NBER WORKING PAPER SERIES

TIME-VARYING RISK PREMIA AND HETEROGENEOUS LABOR MARKET DYNAMICS

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Working Paper 31968
http://www.nber.org/papers/w31968

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2023, Revised March 2025

We are grateful to Marios Angeletos, Nittai Bergman, Jarda Borovicka, Carlos Burga, John Campbell, Daniel Greenwald, Kyle Herkenhoff, Christian Heyerdahl-Larsen, Killian Huber, Loukas Karabarbounis, Ellen McGrattan, Guido Menzio, Virgiliu Midrigan, Indrajit Mitra, Simon Mongey, Giuseppe Moscarini, Stijn Van Nieuwerburgh, Venky Venkateswaran, and Wenyu Wang for helpful comments and discussions. We also thank seminar and conference participants at the Capri Conference on Finance, Labor and Inequality, Chicago FRB, CUHK, Dartmouth, Econometric Society, EPFL, HEC Lausanne, HKU, Holden Conference, Imperial College London, Macro-Finance Society, Minneapolis FRB, MIT, NBER Summer Institute (EFEL), NYU, Princeton, SED, Stanford SITE, St. Louis FRB, UC Chile, UCL, UCLA Anderson, UIUC, University of Wisconsin–Madison, USC, Washington University in St. Louis, WFA, Yale, and others. The U.S. Census Bureau has not reviewed the paper for accuracy or reliability and does not endorse its contents. Any conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product (Data Management System (DMS) number: P-7503840, Disclosure Review Board (DRB) approval numbers: CBDRB-FY24-SEHSD003-092, CBDRB-FY25-0099). The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 31968
December 2023, Revised March 2025
JEL No. E3, E40, G1, J20, J30

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.

A natural concern is that fluctuations in risk premia are countercyclical (Campbell and Cochrane, 1999), hence it is not obvious that we are isolating the effect of risk premia from the business cycle

[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, 2003, 2007; Barro, 2009; Wachter, 2013; Christiano, Motto, and Rostagno, 2014; Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry, 2018; Kilic and Wachter, 2018; Auclert, Rognlie, and Straub, 2020; Itskhoki and Mukhin, 2021; Basu, Candian, Chahrour, and Valchev, 2021).

[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.

itself. One potential concern, for instance, is that lower-paid workers are employed in weaker firms that fare worse in recessions than the average firm. However, our definition of lower-paid workers is based on the within-firm distribution of pay, and therefore these differences in worker earnings responses are unlikely to reflect firm heterogeneity. Indeed, when we focus purely on within-firm fluctuations, we find that increases in risk premia lead to a decline in earnings for the lowest-paid workers relative to other workers in the same firm and calendar year.

More generally, however, there are other alternative explanations that could be harder to rule out. For instance, recessions may coincide with certain types of shocks that lead firms to lay off their lower-paid workers. These shocks could either be common across firms (for example, fluctuations in aggregate demand) or could be firm-specific and their intensity can be correlated with the business cycle. Using several empirical strategies, we argue that fluctuations in risk premia likely represent a driver of employment and earnings dynamics that is distinct from other economic forces that occur during recessions. First, we show that controlling for different measures of firm performance (revenue or productivity growth) interacted with worker earnings does not materially affect our estimated sensitivity of worker earnings to risk premium shocks. Second, we include various controls for the business cycle (aggregate productivity, output, or recession indicators) interacted with worker earnings, which again has a minimal impact on our estimates. Last, we use a shift-share design that exploits firms' heterogeneous exposure to risk premium shocks—but not the business cycle itself. We find that when risk premia rise, workers in highly exposed firms experience larger earnings declines relative to workers in less exposed firms. Importantly, these differences are significantly larger for lower-paid workers than the average worker.

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, 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.

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. Since worker productivity rises faster during employment than nonemployment, the value of employment has a higher (Macaulay) duration than the value of nonemployment and is therefore more sensitive to risk premia. An increase in risk premia thus lowers the value of existing matches relative to the value of nonemployment. This relative decline has the largest impact on lower-skill workers, whose productivity is expected to grow faster and whose value of employment is closer to their outside option than the average worker. Some of the marginal matches are subsequently destroyed, leading to nonemployment for the affected workers and earnings declines. At the same time, an increase in risk premia reduces the rate at which firms hire new workers, since the value of new jobs has declined. As a consequence, job-finding rates decline across the worker skill distribution, and wages for new matches decline, which further exacerbates earnings losses for affected workers.

We calibrate the model to match the dynamics of asset prices and labor markets. The parameters governing the dynamics of risk premia are calibrated to match key asset pricing moments, following Lettau and Wachter (2007). The remaining parameters are calibrated to labor market moments. In particular, we focus on matching the cross-sectional and time-series variation in separation and job-finding rates in the data. Using panel data from the Survey of Income and Program Participation (SIPP), we document that job-finding rates are largely similar across workers with different prior earnings, not only on average but also in terms of their fluctuations over the business cycle. By contrast, separations are highly heterogeneous across workers: lower-paid workers face higher average rates of separation, and these rates increase disproportionately more in recessions relative to higher-paid workers. These patterns are consistent with existing evidence on separation and finding rates by age, education, and wealth (Menzio, Telyukova, and Visschers, 2016; Cairó and Cajner, 2018; Krusell, Mukoyama, Rogerson, and Sahin, 2017). Importantly, our model also generates realistic responses of job creation and job destruction to risk premium shocks, even though these are not explicit targets in our calibration. Specifically, the model quantitatively matches both the observed decline in firm hiring and the increased rate of separations, particularly for lower-paid workers, in response to increases in risk premia.

Using the calibrated model as a guide, we then revisit the importance of the job finding and separation margins for labor market fluctuations. Consistent with the stylized facts in Shimer (2012), in our calibration the job-finding rate is more important than the separation rate for generating fluctuations in the unemployment rate—a key reason for the existing literature's focus on the job creation margin (Hall, 2017; Kehoe et al., 2023). However, the endogenous separation margin is a crucial driver of heterogeneity in the dynamics of worker earnings. Our calibrated model assigns approximately two-thirds of the overall decline in worker earnings of lower-paid workers in response to risk premia to the increased risk of termination. Absent endogenous separations, the model cannot quantitatively reproduce the observed differences in earnings responses to risk premium shocks across workers. These results indicate that both channels are quantitatively important for labor market dynamics, but their relative importance depends on the exact object of focus.

A key advantage of our data is that it allows us to directly test the predictions of our model that are specific to the mechanisms through which risk premia affect worker earnings. The model predicts that worker exposure to risk premium shocks is driven by the interaction of distance to the separation threshold and duration of the match surplus. Holding current worker earnings constant, workers with higher expected earnings growth should be more adversely affected by risk premia—because their employment surplus has a longer duration—than workers with lower expected earnings growth. Consistent with this prediction, we find that workers with higher expected earnings growth experience larger earnings declines when risk premia rise than workers with lower expected growth, and that this difference in exposure is concentrated among low-earning workers.[3] 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.

Importantly, our model is also able to quantitatively replicate the realized paths of key labor market variables over the business cycle. Specifically, we feed into the calibrated model our empirical measure of risk premium shocks and compare the model-implied series to their empirical equivalents. We find that fluctuations in risk premia account for a significant fraction of labor market dynamics: the correlation between these model-implied series and their empirical counterparts ranges from approximately 50% to 80% and the two sets of series have comparable volatility. Notably, our model can also replicate the slow recovery of employment after the Great Recession. This slow recovery is driven by elevated risk premia post financial crisis leading to depressed firm labor demand (job creation), as well as a decline in human capital among nonemployed workers resulting from protracted nonemployment spells. Last, our model can also replicate the realized path of labor income inequality. Since increases in risk premia are associated with earnings declines for lower-paid workers, our model can replicate the persistent rise in left-tail (and not right-tail) income inequality following recessions (Heathcote, Perri, and Violante, 2020).

Our work contributes to a voluminous literature that focuses on resolving the unemployment volatility puzzle noted by Shimer (2005): the canonical DMP model (Mortensen and Pissarides, 1994) is unable to generate a realistic level of volatility in the unemployment rate. Hall (2017) proposes a resolution of the puzzle: an increase in discount rates during recessions lowers firms' willingness to search for workers (post vacancies) and therefore leads to higher unemployment. Kehoe et al. (2023) model countercyclical variation in the market price of risk in the spirit of Campbell and Cochrane (1999) and show how doing so can overcome the challenges posed by existing models, which have implications that conflict with the high cyclicality of the opportunity cost of labor (Chodorow-Reich and Karabarbounis, 2016), the high cyclicality of the user cost of labor (Kudlyak, 2014), or the low

[3] A similar logic implies that the net value of employment should be more sensitive to risk premium shocks for workers with longer employment horizons. Consistent with this prediction, we find that exposure to risk premium shocks declines with age, again controlling for current earnings.

volatility of risk-free rates in the data.[4] We contribute to this literature by providing direct evidence using administrative micro data and a new measure of risk premium shocks that fluctuations in discount rates are a significant driver of employment fluctuations and worker earnings, thereby providing direct support for the work of Hall (2017); Kehoe et al. (2019, 2023).

Last, our work also connects to a burgeoning literature that examines employment outcomes in response to firm-level financial shocks (Chodorow-Reich, 2014; Giroud and Mueller, 2017; Berton, Mocetti, Presbitero, and Richiardi, 2018; Caggese, Cuñat, and Metzger, 2019; Benmelech, Frydman, and Papanikolaou, 2019; Benmelech, Bergman, and Seru, 2021). Closest to our work is Caggese et al. (2019), who show that exporting firms with worse credit ratings facing an adverse terms-of-trade shock are more likely to fire workers with shorter tenures. Caggese et al. (2019) interpret their finding as evidence for inefficiencies arising from financial frictions, since shorter-tenured workers also have higher future expected productivity. This prediction is consistent with our model since higher future productivity leads to a match surplus that is more sensitive to fluctuations in risk premia.

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 baseline analysis focuses on workers employed in public firms. We use a 20% random sample of worker earnings data from the Longitudinal Employer–Household Dynamics (LEHD) database matched to firm-level data from Compustat. The resulting dataset is a panel of earnings and employer information for U.S. workers covering years between 1990 and 2019. Appendix A.1 contains further details on the sample construction.

Our main outcome variable is the growth rate in worker earnings. We follow Autor, Dorn, Hanson, and Song (2014) and Guvenen, Ozkan, and Song (2014) and focus on cumulative age-

[4] In related work, Kilic and Wachter (2018) focus on time-varying disaster risk as a source of unemployment fluctuations. As in Hall (2017), the model relies on wage rigidities leading to inefficient allocations and a low cyclicality of the user cost of labor. Mitra and Xu (2020) propose a model based on learning about match quality through which increases in discount rates lead to larger employment losses for young workers and provide empirical support using aggregate data. Borovička and Borovičková (2018) argue that a stochastic discount factor that is consistent with observed properties of asset returns can only partially explain the Shimer puzzle. The fact that our model not only matches labor market moments but also financial market moments addresses their concern.

adjusted earnings growth rates:

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

The term $D(\text{age}_{i,\tau})$ is an adjustment for the average life-cycle path in worker earnings. Focusing on growth in average earnings over multiple horizons in (1) emphasizes persistent changes in earnings. To be included in the sample in base year t, a worker has to be employed by a public firm in Compustat in that year. However, given that we can track individuals over time regardless of employment status, a worker's labor income growth in (1) will include any earnings from different employers, public or private, and any periods of nonemployment (with zero reported wage earnings). We winsorize all worker earnings growth rates $g_{i,t:t+h}$ at the 1st and 99th percentiles by year.

The top two panels of Appendix Table A.1 summarize our key variables of interest. Panel A shows that the average worker in our sample is 42 years old and 58 percent of our observations correspond to male workers. In Panel B, we summarize the distribution of our measure of real earnings growth $g_{i,t:t+h}$ over various horizons. We see that the earnings growth of individual workers is substantially volatile and negatively skewed.

Worker heterogeneity plays an important role in our analysis. Therefore, in Panel B we also report 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. Examining Panel B, we see that the volatility and negative skewness of worker earnings growth varies by workers' labor income level, consistent with Guvenen, Karahan, Ozkan, and Song (2021).

Risk Premium Shocks

We create an index capturing fluctuations in risk premia due to either fluctuations in the level of risk or fluctuations in the risk-bearing capacity of investors. To do so, we rely on existing series from the literature. These include 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, 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 from Bekaert and Hoerova (2014); the CBOE VIX index; and the SVIX of Martin (2016). These series are at the monthly level, and we sign the indicators such that high values indicate elevated risk premia. Appendix A.2 contains additional details.

Since each one of these series is likely a noisy proxy for fluctuations in risk premia, we focus on their common source of variation. To extract our risk premium shocks from these series, we first estimate the residuals from an AR(1) process for each series separately (since they have different levels of persistence), and then we extract the first principal component of these residuals. We denote the resulting risk premium shocks by ϵ_t^{rp}. This series effectively summarizes the information in the nine components: the first principal component explains 60% of the overall variation, and the average (minimum) correlation between ϵ_t^{rp} and the residuals of each of these series is 75% (51%).

We plot the resulting time series of risk premium shocks in Figure 1. Our risk premium shocks are strongly related to fluctuations in financial markets: the contemporaneous correlation between stock market returns and risk premium shocks is significantly negative at −77%. Most importantly, our risk premium measure predicts higher excess stock market returns over the medium run (Figure 2)—consistent with our interpretation of these shocks as shocks to the required rate of return for risky investments.[5] Given the strong link between our risk premium shocks and the stock market, to interpret the magnitude of risk premium shocks, we scale ϵ_t^{rp} so that a 1% shock corresponds to a 1% contemporaneous decline in the stock market.

Not surprisingly, the risk premium shocks are countercyclical: the correlation at an annual frequency between our risk premium shocks and output growth is −39%. However, examining Figure 1, we see that there are several periods outside recessions during which risk premia rise. Some of these events include the Black Monday crash of 1987, the Asian financial crisis of 1997–98, the WorldCom bankruptcy in 2002, the Greek default and the European sovereign debt crisis of 2010–12, the U.S. credit rating downgrade by S&P in 2011, and the imposition of tariffs on China in 2018. Thus, our risk premium shock series picks up time variation in either (perceived) uncertainty or risk aversion. Some, though not all, of these events appear to originate in financial markets.

1.2 Worker Earnings Exposure to Risk Premium Shocks

We begin by estimating the following specification:

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

Here, i indexes workers, while $f(i,t)$ indexes the employer of worker i. The vector of controls $\mathbf{Z}_{i,t}$ includes 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 × age × gender fixed effects. We cluster standard errors by worker and year.

Our main coefficient of interest is b, which captures a worker's exposure to risk premium shocks ϵ_t^{rp} constructed in the previous section. Given that (2) is estimated at an annual frequency, and earnings correspond to a flow variable over a year, we accumulate our risk premium shocks from the midpoint of the year. Thus, for example, the earnings growth of workers from calendar year 2000 to 2001 is aligned with the cumulative risk premium shock from July 2000 until June 2021.

In our baseline specifications, we control for firm productivity growth, $\epsilon_{f,t}^{tfp}$. To do so, we build

[5]To construct the level of risk premia from our measured shock series, we compute the exponentially weighted moving average of ϵ_t^{rp}, assuming a decay parameter of 0.0068 per month (consistent with our model calibration in Section 2 that targets the persistence of the log price-earnings ratio).

on Olley and Pakes (1996) and İmrohoroğlu and Tüzel (2014) to obtain estimates of annual revenue-based total factor productivity (TFPR)—Appendix A.3 contains further details. Importantly, we allow b and c 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.

