Time-Varying Risk Premia, Labor Market Dynamics, and Income Risk*

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Abstract

We show that time variation in risk premia leads to time-varying idiosyncratic income risk for workers. Using US administrative data on worker earnings, we show that increases in risk premia lead to lower earnings for low-wage workers; these declines are primarily driven by job separations. By contrast, productivity shocks affect the earnings mainly of highly paid workers. We build an equilibrium model of labor market search that quantitatively replicates these facts. The model generates endogenous time-varying income risk in response to changes in risk premia and matches several stylized features of the data regarding unemployment and income risk over the business cycle.

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Recent studies in macroeconomics and finance have emphasized the importance of time-varying risk premia for generating significant fluctuations in aggregate quantities and prices.[1] In particular, risk premia tend to rise sharply in recessions, which coincide with increases in unemployment, in workers' idiosyncratic income risk (Storesletten, Telmer, and Yaron, 2004; Guvenen, Ozkan, and Song, 2014) and in inequality at the bottom of the earnings distribution (Heathcote, Perri, and Violante, 2020). Using a combination of micro data and a structural model, we show that these facts are strongly related: an increase in risk premia increases the likelihood of job destruction and therefore leads to higher income risk, particularly for workers at the lower end of the pay distribution. We feed realizations of risk premium shocks in the data into our model and find that it can quantitatively replicate the realized path of unemployment, income risk, and inequality over the last few decades.

We begin by documenting a new stylized fact: an increase in risk premia is followed by a decline in worker earnings and an increase in the likelihood of job loss (defined as a worker's experiencing a nonemployment spell or leaving her current employer and simultaneously experiencing a significant decline in earnings). We show this pattern in administrative data on workers' wage earnings in the United States combined with a composite index of existing measures of risk premium shocks. The decline in earnings is significantly larger for job movers rather than job stayers and is both larger and more persistent for workers with low prior earnings relative to those of other workers in the same firm. Using a shift-share design, we show that the effect of risk premia on worker earnings is distinct from the effect of recessions on earnings of low-income workers: when risk premia rise, lower-paid workers in firms that are highly exposed to risk premium shocks experience larger earnings declines relative to lower-paid workers in less exposed firms. This new pattern is in sharp contrast to the exposure of worker earnings to productivity shocks, which is higher for higher-paid workers (a pattern consistent with the evidence in Friedrich, Laun, Meghir, and Pistaferri, 2019).

We interpret this fact through the lens of a structural model that features heterogeneous workers, directed labor market search, and shocks to risk premia. Workers are heterogeneous in their (general) skill, which determines their productivity across different matches. The key mechanism in the model operates through job destruction: an increase in risk premia leads to a reduction in the value of existing matches, in particular for lower-skill workers. Increases in risk premia disproportionately affect the value of low-skill matches because the benefits of employment for these workers are significantly more backloaded than the benefits of nonemployment, partly because workers' human capital grows faster in employment and partly because the benefits of nonemployment (leisure and benefits) do not scale with workers' skill. Some of these marginal matches are subsequently destroyed because they are inefficient: the present value of the benefits of employment is lower than the present

[1] A partial list includes 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); Auclert, Rognlie, and Straub (2020); Itskhoki and Mukhin (2021); Basu, Candian, Chahrour, and Valchev (2021) and Kehoe, Lopez, Midrigan, and Pastorino (2022).

value of nonemployment. This increase in the rate of job destruction leads to higher unemployment in response to increases in risk premia. The increase in unemployment is also amplified by the fact that firms are less likely to post new vacancies (a mechanism similar to that highlighted in Kehoe et al., 2022), which in turn increases the duration of nonemployment and, combined with the loss of human capital when workers are out of a job, magnifies the impact of job loss on worker earnings. In sum, transitory increases in risk premia lead to highly persistent losses in worker earnings.

Our model also has implications for the exposure of wages for continuing workers to aggregate productivity and risk premium shocks. To derive these predictions, we introduce a number of assumptions on how per-period wages are determined. First, whenever possible, firms choose to smooth worker wages. Second, both workers and firms have limited ability to commit: workers cannot commit to remaining in existing matches when they can obtain a higher surplus by walking away, and firms cannot commit to not terminating workers when their share of the surplus is negative. We calibrate the degree of limited commitment by introducing a symmetric reputational cost of either the worker or the firm inefficiently terminating the existing match. Though no matches are inefficiently terminated in equilibrium, whenever these constraints are binding, worker wages adjust to aggregate and idiosyncratic shocks, similarly to what emerges from models with limited commitment (Thomas and Worrall, 1988). These limited commitment constraints—especially on the firm side—are more likely to bind for highly paid workers, especially when their current level of productivity is low. As a result, conditional on workers' staying employed, the wages of highly paid workers are more sensitive to productivity (and risk premium) shocks than are those of lower-paid workers.

Overall, our model implies that the pass-through of idiosyncratic productivity shocks to worker earnings is highly nonlinear and state dependent. A negative worker productivity shock increases the likelihood of job loss and therefore has a larger effect on worker earnings than a positive productivity shock of the same magnitude. The level of risk premia determines the likelihood of job destruction; hence, this asymmetry becomes starker as risk premia rise. Further, firms aim to smooth wages but are limited in their ability to do so because of the two-sided lack of commitment. Therefore, smaller shocks to productivity have a (proportionally) smaller pass-through than larger shocks since these shocks are more likely to lead to binding commitment constraints. Last, changes in worker earnings are significantly more persistent than changes in worker productivity because of a combination of wage smoothing and labor market frictions.

The fact that the pass-through of worker productivity shocks to worker earnings is both asymmetric and state dependent implies that our model can match a number of stylized features of labor income risk. Specifically, the distribution of workers' labor income is significantly more skewed and fat-tailed than the underlying productivity shocks, consistent with the findings of Guvenen, Karahan, Ozkan, and Song (2021). Further, the distribution of earnings growth becomes more negatively skewed as risk premia rise, particularly for low-income workers, which in turn leads to an increase in both income risk and income inequality at the bottom of the distribution.

We calibrate the model to match the dynamics of asset prices and the earnings responses to risk premium and productivity shocks, as well as average separation rates and job finding rates across the income distribution, using panel data from the Survey of Income and Program Participation (SIPP). The model is able to deliver a realistic volatility of unemployment while at the same time quantitatively reproducing the moments from micro data that we target: the exposure of workers to risk premium and productivity shocks as a function of their prior income as well as the strong heterogeneity in job separation rates across workers with different income levels. Last, even though these are not explicit calibration targets, the model delivers a procyclical job-finding rate and countercyclical flows into unemployment that are consistent with the data.

The model generates testable predictions that are validated by our analysis of administrative income data and our measure of risk premium shocks. First, our model implies that the surplus value of employment should be more sensitive to risk premium shocks for workers with longer employment horizons. We find support for this prediction in the data: an increase in risk premia implies a larger decline in worker earnings for younger workers than for older workers; this pattern is distinct from the income pattern that we focus on in most of the paper. Second, our model implies that the earnings of low-tenure workers should be more sensitive to risk premium shocks than the earnings of high-tenure workers. In the model, worker tenure is strongly related to worker productivity since more productive workers are more likely to retain their job. Our empirical findings confirm this pattern: the relationship between tenure and exposure to risk premium closely aligns with the quantitative predictions of our model.

In addition, the calibrated model quantitatively replicates several aspects of the data that are not explicit calibration targets. The job destruction margin in the model is quantitatively plausible: the model can quantitatively replicate the increase in the probability of job loss in response to a risk premium shock across the income distribution that we see in the data. Further, in both the model and the data, the earnings of movers, especially low-income movers, are more exposed to risk premium shocks than the earnings of stayers. By contrast, the exposure of workers to productivity shocks is similar between stayers and movers. The model can quantitatively replicate these facts through the combination of endogenous job destruction and our assumptions on the wage contract that allow for partial wage adjustments, in the spirit of Balke and Lamadon (2022) and Ai and Bhandari (2021).

Importantly, our model is able to quantitatively replicate the realized fluctuations in unemployment, labor force participation, labor income risk, and left-tail income inequality. In particular, we feed into the calibrated model our empirical measures of risk premium and productivity shocks and compare the model-implied series to their empirical equivalents. Even though the model is missing several other factors that could potentially drive these variables in the data, the correlation between these model-implied series and their (detrended) empirical counterparts ranges from 50% to 70%. Realized fluctuations in risk premia drive most of the time-series behavior of these quantities. An increase in risk premia in our model implies an increase in the probability of job loss, while it lowers output and employment, thereby generating countercyclical skewness in labor earnings and quantitatively replicating the fluctuations in income risk in the data (Guvenen et al., 2014). In addition to earnings risk, our model can replicate the persistent rise in income inequality in the left tail following recessions (Heathcote et al., 2020). In the model, an increase in risk premia leads to a higher rate of job destruction, which has highly persistent effects on low-income workers because of the lack of human capital accumulation while they are unemployed. Since searching for a job involves a cost, workers can remain out of the labor force for a long time if they are sufficiently unproductive.

The mechanism in our model that generates job destruction and income risk in response to changes in risk premia can also apply more broadly to other shocks that affect the present value of employment matches, such as changes in interest rates or shocks to the availability of credit that can increase the marginal value of a dollar today relative to in the future. In this sense, our work is related to that of Caggese, Cuñat, and Metzger (2019), who use employer–employee matched data from Sweden and show that exporting firms with worse credit ratings facing an adverse terms-of-trade shock are more likely to lose workers with shorter tenures than firms with better ratings. Caggese et al. (2019) argue that, from the perspective of the firm, these workers are high-duration investments. 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.

A large literature on labor market search has focused on resolving the unemployment volatility puzzle noted by Shimer (2005): namely, that the textbook search model (Diamond, 1982; Mortensen, 1982; Pissarides, 1985) is unable to generate a realistic level of volatility in the unemployment rate. In this respect, Hall (2017), Kilic and Wachter (2018) and Kehoe et al. (2022) are closest to our work. Hall (2017) proposes a resolution of the puzzle: an increase in discount rates lowers firms' willingness to search for workers (post vacancies) and therefore leads to higher unemployment. Kilic and Wachter (2018) focus on time-varying disaster risk. Kehoe et al. (2022) 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 proposed by existing explanations which have counterfactual implications for the cyclicality of the opportunity cost of labor, the cyclicality of the user cost of labor, or the volatility of risk-free rates.

We contribute to this discussion along two key dimensions. First and foremost, we provide direct empirical evidence using administrative micro data from the United States that risk premium shocks affect worker earnings, primarily through the job separation margin. Second, we use these micro data estimates to calibrate a quantitative model of labor market search that generates realistic fluctuations in unemployment and thus resolves the Shimer puzzle. Our model proposes a new mechanism through which risk premia increase unemployment—endogenous destruction of inefficient matches—rather than relying only on lower search effort on the part of workers and firms as in Hall (2017); Kilic and Wachter (2018) and Kehoe et al. (2022). This new margin through which risk premia lead to unemployment is directly disciplined with our micro data, and it implies that job separations are countercyclical, therefore addressing the concerns of Martellini, Menzio, and Visschers (2021). The fact that the model is calibrated to micro data and is able to generate realistic unemployment fluctuations addresses the concerns raised by Borovička and Borovičková (2018), who argue that a stochastic discount factor that is consistent with observed properties of asset returns can only partially explain the Shimer puzzle.

Using both theory and data, our paper identifies a new mechanism through which changes in risk premia affect the likelihood of job destruction and income risk. However, we recognize that risk premia are endogenous to the state of the economy and are only proximate causes of these fluctuations. Nevertheless, our findings imply that whatever economic forces generate time variation in risk premia will also affect unemployment, labor income risk, and inequality at the bottom of the distribution. For example, the literature has identified a number of mechanisms that generate time-varying risk premia: risk shocks that propagate through the economy via a financial accelerator mechanism (Christiano et al., 2014); fluctuations in the level of uncertainty that feed into firms' cost of capital through changes in the equity risk premium (see, e.g. Wachter, 2013; Bloom, 2014); nonhomothetic preferences (Campbell and Cochrane, 1999); temporary financial market dislocations due to a reduction in the net worth of the suppliers of capital (He and Krishnamurthy, 2013); and monetary policy (Moreira and Savov, 2017; Campbell, Pflueger, and Viceira, 2020; Caballero and Simsek, 2020, 2022).[2] For our purposes, we do not need to take a stance on the economic drivers behind fluctuations in risk premia but instead focus on their role as proximate causes, or sources of amplification, for fluctuations in unemployment, labor income risk, and inequality.

That fluctuations in risk premia are an important determinant of idiosyncratic labor income risk implies that they can affect aggregate demand—in addition to aggregate supply, which has been the main focus of the literature thus far (Christiano et al., 2014; Bloom et al., 2018). In particular, fluctuations in the level of idiosyncratic income risk can be an important determinant of aggregate demand in a heterogeneous agent neo-Keynesian (HANK) framework (Kaplan, Moll, and Violante, 2018; Bayer, Luetticke, Pham-Dao, and Tjaden, 2019). Our central thesis that increases in risk premia lead to higher idiosyncratic income risk implies that fluctuations in risk premia should also affect aggregate demand by disproportionately affecting the wage income of households with

[2] In this respect, our empirical findings complement the findings of Bergman, Matsa, and Weber (2022) and Coglianese, Olsson, and Patterson (2022). Bergman et al. (2022) use group-level employment data and document that employment of lower-income workers is more sensitive to monetary policy shocks in the United States than employment of high-income workers. Coglianese et al. (2022) use employer–employee administrative data from Sweden and document that monetary policy shocks have a disproportionately larger impact on the employment of lower-income workers.

a high marginal propensity to consume (MPC). To the extent that low-wage workers have larger MPCs than high-wage workers (Patterson, 2022), our model mechanism implies that changes in risk premia can have a significant impact on aggregate demand by affecting the earnings of low-income workers. Last, to the extent that monetary policy also affects risk premia, our findings provide a novel channel through which monetary policy can affect aggregate demand, by disproportionately affecting the earnings dynamics of lower-paid workers.

1 Worker Exposure to Risk Premium and Productivity Shocks

We begin by documenting a new stylized fact: low-income workers are significantly more exposed to shocks to risk premia than workers in the middle or the top of the earnings distribution, and this increased exposure manifests primarily through changes in the likelihood of job loss. This pattern is in sharp contrast to that observed for earnings exposure to productivity shocks.

1.1 Data Description

Worker Earnings. 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 et al. (2014) and focus on cumulative age-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 income 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 income growth in (1) may include earnings from different employers, public or private, and periods of nonemployment (with zero reported W2 earnings). We winsorize all worker income growth rates $g_{i,t:t+h}$ at the 1st and 99th percentiles.

Table A.1 summarizes our key variables of interest in our main sample of public firm employees between base years 1992 and 2018. Worker heterogeneity plays an important role in our analysis; therefore, we report moments separately across the income distribution. We rank workers by their last three years of total age-adjusted wage earnings, $w_{i,t-2,t}$, and compute the income rank of workers relative to other workers in the same firm and over the same period. We report real earnings growth $g_{i,t:t+h}$ over various horizons as well as the probability of some nonemployment (at least one zero-earnings quarter) and the probability of a move coinciding with a tail loss (income growth below the 10th percentile) between the end of year t and the end of year $t+h$. An individual is characterized as a stayer if the main employer in year $t+h$ is the same as the main employer in year t and is characterized as a mover in all other cases.

Risk Premium Shocks. Our goal is to 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 this end, we rely on existing series from the literature.[3] To extract our risk premium shocks, we first estimate 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, denoting the resulting risk premium shocks by ϵ_t^{rp}. To construct the level of risk premia from the shock series, we compute the exponentially weighted moving average of ϵ_t^{rp}, assuming a decay parameter of 0.0063 per month (consistent with our model calibration in Section 2 that targets the persistence of the log price–dividend ratio). Appendix A.2 contains more details.

We plot the resulting time series of risk premia in Figure 1a along with each individual series. All series are strongly countercyclical, but there are also fluctuations in risk premia outside recessions. Our risk premium shocks are strongly related to stock market fluctuations: the contemporaneous correlation between stock market returns and risk premium shocks is significantly negative at -77%. Most importantly, our risk premium measure predicts higher stock market returns over the medium run (Figure 1b)—consistent with our interpretation of these shocks as shocks to the required rate of return for risky investments. Given the strong link between our risk premium shocks and the stock market, to interpret the magnitudes of the risk premium shocks, we scale ϵ_t^{rp} so that a 1% increase in our index corresponds to a 1% contemporaneous decline in the stock market.

Productivity Shocks. We measure productivity shocks using estimates of annual firm revenue-based total factor productivity (TFPR) growth, aggregated to the 4-digit NAICS level. We build on the approach from İmrohoroğlu and Tüzel (2014), which is based on Olley and Pakes (1996), to estimate firm-level TFPR and modify their approach to facilitate aggregation; see Appendix A.3 for more details. The advantage of this series relative to Bureau of Labor Statistics (BLS) measures of productivity is that it takes into account changes in prices and has broader and more granular coverage across industries. We denote the resulting series for industry-level productivity shocks by $\epsilon_{I,t}^{tfp}$. Aggregated over all firms, TFP growth has a correlation of -47% with the risk premium shock.

