2.41)	(-2.60)	(2.51)	(-1.32)	(2.64)
Q2	-1.13	0.69	-1.01	0.72	-0.52	0.77
	(-4.27)	(3.25)	(-3.13)	(3.07)	(-1.50)	(2.94)
Q3	-1.32	0.72	-1.25	0.78	-0.70	0.88
	(-4.65)	(3.65)	(-3.61)	(3.55)	(-2.01)	(3.59)
High Expected Earnings Growth (Q4)	-2.40	0.52	-2.46	0.55	-1.90	0.59
	(-6.41)	(2.96)	(-5.06)	(2.91)	(-3.45)	(2.85)
High – Low Expected Earnings Growth	-1.49	0.03	-1.53	-0.02	-1.42	-0.07
	(-9.14)	(0.23)	(-7.06)	(-0.16)	(-5.43)	(-0.49)
Observations	37.9m		35.6m		31.3m	

This table reports the regression coefficients b and c from estimates of equation (2) with cumulative earnings growth over various horizons h as the dependent variable. We report worker exposure by quartile of expected earnings growth, which is estimated as the average three-year earnings growth of continuing workers by industry $\times$ age $\times$ gender bin and industry $\times$ prior earnings $\times$ tenure bin. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.14: Worker Exposure to Risk Premium and Productivity Shocks: By Age and Income

	A. Age					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Younger (25–30 Years)	-1.99	0.55	-2.10	0.59	-1.63	0.61
	(-4.39)	(3.84)	(-3.78)	(3.73)	(-2.52)	(3.63)
Age, 30–40 Years	-1.42	0.57	-1.46	0.59	-1.12	0.63
	(-4.49)	(4.64)	(-3.75)	(4.51)	(-2.41)	(4.47)
Age, 40–50 Years	-1.26	0.61	-1.27	0.65	-0.91	0.72
	(-5.30)	(4.24)	(-4.20)	(4.17)	(-2.55)	(4.13)
Older (50–60 Years)	-1.20	0.70	-1.11	0.82	-0.48	1.03
	(-3.84)	(2.29)	(-2.94)	(2.39)	(-1.25)	(2.60)
Younger – Older	-0.80	-0.15	-0.98	-0.24	-1.15	-0.42
	(-3.26)	(-0.64)	(-2.98)	(-0.90)	(-2.32)	(-1.34)
	B. Age and Relative Earnings Level					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Younger (25–30 Years)	—	—	—	—	—	—
Age, 30–40 Years	0.66	0.01	0.75	0.00	0.62	0.02
	(1.38)	(0.10)	(1.26)	(0.03)	(0.88)	(0.13)
Age, 40–50 Years	0.92	0.05	1.06	0.06	0.95	0.11
	(2.10)	(0.41)	(1.98)	(0.41)	(1.53)	(0.71)
Older (50–60 Years)	1.07	0.14	1.30	0.23	1.47	0.42
	(2.61)	(0.99)	(2.67)	(1.45)	(2.67)	(2.46)
Worker Earnings, 0–25th Percentile	-2.91	0.56	-3.18	0.59	-2.72	0.57
	(-5.03)	(2.91)	(-4.33)	(2.90)	(-2.94)	(2.68)
Worker Earnings, 25–50th Percentile	-2.15	0.50	-2.30	0.54	-1.83	0.57
	(-4.48)	(3.57)	(-3.88)	(3.53)	(-2.60)	(3.42)
Worker Earnings, 50–75th Percentile	-1.81	0.48	-1.91	0.51	-1.46	0.54
	(-4.11)	(3.59)	(-3.56)	(3.54)	(-2.36)	(3.38)
Worker Earnings, 75–95th Percentile	-1.62	0.57	-1.66	0.60	-1.21	0.63
	(-3.95)	(3.92)	(-3.39)	(3.73)	(-2.20)	(3.70)
Worker Earnings, 95–100th Percentile	-2.12	1.18	-1.98	1.19	-1.35	1.20
	(-4.77)	(5.63)	(-4.08)	(5.19)	(-2.68)	(4.88)
Bottom (1) – Middle (3) Earners	-1.11	0.08	-1.27	0.08	-1.26	0.03
	(-6.75)	(0.92)	(-5.69)	(0.84)	(-3.78)	(0.34)
Middle (3) – Top (5) Earners	0.31	-0.70	0.07	-0.68	-0.12	-0.66
	(1.05)	(-4.41)	(0.26)	(-3.84)	(-0.39)	(-3.31)
Bottom (1) – Top (5) Earners	-0.80	-0.62	-1.20	-0.60	-1.38	-0.63
	(-2.09)	(-3.47)	(-2.81)	(-3.04)	(-2.38)	(-2.74)
Observations	47.6m		45.2m		40.4m	