Panel A of Table 1 reports the estimated coefficients b and c from equation (2) over horizons h of two to five years. Examining how the estimates of b vary across workers with different (relative) earnings levels reveals our main empirical finding: risk premium shocks ϵ^{rp} have a significantly larger negative impact on the earnings of lower-paid workers, relative to the earnings of more highly paid workers. These differences are quantitatively significant: over the next two to five years, a 10% increase in ϵ^{rp} leads to an approximately 1.8 to 2.2 percentage point decline in earnings for workers at the bottom of the earnings distribution. Here, recall that we have scaled risk premium shocks ϵ_t^{rp} so that a 1% shock corresponds to a 1% contemporaneous decline in the stock market. By contrast, earnings at the middle of the earnings distribution (between the median and the 75th percentile) experience a 0.7 to 1.1 percentage point decline over the same horizon. Contrasting the estimated coefficients b and c, we see that the patterns of these coefficients as a function of the worker's prior relative earnings are sharply different: top workers have somewhat higher exposure to firm productivity shocks ϵ^{tfp} than lower-paid workers—a pattern that is consistent with the existing literature (Friedrich et al., 2019).

In our baseline analysis, we have restricted the sample to workers employed in publicly traded firms. Panel B of Table 1 reveals that this restriction does not drive our key empirical finding. Specifically, in Panel B 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). Comparing the estimates in Panel B with Panel A, we see that the corresponding estimates of b are quantitatively similar, and slightly larger, when we expand the analysis to all workers.

1.3 Controlling for the Business Cycle

Given that fluctuations in risk premia are countercyclical, a key concern is whether the main driving force behind our findings is the business cycle and fluctuations in risk premia are a sideshow. One possibility is that lower-paid workers are employed in firms that are systematically distinct from the firms that employ higher-paid workers—and those firms are differentially exposed to business cycle fluctuations. However, recall that we are ranking workers by their earnings relative to other workers *in the same firm*, which strongly ameliorates this concern. That said, to further remove the impact of firm-specific heterogeneity in business cycle exposure, we next modify our estimating equation (2) by including firm $\times$ year fixed effects as controls. Including firm–year dummies absorbs a common source of firm heterogeneity in business cycle exposure that affects all workers in the firm. The downside of doing so is that we can now only identify relative differences in worker earnings exposure within the same firm. As we see in Columns (1) and (2) of Table 2, controlling for firm–year effects has essentially no impact on our empirical results: lower-paid workers are significantly more exposed to risk premium shocks than other workers in the same firm. In particular, a 10% increase in our risk premium shock is followed by a 1.1 percentage point decline in the earnings of the lowest-paid workers relative to workers in the middle bin (the omitted category).

Including firm–year effects in our specification ameliorates, but does not fully eliminate, the main concern. That is, including firm–year fixed effects in our specification still cannot rule out the possibility that there is variation in firm labor demand over the business cycle that is not captured by firm TFP and is more relevant for the lowest-paid workers in that firm. This variation can arise either in response to a common shock (for example, fluctuations in aggregate demand) or in response to idiosyncratic firm shocks whose volatility is correlated with the business cycle and which may affect worker earnings asymmetrically.

We address these challenges in several ways. First, we replace firm TFP with growth in the firm's total revenue that year. A firm's total revenue is likely to be more responsive to fluctuations in demand for a firm's product than its measured productivity. As we see in Columns (3) and (4) of Table 2, doing so has no material impact on our estimates. Second, we include direct controls for the business cycle itself, interacted with the worker's prior earnings levels relative to her peers: aggregate productivity growth (Columns (5) and (6)); aggregate output growth (Columns (7) and (8)); and the fraction of the year spent in a recession according to NBER dates (Columns (9) and (10)). Contrasting the estimates of b across these columns reveals that including these controls does not materially affect our estimates.

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 construct a shift-share empirical design that aims to isolate the impact of risk premium shocks on workers by exploiting heterogeneity in firms' exposure to these shocks. Given the challenge in measuring ex-ante heterogeneity in firms' exposure to risk premium shocks, we use 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.

Individually, all of these variables are likely noisy proxies for firms' exposure to risk premium shocks. To reduce the impact of this measurement error, we again focus on the common source of variation by extracting the first principal component of these proxies. We denote this principal component by $\chi_{f,t}$ and scale it so that its cross-sectional standard deviation is equal to one. Averaged across years, the first principal component explains 31% of the total cross-sectional variation in the five exposure measures. Appendix A.4 contains additional 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 3 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 3, 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 3, 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,

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

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 b 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 4 reports the corresponding estimates of equation (4). Column (1) shows that lower-paid workers that are employed in firms that are highly exposed to risk premia experience larger declines in earnings compared to lower-paid workers employed in less exposed firms. The magnitudes are quantitatively significant: following a 10% percentage point increase in risk premia, lower-paid workers employed in firms that are one standard deviation more exposed experience a 0.8 percentage point greater decline in earnings compared to lower-paid workers employed in the average firm. Column (2) of the same table shows that including firm–year effects does not alter this conclusion—except that now we can only identify relative earnings changes of the lower-paid workers compared to the average worker in a given firm. Columns (3) and (4) show that replacing firm productivity with total revenue leads to similar estimates.

Next, we include the interaction of our firm exposure measure $\chi_{f,t}$ with business cycle controls—aggregate productivity or output growth, or a recession indicator. Doing so helps alleviate the concern that $\chi_{f,t}$ is correlated with some other source of firm heterogeneity that results in differences in earnings growth rates over the business cycle. However, as we see in Columns (5) through (10), doing so has no material impact on our key findings—if anything, the point estimates of b are somewhat larger than before. This is not particularly surprising given our prior evidence in Table 3 that the interaction of χ_f with business cycle dummies is not a statistically significant predictor of employment growth, which strongly suggest that $\chi_{f,t}$ primarily captures firms' exposure to risk premium shocks rather than the cycle itself.

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 5 report the estimated coefficients b 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 5 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.3 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.

Table 6 shows that, using our shift-share design in equation (4), we obtain qualitatively similar results on the likelihood of job loss to those in Table 5; 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 7 report the estimated coefficients b 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 the overall earnings exposures in Table 1.

1.6 Robustness to Alternative Assumptions

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

First, Appendix Table A.4 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, Appendix Table A.5 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, Appendix Table A.6 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.

1.7 Summary

Overall, the results in this section show that low-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.

These patterns remain quantitatively similar after controlling for common proxies for the business cycle—fluctuations in aggregate productivity or output or recession indicators—as well as absorbing time-varying variation in firm performance such as firm productivity or revenue growth. Our shift-share design in Section 1.4 lends further support to the idea that fluctuations in risk premia are the main driving force behind our estimates, by leveraging cross-sectional variation in firm exposures to risk premia that does not translate into heterogeneous exposures to the business cycle. In particular, in our baseline specification, the effect of risk premium shocks is identified by comparing the earnings growth of two workers in the same firm with different levels of earnings at times when risk premia rise or fall. In our shift-share design, we instead compare the earnings growth of lower-paid workers in firms more exposed to risk premia with that of lower-paid workers in less exposed firms.

Can we conclude that fluctuations in risk premia are the cause of heterogeneous earnings responses rather than the cycle itself? Likely, though there are some alternatives that cannot be entirely ruled out. Specifically, we cannot rule out the possibility that fluctuations in risk premia are indeed a side-show, but they are correlated with an unobserved aggregate shock that leads firms to fire their lower-paid workers.[6] Examples of such a shock that would lead firms to terminate their lower-paid workers could be fluctuations in the opportunity cost of working or a shock that induces the systematic adoption of automation technologies. However, for these shocks to be the main driver of our findings, they would not only need to be related to increases in risk premia, but firms would also need to be differentially exposed to these shocks in a way that lines up with our exposure measure $\chi_{f,t}$. For instance, if automation were the main driver of these earnings losses in recession, it would have to be that smaller (i.e. high $\chi_{f,t}$) firms are more likely to adopt automation technologies than larger firms in recessions. Given that the adoption decision likely entails significant fixed costs, we think this alternative is less plausible.

2 Model

What type of model could quantitatively rationalize the facts we have documented so far? 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.

[6]Fluctuations in firms' ability to access external finance is not such an alternative, but rather part of the mechanism we are trying to capture, since a model with financial frictions is often isomorphic to one in which firms face a higher effective discount rate in their investment decisions (Whited, 1992; Kehoe et al., 2019).

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

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

Equation (13) implies that the probability that a vacancy is filled in a market with tightness θ is $q(\theta) = (1+\theta^\alpha)^{-\frac{1}{\alpha}}$ and the probability that a job searcher obtains a new match is $p(\theta) = \theta(1+\theta^\alpha)^{-\frac{1}{\alpha}}$.

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 the current level of worker productivity z.

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 during times when the labor market is weak, which is consistent with the data (Mukoyama et al., 2018; Faberman and Kudlyak, 2019).

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 $J^O_{t+1}(z')$ 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 $J^{MC}_t(z)$ of the worker's lifetime value and the present value of the firm's profits from this match satisfies

$$J^{MC}_t(z) = A_t\, z + (1-\zeta)\, \mathbb{E}_{t,z} \left[\Lambda_{t+1} \left\{ s J^O_{t+1}(z') + (1-s) J^M_{t+1}(z') \right\} \right], \tag{19}$$

where

$$J^M_t(z) = \max \left\{ J^{MC}_t(z),\ J^O_t(z) \right\} \tag{20}$$

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:

$$\mathbb{1}^C_t(z) = 1 \quad \Leftrightarrow \quad J^{MC}_t(z) \geq J^O_t(z). \tag{21}$$

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,

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

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

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

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 in this model consists of value functions $J_t^O(z)$, $J_t^N(z)$, and $J_t^U(z)$ for nonemployed workers, with a corresponding policy rule for job search, value functions $J_t^{MC}(z)$ and $J_t^M(z)$ for (continuing) matches, with a corresponding policy rule for terminating existing matches, a market tightness function $\theta_t(z)$, and an employment offer function $W_t(z)$, such that (i) the value functions satisfy equations (16), (17), (18), (19), and (20); (ii) the offered employment value and corresponding market tightness satisfy the firm optimality in (23); and (iii) the free-entry condition (22) holds. The competitive search equilibrium in our model is efficient, as can be seen directly from equation (23), which is equivalent to a Nash bargaining solution where the Hosios condition holds. In the equilibrium, all value functions are proportional to A_t, and $\theta_t(z)$ does not depend on A_t. Appendix B.2 contains further details.

Per-Period Wages

Equation (23) determines the present value of wages when the worker is hired. However, it is not sufficient to determine the full path of realized worker wages. To derive explicit predictions for wage earnings—and map model quantities (worker productivity z) to observables (worker earnings)—we need to make an additional assumption for how per-period wages are set. Under full commitment, this assumption plays no role for equilibrium labor market allocations; all that is required for flow wages to be consistent with the equilibrium above is that their present value delivers the ex-ante contracted value in (23) to the worker when she is hired.

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 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 at the time of hiring to satisfy (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 some of the parameters in the model based on a priori information. We summarize these parameters in Panel A of Table 8. We set the mean of the productivity process μ_A equal to the average growth rate of BLS labor productivity between 1947 and 2019 (equal to 2.2% per year). We select σ_A to match the volatility of TFP growth at the aggregate level (3.5% per year) that we obtain by aggregating our measure of firm-level TFP growth over all public firms in the sample. We choose $\rho = -0.39$ to match the correlation between our measures of aggregate TFP growth and risk premium shocks. The real risk-free rate is 1.91% per year (Lettau and Wachter, 2007). We calibrate the model at a monthly frequency and convert the above values to their monthly equivalents where applicable.

We normalize the long-run mean of z in employment to $\bar{z}_E = 1$. We calibrate the worker productivity process to have a persistence of $\psi_z = 0.991$ at monthly frequency, following Menzio et al. (2016). Our choice implies that the half-life of an idiosyncratic productivity shock is approximately 6 years. We choose the dispersion in initial human capital levels $\sigma_{z0} = 0.666$ to match the interquartile range of initial earnings at age 25 over the period 1957–2011 based on Guvenen, Kaplan, Song, and Weidner (2022).

We choose the mortality rate ζ so that the average life span of a worker in the model is 30 years. Following Hagedorn and Manovskii (2008), we set the curvature α of the matching function to 0.407. To calibrate the wage smoothing parameter ϕ, we note that both aggregate and idiosyncratic productivity shocks in the model not only affect the current match but also the outside option of a worker. Therefore, we choose $\phi = 0.149$ 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 main driving force in our model. Accordingly, we calibrate the parameters driving the dynamics of risk premia to match key moments of asset prices. Since the model's main mechanism operates through valuation changes in employment surplus that accrues over relatively long horizons, we choose $\bar{x}$, ψ_x, σ_x, and δ to target not only the moments of the stock market as a whole, but also the moments of a risky portfolio of long-duration stocks based on Gormsen and Lazarus (2023). Our calibration of the stochastic discount factor ($\bar{x} = 0.386, \psi_x = 0.993, \sigma_x = 0.037, \delta = 0.364$) is consistent with the moments of the aggregate stock market, the predictability of excess market returns across horizons by our composite risk premium proxy, and the stylized fact that the Sharpe ratios of risky assets decline with the duration of their cashflows (van Binsbergen, Brandt, and Koijen, 2012; Gormsen and Lazarus, 2023). Panel B of Table 8 lists our parameter choices and the model fit. See Appendix B.3 and Figures A.2–A.3 for further details on these calculations.[7]

Parameters Calibrated to Labor Markets

We choose the remaining parameters governing the dynamics of worker productivity z, vacancy cost $\kappa_t(z)$, nonemployment benefits $b_t(z)$, search cost c_t, and exogenous separation s to match aggregate and cross-sectional labor market moments. Appendix B.4 contains additional details on the calibration approach. We target five sets of moments.

First, we target the mean (6.5%) and volatility (1.4%) of the unemployment rate.[8] Second, we target the cyclicality of the labor force participation rate, defined by its unemployment beta—the slope coefficient on the unemployment rate. Third, we target the mean and cyclicality (unemployment beta) of the aggregate job-finding rate and separation rate into unemployment. We measure these series using microdata from the Current Population Survey (CPS) from 1978 to 2019, following

[7] The persistence of the risk premium shocks is higher than the persistence of most of our empirical risk premium proxies, likely due to measurement error in these individual series. If we were to calibrate the stochastic discount factor to the average persistence of these series, it would lead to counterfactually high levels of predictability in excess market returns at shorter horizons (see Appendix Figure A.3).

[8] 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.

the approach of Elsby, Hobijn, and Şahin (2015); Krusell et al. (2017) to compute Abowd-Zellner corrected estimates of aggregate transition rates between employment states (see Appendix A.5) .

Fourth, we also target the mean and cyclicality (unemployment beta) of relative job-finding and separation rates by prior earnings level using data from the Survey of Income and Program Participation (SIPP) between 1990 and 2019. Details on the data construction are in Appendix A.6. As we discuss below, our empirical estimates imply a job-finding rate that is similar across workers with different levels of earnings, both on average and in terms of cyclicality. By contrast, separation rates are significantly higher, and more cyclical, for lower-paid workers than the average worker. Last, we also target the average growth rate of earnings of continuing incumbent workers across different earnings levels. As we see in Appendix Figure A.5, lower-paid workers experience higher earnings growth rates, conditional on staying with their employer, than higher-paid workers.

Panel C of Table 8 lists our calibrated parameters together with the targeted moments. We choose 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 $\bar{b}_1 = 0.58$ drive the level of employment surplus across worker types z. Among others, this level determines the separation threshold $z^*(x)$ and therefore the rate of endogenous separations. The calibrated benefits function $b_t(z)$ implies that the ratio of average nonemployment benefits to the average wage in the economy is 0.56, which is within the range $[0.4, 0.96]$ of values considered in the literature (Shimer, 2005; Hagedorn and Manovskii, 2008; Chodorow-Reich and Karabarbounis, 2016).

The vacancy cost parameters $\bar{\kappa}_0 = 0.036$ and $\bar{\kappa}_1 = 1.48$ are pinned down by the average job-finding rates for higher-wage workers. The search cost parameters $\bar{c}_0 = 0.0036$ and $\bar{c}_1 = 6.05$ are selected to target the job-finding rate for low-wage workers, the level of the unemployment rate, and the cyclicality of the labor force participation rate. Since the nonemployment pool is adversely selected, our calibration implies modest values for both the vacancy cost and the search cost: the vacancy cost is 2.5% of monthly output for a worker with $z = \bar{z}_O$ and 3.6% for a worker with $z = \bar{z}_E$, and the search cost is 0.8% of monthly output for a worker with $z = \bar{z}_O$ and 0.4% for a worker with $z = \bar{z}_E$ when $x_t = \bar{x}$.