[3] 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; 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.

1.2 Income Exposure to Risk Premium and Productivity Shocks

We estimate the following specification at the worker level:

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

Our main coefficients of interest are β and γ, which capture workers' exposure to risk premium and productivity shocks, respectively. The vector of controls $\mathbf{Z}_{i,t}$ includes a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted with income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income bin. Given that the underlying data on risk premium shocks is at monthly frequency while worker earnings are at annual frequency, 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 and later is aligned with the cumulative risk premium shock from July 2000 until June 2021.

On average, increases in risk premia are associated with lower worker earnings. Panel A of Table 1 shows that the earnings of the average worker are negatively exposed to risk premium shocks: a 10% increase in the risk premium shock ϵ^{rp}, which is close to its unconditional standard deviation, is associated with a decline of approximately 1.2 to 1.5 percentage points in worker earnings over the next two to five years. By contrast, worker earnings and productivity are positively related: a 10% increase in the industry productivity shock ϵ^{tfp}, also close to its unconditional standard deviation, is associated with a 0.7- to 0.8-percentage-point increase in worker earnings over the same period.

Our main empirical finding is that the two shocks ϵ^{rp} and ϵ^{tfp} have markedly different implications for income growth across the worker earnings distribution (relative to the earnings of other workers in the same firm). In Panel B of Table 1, we allow β and γ to vary with the worker's prior income level relative to that of other workers in the same firm. We see that low-wage workers are significantly more exposed to risk premium shocks than other workers in the same firm, especially at longer horizons: a 10% increase in ϵ^{rp} leads to an approximately 2-percentage-point decline in earnings for workers at the bottom of the earnings distribution at horizons of two to five years. By contrast, earnings at the middle of the earnings distribution (between the median and the 75th percentile) experience a 1.2-percentage-point decline in the short run (two to three years), and the magnitude falls to a decline of 0.8 percentage points at the five-year horizon. There are no significant differences in risk premium exposure between middle and top earners. This pattern is sharply different when we examine the response of earnings to productivity shocks. All workers have similar exposure to productivity shocks, with the exception of the workers at the very top of the earnings distribution, who have significantly larger exposure to industry TFP growth.

In sum, we see that low-income workers experience larger and more persistent declines in earnings in response to the same risk premium shock as workers in the middle or the top of the earnings distribution within the firm. Importantly, the fact that we compare workers within the same firm implies that we implicitly difference out common sources of exposure to risk premium shocks that vary across firms. Our removing this firm-level component of worker exposure to risk premia helps alleviate concerns that our results reflect unobservable time-varying differences across firms such as differences in average worker or firm quality.

Shift-Share Design. Risk premia are strongly countercyclical (Figure 1a). Thus, a key question when we interpret the results in Table 1 is whether we are identifying the effects of risk premium shocks or merely the effects of recessions and the fluctuations in risk premia are just a sideshow. To isolate the effects of risk premium shocks from the effects of a recession, we estimate a modified version of equation (2):

$$g_{i,t:t+h} = \beta \left(\chi_{f,t}\, \epsilon^{rp}_{t+1}\right) + c'\mathbf{Z}_{i,t} + a_{I,s,t} + \eta_{i,t+h}. \tag{3}$$

We introduce three modifications to our previous empirical design in (2). First, we interact the risk premium shocks with different characteristics χ_f that capture the exposure of the firm f (that employs worker i) to risk premium shocks ϵ^{rp}_{t+1}. The interaction of these exposure measures with our proxy for risk premium shocks can be viewed as a shift-share design (Bartik, 1991; Blanchard and Katz, 1992). Second, we include income group×industry and income group×year fixed effects; doing so fully absorbs the variation in productivity at the industry level, and thus, the coefficient γ in (2) is no longer identified. The coefficient β is now identified by comparing the wage earnings response for 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 χ_f to risk premium shocks. Third, since some of our exposure proxies χ_f may also capture differential exposure to aggregate productivity shocks, we also interact χ_f with shocks to the aggregate level of productivity and include those in the vector of controls.

We consider several types of proxies for firms' exposure χ_f to risk premium shocks. The first is the firm's stock market beta since it measures the sensitivity of its cost of capital to aggregate shocks (Sharpe, 1964). Second, we directly estimate the sensitivity of firm valuations to risk premia by regressing firm equity returns on our proxy of risk premium shocks. Third, we follow Almeida, Campello, Laranjeira, and Weisbenner (2011) and focus on firms that need to refinance a significant amount of debt at years $t+1$ and $t+2$ (as of year $t-1$). We expect that changes in risk premia are more salient for these firms that need to access financial markets. Last, we consider various proxies for firms' exposure to aggregate financial conditions that are commonly used in the literature: (minus) the level of cash holdings relative to assets (Jeenas, 2019), since it is related to firm needs to access financial markets; firm size (Gertler and Gilchrist, 1994), since smaller firms are riskier; the distance to default (Ottonello and Winberry, 2020), since these firms are riskier and therefore more exposed to fluctuations in risk premia; and the Whited and Wu (2006) index of financial constraints, since these firms are more sensitive to conditions in financial markets. Appendix A.4 contains additional details on these proxies. To help interpret magnitudes, we scale the exposure measures χ_f so that the cross-sectional standard deviation is equal to one.

As we see in Table 2, this alternative empirical design leads to similar conclusions as our baseline analysis: an increase in risk premia leads to larger earnings declines for low-income workers in more exposed firms than for low-income workers in less exposed firms and high-income workers in more exposed firms. In terms of magnitudes, following a 10% increase in the risk premium shock ϵ^{rp}_{t+1}, low-income workers experience a 0.26- to 0.48-percentage-point greater decline in earnings if they are employed in firms that are one standard deviation more exposed than the average firm; these differences are strongly statistically significant across all of our empirical measures of exposure χ_f. The differences between the wage responses of low-income workers in highly exposed firms and those of high-income workers in the same firms are of comparable magnitude (0.23 to 0.46 percentage points), though not always precisely estimated.

We conclude that the differential exposure of low-income workers to risk premium shocks is not merely reflecting these workers' differential exposure to recessions and the countercyclical nature of these shocks; rather, shocks to risk premia appear to affect the earnings of low-income workers directly.

Intensive versus Extensive Margin. Worker earnings can decline because the worker remains employed with the same firm but receives a pay cut in hourly wages or works fewer hours, because she becomes unemployed and receives no wage income, or because she moves to a new job that pays a lower wage. We next focus on the role of job transitions in generating the patterns in Table 1. First, in Table 3, we report estimates of β and γ from a modified version of equation (2) where we replace the dependent variable with indicators for job loss over the next h years: whether the worker experiences at least one full quarter with zero wage earnings or whether the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile. Second, in Table 4, we report estimates of β and γ from separately estimating equation (2) for job stayers versus movers over the next h years.

Overall, we see that the negative effects of risk premium shocks on wage earnings operate largely through the extensive margin—the increased probability of job loss. Focusing on the workers at the bottom of the pay distribution, we observe that a 10% risk premium shock ϵ^{rp} is associated with an approximately 1- to 1.1-percentage-point increase in the likelihood of a nonemployment spell (at least one quarter of zero wage earnings). Similarly, a 10% risk premium shock ϵ^{rp} leads to a 0.8- to 0.9-percentage-point increase in the likelihood of the worker separating from her initial employer and experiencing a significant drop in income. For workers who fall under this definition of job loss, the conditional mean of earnings growth over the next 3 years is equal to -144 log points. Thus, these estimates imply that the increased likelihood of job loss accounts for more than half of the total effect of risk premium increases on wage earnings. Reinforcing the importance of the job destruction channel, the negative effects of risk premium shocks on low-income workers are significantly larger (by a factor of more than five) for those workers who end up leaving the firm than for workers who remain with the firm. Importantly, the corresponding magnitudes for workers at the middle or the top of the income distribution are significantly smaller, in both economic and statistical terms.

These patterns stand in sharp contrast to those of the impact of productivity shocks. Though adverse productivity shocks are associated with a modest degree of job destruction, the magnitudes are smaller than those of the effects of risk premium shocks, and the estimated coefficients γ do not vary significantly by income. Likewise, the response of earnings to productivity shocks are somewhat larger for movers than for stayers, but the differences are significantly smaller than in the case of risk premium shocks—and there is no clear pattern as a function of worker income.

1.3 Robustness Checks

We briefly discuss a number of robustness checks of our main findings; all details are relegated to the appendix (A.5). Table A.2 shows that extending our analysis to all workers (as opposed to workers employed in public firms in Compustat) leads to quantitatively similar results. Table A.3 shows that differentiating between workers on the basis of their income relative to that of their industry peers (as opposed to that of other workers in the same firm) leads to similar conclusions. Table A.4 examines the extent to which our results are sensitive to the exact measurement of risk premium or productivity shocks; our results are largely insensitive to these choices. Table A.5 shows that alternative assumptions on time aggregation, specifically whether worker earnings are paid at the end of the year or the beginning of the year—as in Campbell (2003)—lead to quantitatively similar outcomes. Table A.6 shows that, using our shift-share design in equation (3), we obtain qualitatively similar results on the likelihood of job loss to those in Table 3; that is, a 10% increase in the risk premium leads to a 0.1- to 0.2-percentage-point increase in the likelihood of job loss (a large income drop combined with separation from the initial employer) for those low-income workers who are employed in highly exposed firms relative to the likelihood of low-income workers employed in less exposed firms.

2 Model

Thus far, we have documented a number of new stylized facts that help guide the model we develop. First, risk premium shocks have a significantly more negative impact on the earnings of low-income workers than on the average worker. Second, this pattern is in sharp contrast to that observed for low-income workers exposed to productivity shocks, which is similar to the pattern for the average worker and less pronounced than the pattern for higher-paid workers. Third, job destruction is an important driver of the impact of risk premium shocks on the earnings of low-income workers; while productivity drops also lead to some instances of job destruction, the magnitudes are smaller, and the effects do not vary significantly by income.

What type of model would quantitatively rationalize these facts? Given that job destruction is an important driver of these patterns in the data, a model that will fit these facts needs labor market frictions; search frictions are a natural starting point (Diamond, 1982; Mortensen, 1982; Pissarides, 1985). We model a directed search process (Montgomery, 1991; Moen, 1997). The next question concerns the structural interpretation of risk premium shocks in such a framework; we model these shocks as shocks to the effective discount rate that agents use to discount future risky cashflow streams, in the spirit of Kehoe et al. (2022). A positive risk premium shock indicates a lower valuation of a stream of risky future cashflows—or equivalently, agents value present cashflows relatively more than future cashflows. Since the decision to maintain an existing worker–firm match involves calculating the present value of the relative benefits of keeping the worker in the job or not and these benefits are uncertain, fluctuations in the discount rate for future cashflows directly affect firms' willingness to keep specific workers.

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 are employed by a firm, are unemployed and searching for a job, or are nonparticipants in labor markets. Firms employ workers to produce output and can post vacancies to attract new workers, targeting workers with a specific productivity level.

Timing

Each period in the model consists of three subperiods. First, a fraction ν 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 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:

$$y_{i,t} = A_t \, z_{i,t}. \tag{4}$$

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

$$\log z_{i,t+1} = \psi_z \log z_{i,t} + (1-\psi_z) \log \bar{z}_{i,t} + \sigma_z \, \varepsilon_{z,i,t+1}, \tag{5}$$

where $\varepsilon_{z,i,t+1}$ is an i.i.d. standard normal random variable. Importantly, 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

$$z_{i,t_0(i)} \quad = \quad \bar{z}_O \, \exp(\sigma_{z0} \, \varepsilon_{z,i,t_0(i)}). \tag{6}$$

Aggregate productivity A_t follows a random walk:

$$\Delta \log A_{t+1} = \mu_A + \sigma_A \, \varepsilon_{A,t+1}, \tag{7}$$

where $\varepsilon_{A,t+1} \sim N(0,1)$. We note that, given (7), 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 spanning the aggregate shocks $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$, and there is a unique stochastic discount factor. The present value of a claim to a stream of future cashflows X is

$$P_t = \mathbb{E}_t \left\{ \sum_{\tau=t+1}^{\infty} \left(\prod_{k=t+1}^{\tau} \Lambda_k \right) X_\tau \right\}, \tag{8}$$

where Λ_τ is the one-period stochastic discount factor (SDF) between periods τ and $\tau+1$. Our assumption of complete markets implies that all agents in the economy, both firms and workers, use (8) to value future cashflows.[4]

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 following Lettau and Wachter (2007), assuming that the market price of risk (the level of risk premia) evolves according to

$$x_{t+1} = \psi_x x_t + (1-\psi_x)\bar{x} + \sigma_x \, \varepsilon_{x,t+1}, \tag{9}$$

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

[4] This assumption can be motivated if each worker is part of a large family, each of which features a continuum of ex ante workers who experience i.i.d. shocks and have identical preferences. All families pool their resources to smooth consumption across members and are therefore able to diversify away idiosyncratic shocks to the income of a single worker. Newborn workers are born into each family in proportion to its size, implying that each family has a constant size and a constant share of aggregate resources.

given by

$$\Lambda_{t+1} = \exp\left\{-r_f - \frac{1}{2}x_t^2\left(1+\delta^2+2\,\delta\,\rho_{A,x}\right) - x_t\,\varepsilon_{A,t+1} - \delta\,x_t\,\varepsilon_{x,t+1}\right\}. \tag{10}$$

The stochastic discount factor (10) 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 (10) 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

$$\kappa_t(z) = \bar{\kappa}\,A_t\,z. \tag{11}$$

The cost of posting a vacancy targeting a specific type of worker is proportional to the worker's productivity. The assumption that search costs are proportional to A ensures that the limiting employment distribution is not degenerate, while the assumption that they scale 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 of the market $\theta_t(z) \equiv v_t(z)/u_t(z)$, where $u_t(z)$ is the unemployment rate and $v_t(z)$ is the number of vacancies posted by firms for each type of worker. 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

$$m(u,v) \equiv \frac{u\,v}{(u^\alpha + v^\alpha)^{\frac{1}{\alpha}}}. \tag{12}$$

Equation (12) 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:

$$b_t = \bar{b}\,A_t. \tag{13}$$

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. (2022), the opportunity cost of employment has a unit elasticity to aggregate productivity, which is consistent with Chodorow-Reich and Karabarbounis (2016).

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: each nonemployed worker can 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 month, 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 will make labor supply decisions to maximize the net present value (NPV) of labor earnings plus the value of unemployment, net of search costs.

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

$$c_t = \bar{c}\, A_t \left(\theta_t(\bar{z}_O)\right)^{\lambda}. \tag{14}$$

As in Mukoyama, Patterson, and Şahin (2018), we assume that the cost of search increases with aggregate tightness in the labor market.[5] 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 Competitive Labor Market Search

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 how many vacancies to post for each type of worker, posting the associated value of employment. 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 x_t and A_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. We consider a symmetric equilibrium where each worker of type z searching for a job at time t is offered the same contract with a total continuation value of employment equal to $W_t(z)$.

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

[5] Our indexing the search cost to the tightness of the labor market corresponding to type $\bar{z}_O$ workers, rather than a cross-sectional average, helps keep the model tractable since otherwise we would need to keep track of the evolution of the cross-sectional distribution of z, an endogenous object that depends on the history of aggregate shocks.

pool for the next period (obtaining a continuation value $J_t^U(z)$). Thus, her continuation value equals

$$J_t^O(z) = \max\{J_t^N(z),\ J_t^U(z)\}. \tag{15}$$

A nonparticipating worker simply collects the nonemployment benefit specified in (13) at time t and, conditional on surviving to $t+1$, begins the next period as a nonemployed worker. Her continuation value

$$J_t^N(z) = b_t + (1-\nu)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1} J_{t+1}^O(z')\right]. \tag{16}$$

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

$$J_t^U(z) = b_t - c_t + (1-\nu)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1}\left\{J_{t+1}^O(z') + p(\theta_{t+1}(z'))\left(W_{t+1}(z') - J_{t+1}^O(z')\right)\right\}\right], \tag{17}$$

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

Firm Search

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

$$J_t^{MC}(z) = A_t\, z + (1-\nu)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1}\left\{s J_{t+1}^O(z') + (1-s) J_{t+1}^M(z')\right\}\right], \tag{18}$$

where

$$J_t^M(z) = \max\left\{J_t^{MC}(z),\ J_t^O(z)\right\} \tag{19}$$

is the current total value of a match.

A match is continued at time t if the continuation value of the match exceeds the value at nonemployment:

$$\mathbb{1}_t^C(z) = 1 \quad \Leftrightarrow \quad J_t^{MC}(z) \geq J_t^O(z). \tag{20}$$

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 (15). As a result, the present value of a continuing match specified in (18) 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 and wage values to target specific workers. Specifically, firms can 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. The equilibrium value of $W_t(z)$ is pinned down by the firm's first-order conditions in its vacancy posting problem together with the free-entry condition:

$$q(\theta_t(z))\left(J_t^{MC}(z) - W_t(z)\right) \leq \kappa_t, \tag{21}$$

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 (21) holds with equality.