This table reports the regression coefficients b and c from estimates of equation (2) with cumulative earnings growth over various horizons h as the dependent variable. In Panel A, we report worker exposure by age bin. In Panel B, we report worker exposure by age and prior earnings bin. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.15: Worker Exposure to Risk Premium and Productivity Shocks: By Tenure and Income

	A. Tenure					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Shorter Tenure (< 1 Year)	-2.90	0.56	-2.94	0.56	-2.28	0.61
	(-6.37)	(3.10)	(-5.22)	(2.84)	(-3.52)	(2.86)
Tenure, 1–3 Years	-2.21	0.59	-2.24	0.61	-1.71	0.63
	(-5.98)	(3.70)	(-4.71)	(3.56)	(-3.28)	(3.33)
Tenure, 3–5 Years	-1.42	0.74	-1.42	0.77	-0.91	0.81
	(-4.81)	(5.24)	(-3.88)	(5.19)	(-2.36)	(4.97)
Longer Tenure (> 5 Years)	-0.96	0.63	-0.89	0.69	-0.43	0.78
	(-3.69)	(2.69)	(-2.81)	(2.68)	(-1.27)	(2.75)
Shorter – Longer Tenure	-1.94	-0.07	-2.05	-0.14	-1.85	-0.18
	(-7.49)	(-0.39)	(-6.47)	(-0.68)	(-4.91)	(-0.76)
	B. Tenure and Relative Earnings Level					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Shorter Tenure (< 1 Year)	—	—	—	—	—	—
Tenure, 1–3 Years	0.61	0.03	0.61	0.06	0.48	0.02
	(1.40)	(0.16)	(1.11)	(0.31)	(0.77)	(0.10)
Tenure, 3–5 Years	1.35	0.18	1.36	0.22	1.22	0.20
	(3.20)	(1.18)	(2.65)	(1.28)	(2.10)	(1.06)
Longer Tenure (> 5 Years)	1.78	0.06	1.86	0.14	1.67	0.17
	(4.36)	(0.37)	(3.83)	(0.68)	(3.11)	(0.76)
Worker Earnings, 0–25th Percentile	-3.29	0.58	-3.38	0.59	-2.69	0.62
	(-6.52)	(2.53)	(-5.34)	(2.42)	(-3.60)	(2.41)
Worker Earnings, 25–50th Percentile	-2.78	0.51	-2.82	0.51	-2.16	0.57
	(-6.33)	(3.01)	(-5.17)	(2.72)	(-3.49)	(2.80)
Worker Earnings, 50–75th Percentile	-2.55	0.47	-2.56	0.46	-1.94	0.51
	(-6.05)	(3.09)	(-4.98)	(2.72)	(-3.34)	(2.66)
Worker Earnings, 75–95th Percentile	-2.45	0.56	-2.42	0.54	-1.79	0.61
	(-6.00)	(3.18)	(-4.97)	(2.69)	(-3.34)	(2.68)
Worker Earnings, 95–100th Percentile	-2.87	1.17	-2.63	1.14	-1.80	1.20
	(-5.94)	(4.37)	(-5.02)	(3.74)	(-3.68)	(3.51)
Bottom (1) – Middle (3) Earners	-0.74	0.11	-0.82	0.12	-0.75	0.11
	(-7.50)	(0.76)	(-6.09)	(0.76)	(-3.92)	(0.58)
Middle (3) – Top (5) Earners	0.32	-0.70	0.06	-0.67	-0.14	-0.68
	(1.11)	(-4.00)	(0.23)	(-3.49)	(-0.51)	(-3.16)
Bottom (1) – Top (5) Earners	-0.41	-0.58	-0.75	-0.55	-0.89	-0.58
	(-1.28)	(-2.51)	(-2.24)	(-2.18)	(-2.06)	(-1.98)
Observations	37.9m		35.6m		31.3m	

This table reports the regression coefficients b and c from estimates of equation (2) with cumulative earnings growth over various horizons h as the dependent variable. In Panel A, we report worker exposure by tenure bin. In Panel B, we report worker exposure by tenure and prior earnings bin. The sample is a 20% subsample of all U.S. workers in the LEHD who are employed by public companies. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by worker and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.