Given the normalization $\bar{z}_E = 1$, the parameter $\bar{z}_O$ captures the difference in human capital accumulation between employment and nonemployment. The larger this difference is, the more sensitive the surplus of employment is to discount rates. We choose $\bar{z}_O$ to match the cyclicality of job-finding and separation rates. The calibrated value $\bar{z}_O = 0.47$ implies a relative productivity decline in nonemployment of 8.0% at an annual rate. This value is in line with the values in Kehoe et al. (2019, 2023) and estimates of human capital depreciation in nonemployment.[9] Last, given the level of

[9]Using a matching estimator that compares displaced workers to other workers with similar ex-ante likelihood of termination, Couch and Placzek (2010) report earnings losses for displaced workers after mass layoffs of 12 percent over the next six years. Since the median nonemployment spell in our model is approximately 3.4 months, the resulting decrease in worker productivity for displaced workers in our calibration is 2.3 percent.

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

Overall, the model does a good job in matching the data, both in terms of the moments that we target in our calibration and in terms of untargeted moments.

Labor Market Dynamics

Panel A of Table 9 compares the dynamics of labor market indicators in the model and in the data. The table reports the volatility, persistence, and cyclicality of key series in the model and in the data, where cyclicality is measured as the slope coefficient (beta) of a regression of each series on the unemployment rate. We see that the model matches the empirical volatility of the unemployment rate. The tightness of the labor market (the ratio of vacancies to unemployment) is substantially volatile and strongly procyclical (it has a correlation of -0.80 with the unemployment rate in the model compared to -0.97 in the data). As in the data, the employment-to-population ratio is also strongly procyclical and the labor force participation rate is weakly procyclical, whereas the long-term unemployment rate—the percent of total unemployed that are jobless for more than six months— is countercyclical. The volatility and persistence of these series is largely consistent with the data. One dimension in which the model calibration overshoots is the volatility of the labor participation rate, even though we match its cyclicality, which is not surprising given that the model lacks reasons for nonparticipation other than (temporarily) low worker productivity.

Unemployment Flows

Panel C of Table 8 and Panel B of Table 9 show that the mean and dynamics of the aggregate job-finding and separation rates in the calibrated model line up well with the data. In addition to these moments, the model also matches how these series vary with worker earnings. In particular, the top row of Figure 3 compares the patterns of average job-finding and separation rates across the labor income distribution between the model and the data. In Figure 3a, we see that the empirical job-finding rate is essentially flat as a function of prior earnings, a pattern that the model approximates reasonably well.[10] By contrast, Figure 3b shows that both in the model and in the data, average separation rates are strongly declining in wage earnings levels. The bottom row of the same figure demonstrates that the model can replicate the degree to which the cyclical behavior

[10]The model still delivers a weak positive relation between (prior) worker earnings and the job-finding rate; this fact is in line with the empirical findings from Gregory, Menzio, and Wiczer (2021), who document based on the LEHD that worker types with higher job-finding rates have higher earnings than worker types with lower job-finding rates.

of these series varies across workers. Specifically, Figure 3c shows that the cyclicality of the job-finding rate (measured by the beta with respect to the unemployment rate) is largely similar across high- and low-earning workers, in both the data and the model. In contrast, Figure 3d shows that the separation rate for low-earning workers is significantly more cyclical than the separation rate for high-earning workers. 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) argues that the volatility of the unemployment rate is primarily driven by the cyclicality of the job-finding rate. Our model is able to match the relative contributions of the separation and job-finding rates to fluctuations in the unemployment rate. To illustrate this, we follow Shimer (2012); Kehoe et al. (2019, 2023) and construct two counterfactual series for the unemployment rate.[11] As we see in Panel C of Table 9, 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.[12]

Firm Labor Demand

As another test of the importance of the job-creation and job-destruction margins in the model, we next examine the extent to which the model can quantitatively replicate the estimates in Table 3 on the link between risk premia and firm employment growth and hiring rates. One caveat is that firm hiring in the data includes job-to-job transitions, which are outside the model. Thus, to ensure the empirical measurement is consistent with the model, we consider a modified measure of firms' hiring intensity that excludes job-to-job transitions and proceed to estimate equation (3) in both the data and in simulated data from the model.[13] Figure 4 compares the estimated coefficients b_0 from equation (3) between the data and the model for total employment growth and for new job creation. We see that the model and the data line up well—even though these are not explicit targets in

[11] The first series assumes that the separation rate is constant: $u^1_{t+1} = \bar{p}^{EU}\,(1 - u^1_t) + p^{UE}_{t+1}\,u^1_t$, 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: $u^2_{t+1} = p^{EU}_{t+1}\,(1 - u^2_t) + \bar{p}^{UE}\,u^2_t$.

[12] These counterfactual series do not account for dynamic interactions of the flows and ignore the nonparticipation margin. As an additional test of the model's implications for the dynamics of labor market flows, Appendix B.5 implements the approach from Elsby et al. (2015), which addresses these concerns, to evaluate the contributions of individual flows to unemployment rate fluctuations. Our model matches the quantitative importance of transitions between employment and unemployment and the cyclicality of flows into and out of nonparticipation (see Appendix Table A.8).

[13] 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 $t+1$.

our calibration—implying that the strengths of the job-creation and job-destruction channels are quantitatively similar between the model and the data both in absolute and in relative terms.

Heterogeneous Worker Earnings Exposures

Next, we briefly examine the ability of the model to match the risk premium exposure of incumbent workers that we document in Section 1, even though they are not explicit calibration targets. Specifically, we plot the model-implied coefficients b from estimates of equation (2) in simulated data and compare them to their direct empirical counterparts. In Figure 5a, we see that the model can largely replicate the exposure of worker earnings to risk premium shocks, especially at horizons of three to five years. In both the model and the data, low-paid workers are significantly more exposed to risk premium shocks than high-paid workers.

In the model, wages for incumbent workers are, by assumption, not directly affected by discount rates. Thus, worker earnings exposures to risk premium shocks are driven by the extensive margin. Figure 5b shows that the model is able to generate realistic rates of job destruction as a function of risk premium shocks. Here, the dependent variable is an indicator for having at least one zero-earnings quarter in the next year. We see that the model coefficients are close to their empirical counterparts.

As shown in Figure 5c, the model can also largely replicate the differential earnings responses to risk premium shocks for stayers versus movers over a three-year horizon. The earnings losses for movers reflect the length of nonemployment spells as well as the wages received in future matches. Importantly, the model is able to quantitatively replicate the magnitude of earnings losses for movers in response to risk premium shocks in the data.

2.5 Model Mechanisms

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

Response to Aggregate Shocks

Figure 6 shows the response of key model variables to an increase in risk premia. An increase in risk premia (Figure 6a) leads to a decline in employment (Figure 6b) and an increase in the unemployment rate (Figure 6c). Part of this increase in unemployment is driven by the increase in the separation rate, especially for low-wage workers (Figure 6d). Figure 6e shows that the job-finding rate also falls, though this decline is largely homogenous across workers. The rise in unemployment in response to discount rates is associated with a decline in labor market tightness (Figure 6f) and a decline in output (Figure 6g). The increase in the separation rate, combined with the decline in the job-finding rate, implies that worker earnings decline, particularly for low-earning workers (Figure 6h). Since the model is scale-independent with respect to aggregate productivity A, these shocks do not have an impact on labor market allocations. Instead, they only affect output and wages (see Appendix Figure A.6). The rest of this section focuses on understanding the economic drivers behind these impulse responses 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. Appendix Figure A.7a 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 5a.

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 Appendix Figure A.7b 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 Appendix Figure A.8a, 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:

$$J_t^{MC}(z^*(x_t)) = J_t^O(z^*(x_t)). \tag{29}$$

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 (29), it follows that an increase in x raises the termination threshold z^*, leading to higher job destruction. This effect is driven by the assumptions that worker productivity is mean-reverting and grows relatively faster when employed than when nonemployed. Both of these properties imply that, for the marginal worker (with $z = z^*$), the payoffs to employment are relatively more backloaded than the payoffs to nonemployment—which directly causes $J_t^{MC}(z)$ to fall relatively more than $J_t^O(z)$ as risk premia rise.[14]

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

$$\theta_t(z) = \left(\left(\frac{J_t^{MC}(z) - J_t^O(z)}{\kappa_t(z)} \right)^{\frac{\alpha}{1+\alpha}} - 1 \right)^{\frac{1}{\alpha}}. \tag{30}$$

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.7c), 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

[14]To see this, recall that the level of risk premia x_t determines the discount rate for risky cashflow streams; the model is scale invariant with respect to A, and thus the only reason why the left- and right-hand sides of (29) have different elasticities with respect to changes in x_t is differences in the timing of their cashflows. Appendix Figure A.8c plots these differences in the timing of cashflows between the value of employment and nonemployment. Since discount rates have a larger impact on the valuation of longer-term claims (Appendix Figure A.8d), the positive difference in the timing of payoffs between employment and nonemployment implies that an increase in the risk premium x_t results in a greater decline in the value of employment J^{MC} relative to the outside option J^O for the marginal worker, and thus to a decline in the surplus of the match. Appendix B.6 discusses these duration differences and the implications for the separation threshold in more detail.

productivity threshold $\underline{z}(x_t)$ above which workers choose to enter the search pool solves

$$J_t^U(\underline{z}(x_t)) = J_t^N(\underline{z}(x_t)). \tag{31}$$

Workers with sufficiently low levels of productivity $z < \underline{z}(x_t)$ choose not to search for a job. 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 Appendix Figure A.8b. 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 6c).

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 (Appendix Figure A.7d). 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. Appendix Figure A.9 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.[15] 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 5c) relative

[15] 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.

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.

Decomposition of Earnings Losses

Summarizing the discussion above, an increase in risk premia affects worker earnings through changes in the probability of job loss, the expected duration of nonemployment spells, and expected wages in future jobs. In Figure 7, we quantify the importance of these separate channels, respectively, in determining worker exposures to risk premium shocks in the model (see Appendix B.7 for further details). Figure 7 shows that the main determinant of the heterogeneity in worker earnings exposure to risk premium shocks is the elevated probability of endogenous separations, which accounts for roughly two-thirds of the overall earnings decline for lower-paid workers in response to risk premium shocks. These workers are also most affected by the increased duration of nonemployment in response to higher risk premium shocks, though the effect of this channel is quantitatively smaller. Last, the decline in the wages of new hires affects workers similarly across the earnings distribution, and therefore does not account for the heterogeneity in earnings responses.

2.6 Role of Specific Assumptions

Relative to Kehoe et al. (2023), our model features two additional mechanisms: endogenous separations and worker search decisions. Here, we illustrate the role of these mechanisms.

First, endogenous separations are a key feature of our model that is necessary to match the heterogeneity in labor market dynamics and in earnings responses to risk premia across workers. Absent endogenous separations, the only reason why lower-paid workers would experience larger declines in earnings when risk premia rise than higher-paid workers is if their job-finding rates fell disproportionately. However, the cyclicality of job-finding rates in the data is largely comparable across workers with different levels of prior earnings (recall Figure 3), so this mechanism cannot explain heterogeneity in outcomes across workers.

To illustrate this key role of endogenous separations for the dynamics of earnings of incumbent workers, we consider a restricted version of the model that eliminates endogenous separations. This version requires that firms and workers commit ex ante to continuing matches whose ex-post total surplus is negative. As in Kehoe et al. (2023), we calibrate this model to match the volatility of the constant-separation unemployment rate series. Even though this model does reasonably well in terms of aggregate moments (see column (4) in Appendix Table A.7), it cannot replicate the heterogeneity in earnings responses as a function of worker earnings (Appendix Figure A.10a). We conclude that, even though endogenous separations may play a secondary role in driving unemployment fluctuations (recall Section 2.4), they are necessary to understand the heterogeneity in worker earnings responses.

Second, the endogenous participation margin helps the model generate a relatively flat job-finding rate as a function of prior earnings, both in terms of levels and in terms of cyclicality. Given that productivity z is a persistent feature of the worker, the model needs a mechanism such that lower-paid workers have a similar likelihood of finding a job as higher-paid workers at different points in the business cycle, even as they may have been recently terminated. The existence of the search cost implies that some of the low-z workers opt out of looking for a job, which helps in generating homogeneity in job-finding rates across workers with different levels of z.

To quantify the importance of the endogenous worker search decisions, we recalibrate a version of the model without worker search costs. As column (5) of Appendix Table A.7 shows, this calibration has a worse fit to the data in terms of heterogeneity in labor market flows by worker earnings, but the effects on the overall fit are quantitatively modest. The worker earnings responses to risk premium shocks across the prior earnings distribution are also virtually unaffected (Appendix Figure A.10b).

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 is determined by two key factors: how close the worker is to the separation threshold for individual productivity, and how much the match surplus value responds to changes in risk premia, with the latter depending on the duration of the surplus. Importantly, this mechanism generates testable predictions regarding the types of workers who are likely to show greater sensitivity of earnings to risk premium shocks. We next explore these predictions in the data.

A direct implication of the model is that an increase in risk premia is more likely to induce separations for workers with high expected productivity growth compared to workers with low expected productivity growth—since the surplus for high-growth workers has a longer duration and is therefore more sensitive to changes in risk premia x_t. To explore this prediction in the data, we estimate the expected longer-term earnings growth of continuing workers as a function of their observable characteristics. Specifically, we regress the cumulative earnings of stayers over the next three years on a set of worker characteristics: dummies for industry (2-digit NAICS) $\times$ age $\times$ gender bins and industry $\times$ prior earnings $\times$ tenure bins. We use the estimated coefficients to compute expected earnings growth (conditional on staying) as a proxy for expected productivity growth for all incumbent workers. 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 8.

The first panel of Figure 8 shows that the earnings of high-growth workers are significantly more exposed to risk premium shocks than the earnings of low-growth workers. Appendix Table A.9

shows that these differences in risk premium exposure persist across horizons, while the exposure to firm productivity shocks does not materially vary across these workers. In addition, we also see in Figure 8 that the model is able to quantitatively replicate these differences in earnings exposure to risk premium shocks between high- and low-growth workers.

The remaining panels of Figure 8 examine whether differences in worker earnings growth are predictive of earnings responses to risk premium shocks after conditioning on worker earnings.[16] Examining the figure, we see that workers' exposure to risk premium shocks is strongly related to the interaction of prior earnings levels and expected growth. Workers with low current earnings and high expected growth rates have by far the largest exposure. A 10 percentage point increase in risk premia leads to a 3.4 percentage point decline in earnings for workers both in the bottom quartile of prior earnings and the top quartile of expected growth, compared to a 1 to 1.5 percentage point decline in earnings for the workers either in the top half of the prior earnings distribution or in the bottom half of the expected growth distribution. Overall, differences in workers' earnings responses to risk premium shocks as a function of expected growth are significant for low-earning workers but not for high-earning workers—which is consistent with the model since the former group is much closer to the endogenous separation threshold than the latter group.

A potential shortcoming of our measure of expected earnings growth is that it is somewhat opaque: it is not obvious which worker characteristics are its main drivers. To this end, we also explore heterogeneity along two directly observable dimensions that should correlate with the duration of the employment surplus: worker age and tenure. Specifically, the value of continued employment in (19) would be significantly more backloaded—and hence more sensitive to changes in risk premia x_t—for a younger worker than for an older worker if the model had a life-cycle component. Similarly, Caplin, Lee, Leth-Petersen, Sæverud, and Shapiro (2024) document that worker productivity grows faster for low-tenure workers compared to high-tenure workers, which again would translate into differences in the duration of the employment surplus.