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

$$W_t(z) = J_t^O(z) + \eta(\theta_t(z))\left(J_t^{MC}(z) - J_t^O(z)\right). \tag{22}$$

Equation (22) 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 share of the surplus upon hiring 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 contains further details.

Equation (22) 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. When workers can commit to not leaving their employer (prematurely) and firms can commit to not firing workers (inefficiently), many paths of wages are consistent with (22): firm owners could make a one-time payment of $W_t(z)$ to the worker at time t or pay a constant (or constantly growing) wage over the life of the match. Absent full commitment, these compensation schemes can be problematic ex post. In the first instance, a worker would have a very strong incentive to quit immediately. In the second, positive shocks to productivity can incentivize the worker to quit to earn higher wages elsewhere (as in Harris and Holmstrom, 1982), and negative shocks could incentivize the firm to terminate the match early and discontinue wage payments. Therefore, limited commitment places some restrictions on admissible wages (Thomas and Worrall, 1988). In the next section, we present a model of limited commitment that pins down per-period wages.

2.3 Worker Wages

To derive explicit predictions for wages, we make an additional assumption: firms aim to smooth workers' wages throughout the match, subject to limited commitment on the part of the firm and the worker. The solution to this smoothing problem ensures that neither party has an incentive to inefficiently terminate the match and pins down a unique set of state-contingent wages for the worker. Matches are only efficiently terminated according to the equilibrium termination policy specified in (20). All that is required for the contract to be consistent with the equilibrium above is that it delivers, in present value terms, the ex ante contracted value in (22) to the worker when she is hired.

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

$$\widehat{W}(\Omega_{i,m,t}) \equiv \widehat{W}^M(\Omega_{i,m,t}) + W_t^S(z_{i,t}). \tag{23}$$

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

The first component in (23) 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

$$\widehat{W}^M(\Omega_{i,m,t}) = w(\Omega_{i,m,t}) + (1-\nu)\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1}(1-s)\,\mathbb{1}_{t+1}^C(z')\,\widehat{W}^M(\Omega_{i,m,t+1})\Big], \tag{24}$$

where the indicator $\mathbb{1}_t^C$ is equal to one if the match is preserved at time t.

The second component of (23) 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

$$W_t^S(z) = (1-\nu)\,\mathbb{E}_{t,z}\Big\{\Lambda_{t+1}\left[J_{t+1}^O(z') + (1-s)\mathbb{1}_{t+1}^C(z')\left(W_{t+1}^S(z') - J_{t+1}^O(z')\right)\right]\Big\}. \tag{25}$$

The worker's total continuation value (23) will fluctuate as idiosyncratic and aggregate shocks are realized. 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 (22) offered to the worker when she is hired:

$$\widehat{W}^M(\Omega_{i,m,\tau}) = W_\tau(z_{i,\tau}) - W_\tau^S(z_{i,\tau}). \tag{26}$$

In subsequent periods, the worker's continuation value is a function of the contract state $\Omega_{i,m,t}$ according to (24).

With limited commitment on the part of both worker and firm, there are bounds on how the present value of wages from the current match as specified in (24) can evolve over time:

$$\Gamma_t^L(z_{i,t}) \le \widehat{W}^M(\Omega_{i,m,t}) \le \Gamma_t^H(z_{i,t}). \tag{27}$$

The bounds in (27) ensure that no party wishes to inefficiently terminate the contract. The bounds must hold state by state over the life of the contract and depend only on the aggregate variables (A_t, x_t) and worker productivity $z_{i,t}$. We next discuss how these bounds are determined.

Firm Participation Constraint (Upper Bound). The upper bound for the present value of the wage contract is determined by the threat of the firm to terminate the match. The firm would like to terminate the match when its share of the surplus—the present value of future output minus wages—is negative. In contrast to the endogenous separations that occur on the equilibrium path—in which both workers and firms agree that separation is mutually beneficial—these off-equilibrium threats to terminate the match early are inefficient because the total surplus of the match may still be positive. We parameterize the degree of limited commitment by assuming that firms (and workers) incur some reputational cost when terminating a match unilaterally. On the firm side, these costs are a stand-in for potential difficulties that the firm may have in retaining current incumbent workers and attracting additional workers in the future if it inefficiently terminates some workers. Specifically, when a worker is fired, the firm needs to pay the flow reputation cost $f_t = \xi A_t$ for the remaining lifetime of the worker. The present value F_t of these costs satisfies

$$F_t = \xi A_t + (1-\nu)\,\mathbb{E}_t\left[\Lambda_{t+1} F_{t+1}\right]. \tag{28}$$

Given these costs, the firm is tempted to terminate the match only when its share of the surplus becomes sufficiently negative:

$$J_t^{MC}(z) - W_t^S(z) - \widehat{W}^M(\Omega_{i,m,t}) < -F_t. \tag{29}$$

Whenever (29) binds, the firm and the worker agree to lower the worker's continuation value to prevent inefficient termination. Therefore, the firm-side limited commitment constraint implies the following upper bound on wages:

$$\widehat{W}^M(\Omega_{i,m,t}) \leq \Gamma_t^H(z) \equiv J_t^{MC}(z) + F_t - W_t^S(z). \tag{30}$$

Worker Participation Constraint (Lower Bound). The lower bound for the wage contract is determined by a worker's off-equilibrium threat to walk away from the match and enter the pool of nonemployed workers. In direct analogy with the firm problem, workers who quit their job inefficiently incur the same reputation cost (28) that firms do whenever they inefficiently terminate a match. On the worker side, these costs are a stand-in for the loss of unemployment benefits or for adverse perceptions of the worker's productivity going forward. Whenever the worker is tempted to quit her job while the value of the match is positive, the firm increases the worker's continuation value to prevent the inefficient dissolution of the match when the total surplus is still positive. Thus, the lower bound on the worker's continuation value equals

$$\widehat{W}^M(\Omega_{i,m,t}) \geq \Gamma_t^L(z) \equiv J_t^O(z) - W_t^S(z) - F_t. \tag{31}$$

Even though (30) and (31) place restrictions on the path of future worker wages, they are not sufficient to fully determine them. The last step in determining wages requires us to assume that workers have a preference for smooth wages, subject to the two limited commitment constraints in (30) and (31). Specifically, firms offer workers a wage contract with state-contingent worker compensation w that solves the following dynamic smoothing problem:

$$\widehat{V}_t(z,\widehat{W}^M) = \max_{w,\{\widehat{W}^{M\prime}\}} \quad \Big\{(1-\chi)\,w^{1-\gamma} + \chi\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1}\,\mathbb{1}^C_{t+1}(z')\,\widehat{V}_{t+1}(z',\widehat{W}^{M\prime})^{1-\gamma}\Big]\Big\}^{\frac{1}{1-\gamma}}\,, \tag{32}$$

subject to the constraint that these wages deliver the promised continuation value $\widehat{W}^M$ in all states of the world,

$$\widehat{W}^M(\Omega_{i,m,t}) = w(\Omega_{i,m,t}) + (1-\nu)(1-s)\,\mathbb{E}_{t,z}\Big[\Lambda_{t+1}\,\mathbb{1}^C_{t+1}(z')\,\widehat{W}^M(\Omega_{i,m,t+1})\Big]\,, \tag{33}$$

and the limited commitment constraints in (27). Here, χ is a time discount factor, and $\gamma > 0$ is a preference parameter that captures the intensity of the desire to smooth wages. We further impose the restriction that $\log\chi = \log(1-\nu) + \log(1-s) + \gamma\,\mu_A$ so that worker wages optimally grow at the same rate as aggregate productivity under full commitment.

Examining equations (30) to (33), we note several points worth discussing. First, the value of the reputation cost ξ allows us to parameterize the severity of the limited commitment problem and thus the scope for insurance within the firm. As long as $\xi \geq 0$, there is always a feasible value for $\widehat{W}^M$ that ensures the firm can retain the worker as long as the surplus created by the match as specified in (20) is positive. As ξ goes to infinity, none of the two limited commitment constraints ever bind, and we are at the full commitment case. When $\xi = 0$, commitment is severely limited, and wages tend to adjust quickly in response to shocks because it is common for either the firm's or the worker's outside option to become binding. Thus, our model nests two extreme cases: fully rigid wages and wages that are renegotiated at high frequency. Our assumption of wage smoothing under limited commitment is in line with the view that firms partially insure (continuing) workers against fluctuations in profitability (Guiso, Pistaferri, and Schivardi, 2005, 2013).[6]

Appendix Figure A.1 illustrates how the two bounds vary as a function of ξ and in response to shocks. In the case of $\xi = 0$, the bounds are relatively close to each other, which implies that wages adjust rapidly to changes in aggregate or worker productivity. Put differently, there is more scope for insurance when ξ is larger. In addition, the risk premium shock x_t can also affect wages for continuing matches. An increase in risk premia lowers the value of employment and the value of the worker's outside option and therefore lowers both bounds relatively more than the value of a given stream of wages—because the wages are smoother (and thus less risky) than the profits from

[6]A common assumption in the literature on optimal contracting with limited commitment is that workers are more risk averse than firms, which leads to a motive for wage smoothing (Thomas and Worrall, 1988; Kocherlakota, 1996; Berk, Stanton, and Zechner, 2010; Ai and Bhandari, 2021; Balke and Lamadon, 2022). In our model, both workers and firms are assumed to be risk neutral over idiosyncratic shocks, but this choice is simply for tractability. Strictly speaking, workers in our model are indifferent between all wage paths that satisfy the initial condition and the limited commitment bounds. Nonetheless, our assumption that the contract seeks to smooth wages is in line with the standard setup in the optimal contracting literature and the conventional view that firms insure (continuing) workers against aggregate and idiosyncratic fluctuations in profitability to the extent that it is incentive compatible (Guiso et al., 2005, 2013). Parameterizing the degree of commitment with ξ, which determines the speed of adjustment of wages to labor productivity, allows the model to match the response of worker earnings to productivity shocks across different horizons in Table 1.

the match. This valuation effect creates downward pressure on wages for workers who are close to the bounds. A secondary effect occurs because the reputation costs have a dynamic component and thus the degree of commitment power declines with discount rates as both workers and firms assign lower valuations to future reputational costs. This implies that workers close to the upper bound are particularly likely to experience wage decreases following a positive risk premium shock.

In sum, we develop a parsimonious model which determines the evolution of wages over the life of a match. Our formulation resolves the issue of indeterminacy of wages in search models in a manner that can deliver realistic dynamics for worker earnings. That said, we emphasize that our assumptions on the wage contract do not affect the allocation of workers to jobs and are therefore less relevant for the response of worker earnings to discount rates at the bottom of the income distribution since these are driven by job separations. The fact that negative productivity shocks do not lead to job destruction (with risk premia held constant) stems from the model's scale invariance with respect to A. This assumption is made for simplicity: wage rigidity can definitely lead to inefficient separations in response to negative productivity, but our model does not need this mechanism to generate a realistic level of job destruction in response to discount rate news. Allowing the wage contract to lead to inefficient separations would only amplify the fluctuations in income risk implied by the model.

2.4 Equilibrium

An equilibrium in this model consists of a market tightness function $\theta_t(z)$, an employment offer function $W_t(z)$, value functions $J_t^g(z)$ with $g \in \{O, N, U\}$ for workers without a job, value functions $J_t^{MC}(z)$ and $J_t^M(z)$ for (continuing) matches with a corresponding policy rule for terminating existing matches, a wage policy function $w_t(z, \widehat{W}^M)$, and value function $\widehat{V}_t(z, \widehat{W}^M)$ for the wage smoothing problem, such that (i) the offered employment value and corresponding market tightness satisfy the firm optimality in (22); (ii) the value functions satisfy equations (15), (16), (17), (18), and (19); (iii) the free-entry condition (21) holds; and (iv) the wage contract solves the constrained dynamic smoothing problem in (32).

The competitive search equilibrium in our model is both efficient and unique. The efficiency of the equilibrium can be seen directly from equation (22), which is equivalent to a Nash bargaining solution where the Hosios condition holds. Last, the fact that our assumptions on the wage contract in Section 2.3 do not affect the equilibrium allocations allows us to solve for the equilibrium in a block-recursive manner: we first solve for labor allocations and then for the path of realized wages. Appendix B.2 contains further details.

2.5 Calibration

Parameters Calibrated a Priori. Some of the parameters in the model can be calibrated from a priori information (Panel A of Table A.7). We set the mean of the productivity process μ_A equal to the average growth rate of labor productivity between 1947 and 2019 (equal to 2.2% per year) based on BLS data. We select σ_A to match the volatility of TFP growth at the aggregate level (3.8% per year) that we obtain by aggregating our measure of firm-level TFP growth over all public firms in the sample. We choose $\rho = -0.47$ to match the correlation between our measures of aggregate productivity and risk premium shocks. The real risk-free rate is 1.93% per year. We calibrate the model at monthly frequency and convert these parameters to their monthly equivalents when 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, Telyukova, and Visschers (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 ν so that the life span of a worker in the model is 30 years on average. Following Hagedorn and Manovskii (2008), we set the curvature α of the matching function to 0.407. We set $\bar{b} = 0.6$ so that the flow value during nonemployment is 0.6 times the long-run average labor productivity of employed workers, consistent with the value of leisure of 0.6 in Ljungqvist and Sargent (2017). Our choice of $\bar{b}$ is within the set $[0.4, 0.96]$ usually considered in the literature (Shimer, 2005; Hagedorn and Manovskii, 2008). Finally, we pick the wage smoothing parameter $\gamma = 1/2$, consistent with agents having a fairly modest smoothing motive (i.e., an elasticity of intertemporal substitution equal to 2), though in practice the results are insensitive to this choice.

Parameters Calibrated to Asset Pricing Moments. We calibrate the parameters of the stochastic discount factor to match moments of asset prices (Panel B of Table A.7). Given that the model's mechanism operates through changes in valuations of employment matches of relatively long maturities, we choose $\bar{x}$, ψ_x, σ_x, and δ to target both the moments of the stock market as a whole and the moments of a risky portfolio of long-duration stocks based on Gormsen and Lazarus (2023). Our calibration of the stochastic discount factor ($\bar{x} = 0.384, \psi_x = 0.994, \sigma_x = 0.032, \delta = 0.431$) is consistent with the moments of the stock market 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). See Table A.8 and Appendix B.3 for further details.

Parameters Calibrated to Worker Moments. The remaining model parameters s, $\bar{c}$, λ, $\bar{\kappa}$, $\bar{z}_O$, σ_z, and ξ are chosen to minimize the distance between the model-implied worker moments and their direct empirical counterparts (Panel C of Table A.7). We choose the monthly exogenous separation rate $s = 0.0030$ and idiosyncratic volatility $\sigma_z = 0.128$ to target the average monthly separation rates into unemployment and nonparticipation by income group for incumbent workers, estimated with public data from the SIPP of the U.S. Census Bureau (see Appendix A.6 for details). We parameterize $\bar{c}$ by setting the monthly search cost of a worker of type $z = \bar{z}_O$ when x_t is at its long-run mean to 0.0060. This parameter drives mainly the division between average separations into unemployment and nonparticipation as a function of prior earnings. We set the elasticity of the search cost to the level of market tightness equal to $\lambda = 2.28$, which primarily affects the volatility of the unemployment rate. We choose the vacancy cost parameter $\bar{\kappa} = 0.094$ to target average monthly job finding rates by prior income for unemployed workers and the mean unemployment rate. In addition, we target the response of worker earnings growth to productivity shocks and risk premium shocks: we estimate our exact same baseline specification (2) in a large panel of simulated worker data from the model, replacing ϵ_t^{rp} and $\epsilon_{I,t}^{tfp}$ by $\varepsilon_{x,t}$ and $\varepsilon_{A,t}$, scaled to have the same standard deviation. We target income growth exposure by prior earnings bin at horizons of two, three, and five years. The responses of worker earnings to aggregate risk premium and productivity shocks across horizons help identify the parameter governing the loss of human capital in nonemployment, $\bar{z}_O = 0.446$, and the parameter that disciplines the degree of commitment power in wage contracting (and therefore the speed at which worker wages during a match respond to aggregate shocks), $\xi = 0.171$. In total, we target 47 moments in our calibration of the seven model parameters.

Model Fit. Overall, the model does a good job fitting the worker-level moments that we target in our calibration. The top panel of Figure A.2 shows that in both the model and the data, average separation rates are strongly declining in income levels. The bottom panel shows that the model can also match the average job-finding rate for workers at the bottom of the distribution; however, in the model, job-finding rates are increasing in income, whereas in the SIPP data, they are mostly flat. That said, the implications of our model are in line with the empirical findings based on the LEHD from Gregory, Menzio, and Wiczer (2021), who document significant heterogeneity by worker type: high-income workers find jobs faster and are more likely to remain employed than low-income workers. The model delivers a realistic average unemployment rate (6.1 versus 5.7 in the data) and volatility of unemployment (1.3 versus 1.2 in the data), thus providing a resolution to the Shimer (2005) puzzle. In Figure 2, we see that the model can largely replicate the exposure to risk premium and productivity shocks, especially at horizons of three to five years. In both the model and the data, low-income workers are more exposed to risk premium shocks, and less exposed to productivity shocks, than high-income workers. Figure A.3 shows that these exposure measures in the model have significant long-run implications for worker earnings.