Next, we re-estimate our baseline empirical specification (2), but we now allow the exposure to risk premium and productivity shocks to vary with the worker's age or tenure. Appendix Table A.10 shows that younger workers are significantly more exposed to risk premium shocks than older workers: a 10% risk premium shock leads to a 2.1 percentage point decline in the earnings of younger workers, compared to a 1.1 percentage point decline for older workers over the next three years. Similarly, in Appendix Table A.11 we see that low-tenure workers are indeed more exposed to risk premium shocks than high-tenure workers: at a horizon of three years, a 10% risk premium shock leads to 3 percentage points lower earnings growth for low-tenure workers compared

[16] 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.

to 0.9 percentage point lower earnings growth for high-tenure workers. In contrast, exposure to productivity shocks is similar across age or tenure groups. Last, we see in the bottom panel of these tables that these patterns are distinct from the earnings pattern documented in Section 1.

In sum, these empirical facts are consistent with the key mechanism in our model: risk premium shocks have heterogeneous effects on workers that differ not only in their current earnings but also in the duration of the surplus value of employment. Importantly, this prediction is somewhat unique to the risk premium channel that we emphasize in this paper and is harder to rationalize under the alternative where our results are driven by unobserved time-varying firm heterogeneity. Under that alternative, firms would have to lay off workers with higher expected growth rates in response to a negative firm-specific shock, but keep workers with lower expected growth, even when both groups of workers earn a similar amount today.

3.2 Can the Model Replicate Realized Fluctuations?

Thus far, we have focused on evaluating the model based on unconditional moments of various variables. However, armed with our empirical measure of risk premium shocks, we next explore whether the model can also replicate the realized path of key series in the data. Specifically, we use our empirical measure of risk premium shocks ϵ^{rp}_{t+1} from Section 1.1 as direct proxies for $\varepsilon_{x,t+1}$, the risk premium shocks in the model. We then accumulate these shocks into levels of x using equation (10). See Appendix B.3 for further details. Given these realizations of x, we then compute several model-implied variables and compare them to their empirical counterparts. Importantly, none of these labor market variables depend on A because the model is scale invariant.

Figure 9a plots the realized path of unemployment in the data versus the model-implied series. Recall that unemployment in the model is driven only by fluctuations in risk premia and that our risk premium index is constructed using data from financial markets. Examining the figure, we see that the model performs quite well in replicating the realized path of unemployment: not only is the volatility of the data and the model-implied series comparable, the correlation between them is 67%. Notably, the relationship is significantly stronger during the Global Financial Crisis of 2008/09 and the subsequent slow recovery; given that this was a period of strong fluctuations in risk premia (Figure 1), we view this pattern as supportive of our model mechanism.

Figure 9b shows that the model also captures fluctuations in the length of nonemployment spells reasonably well, as measured by the fraction of unemployed workers that have been without a job for at least six months. In addition, the calibrated model can replicate the realized paths for transition rates between employment and unemployment. In Figures 9c and 9d, we see that the trajectories of the job-finding and separation rates in the model are comparable to the data (the correlations are 62% and 53%, respectively. Figure 9e shows that the model can also largely match the dynamics of labor market tightness (vacancies V to unemployment U) to provide a quantitative resolution to the Shimer

(2005) puzzle. Figure 9f shows that the model generates empirically plausible paths for aggregate employment, though the employment-to-population ratio is somewhat more volatile than in the data.

In sum, these figures show that fluctuations in risk premia account for a significant fraction of labor market fluctuations in the data. That is, 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. To measure income inequality in the data, we use the series from Heathcote et al. (2020).[17] Figure 9g focuses on the level of income inequality at the bottom of the distribution (the ratio of the median to the 20th percentile of earnings), while Figure 9h examines inequality at the right tail (the ratio of the 90th percentile to the median). We see that, in both the data and the model, there is a strong cyclical component to the level of inequality at the bottom; the correlation between the data and the model-implied series is 81%. Left-tail inequality rises when risk premia rise because the workers at the bottom of the earnings distribution experience larger and more persistent declines in earnings than workers at the middle of the distribution. By contrast, inequality at the top is essentially acyclical in the model—consistent with the findings of Heathcote et al. (2020).

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,

[17] Heathcote et al. (2020) focus on prime-age men between ages 25 and 55. We impose a similar (weak) attachment restriction in the simulated data by computing earnings quantiles for workers who have been employed for at least one month in the last 5 years.

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 (Moreira and Savov, 2017; Caballero and Simsek, 2020; Campbell, Pflueger, and Viceira, 2020; Caballero and Simsek, 2022), our work suggests a novel channel through which monetary policy can affect aggregate demand. Third, in a model of firm heterogeneity and on-the-job search (Menzio and Shi, 2011; Moscarini and Postel-Vinay, 2018; Acabbi, Alati, and Mazzone, 2023; Moscarini and Postel-Vinay, 2023), our mechanism would imply that fluctuations in risk premia also affect the allocation of workers to firms, leading to greater misallocation when risk premia rise. Fourth, 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). Last, an increase in risk premia in our model leads to an increase in the average wage, as low-skill matches are destroyed, while at the same time employment falls, which speaks to the weak cyclicality of the average wage (Solon, Barsky, and Parker, 1994).

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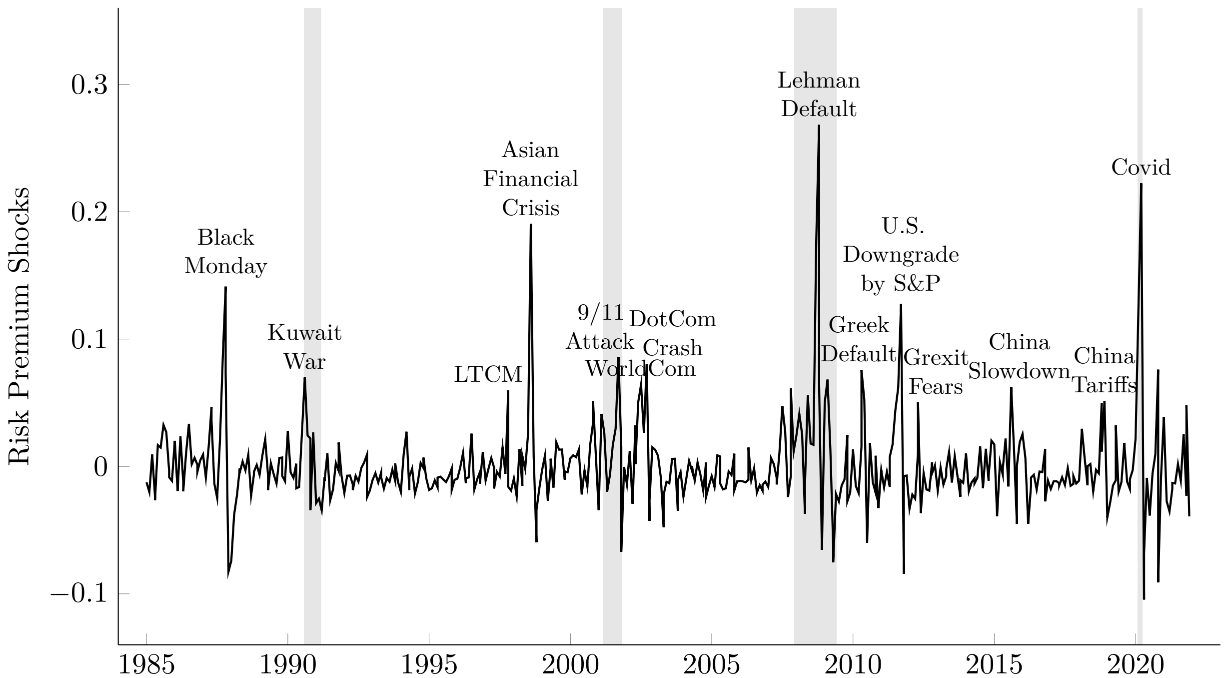
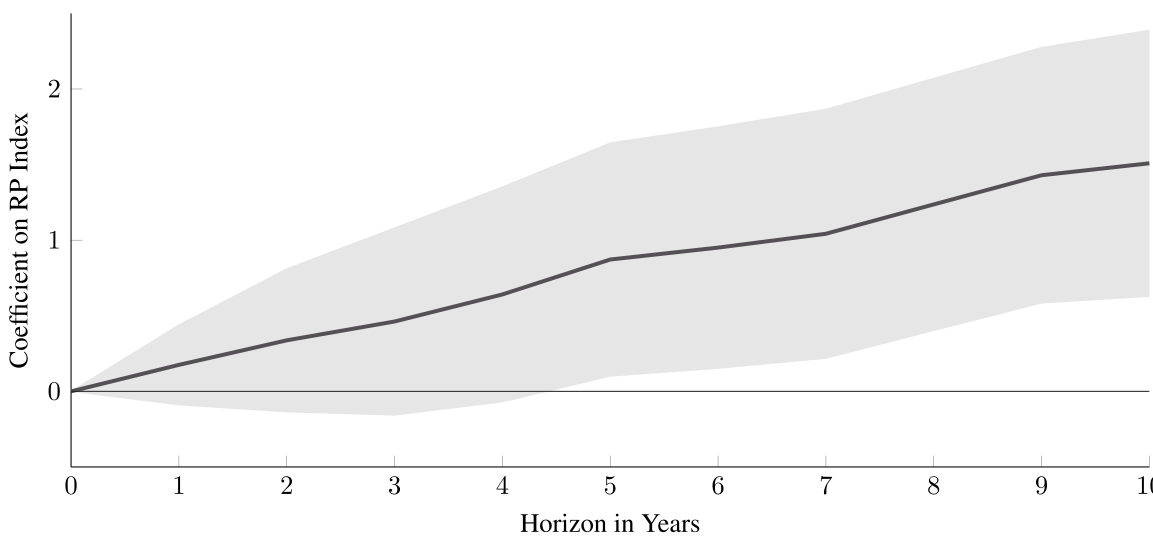
Figure 1: Risk Premium Shocks



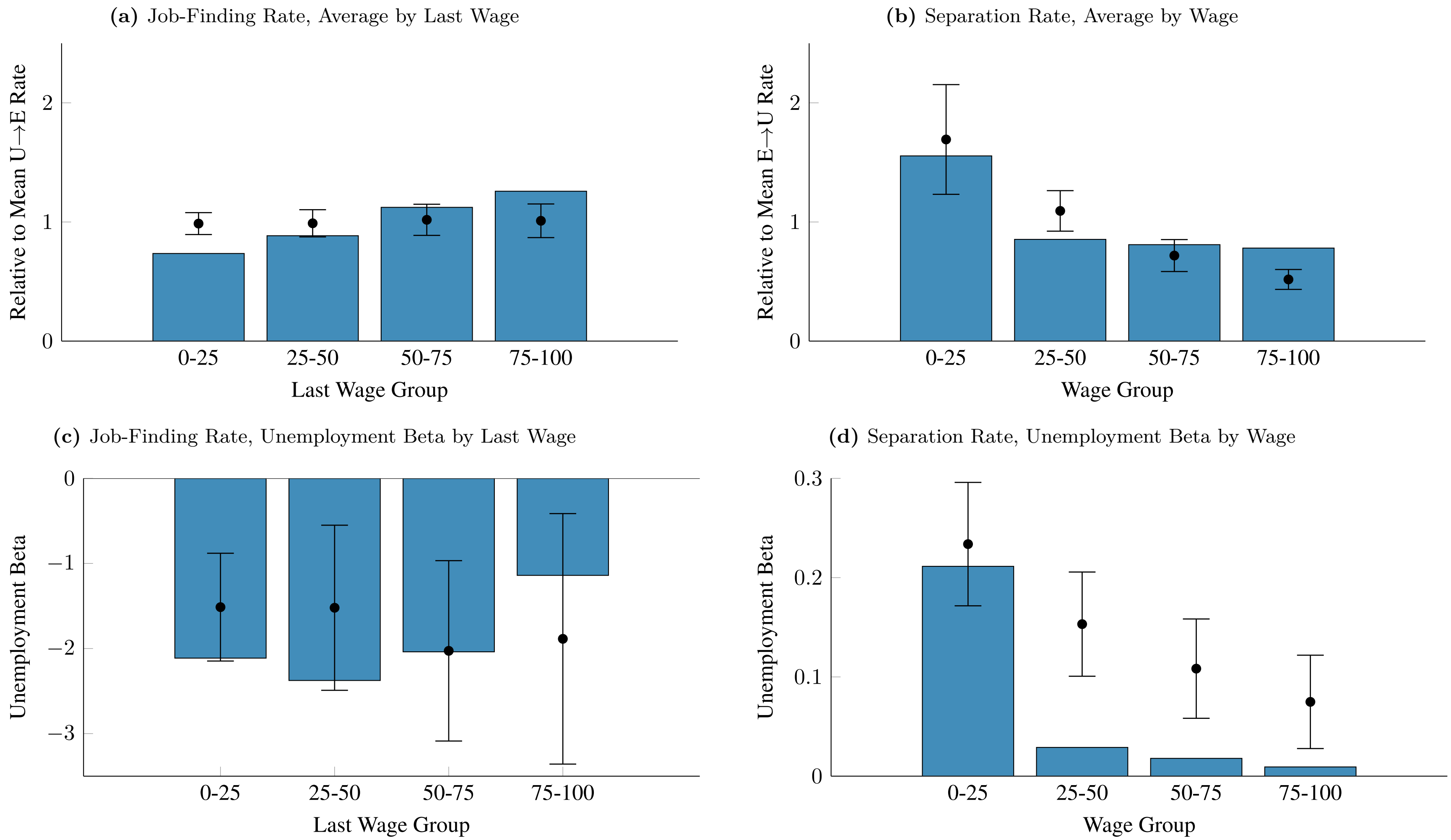
This figure plots our monthly risk premium shocks, measured as the PC1 of the AR(1) residuals of nine series from the literature (see text for details). The shocks are scaled so that a 1% positive shock corresponds to a 1% contemporaneous decline in the stock market.

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 $\sum_{s=1}^{h} r^e_{t+s}$ 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)



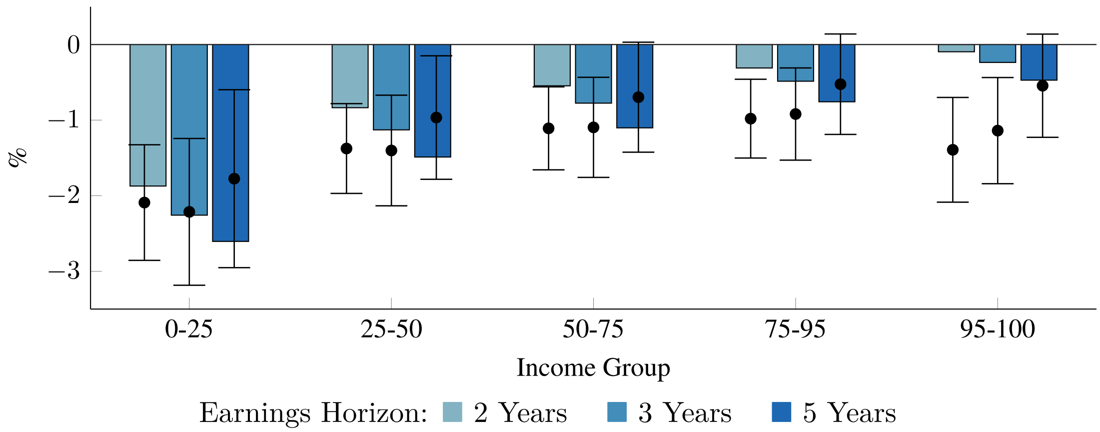
This figure compares the average and cyclicality (unemployment beta) of the job-finding rate (U→E) and the separation rate into unemployment (E→U) by income group in the model and in the data. The empirical counterparts are computed from the SIPP, adjusted for flow level differences from the CPS. Unemployed 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: Firm Employment and Risk Premium Shocks: Model vs. Data (Non-Targeted)

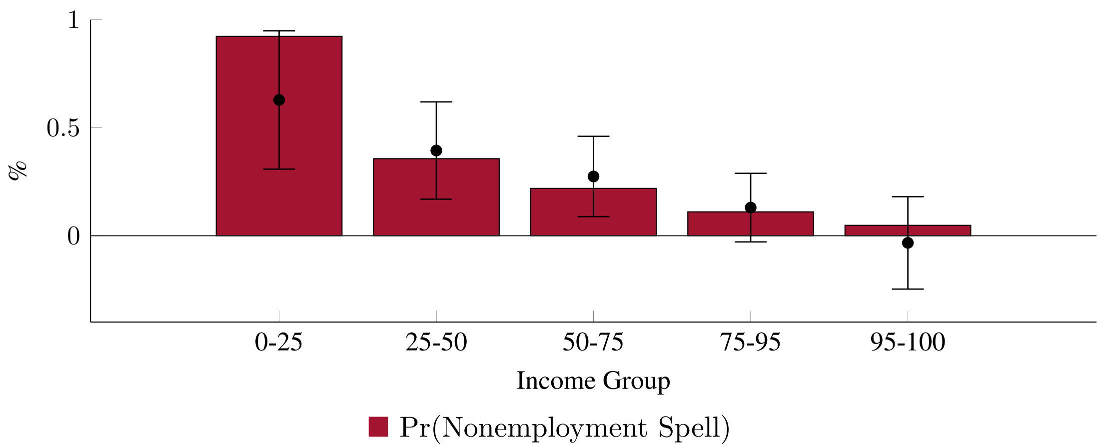
This figure reports the regression coefficients b_0 from estimates of equation (3) in the model and in the data. The outcome variables are one-year firm employment growth (left) and firm hiring of workers out of unemployment (right), defined as the ratio of new employees in year $t+1$ with at least one 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 5: Worker Exposure to Risk Premium Shocks: Model vs. Data (Non-Targeted)

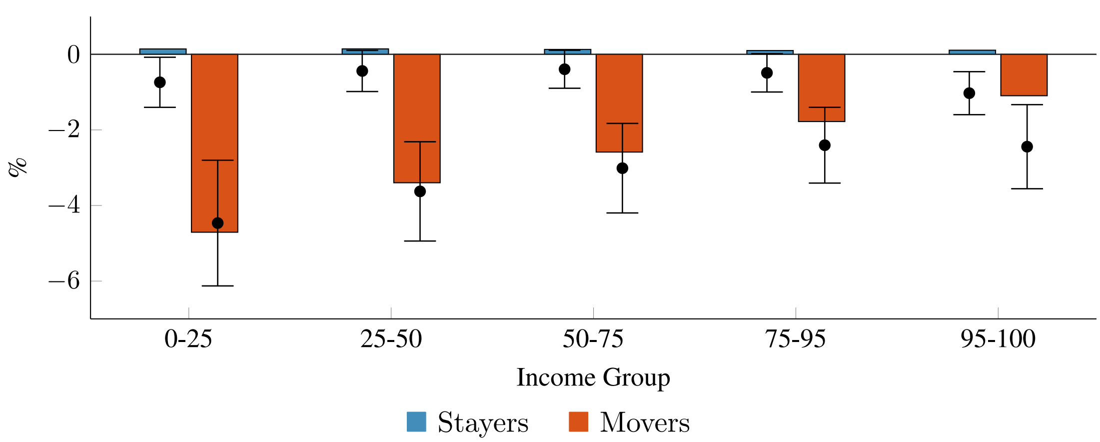
(a) Earnings Growth



(b) Probability of Nonemployment

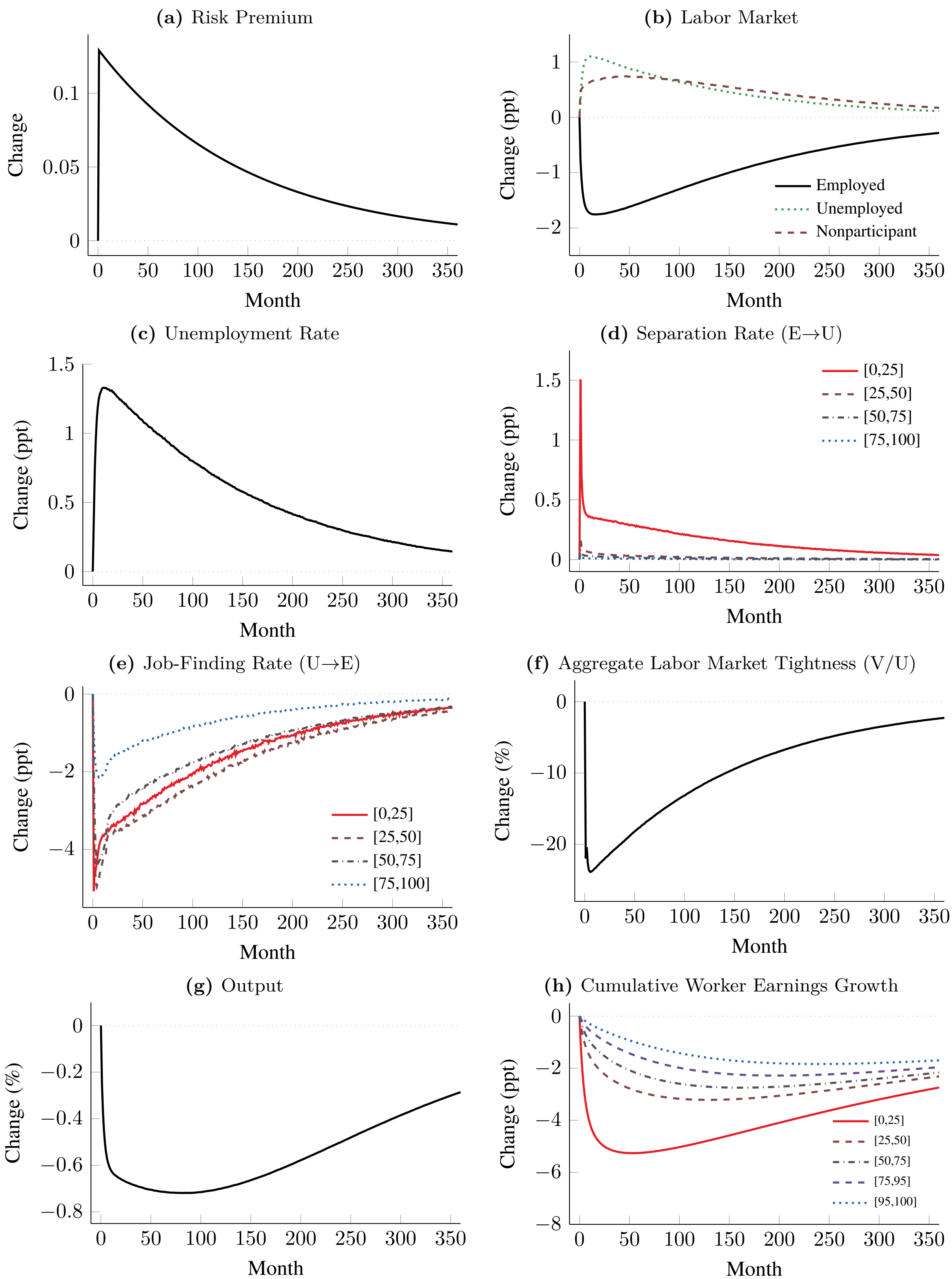


(c) Earnings Growth Conditional on Job Transition Status



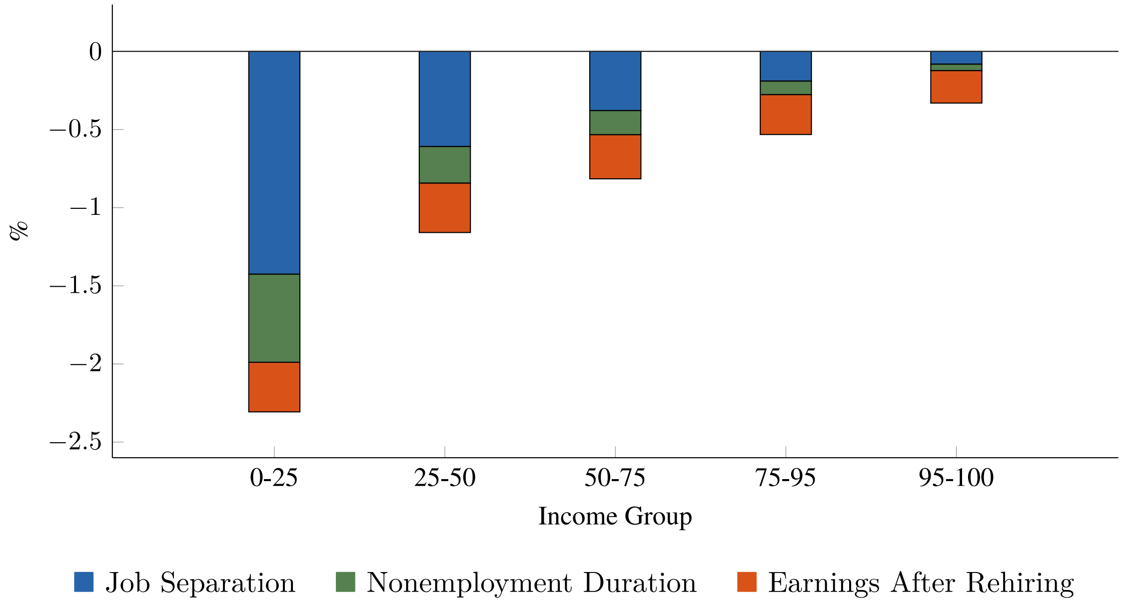
This figure reports the regression coefficients b from estimates of equation (2) by prior worker earnings. Panel (a) reports cumulative earnings exposure over different horizons h. Panel (b) reports effects on the probability of having at least one zero-earnings quarter over the next year. Panel (c) 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 6: 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 7: Worker Exposure to Risk Premium Shocks in Baseline Model: Decomposition



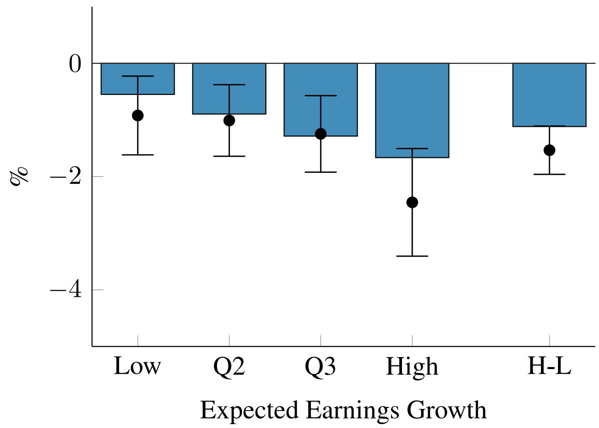
This figure presents a decomposition of the regression coefficient b from estimates of equation (2) for cumulative three-year earnings growth in the model. We decompose cumulative earnings growth as follows:

$$g_{i,t:t+h} = \underbrace{w^{stay}_{i,t+1,t+h} - w_{i,t-2,t}}_{g^{stay}_{i,t:t+h}} + \underbrace{w^{sep}_{i,t+1,t+h} - w^{stay}_{i,t+1,t+h}}_{g^{sep}_{i,t:t+h}} + \underbrace{w^{ext}_{i,t+1,t+h} - w^{sep}_{i,t+1,t+h}}_{g^{src}_{i,t:t+h}} + \underbrace{w_{i,t+1,t+h} - w^{ext}_{i,t+1,t+h}}_{g^{rehire}_{i,t:t+h}}. \quad (32)$$

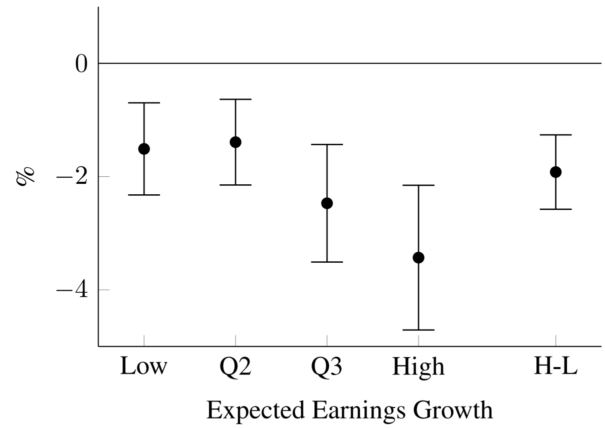
Here, $w^{stay}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker remains in her current job for the full h periods, $w^{sep}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker earns the same wage she would have received had she stayed in her initial job for all periods 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 8: Worker Exposure to Risk Premium Shocks: Heterogeneity by Worker Expected Earnings Growth

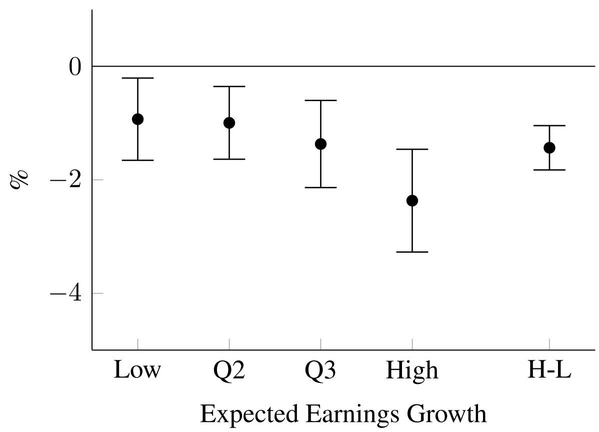
(a) Expected Growth, All



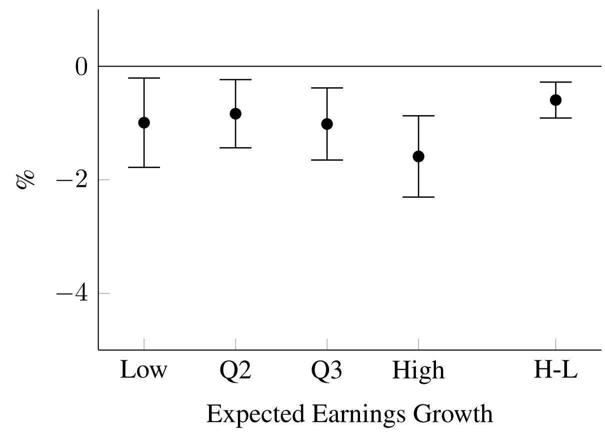
(b) Expected Growth, Prior Earnings: p0–p25



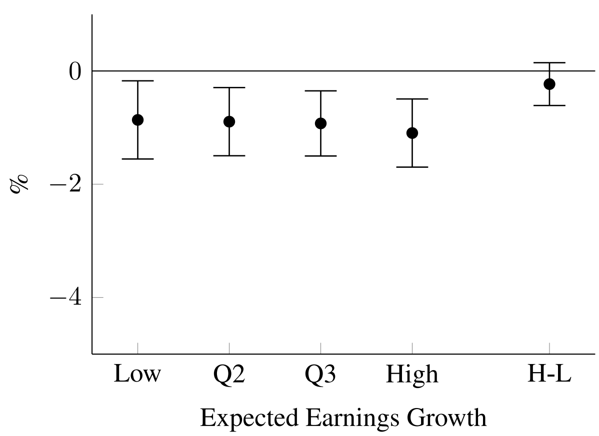
(c) Expected Growth, Prior Earnings: p25–p50



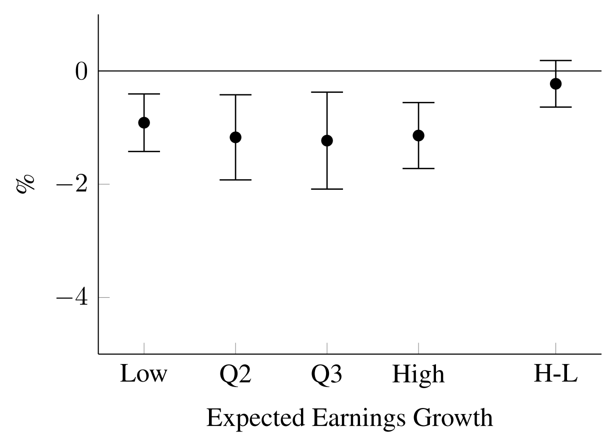
(d) Expected Growth, Prior Earnings: p50–p75