2.6 Model Mechanisms

In our model, idiosyncratic income risk fluctuates in response to changes in risk premia. Here, we discuss the model mechanisms that give rise to this result, together with their quantitative importance in our main calibration.

Sources of Worker Heterogeneity. There are two sources of worker heterogeneity in the model that determine how worker earnings respond to risk premium and productivity shocks. The first is the worker's current level of productivity z, which determines her unemployment risk, as we discuss below. In the model, the worker's current productivity z is positively correlated with her current flow wage w, as we see in Figure A.4a. The second source of relevant worker heterogeneity is the worker's current continuation value $\widehat{W}^M$ relative to the wage bounds defined by (30) and (31),

$$\omega(\Omega_{i,m,t}) \equiv \frac{\widehat{W}^M(\Omega_{i,m,t}) - \Gamma_t^L(z)}{\Gamma_t^H(z) - \Gamma_t^L(z)}. \tag{34}$$

A worker's current promised continuation value $\widehat{W}^M$ depends on the entire history of shocks that are reflected in the contract state $\Omega_{i,m,t}$ of the current match.

The worker's value of ω summarizes the present value of the future wages promised to the worker, evaluated relative to the firm's and worker's outside option, which depend on z and the aggregate state. The relation between ω and either the worker's current productivity z_t or wage w_t is rather complex and nonmonotone, as we see in Figures A.4b and A.4c. Instead, ω is most closely related to the ratio of the worker's current wage relative to her current productivity (Figure A.4d).

Job Separations. A key component of the model mechanism is the endogenous job destruction in response to changes in risk premia. 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:

$$J_t^{MC}(z^*(x_t)) = J_t^O(z^*(x_t)). \tag{35}$$

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

An increase in risk premia increases the likelihood of job destruction, especially for low-productivity workers (Figure 3a). This result rests on two features of the model: first, nonemployment benefits are not indexed to current worker productivity z; second, worker productivity grows relatively faster, on average, during employment than during nonemployment. These features have two important implications. First, low-productivity workers are low-surplus workers—that is, $J_t^{MC}(z) - J_t^O(z)$ is strictly increasing in z because the worker's outside option is less sensitive to the current value of z than to the value of employment. Second, the payoffs to employment are relatively more backloaded than the payoffs to nonemployment (the worker's outside option), as we can see in Figure A.5a.

This difference in the timing of payoffs to employment versus nonemployment implies that an increase in the risk premium x_t leads to a greater decline in the value of employment relative to the outside option for the marginal worker, which in turn implies that the separation threshold $z^*(x_t)$ is increasing in x_t. To see this, recall that the risk premia x_t determine 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 (35) have different elasticities with respect to changes in x_t is the differences in the timing of their cashflows. Appendix B.4 discusses this difference in timing and the implications for the separation threshold in detail.

Duration of Nonemployment Spells. The duration of nonemployment spells also depends on risk premia: for any given worker, both the expected duration of nonemployment and uncertainty about its length increase when risk premia rise (Figure 3b). This result obtains because of two forces in the model. First, the job-finding rate falls as the risk premium x_t increases since firms post fewer vacancies and the rate of job destruction increases. Second, workers are less likely to search for a job when risk premia increase. Specifically, when deciding to search for a job, workers trade off the benefits of finding a job against the cost of search and the benefits of nonemployment. The productivity threshold $\underline{z}(x_t)$ above which workers choose to enter the search pool solves

$$J_t^U(\underline{z}(x_t)) = J_t^N(\underline{z}(x_t)). \tag{36}$$

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 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 force that mutes the increase in the threshold: the cost of searching for a job declines as the job market becomes weaker—recall equation (14). In our calibration, the search threshold $\underline{z}(x_t)$ increases with risk premia, though relatively less than the separation threshold $z^*(x_t)$, as we see in Figure A.6.

Wage Risk Exposure for Continuing Workers. The worker's current value of ω (the worker's current promised value relative to the limited commitment bounds) determines the exposure of wages to risk premium and productivity shocks, conditional on the match not being destroyed (Figures 3c and 3d). In the long run, an increase in aggregate productivity leads to an increase in wages, while an increase in risk premia leads to a decline in wages, as the value of all existing matches declines. However, the short-run responses can be different, as firms also aim to smooth wages when possible; their ability to do so is constrained by the two limited commitment bounds in (30) and (31). Wages become increasingly sensitive to productivity and risk premium shocks as the worker's current promised value in (24) approaches the bounds.

In the short run, wages are essentially insensitive to risk premium or productivity shocks unless the worker is already close to the low or the high end of the feasible wage contract values (ω is close to 0 or 1). An increase in risk premia lowers the value of all employment matches while at the same time tightening the bounds—as the present value of the termination cost falls. Therefore, continuing workers near the lower bound ($\omega = 0$) experience an increase in wage earnings, while workers at the upper bound ($\omega = 1$) experience wage declines. An increase in aggregate productivity increases wages for workers near either of the limited commitment bounds since firms cannot perfectly smooth wages for these workers. Workers near the edge of the bounds are more likely to be high-income workers (Figure A.4c), and thus, their earnings exhibit greater sensitivity to productivity shocks. In the medium run, a worker's position can shift closer to the bounds, and thus, exposure increases with the horizon. However, the full pass-through of productivity shocks to wage earnings can be very slow, as we discuss below.

2.7 Pass-Through of Shocks and Worker Earnings Risk

A direct consequence of the mechanisms discussed in the previous section is that the distribution of worker earnings growth is highly left skewed and leptokurtotic (fat-tailed) even though the underlying productivity shocks are log-normally distributed (Figure 4a); in addition, the distribution is more negatively skewed for workers who leave the firm. These patterns are driven by the interaction of two model mechanisms: the possibility of job destruction, which leads to negative skewness, and the increasing sensitivity of wages to shocks as the likelihood of the limited commitment constraints in (30) and (31) binding increases. We next illustrate these economic mechanisms in the model, emphasizing how time variation in risk premia x_t leads to endogenous time variation in idiosyncratic income risk for workers.

Pass-Through of Worker Productivity Shocks to Earnings Is Nonlinear and Asymmetric. The fact that the distribution of worker earnings is left skewed (Figure 4a) is the result of the nonlinear pass-through of worker productivity (z) shocks to worker earnings. This pass-through is highly asymmetric, especially for workers at the bottom of the earnings distribution (Figure 4b). Part of the asymmetry is driven by the possibility of job destruction: negative shocks are more likely to lead to job separations and therefore lead to proportionally greater wage losses than the wage gains associated with positive shocks. Since low-productivity workers are closer to the separation threshold $z^*(x_t)$, the pass-through is more asymmetric for these workers. A second reason for the nonlinear pass-through is that it is easier for the firm to insure the worker against small shocks to z than against larger shocks since larger shocks are more likely to lead to the limited commitment constraints binding.

Pass-Through of Worker Productivity Shocks to Earnings Is State Dependent. The pass-through of idiosyncratic worker productivity shocks to worker wages is also state dependent—it varies with the level of risk premia for all workers (Figure 4c). Increases in risk premia imply that the risk of job loss rises ($z^*(x_t)$ increases), and hence, the pass-through of idiosyncratic z shocks to earnings is amplified when the risk premium x_t is high. As a result, a positive shock to x_t implies that the distribution of earnings growth becomes more left skewed (recall Figure 4a), which allows the model to generate countercyclical idiosyncratic risk for workers (Guvenen et al., 2014).

Pass-Through of Worker Productivity Shocks to Earnings Is Persistent. Figure 4d shows that, even though shocks to workers are transitory, they have a persistent effect on worker earnings. In the short run, firms try to smooth wages, so earnings respond less than productivity to a negative z shock. However, in the long run, the response of earnings increases for two reasons: first, a negative z shock increases the likelihood of job loss, which can have a persistent effect on earnings as human capital depreciates; second, a shock to z may lead the worker to be closer to the wage bounds in (27) and therefore may increase the likelihood of wage adjustment. The end result is that worker earnings responses are significantly more persistent than productivity responses: the long-run response of earnings is higher than the short-run response, even as productivity is mean reverting.

Response to Aggregate Shocks. Figure 5 shows the response of key model variables to shocks to risk premia. An increase in the risk premium leads to a decline in employment and output (Figures 5a to 5c).[7] From the perspective of an individual worker, this leads to an increase in the likelihood of job loss (Figure 5d), which implies an increase in the left-skewness of her income growth (Figures 5e and 5f). The patterns are particularly pronounced for low-income workers—workers whose current earnings are below the 25th percentile. Overall, an increase in risk premia leads to lower earnings growth for workers, primarily for workers who end up leaving the firm (Figures 5g and 5h).

By contrast, productivity shocks have no impact on either unemployment or labor force participation—since the model is scale invariant with respect to A. Appendix Figure A.7 shows that a negative aggregate productivity shock leads to a decline in worker earnings, with the largest effects for high-wage workers. Because firms aim to smooth wages, there is considerable delay in the full pass-through of the productivity shock to wages; even at horizons of five years, less than half of the original decline in productivity is passed on to worker earnings. Workers who are further away from the limited commitment constraints are better insured than workers closer to the bounds.

3 Model Implications

Here, we revisit the links between the model and the data.

3.1 Nontargeted Stylized Facts

First, we examine the ability of the model to match empirical facts that are not explicit calibration targets.

Labor Market Dynamics. Table 5 compares the dynamics of key labor market indicators in the model and in the data. Recall that, out of these moments, only the volatility of the unemployment

[7] The overall sensitivity of employment to risk premia depends not only on how the thresholds $z^*(x_t)$ and $\underline{z}^*(x_t)$ vary with risk premia x but also on the distribution of worker types around the thresholds. Figure A.6 plots the joint distribution of employment status and worker productivity z along the balanced growth path, together with the separation and job searching thresholds at different levels of x_t.

rate is an explicit calibration target. However, we see that the model delivers realistic labor market dynamics. As in the data, the employment–population ratio, labor force participation rate, vacancy–unemployment ratio, separation into nonparticipation, and job-finding rate are procyclical, and the long-term unemployment rate and separation into unemployment are countercyclical. Compared with the data, the model somewhat overstates the volatility of the participation margin. The persistence of most variables is comparable in the model and the data. Importantly, the model matches both the volatility and the cyclicality of separation and job-finding rates.

Risk Premium Shocks and Job Destruction. The model generates time-varying skewness in worker earnings risk through job destruction. However, is the magnitude of job destruction implied by the model in response to risk premium shocks empirically realistic? Figure 6 shows that it is. Specifically, we plot the estimated coefficients β and γ when estimating equation (2) in simulated data, with the dependent variable being one of our two indicators for job loss over the next three years—a zero-earnings quarter or a job separation combined with a tail loss. Even though these parameters are not explicit calibration targets, the model coefficients are close to their empirical counterparts shown in Table 3.

Earnings Exposure for Stayers versus Movers. The model can also largely replicate the differential exposure of stayers versus movers in response to risk premium shocks (Table 4). When we estimate the same specification in simulated data, movers are significantly more adversely exposed to the risk premium shock than stayers, with the difference being particularly salient for low-income workers (Figure 7). By contrast, both stayers and movers have comparable exposure to productivity shocks. One difference between the model and the data is that stayers' earnings exposure to risk premium shocks is somewhat more negative in the data. This difference likely reflects that workers who stay are more positively selected in the model than in the data.

3.2 Testable Predictions

Next, we outline the testable predictions of our model and provide supporting evidence in the data.

Heterogeneity by Worker Tenure. In our model, a worker's tenure at her current job is positively correlated with her productivity (Figure A.8a). The reason for this correlation is selection: high-productivity workers are more likely to remain in their current matches. As a result, our model implies that low-tenure (and therefore low-productivity) workers should be more exposed to risk premium shocks than high-tenure workers. To test this prediction in the data, we re-estimate our baseline empirical specification in (2) but now allow the estimated measures of exposure to risk premium and productivity shocks β and γ to vary with the worker's tenure at her current firm. We then repeat the same exercise in simulated data from the model. Figure 8 compares the estimated exposure measures β and γ between the data and the model. We see that low-tenure workers have higher exposure to risk premium shocks both in the data and in the model: a 10-percentage-point increase in x leads to 2 to 3 percentage points lower earnings growth for low-tenure workers and 0.5 to 1 percentage point lower earnings growth for high-tenure workers. The empirical difference in exposure is significant (Panel A of Table A.9) and is distinct from the differences by prior earnings (Panel B of Table A.9). By contrast, the exposure to productivity shocks is similar for workers with different tenure in both the data and the model. In the model, there is essentially no correlation between a worker's tenure and her position ω in the wage bounds, which determines her exposure to productivity shocks (Figure A.8b).

Heterogeneity by Worker Age. Age plays no explicit role in our model since all workers have the same expected remaining lifetime. However, if it were the case that the model had variation in a worker's expected lifetime, our model mechanism would imply that an increase in risk premia would be significantly more likely to induce separations for younger than for older workers. The reason is that the value of continued employment in (18) for a younger worker would be significantly more backloaded—and hence more sensitive to changes in risk premia x_t—than the employment value of an older worker. To test this implication in the data, we re-estimate our baseline empirical specification from (2), but we now allow the estimated measures of exposure to risk premium and productivity shocks β and γ to vary with the worker's age. Panel A of Table 6 shows that younger workers are significantly more exposed to risk premium shocks than older workers: a 10-percentage-point increase in the risk premium leads to a 2.2-percentage-point decline in the earnings of younger workers and a 1.3-percentage-point decline for older workers. By contrast, the exposure to productivity shocks is similar between younger and older workers. Moreover, this age pattern is distinct from the income pattern that we documented in Section 1, as we see in Panel B.

3.3 Replicating Realized Fluctuations of Unemployment and Income Risk

Thus far, we have focused on evaluating the model based on its unconditional correlations between different variables. However, armed with empirical measures of the two structural shocks ε_x and ε_A, we next explore whether the model can also replicate the realized path of key variables in the data. Specifically, we take the two empirical shocks ϵ^{rp} and ϵ^{tfp} that we constructed in Section 1.1, normalize them to zero mean and unit standard deviation, and accumulate these shocks into levels for A and x using equations (7) and (9). Given these realizations of A and x, we then compute several model-implied variables and compare them to their empirical counterparts. We de-mean the stationary series and remove the long-run trends from the nonstationary series using a band-pass filter.

Labor Market. 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 our risk premium index is constructed primarily using data from financial markets. Examining the figure, we see that the model does fairly well in replicating the realized path of unemployment (the correlation between the data and the model-implied series is 55%). Further, the correlation is significantly higher for the period of the financial crisis of 2008/09 and the subsequent recovery; given that this was a period of strong fluctuations in risk premia (Figure 1a), we view this pattern as supportive of our model mechanism. In addition, the model can capture reasonably well the fluctuations in long-term unemployment (Figure 9b) and the employment–population ratio (Figure 9c). Last, Figure 9d shows that the model can also largely match the realized ratio of labor market tightness (vacancies to unemployment) and therefore provides a quantitative resolution to the Shimer (2005) puzzle.

Labor Income Risk. The top panel of Figure 10 compares the model-implied realization of labor income risk with the time series of income risk from Guvenen et al. (2014). The top left panel (Figure 10a) plots the left tail of earnings growth—the difference between the median and the 10th percentile of earnings growth over the next year. The data and the model-implied series are highly correlated (72%). The right panel (Figure 10b) plots the right tail of income risk—the difference between the 90th percentile and the median of earnings growth rates. Overall, we see that, in both the model and the data, periods of depressed economic activity are times when the left tail of the distribution becomes fatter and the right tail of the distribution becomes thinner. By contrast, expansions are periods when income risk falls: the left tail of the distribution becomes thinner while the right tail increases. The model does a better job replicating the fluctuations in the left tail, which are largely driven by the job destruction margin, than those in the right tail of income growth.

Income Inequality. Last, the bottom two panels of Figure 10 compare the model-implied path of income inequality to the data, using the series from Heathcote et al. (2020).[8] Figure 10c 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 10d 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 in the level of inequality at the bottom; the correlation between the two series is 48%. In the model, left-tail inequality rises when risk premia rise because the workers at the bottom of the earnings distribution suffer larger and more persistent declines in earnings than workers at the middle of the distribution; our findings in Section 1 show that this is also true in the data. By contrast, inequality at the top is essentially acyclical in the model—consistent with the findings of Heathcote et al. (2020).

3.4 Evaluating the Role of Specific Modeling Assumptions

We conclude our analysis by evaluating the role of specific modeling assumptions in generating our key findings. We do so by recalibrating restricted versions of the model to the same target moments.

[8] 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 income quantiles for workers who have been employed for at least one month in the last 5 years.

Tables A.10 and A.11 summarize the parameters and model fit for these restricted versions of the model.