(e) Expected Growth, Prior Earnings: p75–p95

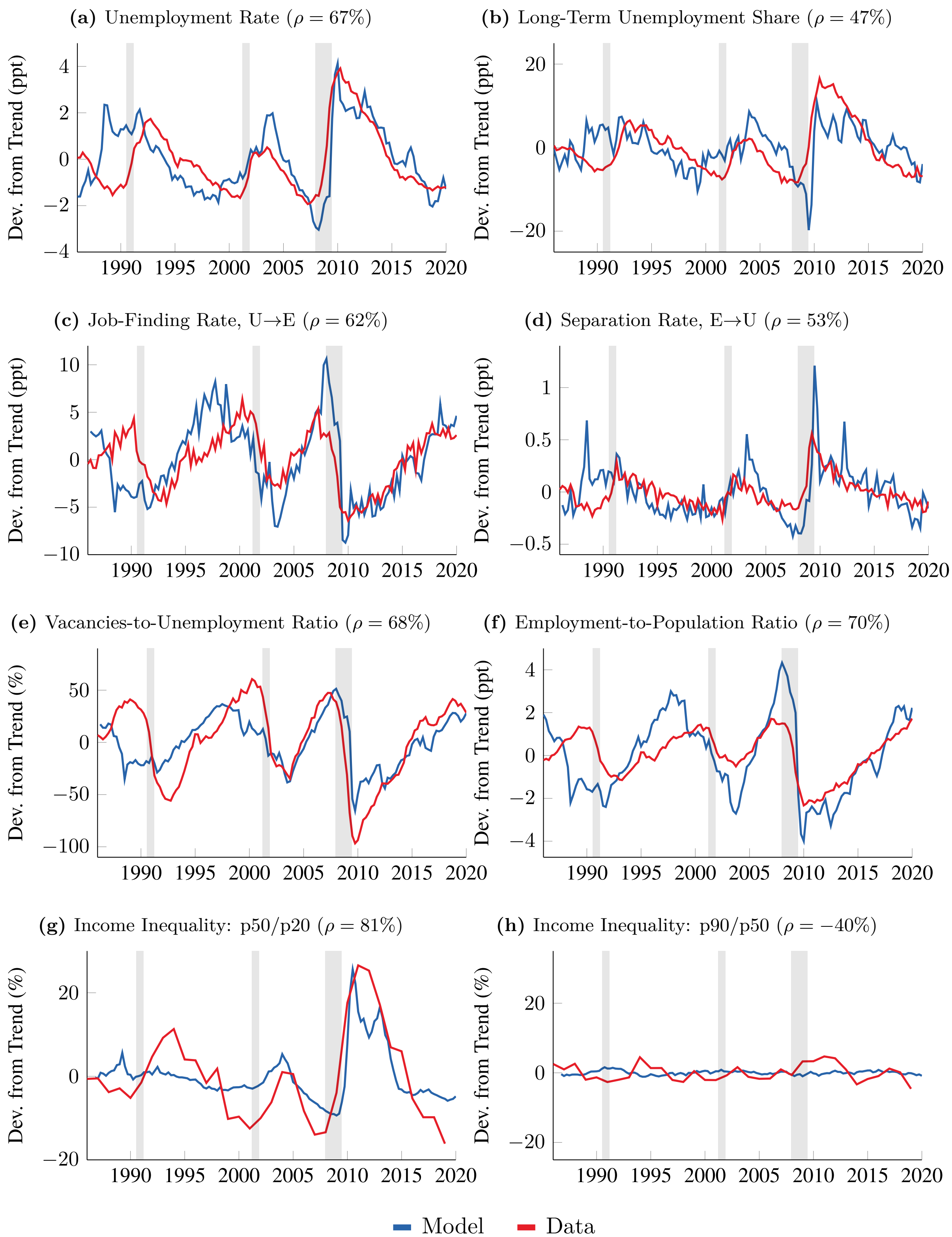


(f) Expected Growth, Prior Earnings: p95–p100



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 $\times$ age $\times$ gender bin and industry $\times$ prior earnings $\times$ 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 9: 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: By Worker Earnings Rank Within Firm

	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 2: Worker Earnings Exposure to Risk Premium Shocks: Additional Controls

	(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 3: 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 4: 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 5: 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 6: 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 7: 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.

Table 8: 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. We report all parameters at the monthly frequency. See Section 2.3 for details.

Table 9: 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.

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.

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.

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 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.6 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.

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 8 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 et al., 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, a constant-separation unemployment rate and a constant-job-finding unemployment rate, to assess the relative importance of these two margins. Here, 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_t^{ij}. The dynamics of the stocks in terms of the flows are given by the Markov chain

$$\begin{bmatrix} E \\ U \\ N \end{bmatrix}_t = \begin{bmatrix} 1 - p^{EU} - p^{EN} & p^{UE} & p^{NE} \\ p^{EU} & 1 - p^{UE} - p^{UN} & p^{NU} \\ p^{EN} & p^{UN} & 1 - p^{NE} - p^{NU} \end{bmatrix}_t \begin{bmatrix} E \\ U \\ N \end{bmatrix}_{t-1} . \tag{A.26}$$

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

$$\underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_t}_{S_t} = \underbrace{\begin{bmatrix} 1 - p^{EU} - p^{EN} - p^{NE} & p^{UE} - p^{NE} \\ p^{EU} - p^{NU} & 1 - p^{UE} - p^{UN} - p^{NU} \end{bmatrix}_t}_{P_t} \underbrace{\begin{bmatrix} E \\ U \end{bmatrix}_{t-1}}_{S_{t-1}} + \underbrace{\begin{bmatrix} p^{NE} \\ p^{NU} \end{bmatrix}_t}_{Q_t} . \tag{A.27}$$

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

$$\Delta S_t = A_t \, \Delta \bar{S}_t + B_t \, \Delta S_{t-1}, \tag{A.28}$$

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.28) 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 $\bar{S}_t$,

$$\Delta S_t = \sum_{k=0}^{t-2} C_{k,t} \, \Delta \bar{S}_{t-k} + D_t \, \Delta S_1, \tag{A.29}$$

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 $\bar{S}_t$:

$$\Delta \bar{S}_t \approx \sum_{i \neq j} \frac{\partial \bar{S}_t}{\partial p_t^{ij}} \Delta p_t^{ij}. \tag{A.30}$$

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

$$\mathrm{Var}(\Delta S_t) \approx \sum_{i \neq j} \mathrm{Cov}(\Delta S_t, \Delta S_t^{ij}), \tag{A.31}$$

where

$$\Delta S_t^{ij} = \sum_{k=0}^{t-2} C_{k,t} \frac{\partial \bar{S}_{t-k}}{\partial p_{t-k}^{ij}} \Delta p_{t-k}^{ij}. \tag{A.32}$$

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,

$$\Delta u_t \approx (1-u_{t-1}) \frac{\Delta U_t}{E_{t-1}+U_{t-1}} - u_{t-1} \frac{\Delta E_t}{E_{t-1}+U_{t-1}}. \tag{A.33}$$

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

$$\text{Var}(\Delta u_t) \approx \sum_{i \neq j} \text{Cov}(\Delta u_t, \Delta u_t^{ij}). \tag{A.34}$$

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

$$\rho^{ij} = \frac{\text{Cov}(\Delta u_t, \Delta u_t^{ij})}{\sum_{i \neq j} \text{Cov}(\Delta u_t, \Delta u_t^{ij})}. \tag{A.35}$$

Table A.8 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 Worker Employment Dynamics in Model

Figure A.8a illustrates that endogenous job destruction in the model is driven by a threshold rule defined in (29): matches in which worker productivity falls below the threshold $z^*(x_t)$ are terminated. When risk premia increase, the threshold increases; there are some workers for whom the total surplus that was positive before now becomes negative. Figure A.8b shows that the decision to enter the unemployment pool and search for a job is similarly driven by a threshold rule defined in (31): a nonemployment worker decides to search if and only if productivity z is above $\underline{z}(x_t)$. 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. In our calibration, the search threshold also increases with risk premia, though less than the separation threshold.

To elaborate on 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 (29) as

$$\overline{J}^{MC}(x, z^*(x)) = \overline{J}^{O}(x, z^*(x)). \tag{A.36}$$

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

$$z^{*\prime}(x) = -\frac{\frac{\partial}{\partial x}\overline{J}^{MC}(x, z^*(x)) - \frac{\partial}{\partial x}\overline{J}^{O}(x, z^*(x))}{\frac{\partial}{\partial z}\overline{J}^{MC}(x, z^*(x)) - \frac{\partial}{\partial z}\overline{J}^{O}(x, z^*(x))}. \tag{A.37}$$

Figure A.8a 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.37) 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:

$$d_t(z, e) = \begin{cases} A_t\, z & \text{if } e = E \\ b_t(z) - c_t - k_t(z) & \text{if } e = U \\ b_t(z) & \text{if } e = N. \end{cases} \tag{A.38}$$

The strip payoffs in (A.38) 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:

$$k_t(z) = \mathbb{E}_{t,z}\left[\Lambda_{t+1}\kappa_{t+1}(z')\theta_{t+1}(z')\right]. \tag{A.39}$$

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):

$$J_t^d(z, e; T) = (1-\zeta)^{T-t}\, \mathbb{E}\left[\left(\prod_{\tau=t+1}^{T} \Lambda_\tau\right) d_T(z_T, e_T) \,\middle|\, \mathcal{F}_t, z, e\right]. \tag{A.40}$$

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:

$$J_t^{MC}(z) = \sum_{\tau=0}^{\infty} J_t^d(z, E; t+\tau) \tag{A.41}$$

$$J_t^{U}(z) = \sum_{\tau=0}^{\infty} J_t^d(z, U; t+\tau) \tag{A.42}$$

$$J_t^{N}(z) = \sum_{\tau=0}^{\infty} J_t^d(z, N; t+\tau). \tag{A.43}$$

Figure A.8c 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.38) 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.8d. 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.

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

$$g_{i,t:t+h} \equiv w_{i,t+1,t+h} - w_{i,t-2,t}, \qquad w_{i,\tau_1,\tau_2} \equiv \log\left\{\sum_{\tau=\tau_1}^{\tau_2} w_{i,\tau}/(\tau_2 - \tau_1 + 1)\right\}. \tag{A.44}$$

For future periods $\tau > t$, we compute two counterfactual outcome variables. First, we define $\hat{w}_{i,\tau}^c$ 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:

$$\begin{aligned} w^{stay}_{i,t+1,t+h} &\equiv \log\left\{ \sum_{\tau=t+1}^{t+h} \hat{w}^c_{i,\tau}/h \right\} \\ w^{sep}_{i,t+1,t+h} &\equiv \log\left\{ \sum_{\tau=t+1}^{t+h} \hat{w}^c_{i,\tau}\mathbb{1}(\hat{e}_{i,\tau} = E)/h \right\} \\ w^{ext}_{i,t+1,t+h} &\equiv \log\left\{ \sum_{\tau=t+1}^{t+h} \hat{w}^c_{i,\tau}\mathbb{1}(e_{i,\tau} = E)/h \right\}. \end{aligned} \tag{A.45}$$

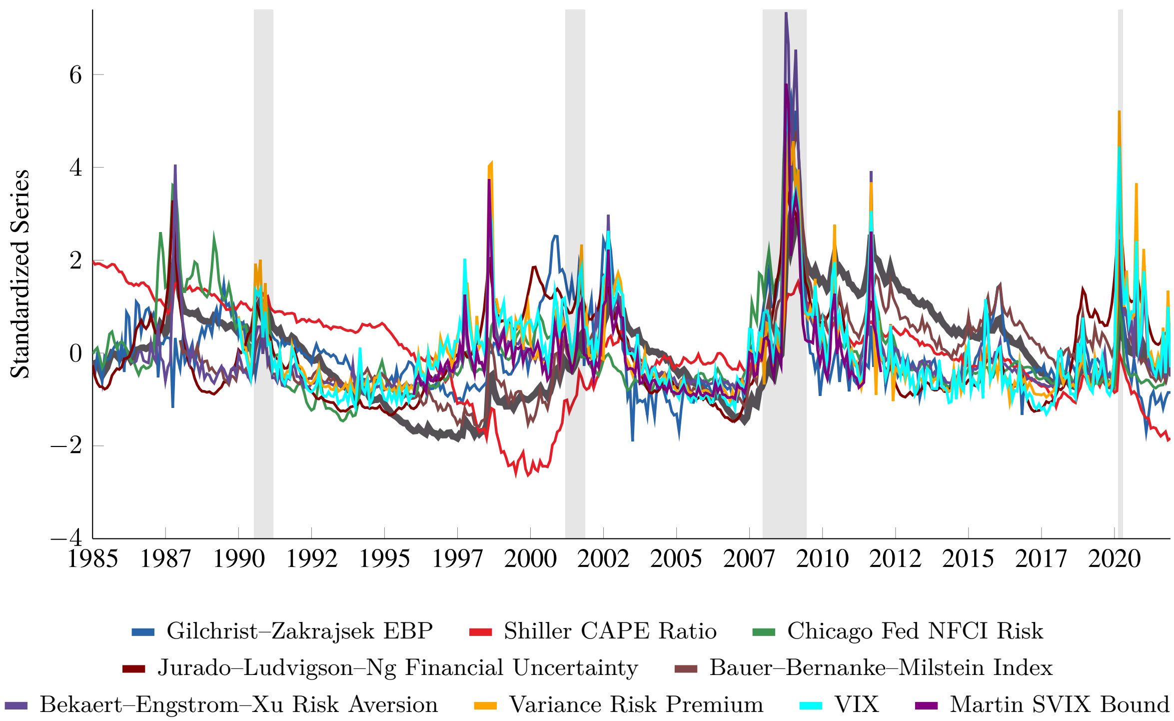
Here, $w^{stay}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker remains in her current job for the full h periods, $w^{sep}_{i,t+1,t+h}$ represents cumulative wage earnings assuming the worker earns the same wage she would have received had she stayed in her initial job for all periods 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:

$$g_{i,t:t+h} = \underbrace{w^{stay}_{i,t+1,t+h} - w_{i,t-2,t}}_{g^{stay}_{i,t:t+h}} + \underbrace{w^{sep}_{i,t+1,t+h} - w^{stay}_{i,t+1,t+h}}_{g^{sep}_{i,t:t+h}} + \underbrace{w^{ext}_{i,t+1,t+h} - w^{sep}_{i,t+1,t+h}}_{g^{src}_{i,t:t+h}} + \underbrace{w_{i,t+1,t+h} - w^{ext}_{i,t+1,t+h}}_{g^{rehire}_{i,t:t+h}}. \tag{A.46}$$

We separately estimate equation (2) with each of these components as the dependent variable. Figure 7 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.

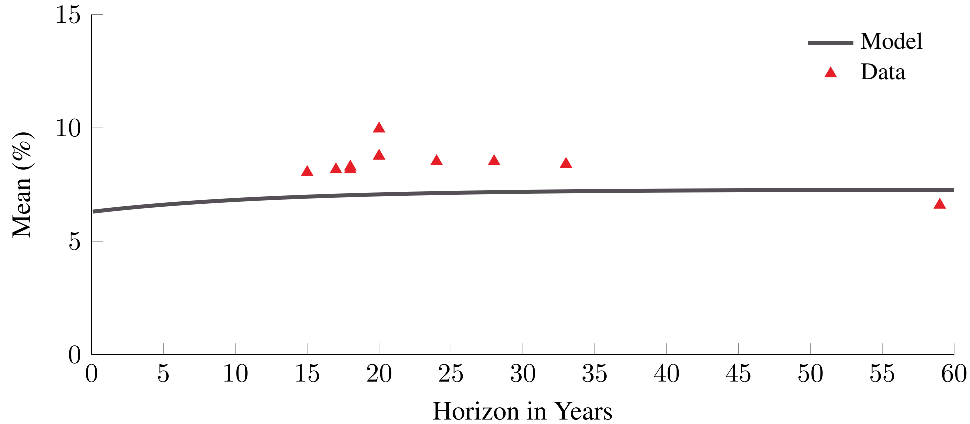
Figure A.1: Time-Varying Risk Premia in the Data



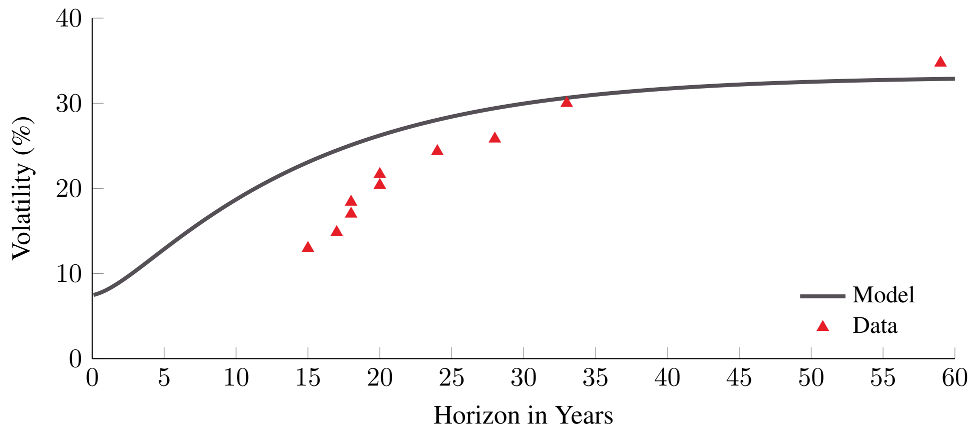
This figure plots nine series from the literature that capture fluctuations in risk premia: the excess bond premium from Gilchrist and Zakrajšek (2012); Robert Shiller's CAPE Ratio; the Chicago Fed's National Financial Conditions Index (NFCI); the financial uncertainty index of Jurado et al. (2015); 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

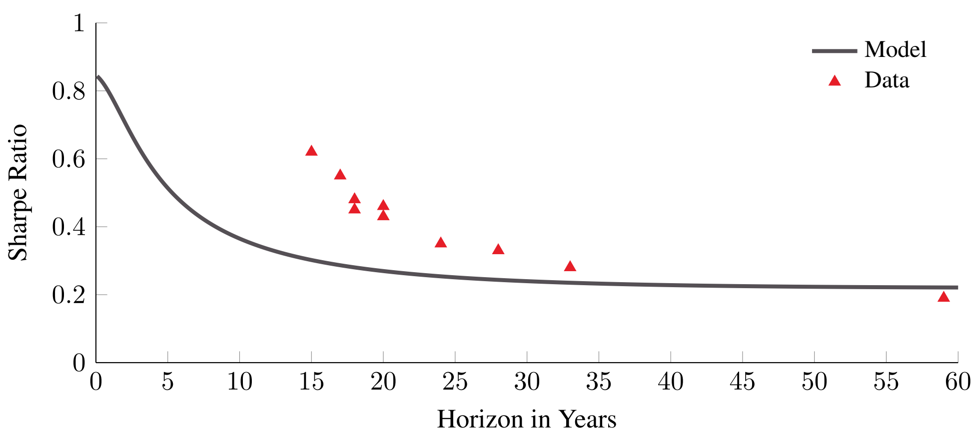
(a) Mean Return, by Cashflow Duration



(b) Return Volatility, by Cashflow Duration

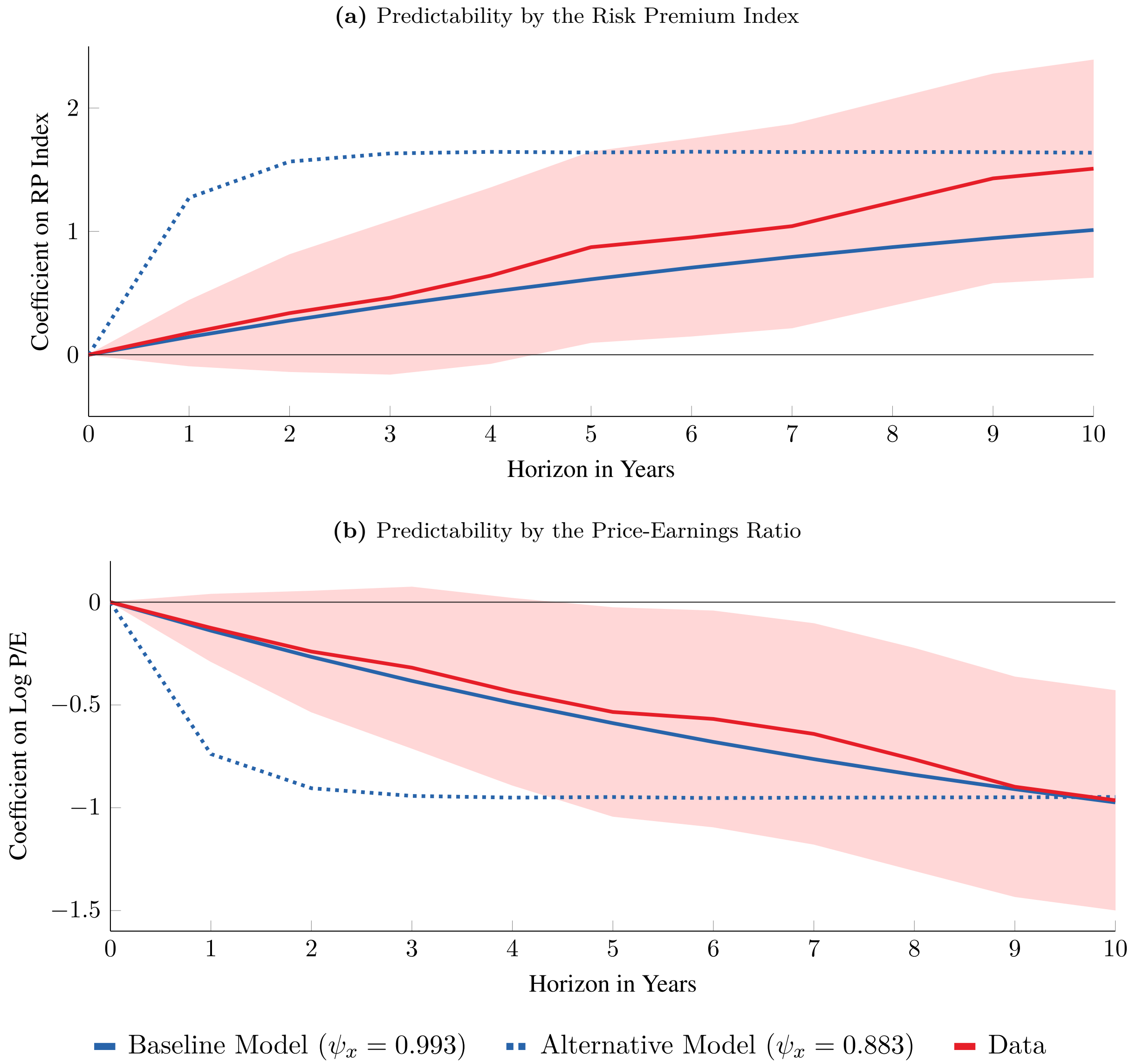


(c) Risk-Return Tradeoff (Sharpe Ratio), by Cashflow Duration



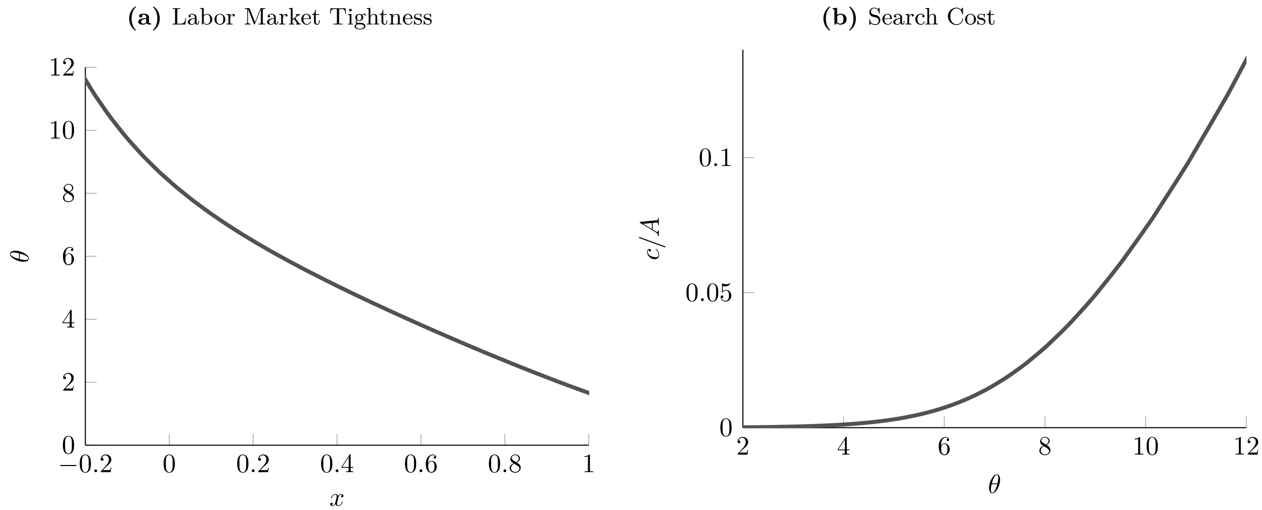
This figure plots the annualized mean (Panel (a)), volatility (Panel (b)), and Sharpe ratio (Panel (c)) of returns on a claim to firm cashflows at a fixed horizon. The data are from the ten duration-sorted portfolios of Gormsen and Lazarus (2023).

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



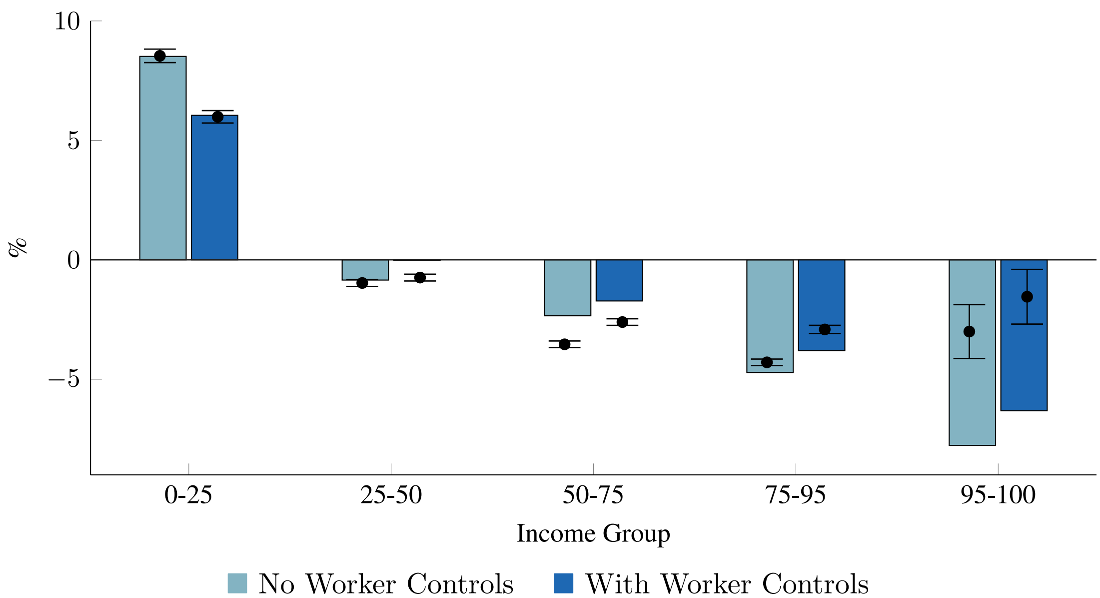
This figure reports estimates of predictive regressions where we project continuously compounded future excess stock market returns $\sum_{s=1}^{H} r^e_{t+s}$ on our risk premium index (Panel (a)) and on the log price-earnings ratio (Panel (b)) at different horizons H, in the model and in the data. The 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



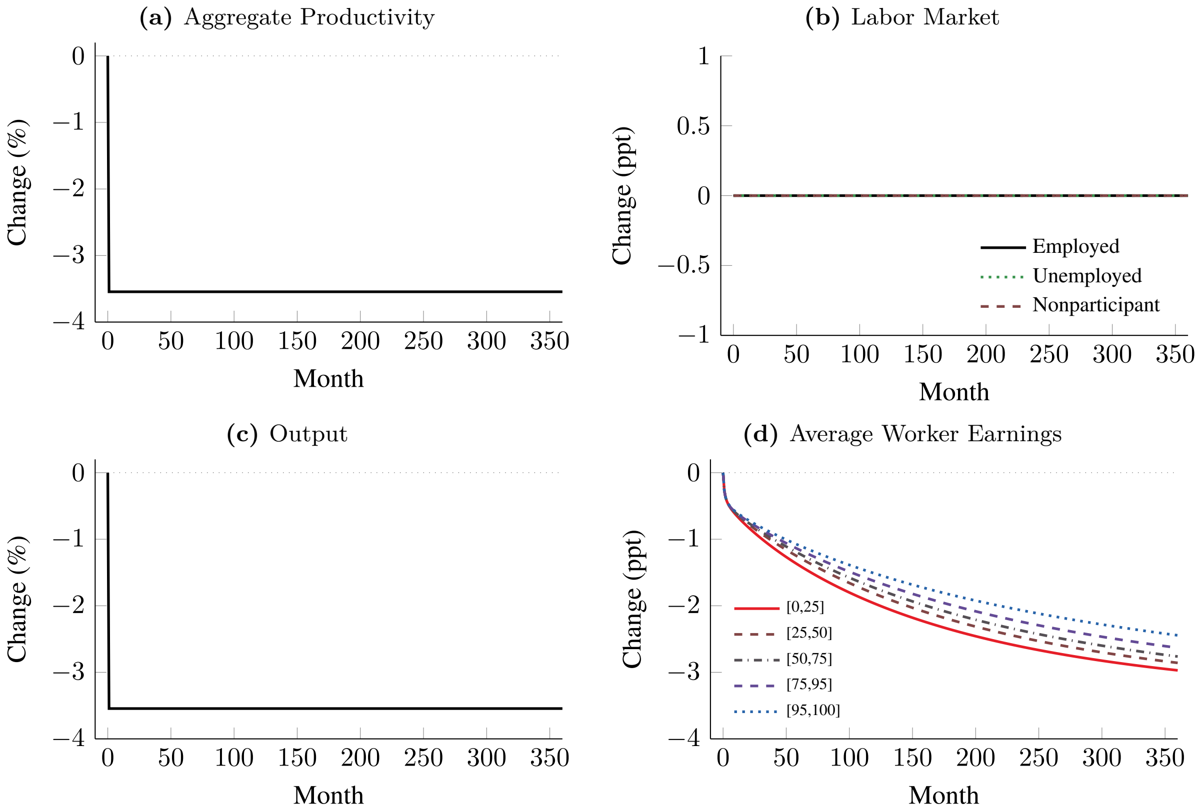
Panel (a) of this figure plots the relation between risk premia x and the labor market tightness θ for a worker with $z = \bar{z}_O$ in our calibrated model. Panel (b) plots the normalized worker search cost c_t/A_t as a function of $\theta_t(\bar{z}_O)$.