First, we evaluate the role of the reputation cost ξ incurred when a match is inefficiently terminated. This cost, which is never incurred along the equilibrium path, allows us to calibrate the degree of wage smoothing that firms can credibly provide to workers. We consider two extreme cases, one in which the cost is zero ($\xi = 0$) and another in which the cost is infinite, which corresponds to the full commitment case. When $\xi = 0$, worker wages become highly correlated with worker productivity $z\,A$, as wages adjust quickly to productivity shocks. As a result, the version of the model with $\xi = 0$ cannot match the response of worker earnings to aggregate productivity shocks (Figure A.9b). By contrast, the model with full commitment (ξ is infinite) has the opposite limitation: worker earnings become too rigid and very weakly correlated with productivity, implying that this version also has difficulty generating the observed level of pass-through to worker earnings. In addition, we evaluate the role of our assumption that this reputation cost represents a flow cost, as opposed to a fixed, one-time cost. This assumption has only a minor impact on the model's predictions: the assumption of a flow versus a one-time cost serves mainly to make the earnings of high-income stayers more sensitive to risk premium shocks (Figure A.9a).

Second, we evaluate the role of endogenous separations. Eliminating endogenous separations requires us to assume full commitment since firms and workers now need to commit ex ante to continue matches whose ex post total surplus is negative. Since the model now features only exogenous separations, it can no longer match the patterns of separation by income (Figures A.9c). More importantly, this version of the model generates paths for labor income risk and unemployment that are significantly disconnected from the data (Figures A.10a and A.10c).

Third, we assume that there is no skill loss in nonemployment ($\bar{z}_O = \bar{z}_E$). Doing so mutes the response of the termination threshold $z^*(x_t)$ to the level of risk premia x_t, implying that the effect of changes in risk premia on separations becomes negligible (Figure A.9d) and significantly dampens the time variation in unemployment implied by the model (Figure A.10b). The volatility of the unemployment rate is now 0.3%, compared to 1.2% in the data.

Last, we modify our assumptions on the search cost of entering the unemployment pool. We consider two alternatives: we set the cost to zero or to a constant that is proportional to aggregate productivity. The version of the model without the search cost cannot match the patterns of separation by income (Figure A.9c) and generates a somewhat less volatile unemployment rate (0.9%). The version of the model with a constant search cost performs comparably to our baseline calibration, except that it also generates a less volatile unemployment rate (0.9%).

Conclusion

Overall, we provide theory and evidence that fluctuations in risk premia lead to fluctuations in unemployment, idiosyncratic risk for workers, and increases in income inequality—primarily at the bottom of the 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. We find that these shocks disproportionately affect the earnings of low-income workers, and to the extent that these workers have larger MPCs than high-income workers (Patterson, 2022), our model mechanism implies that fluctuations in risk premia should have a significant impact on aggregate demand. Further, to the extent that monetary policy affects risk premia (Moreira and Savov, 2017; Caballero and Simsek, 2020; Campbell et al., 2020; Caballero and Simsek, 2022), our work suggests a novel channel through which monetary policy can affect aggregate demand. Second, the same model mechanism that leads to fluctuations in job destruction, and therefore idiosyncratic income risk, in response to risk premium shocks is also likely to lead to similar fluctuations in response to other forces that potentially drive asset returns. One promising example is deviations from rational expectations (Bordalo, Gennaioli, LaPorta, and Shleifer, 2019) that could lead to amplified responses of unemployment and income risk to productivity shocks. 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. Last, an increase in risk premia in our model lead to an increase in average wages, as marginal 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). We will explore these aspects in future work.

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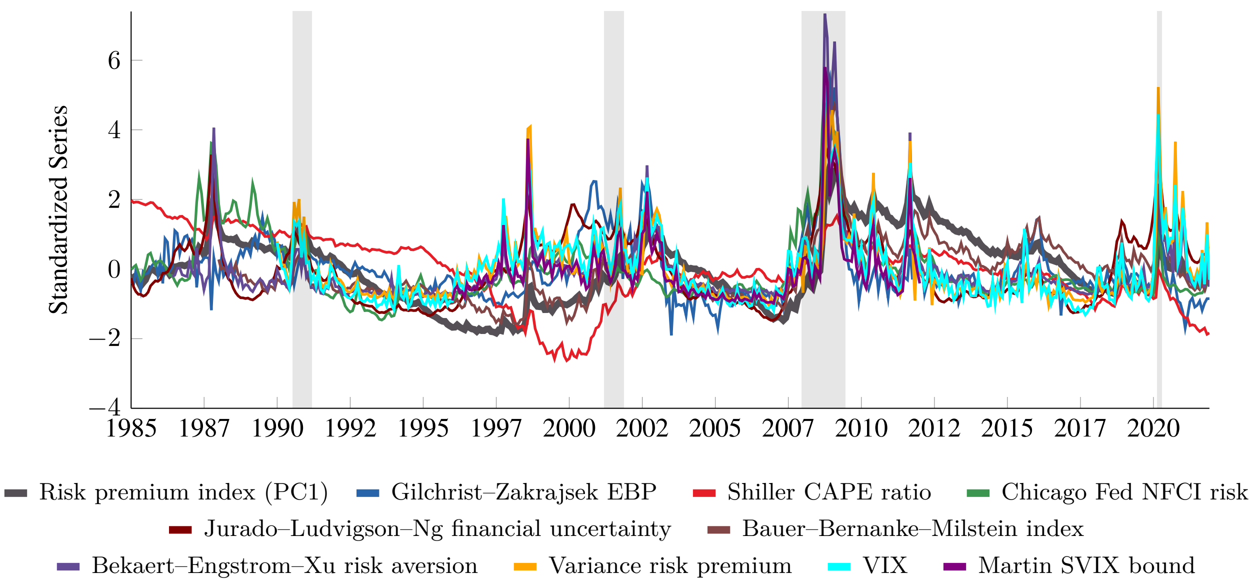
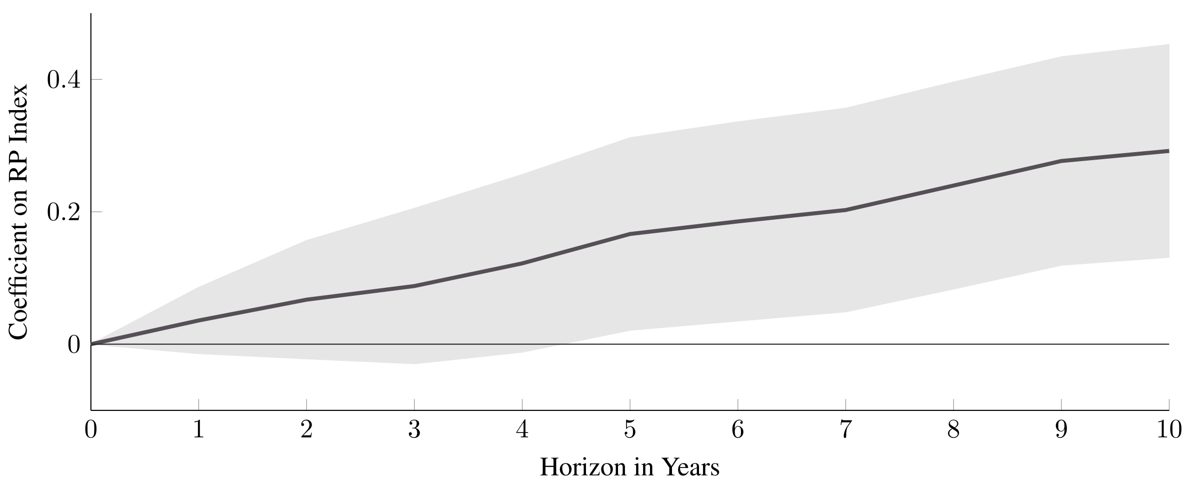
Figures and Tables

Figure 1: Time-Varying Risk Premia in the Data

(a) Risk Premium Measures



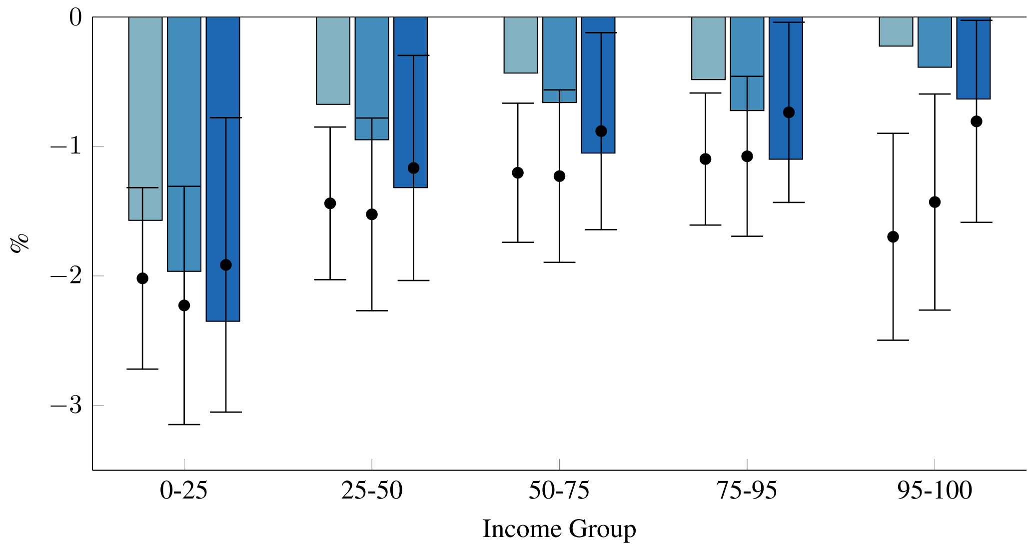
(b) Risk Premium and Future Stock Market Returns



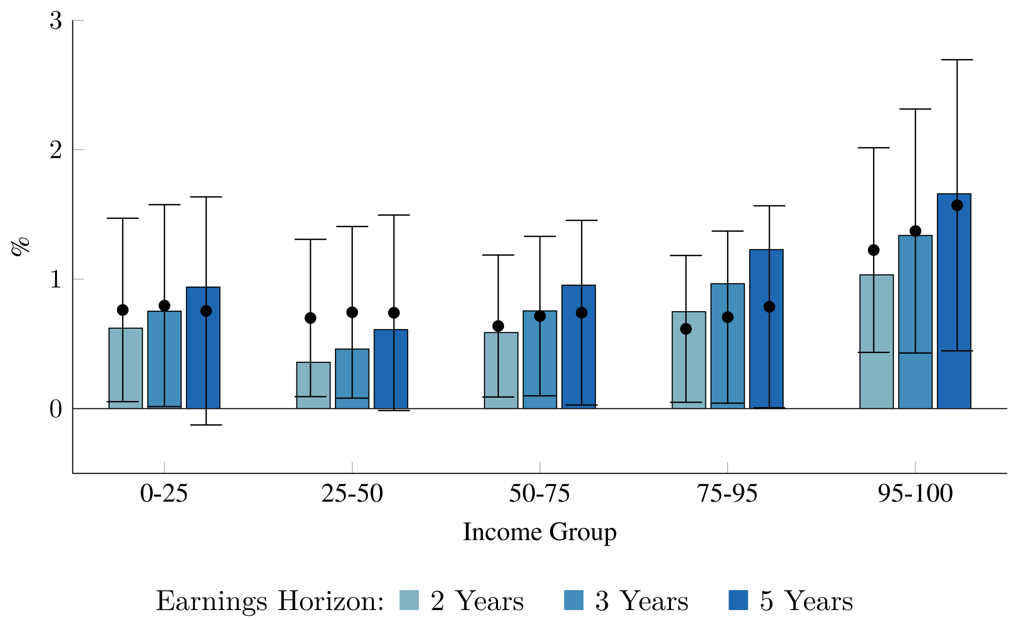
The top panel of this figure plots our risk premium index and the nine series that we use as inputs from the literature: the excess bond premium from Gilchrist and Zakrajšek (2012); Robert Shiller's CAPE Ratio; the Chicago Fed's National Financial Conditions Index (NFCI); the financial uncertainty index 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 of Martin (2016). We measure risk premium shocks as the PC(1) of the AR(1) residuals from each series. The risk premium index is the EWMA(0.0063) of the risk premium shock. All series are standardized. The bottom panel 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 at different horizons H. The shaded area shows pointwise 95% confidence bands, calculated with Hansen–Hodrick standard errors.

Figure 2: Model versus Data: Worker Risk Exposures (Targeted)

(a) Exposure to Risk Premium Shocks

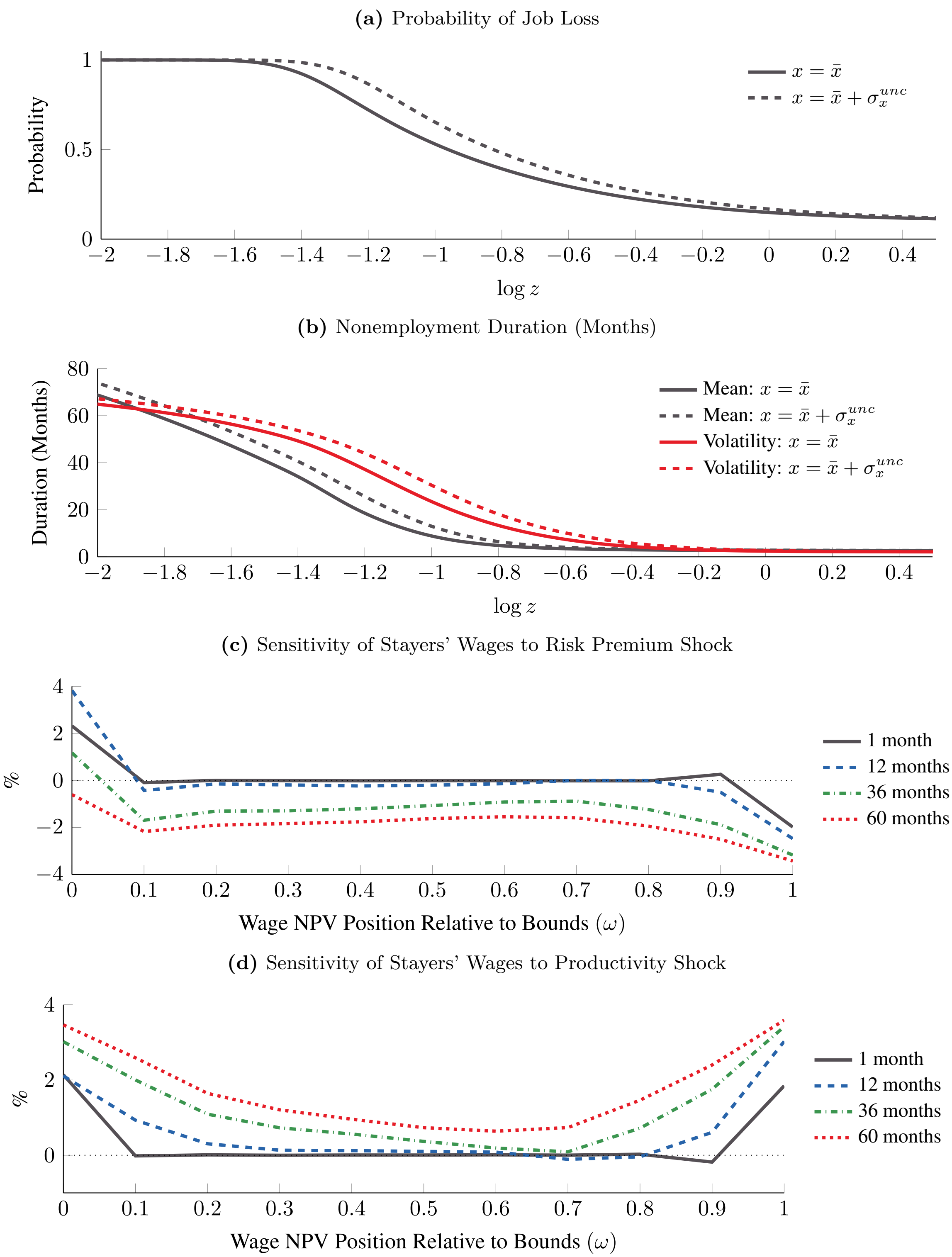


(b) Exposure to Productivity Shocks



This figure reports the regression coefficients β and γ from estimates of equation (2) in the model and in the data, with cumulative income growth over various horizons h as the dependent variable. Panel (a) reports exposure to risk premium shocks, and Panel (b) reports exposure to productivity shocks. We estimate exposures across the worker earnings distribution by interacting the two shocks with indicators for the worker's prior earnings bin. Model coefficients are indicated by the bars; empirical coefficients are indicated by the black dots, with 95% confidence intervals. Coefficients are scaled so that they correspond to a 10% shock.

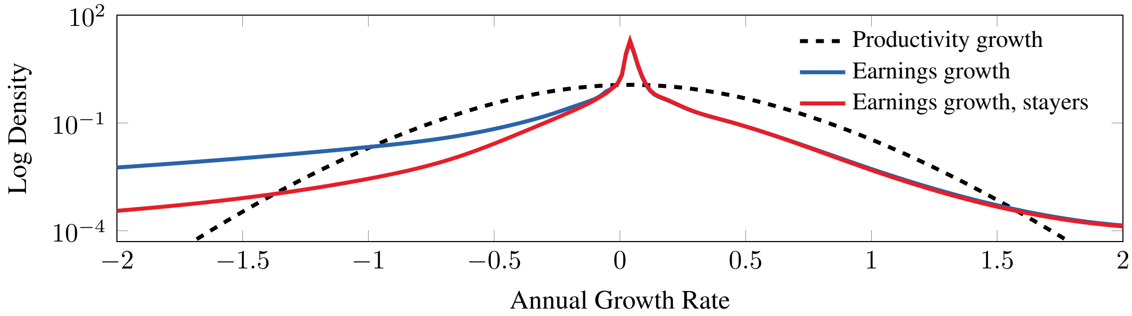
Figure 3: Model: Determinants of Worker Risk



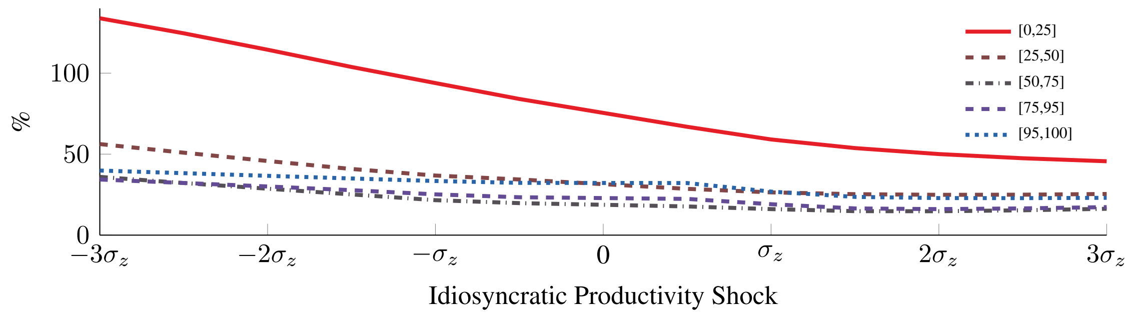
Panel (a) of this figure plots the probability of match termination over the next three years by z for incumbent workers. Panel (b) plots the expected nonemployment duration (in months) by z for nonemployed workers. Panels (c) and (d) plot the average change in stayers' wages following a risk premium shock and productivity shock of one annual standard deviation, respectively, as a function of the wage continuation value relative to the bounds, for incumbent workers with $z \sim N(\bar{z}_E, \sigma_z)$.

Figure 4: Model: Pass-Through of Worker Productivity to Earnings

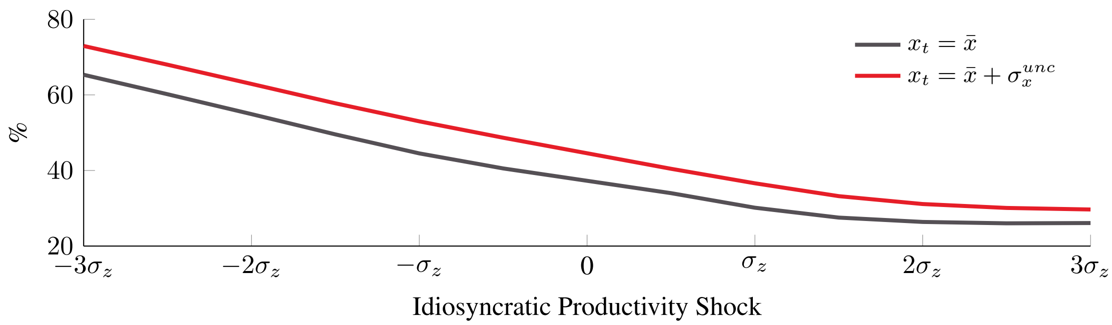
(a) Unconditional Distribution of Productivity and Earnings Growth



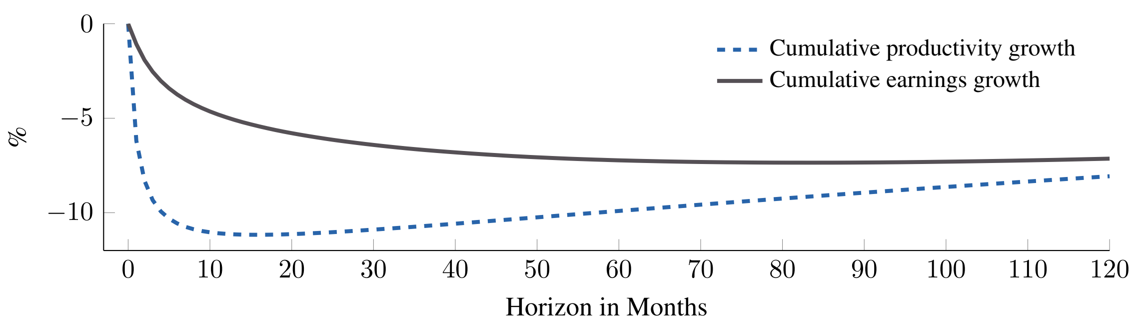
(b) Pass-Through of Worker Productivity Shock by Shock Size and Income Level



(c) Pass-Through of Worker Productivity Shock by Shock Size and Aggregate State

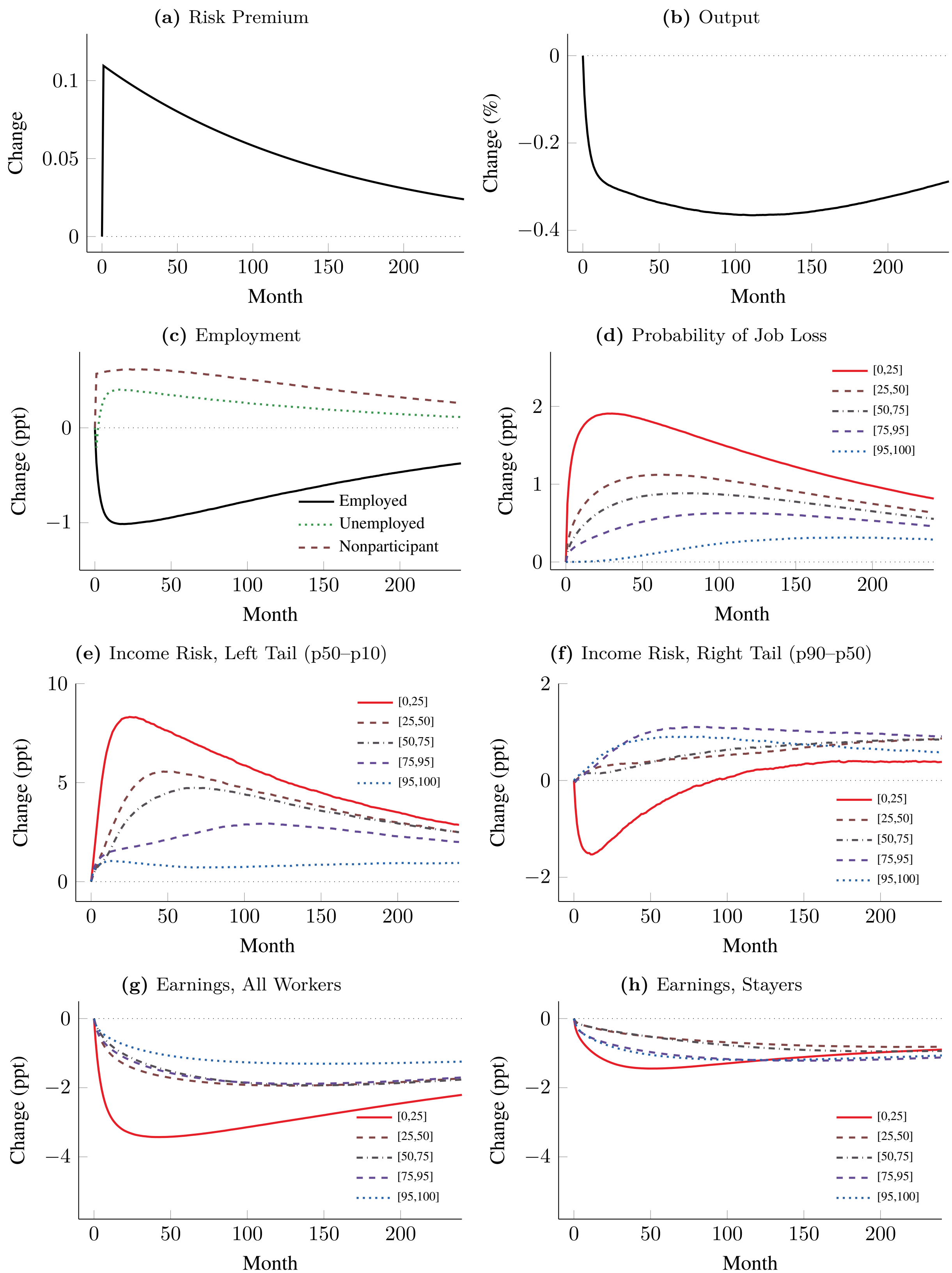


(d) Response to Negative Worker Productivity Shock by Horizon



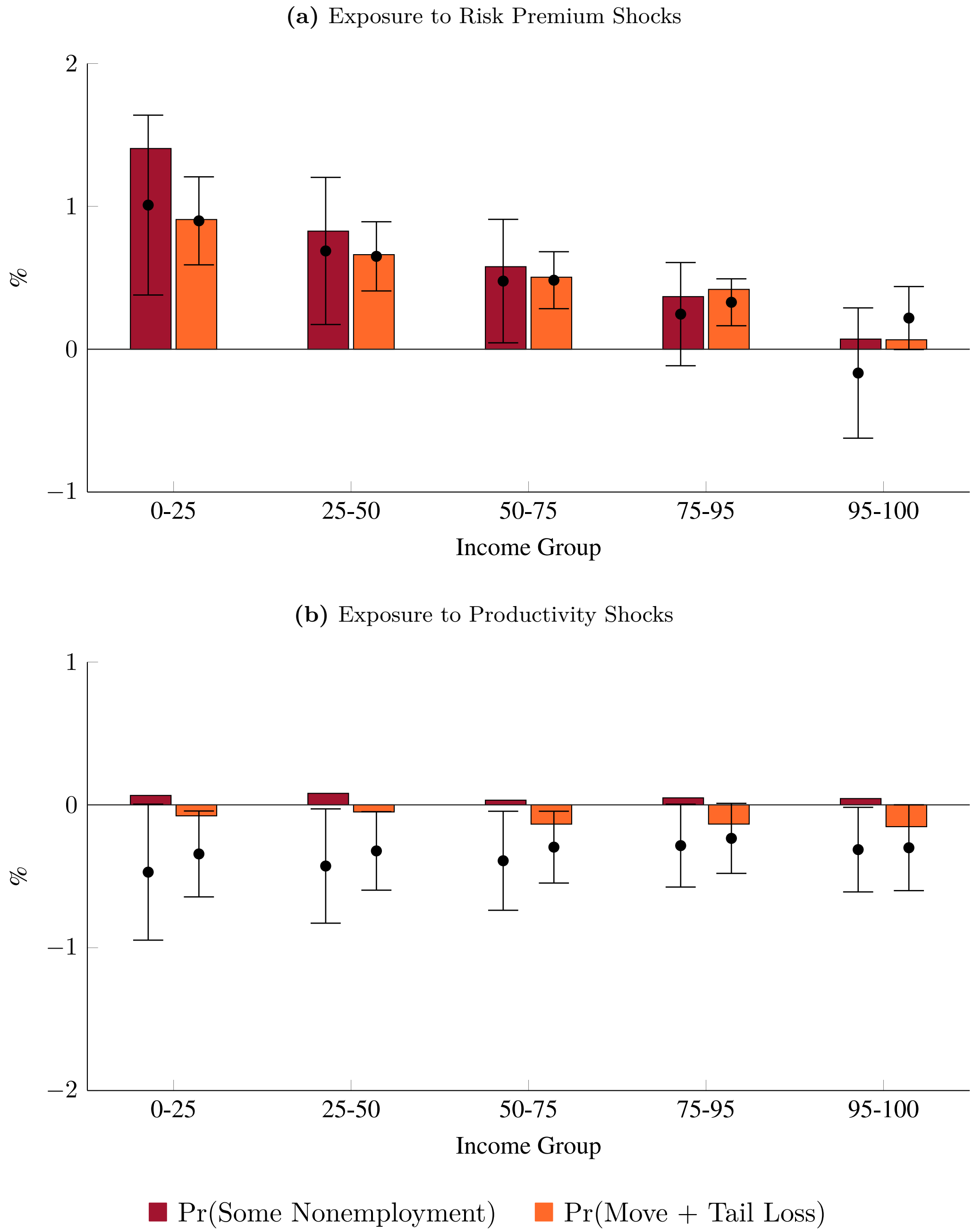
Panel (a) of this figure plots the unconditional distributions of annual productivity growth, earnings growth, and stayers' earnings growth, for workers with full-year employment in the prior year. Panels (b)–(d) illustrate heterogeneity in the response of incumbent worker earnings to a worker productivity shock z, as a function of the size of the shock, the worker's current income, the current level of discount rates x_t, and the horizon, starting from the ergodic distribution. The pass-through coefficient is defined as the average change in log (cumulative) income relative to the change in log (cumulative) worker productivity z after one year, for everyone or by income group.

Figure 5: Model: Impulse Responses to Risk Premium Shocks



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

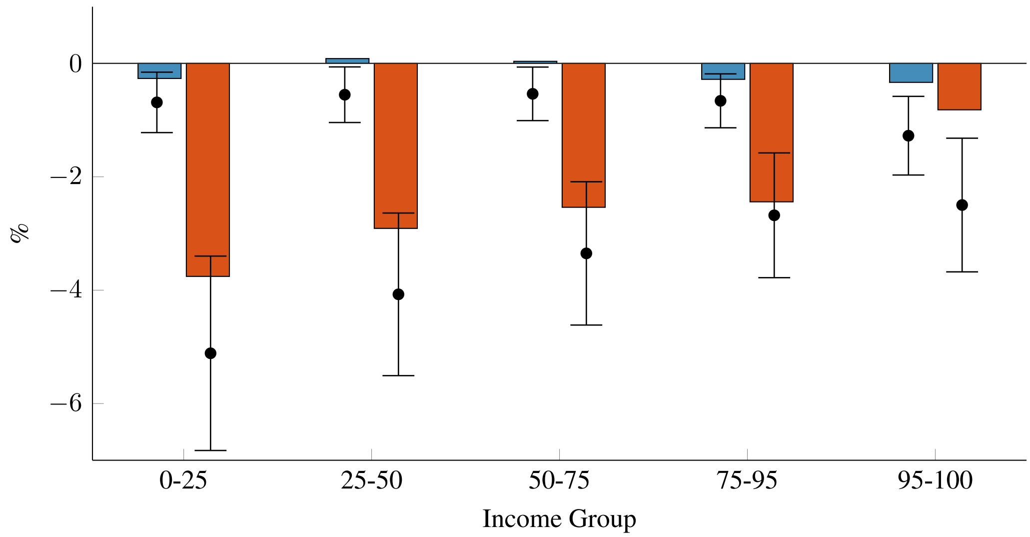
Figure 6: Model versus Data: Risk of Job Loss (Nontargeted)



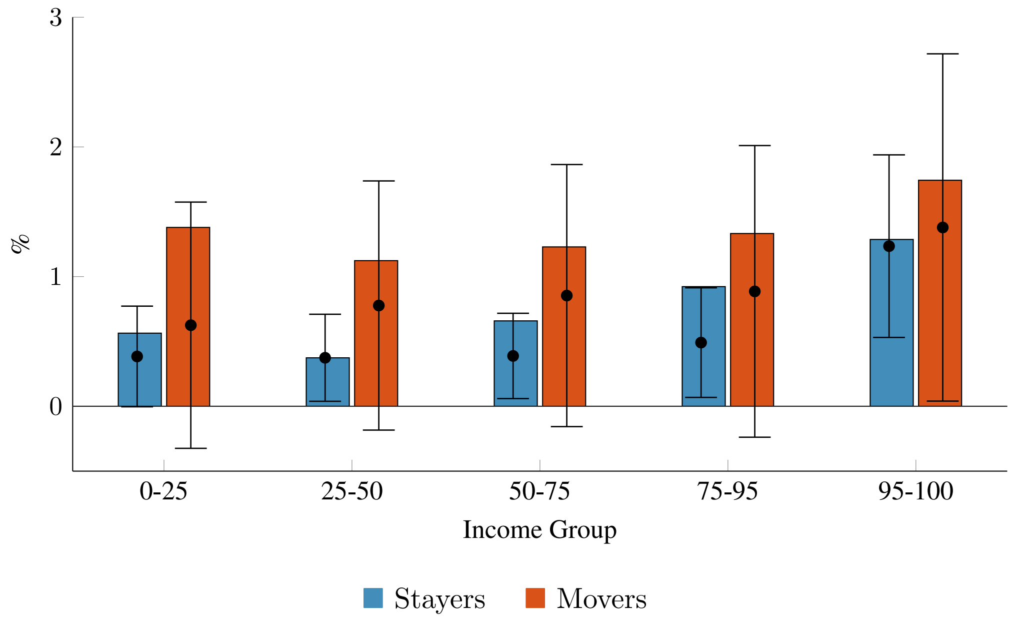
This figure reports the regression coefficients β and γ from estimates of modified versions of equation (2) in the model and in the data, where we replace the dependent variable with two indicators for job loss over the next three years: whether the worker experiences at least one full quarter with zero wage earnings (some nonemployment) or whether the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile (move + tail loss). Panel (a) reports exposure to risk premium shocks, and Panel (b) reports exposure to productivity shocks. We estimate exposure across the worker earnings distribution by interacting the two 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.