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



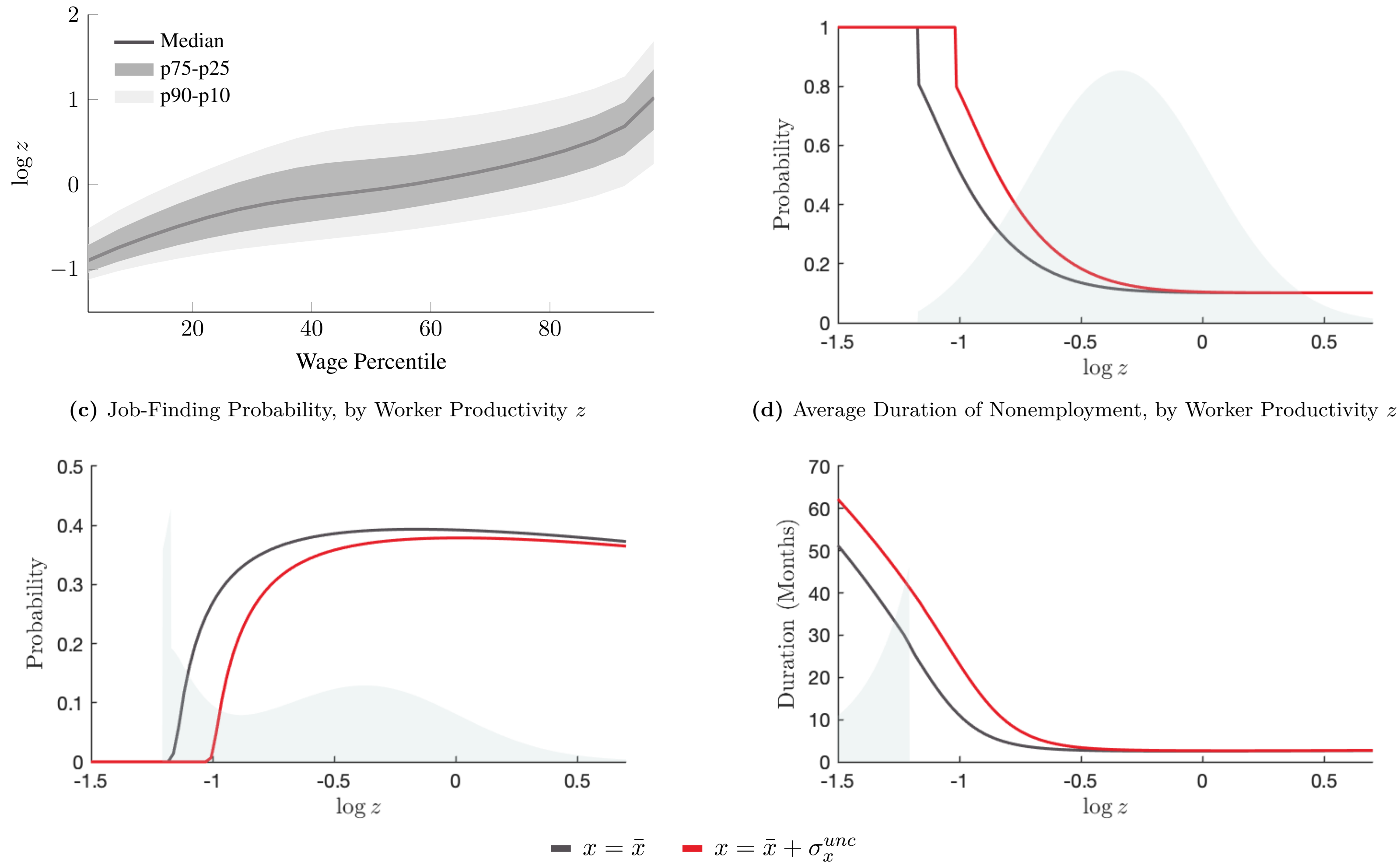
This figure reports average three-year cumulative worker earnings growth for continuing workers in the model and in the data. We report the regression coefficient of earnings growth on a dummy for a worker's relative earnings rank, restricting the sample to workers who remain employed by their initial 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: 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.7: Model Mechanism (I)



(a) Worker Productivity and Wages

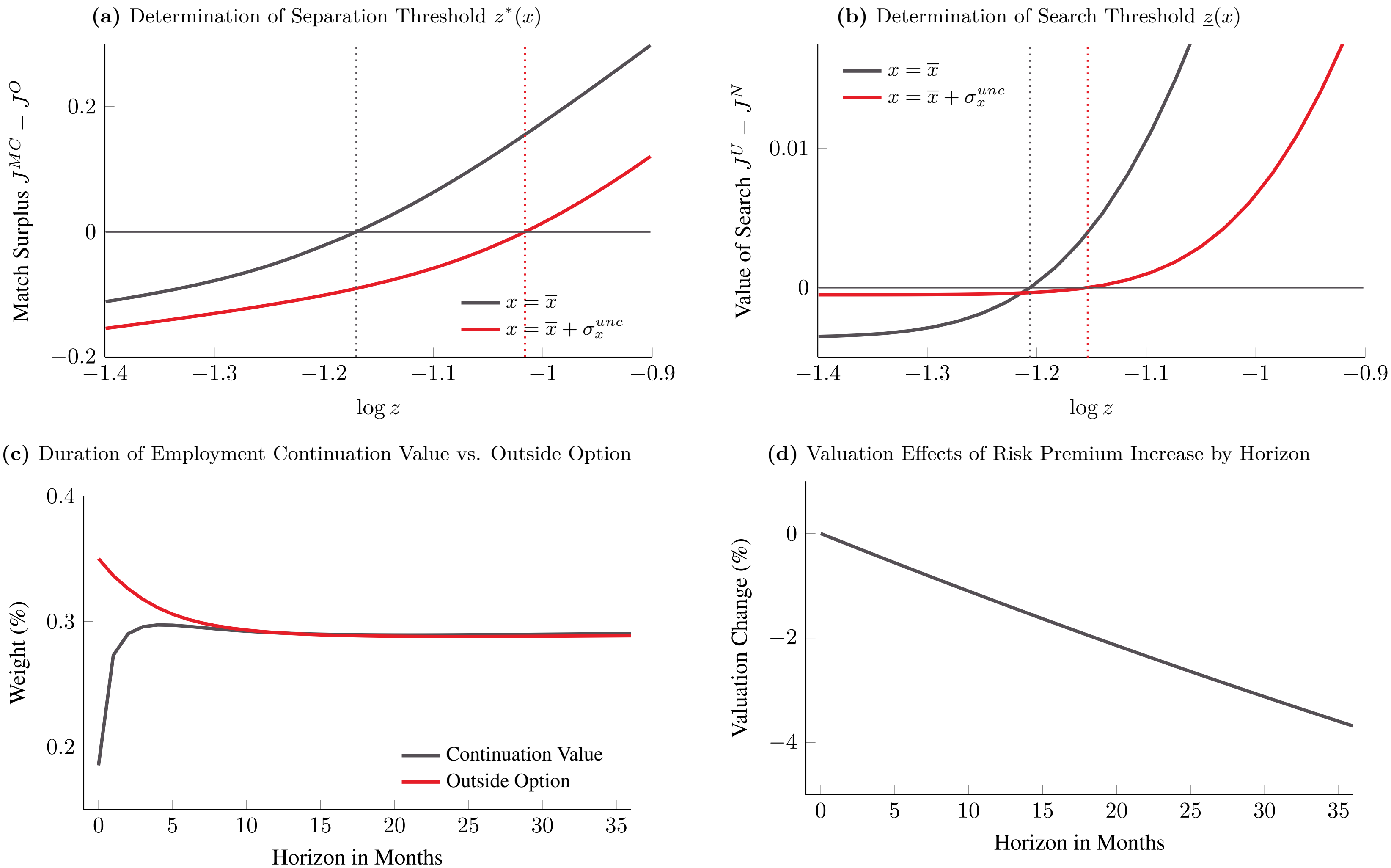
(b) One-Year Termination Probability, by Worker Productivity z

(c) Job-Finding Probability, by Worker Productivity z

(d) Average Duration of Nonemployment, by Worker Productivity z

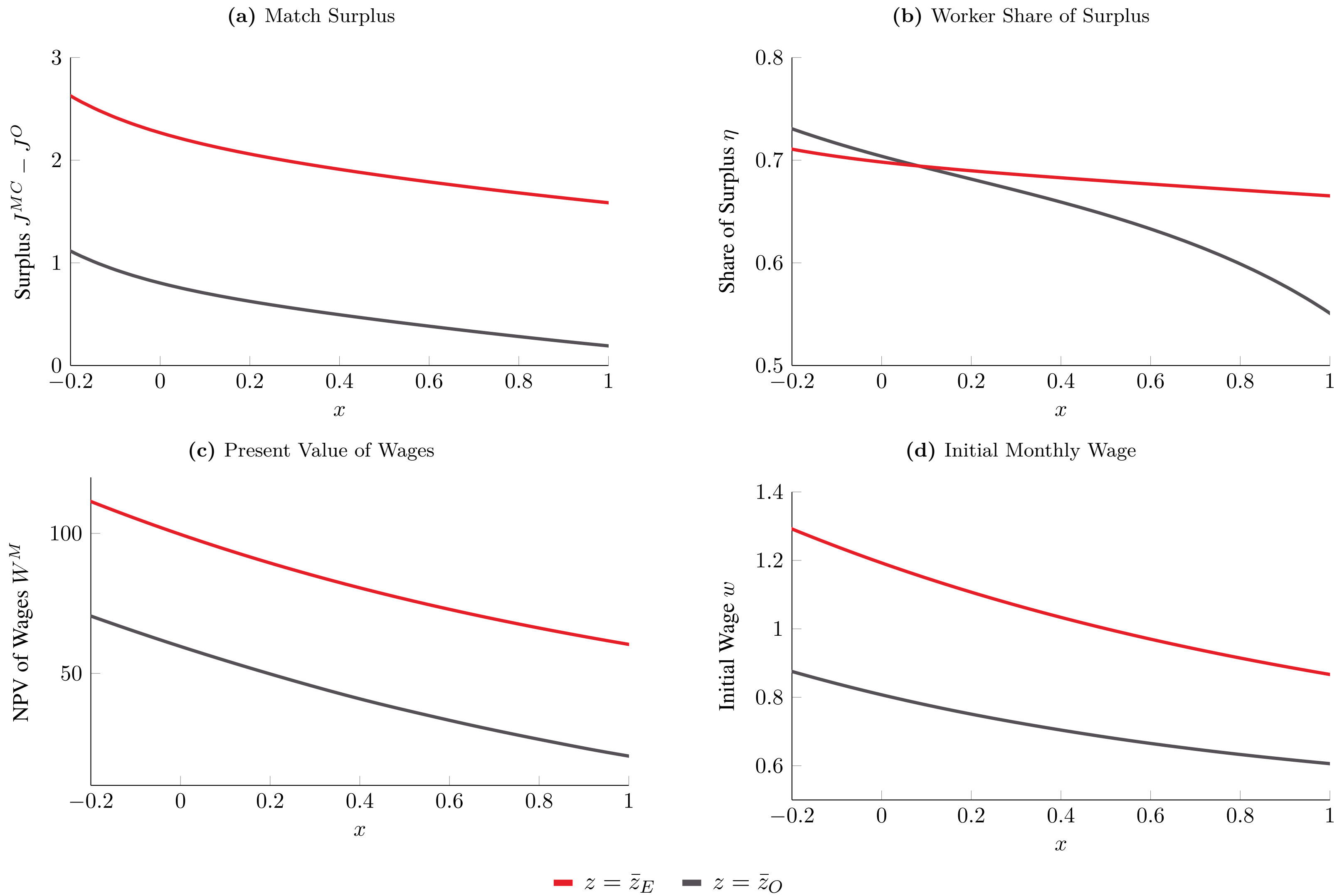
Panel (a) plots the distribution of z for incumbent workers as a function of current wage percentile. Panel (b) plots the probability of match termination over the next year by z for incumbent workers. Panel (c) plots the monthly probability of job finding by z for workers in the unemployment pool. Panel (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.8: 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.

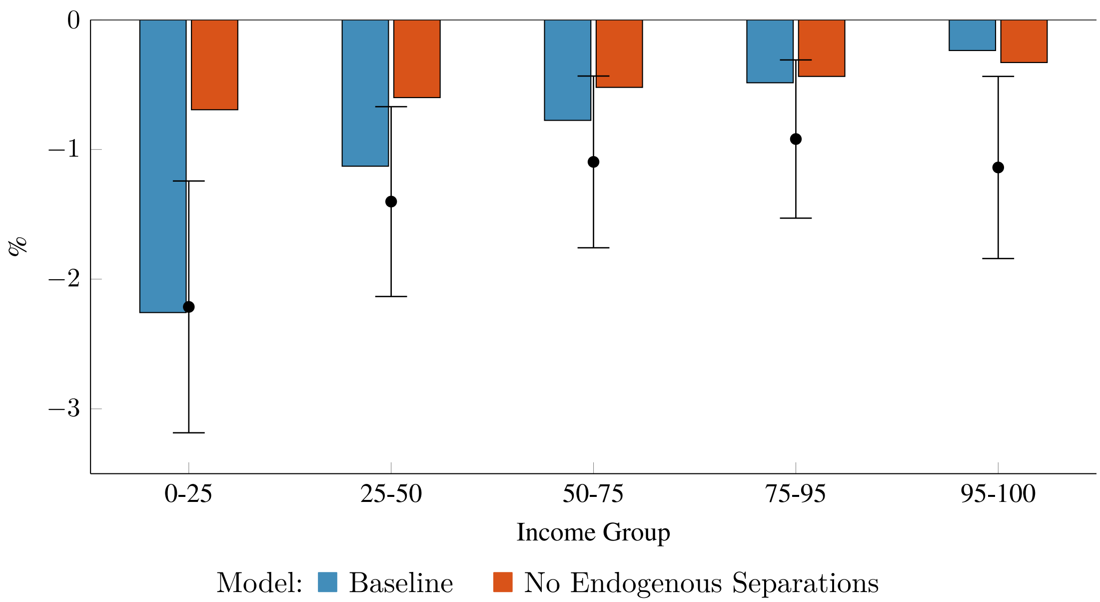
Figure A.9: Model Mechanism (III)



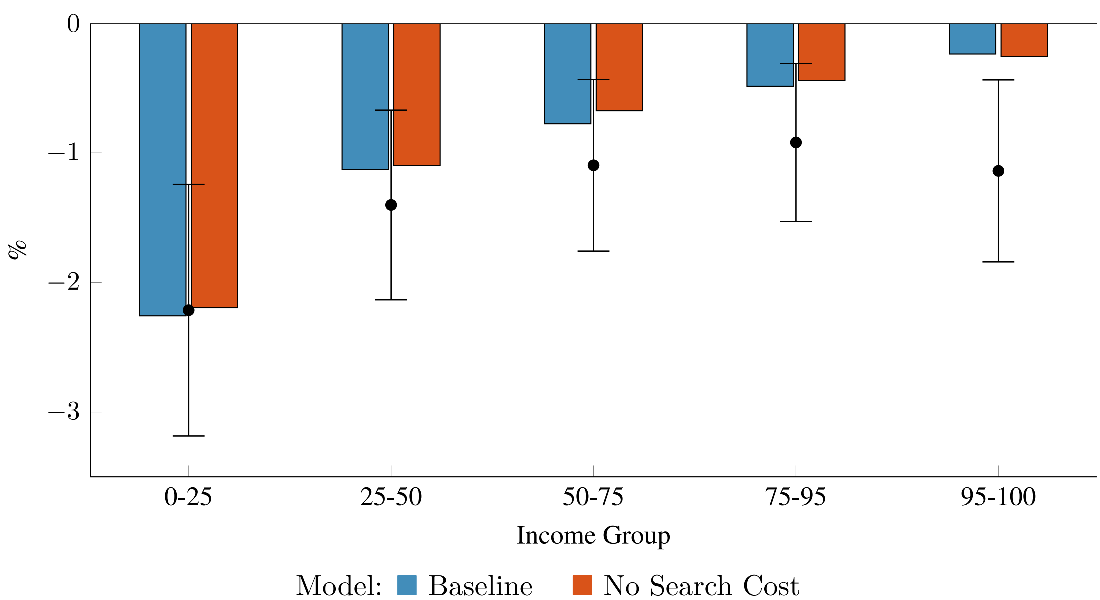
This figure plots values for newly hired workers in the model as a function of current risk premia x, for different values of z. Panel (a) plots the total surplus of the match. Panel (b) plots the share of the total surplus that goes to the worker. Panel (c) plots the value that the worker derives from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

Figure A.10: 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 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.4: 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.5: 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.6: 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.7: 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.8: 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.9: 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.10: 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.11: 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.