Figure 7: Model versus Data: Worker Risk Exposure for Stayers and Movers (Nontargeted)

(a) Exposure to Risk Premium Shocks

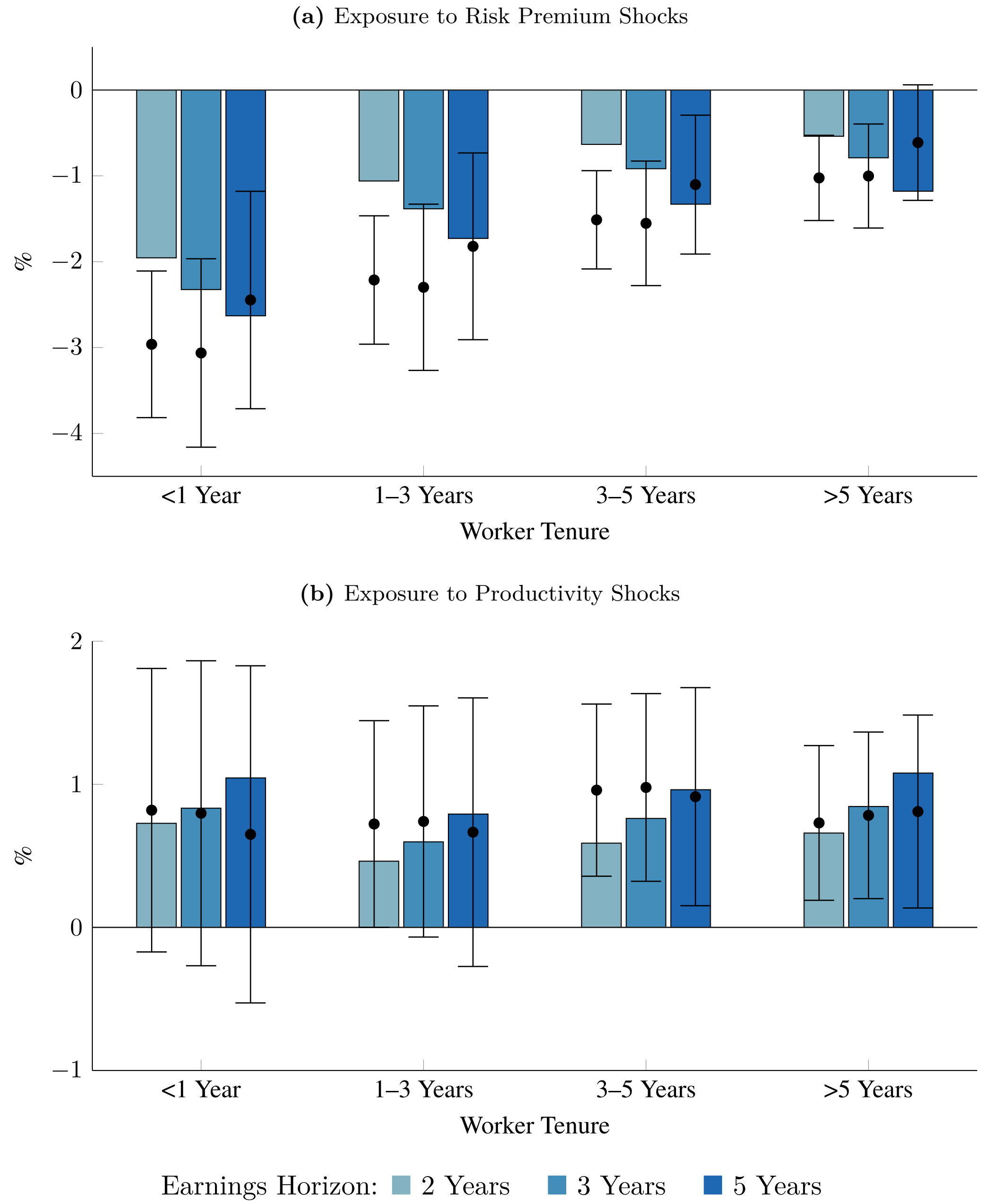


(b) Exposure to Productivity Shocks



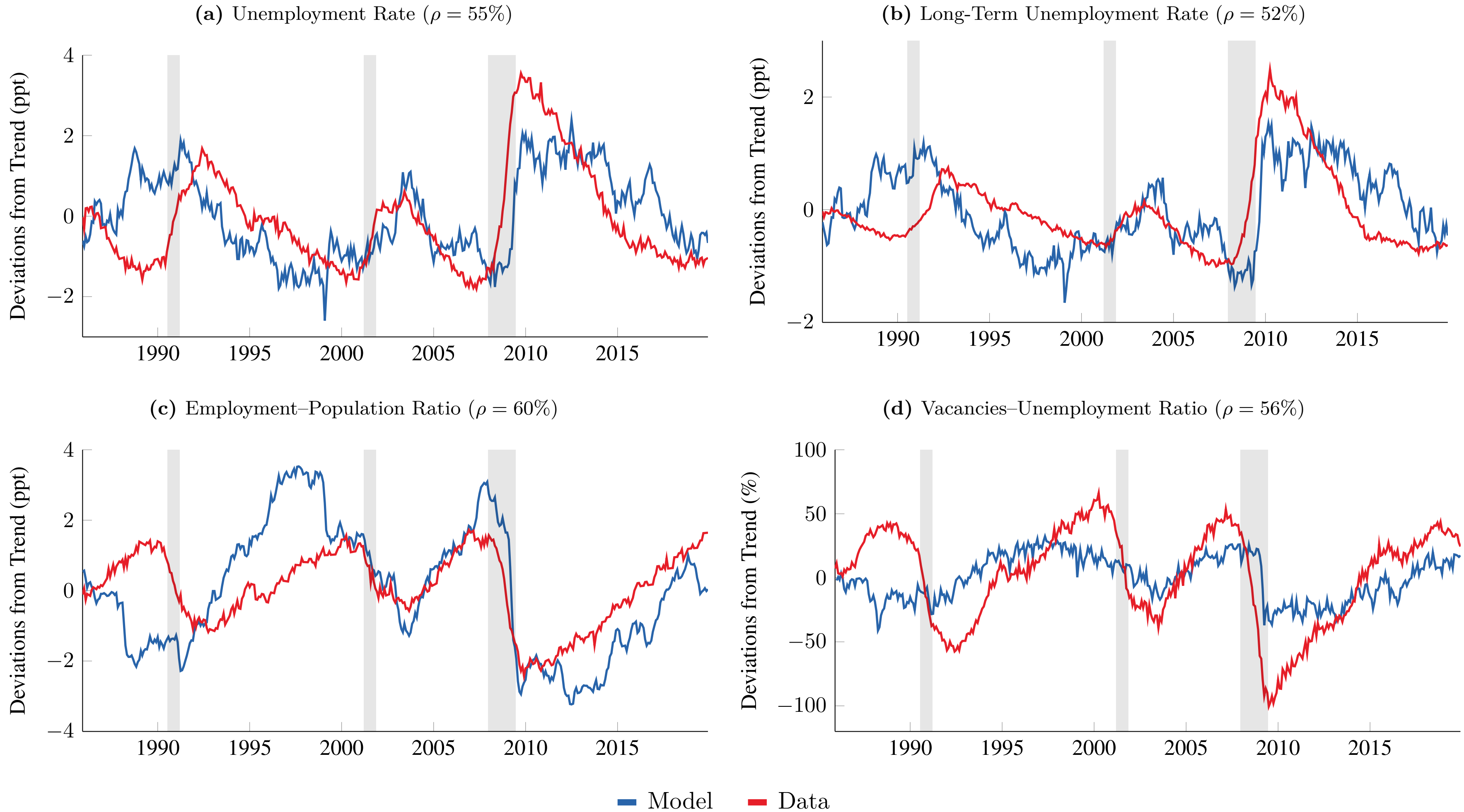
This table reports the regression coefficients β and γ from estimates of equation (2) in the model and in the data, with cumulative income growth over the next three years as the dependent variable, separately estimated for job movers and job stayers. Panel (a) reports exposure to risk premium shocks, and Panel (b) reports exposure to productivity shocks. We estimate exposure across the worker earnings distribution by interacting the two 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.

Figure 8: Model versus Data: Worker Risk Exposure by Worker Tenure (Nontargeted)



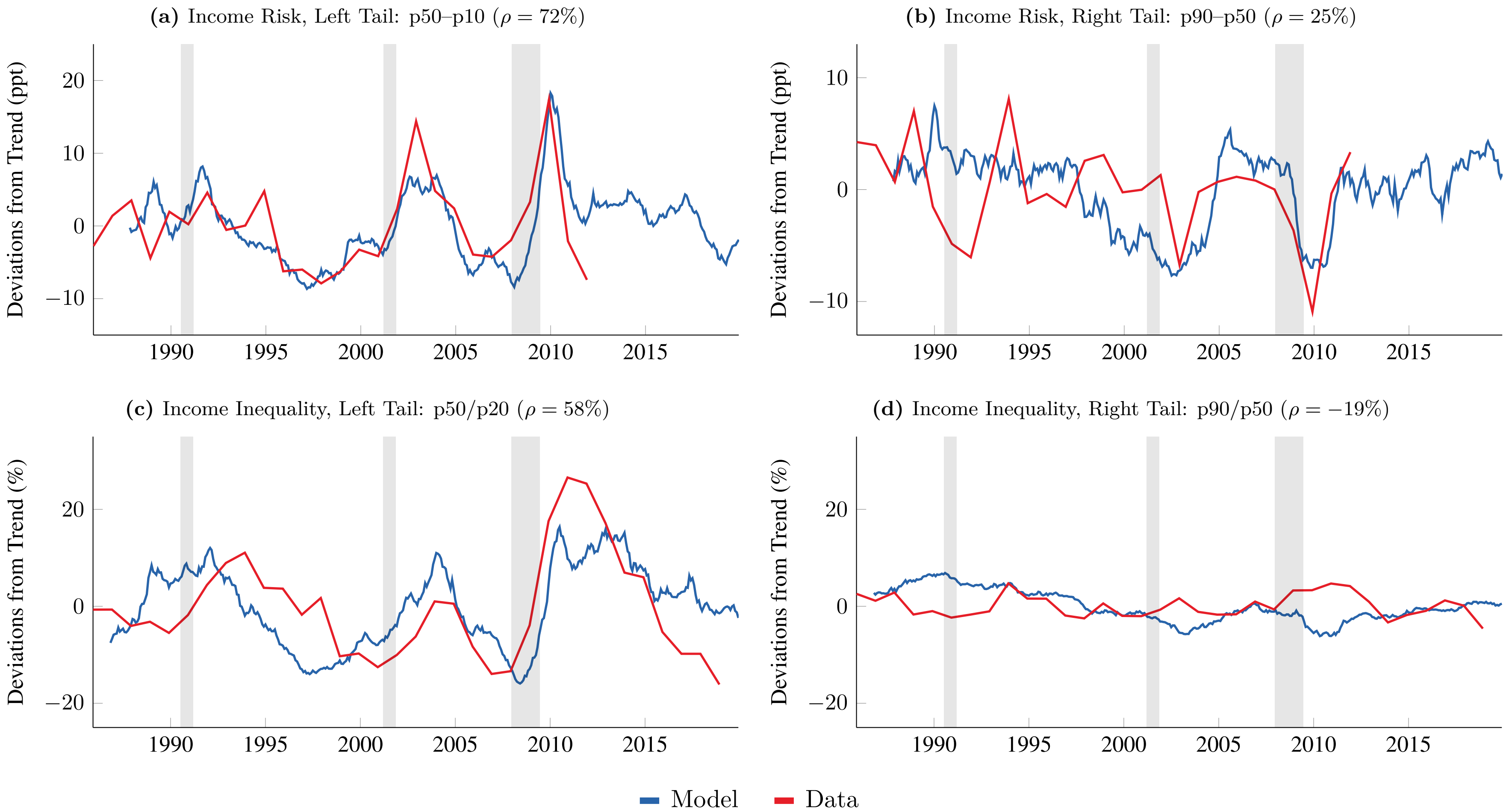
This table reports the regression coefficients β and γ from estimates of equation (2) in the model and in the data, with cumulative income growth over various horizons h as the dependent variable. Panel (a) reports exposure to risk premium shocks, and Panel (b) reports exposure to productivity shocks. We estimate exposure by worker tenure by interacting the two shocks with indicators for the worker's current employment tenure. 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: Model versus Data: Labor Market Dynamics



This figure compares the unemployment rate, employment–population ratio, labor market tightness (ratio of aggregate vacancies to unemployed workers), and long-term unemployment rate (ratio of workers unemployed for more than 6 months to the labor force) between the data and the model. We directly feed into the model our measures of risk premium and productivity shocks ϵ^{rp} and ϵ^{tfp} from Section 1.1, normalized to have zero mean and unit standard deviation, and accumulate these shocks into levels for A and x using equations (7) and (9). We remove the means from the stationary series and detrend the nonstationary series using a band-pass filter with quarterly smoothing parameter 10^5.

Figure 10: Model versus Data: Dynamics of Income Risk and Inequality



This figure compares the realized paths of income risk and income inequality between the data and the model. In the first two panels, we plot the difference between the median and the 10th percentile (p50–p10) of income growth and the difference between the 90th percentile and the median (p90–p50). The empirical series are from Guvenen et al. (2014). In the last two panels, we plot the log ratio of the median to the 20th percentile of labor income (p50/p20), and the log ratio of the 90th percentile to the median (p90/p50). The empirical series are from Heathcote et al. (2020). We directly feed into the model our measures of risk premium and productivity shocks ϵ^{rp} and ϵ^{tfp} from Section 1.1, normalized to have zero mean and unit standard deviation, and accumulate these shocks into levels for A and x using equations (7) and (9). We remove the means from the stationary series and detrend the nonstationary series using a band-pass filter with quarterly smoothing parameter 10^5.

Table 1: Worker Exposure to Risk Premium and Productivity Shocks

	A. Average Exposure					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
All Workers	-1.48	0.71	-1.54	0.77	-1.18	0.80
	(-4.98)	(2.30)	(-4.12)	(2.24)	(-2.72)	(2.00)
Observations	60.2m		57.3m		51.3m	
Fixed Effects	NAICS4		NAICS4		NAICS4	
Clustering	N4, Year		N4, Year		N4, Year	

	B. By Worker Earnings (Within Firm)					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	-2.02	0.76	-2.23	0.80	-1.92	0.76
	(-5.65)	(2.11)	(-4.75)	(2.00)	(-3.30)	(1.68)
Prior Earnings, 25–50th Percentile	-1.44	0.70	-1.52	0.74	-1.17	0.74
	(-4.79)	(2.26)	(-4.02)	(2.20)	(-2.63)	(1.92)
Prior Earnings, 50–75th Percentile	-1.20	0.64	-1.23	0.71	-0.88	0.74
	(-4.40)	(2.28)	(-3.62)	(2.28)	(-2.28)	(2.04)
Prior Earnings, 75–95th Percentile	-1.10	0.62	-1.08	0.71	-0.74	0.79
	(-4.22)	(2.13)	(-3.42)	(2.09)	(-2.08)	(1.98)
Prior Earnings, 95–100th Percentile	-1.70	1.23	-1.43	1.37	-0.81	1.57
	(-4.17)	(3.04)	(-3.36)	(2.85)	(-2.03)	(2.74)
Bottom (1) – Middle (3) Earners	-0.81	0.12	-1.00	0.08	-1.03	0.01
	(-7.87)	(1.11)	(-6.71)	(0.64)	(-4.74)	(0.09)
Middle (3) – Top (5) Earners	0.49	-0.59	0.20	-0.66	-0.08	-0.83
	(1.55)	(-2.63)	(0.66)	(-2.56)	(-0.27)	(-2.76)
Bottom (1) – Top (5) Earners	-0.32	-0.46	-0.80	-0.58	-1.11	-0.82
	(-1.01)	(-1.75)	(-2.37)	(-1.82)	(-2.68)	(-2.09)
Observations	60.2m		57.3m		51.3m	
Fixed Effects	N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp	
Clustering	N4, Year		N4, Year		N4, Year	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income growth over various horizons h as the dependent variable. In Panel A, we report average worker exposure. In Panel B, we report exposure across the worker earnings distribution, which we estimate by interacting the two shocks with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted with income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income 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 industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table 2: Worker Exposure to Risk Premium Shocks, Shift-Share Design

	Measure of Firm Exposure to Risk Premium Shocks						
	Stock Return Exposure to Market	Stock Return Exposure to RP	Maturing Debt Next 2 Years	Cash to Assets	Firm Size	Distance to Default	Whited–Wu Index
	RP	RP	RP	RP	RP	RP	RP
Prior Earnings, 0–25th Percentile $\times \chi_f$	-0.26	-0.41	-0.42	-0.48	-0.27	-0.41	-0.34
	(-2.37)	(-3.84)	(-4.12)	(-2.38)	(-2.60)	(-4.07)	(-2.98)
Prior Earnings, 25–50th Percentile $\times \chi_f$	-0.13	-0.25	-0.21	-0.38	-0.21	-0.40	-0.31
	(-1.37)	(-2.73)	(-2.59)	(-2.01)	(-2.25)	(-4.37)	(-3.19)
Prior Earnings, 50–75th Percentile $\times \chi_f$	-0.11	-0.22	-0.20	-0.34	-0.21	-0.38	-0.31
	(-1.27)	(-2.59)	(-2.61)	(-1.99)	(-2.42)	(-4.36)	(-3.16)
Prior Earnings, 75–95th Percentile $\times \chi_f$	-0.10	-0.13	-0.23	-0.34	-0.03	-0.28	-0.12
	(-0.98)	(-1.36)	(-2.94)	(-1.69)	(-0.33)	(-3.36)	(-1.27)
Prior Earnings, 95–100th Percentile $\times \chi_f$	-0.04	-0.14	-0.17	-0.06	0.19	-0.14	0.06
	(-0.24)	(-0.79)	(-1.43)	(-0.22)	(1.10)	(-1.09)	(0.36)
Bottom (1) – Middle (3) Earners	-0.15	-0.19	-0.22	-0.13	-0.06	-0.03	-0.03
	(-1.96)	(-2.25)	(-2.73)	(-1.05)	(-0.83)	(-0.43)	(-0.46)
Middle (3) – Top (5) Earners	-0.08	-0.08	-0.03	-0.29	-0.40	-0.24	-0.37
	(-0.53)	(-0.52)	(-0.25)	(-1.15)	(-2.46)	(-2.15)	(-2.24)
Bottom (1) – Top (5) Earners	-0.23	-0.27	-0.24	-0.42	-0.46	-0.26	-0.40
	(-1.29)	(-1.40)	(-1.72)	(-1.33)	(-2.57)	(-2.13)	(-2.28)
Observations	49.7m	49.1m	47.8m	56.4m	56.4m	52.4m	55.9m
Fixed Effects	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc
Clustering	Firm	Firm	Firm	Firm	Firm	Firm	Firm

This table reports the regression coefficient β from estimates of equation (3) with cumulative three-year income growth as the dependent variable, for various measures of firm-level exposure $\chi_{f,t}$. We report exposure across the worker earnings distribution that we estimate by interacting $\chi_{f,t} \times \epsilon^{rp}_{t+1}$ with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, and fixed effects for the worker's industry I (4-digit NAICS) by year t, interacted with her income 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 clustered by firm in parentheses. Exposures χ_f are standardized to have unit cross-sectional standard deviation, and coefficients are scaled so that they correspond to a 10% shock.

Table 3: Worker Exposure to Risk Premium and Productivity Shocks, Likelihood of Job Loss

	Pr(Some Nonemployment)				Pr(Move + Tail Loss)			
	2 Years		3 Years		2 Years		3 Years	
	RP	TFP	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	1.11	-0.44	1.01	-0.47	0.75	-0.32	0.90	-0.34
	(4.33)	(-2.07)	(3.14)	(-1.94)	(6.95)	(-2.24)	(5.72)	(-2.24)
Prior Earnings, 25–50th Percentile	0.79	-0.36	0.69	-0.43	0.54	-0.30	0.65	-0.32
	(3.94)	(-2.08)	(2.62)	(-2.10)	(6.36)	(-2.36)	(5.26)	(-2.30)
Prior Earnings, 50–75th Percentile	0.58	-0.29	0.48	-0.39	0.43	-0.26	0.48	-0.30
	(3.50)	(-1.97)	(2.16)	(-2.21)	(5.94)	(-2.32)	(4.75)	(-2.30)
Prior Earnings, 75–95th Percentile	0.35	-0.21	0.25	-0.29	0.30	-0.21	0.33	-0.23
	(2.38)	(-1.61)	(1.33)	(-1.93)	(4.82)	(-2.13)	(3.92)	(-1.87)
Prior Earnings, 95–100th Percentile	0.02	-0.20	-0.17	-0.31	0.23	-0.24	0.22	-0.30
	(0.11)	(-1.52)	(-0.72)	(-2.07)	(2.72)	(-2.27)	(1.94)	(-1.96)
Bottom (1) – Middle (3) Earners	0.53	-0.15	0.53	-0.08	0.32	-0.06	0.42	-0.05
	(5.09)	(-1.60)	(4.51)	(-0.80)	(7.46)	(-1.19)	(6.85)	(-0.88)
Middle (3) – Top (5) Earners	0.56	-0.09	0.64	-0.08	0.20	-0.02	0.27	0.00
	(-1.56)	(-0.97)	(-1.50)	(-0.89)	(-0.67)	(-0.36)	(-0.82)	(0.06)
Bottom (1) – Top (5) Earners	1.09	-0.24	1.18	-0.16	0.52	-0.08	0.68	-0.04
	(5.70)	(-1.66)	(4.23)	(-1.04)	(6.72)	(-0.91)	(5.66)	(-0.40)
Observations	60.2m		57.3m		60.2m		57.3m	
Fixed Effects	N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp	
Clustering	N4, Year		N4, Year		N4, Year		N4, Year	

This table reports the regression coefficients β and γ 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 (some nonemployment) 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 that we estimate by interacting the two shocks with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted by income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income 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 industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table 4: Worker Exposure to Risk Premium and Productivity Shocks, Stayers versus Movers

	Risk Premium Shocks						Productivity Shocks					
	2 Years		3 Years		5 Years		2 Years		3 Years		5 Years	
	Move	Stay	Move	Stay	Move	Stay	Move	Stay	Move	Stay	Move	Stay
Prior Earnings, 0–25th Percentile	-5.84	-0.79	-5.11	-0.69	-3.59	-0.62	0.50	0.43	0.63	0.38	0.77	0.25
	(-7.47)	(-3.19)	(-5.84)	(-2.53)	(-3.86)	(-1.99)	(0.94)	(2.27)	(1.29)	(1.94)	(1.48)	(1.13)
Prior Earnings, 25–50th Percentile	-4.71	-0.65	-4.07	-0.55	-2.66	-0.43	0.75	0.41	0.78	0.37	0.92	0.28
	(-7.08)	(-2.78)	(-5.57)	(-2.21)	(-3.64)	(-1.61)	(1.37)	(2.43)	(1.59)	(2.19)	(1.89)	(1.52)
Prior Earnings, 50–75th Percentile	-3.96	-0.62	-3.35	-0.54	-2.12	-0.39	0.84	0.41	0.85	0.39	0.94	0.36
	(-6.67)	(-2.78)	(-5.20)	(-2.23)	(-3.42)	(-1.52)	(1.52)	(2.43)	(1.66)	(2.31)	(1.89)	(1.86)
Prior Earnings, 75–95th Percentile	-3.25	-0.73	-2.68	-0.66	-1.71	-0.47	0.71	0.48	0.89	0.49	1.04	0.50
	(-6.20)	(-3.30)	(-4.77)	(-2.72)	(-3.17)	(-1.80)	(1.19)	(2.38)	(1.54)	(2.28)	(1.92)	(1.97)
Prior Earnings, 95–100th Percentile	-2.85	-1.56	-2.50	-1.28	-1.71	-0.77	0.98	1.16	1.38	1.23	1.71	1.30
	(-5.07)	(-4.30)	(-4.15)	(-3.60)	(-2.91)	(-2.58)	(1.51)	(3.44)	(2.02)	(3.44)	(2.41)	(3.21)
Bottom (1) – Middle (3) Earners	-1.87	-0.17	-1.76	-0.15	-1.47	-0.23	-0.34	0.03	-0.23	-0.00	-0.17	-0.11
	(-7.19)	(-2.86)	(-6.23)	(-2.24)	(-4.26)	(-2.76)	(-1.08)	(0.42)	(-0.75)	(-0.05)	(-0.58)	(-1.01)
Middle (3) – Top (5) Earners	-1.12	0.94	-0.85	0.74	-0.41	0.38	-0.13	-0.75	-0.53	-0.85	-0.77	-0.95
	(-2.19)	(3.25)	(-1.75)	(2.57)	(-0.89)	(1.80)	(-0.36)	(-3.57)	(-1.49)	(-3.53)	(-2.26)	(-3.32)
Bottom (1) – Top (5) Earners	-2.99	0.77	-2.61	0.59	-1.88	0.15	-0.48	-0.72	-0.75	-0.85	-0.94	-1.05
	(-4.55)	(2.71)	(-3.94)	(1.96)	(-2.60)	(0.66)	(-0.87)	(-3.02)	(-1.45)	(-2.99)	(-1.74)	(-3.09)
Observations	13.0m	47.1m	18.5m	38.8m	24.2m	27.1m	13.0m	47.1m	18.5m	38.8m	24.2m	27.1m
Fixed Effects	N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp	
Clustering	N4, Year		N4, Year		N4, Year		N4, Year		N4, Year		N4, Year	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income growth over various horizons h as the dependent variable, separately estimated for job movers and job stayers. Individuals are characterized as stayers if the main employer in year $t+h$ is the same as the main employer in year t and as movers in all other cases. We report exposure across the worker earnings distribution that we estimate by interacting the two shocks with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted by income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income 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 industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table 5: Macro Moments in the Model and Data

	Volatility		Autocorrelation		Correlation w/ Unemployment	
Variable	Model	Data	Model	Data	Model	Data
Unemployment rate	1.280	1.238	0.974	0.986	1.000	1.000
Long-term unemployment rate	0.886	0.572	0.970	0.993	0.964	0.863
Employment–population ratio	2.753	0.959	0.997	0.977	-0.950	-0.921
Labor force participation rate	1.858	0.403	0.987	0.883	-0.869	-0.273
Log V/U ratio	0.224	0.395	0.953	0.988	-0.881	-0.955
Separation rate into U	0.173	0.149	0.741	0.723	0.782	0.517
Separation rate into N	0.122	0.216	0.521	0.562	-0.596	-0.336
Job-finding rate	3.377	4.767	0.671	0.588	-0.776	-0.683

This table reports moments of the monthly unemployment rate, long-term unemployment rate (ratio of workers unemployed for more than 6 months to the labor force), employment–population ratio, log aggregate vacancy–unemployment rate, separation rates into unemployment (U) and nonparticipation (N), and job-finding rate, in the data and in the baseline calibration of our model. The empirical series are from the CPS (first four series, 1948–2019); Barnichon (2010) (vacancies, 1951–2019); and SIPP (last three series, 1996–2013). We remove the means from the stationary series and detrend the nonstationary series using a band-pass filter with quarterly smoothing parameter 10^5.

Table 6: 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)	-2.01	0.54	-2.17	0.59	-1.77	0.52
	(-4.88)	(1.50)	(-4.19)	(1.47)	(-2.86)	(1.09)
Age, 30–40 Years	-1.47	0.69	-1.55	0.73	-1.26	0.74
	(-4.79)	(2.27)	(-4.02)	(2.20)	(-2.72)	(1.94)
Age, 40–50 Years	-1.35	0.76	-1.39	0.81	-1.08	0.85
	(-5.31)	(2.73)	(-4.31)	(2.63)	(-2.80)	(2.44)
Older (50–60 Years)	-1.30	0.76	-1.30	0.87	-0.81	0.94
	(-4.44)	(2.05)	(-3.56)	(2.01)	(-2.09)	(1.85)
Younger – Older	-0.71	-0.22	-0.87	-0.28	-0.97	-0.42
	(-3.36)	(-1.10)	(-3.23)	(-1.27)	(-2.47)	(-1.60)
Observations	60.2m		57.3m		51.3m	

	B. Age and Relative Income					
	2 years		3 years		5 years	
	RP	TFP	RP	TFP	RP	TFP
Younger (25–30 Years)	*Omitted Category*					
Age, 30–40 Years	0.62	0.13	0.72	0.14	0.61	0.23
	(1.41)	(0.36)	(1.29)	(0.35)	(0.91)	(0.48)
Age, 40–50 Years	0.82	0.19	0.98	0.21	0.89	0.33
	(2.05)	(0.55)	(1.95)	(0.56)	(1.51)	(0.73)
Older (50–60 Years)	0.93	0.19	1.15	0.27	1.25	0.44
	(2.50)	(0.55)	(2.50)	(0.67)	(2.33)	(0.92)
Prior Earnings, 0–25th Percentile	-2.75	0.60	-3.11	0.60	-2.77	0.44
	(-5.46)	(1.41)	(-4.72)	(1.32)	(-3.31)	(0.82)
Prior Earnings, 25–50th Percentile	-2.12	0.55	-2.34	0.57	-1.95	0.45
	(-4.86)	(1.47)	(-4.22)	(1.42)	(-2.90)	(0.96)
Prior Earnings, 50–75th Percentile	-1.83	0.50	-1.97	0.55	-1.59	0.47
	(-4.56)	(1.44)	(-3.94)	(1.45)	(-2.67)	(1.04)
Prior Earnings, 75–95th Percentile	-1.68	0.48	-1.76	0.55	-1.38	0.54
	(-4.49)	(1.37)	(-3.84)	(1.38)	(-2.56)	(1.13)
Prior Earnings, 95–100th Percentile	-2.36	1.06	-2.21	1.18	-1.54	1.26
	(-5.00)	(2.32)	(-4.21)	(2.24)	(-2.84)	(2.01)
Bottom (1) – Middle (3) Earners	-0.92	0.10	-1.13	0.05	-1.19	-0.03
	(-7.50)	(0.93)	(-6.37)	(0.40)	(-4.44)	(-0.21)
Middle (3) – Top (5) Earners	0.53	-0.56	0.24	-0.62	-0.04	-0.78
	(1.67)	(-2.51)	(0.80)	(-2.43)	(-0.16)	(-2.63)
Bottom (1) – Top (5) Earners	-0.40	-0.46	-0.90	-0.58	-1.23	-0.82
	(-1.18)	(-1.75)	(-2.49)	(-1.84)	(-2.74)	(-2.11)
Observations	60.2m		57.3m		51.3m	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income 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 and controls are the same as in our baseline specification. We report t-statistics based on standard errors double clustered by industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

A Additional Details on the Empirical Analysis

Here, we provide further details on the empirical analysis, along with additional results and robustness checks.

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 covered 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 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 pretreatment 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 productivity and risk premium 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. 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.

A.2 Risk Premium Shocks

Table A.12 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 for years 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.

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 above 0.5. Table A.13 lists the five monthly observations with the largest risk premium shocks and shows that these coincide with large negative stock returns and large increases in the VIX and credit spreads.

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 and aggregate TFP growth to the 4-digit NAICS level (starting from 1986) and over all firms to obtain measures of industry-level TFP growth and aggregate TFP growth, respectively.

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 firms' revenue-based total factor productivity (TFPR), 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. 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

We construct our various measures of firm exposure to risk premium shocks 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 stock market betas at the end of each year by regressing monthly firm equity returns on the market return over the past ten years, requiring at least 60 monthly observations. We also compute firm betas with respect to our measure of risk premium shocks using the same approach. As measures of firm exposure $\chi_{f,t}$ in (3), 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 $\chi_{f,t}$ 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 $\chi_{f,t}$ in (3), we use the firm's distance to default as of the end of calendar year $t-1$.

A.5 Robustness of Earnings Exposures to Aggregate Shocks

Here, we provide additional details and discussions of the robustness checks in Section 1.3. We show that our main findings are robust to our use of various alternative definitions of the treatment variables and different empirical specifications.

First, one may wonder to what extent our findings are specific to employees of public companies observed in Compustat. In Table A.2, we show that our main findings extend to all workers. Specifically, we estimate our main aggregate specification in (2) in an alternative sample of all workers. To do so, we construct a 5% subsample of all U.S. workers in the LEHD who are employed by any firm, private or public, as of base year t; the data construction is otherwise identical. We find that the exposure to risk premia is approximately the same as in our main sample, again with a significant gradient in income. Exposure to TFP growth is lower, in particular for top earners, likely because our measure of TFP growth does not capture the productivity news of nonpublic firms well.

Second, in Table A.3, we consider an alternative sort of workers, where we construct income bins based on the rank of the worker's prior earnings within her industry rather than her own firm. Again, the exposure to risk premium shocks is nearly identical, and the spread between low-wage workers and middle or top earners is highly significant. The spread in exposure to TFP growth between top workers and other workers becomes weaker, suggesting that only the top earners within their own firm are significantly more exposed to productivity shocks.

Third, Table A.4 shows that our findings are robust to alternative measurement of the two types of shocks. In the top panel, we consider two variations to our measure of risk premium shocks. In the first alternative, we define the risk premium shock as the first principal component of innovations to the four indicators for risk appetite considered in Bauer et al. (2023): their own risk appetite index, the excess bond premium from Gilchrist and Zakrajšek (2012), the Chicago Fed's National

Financial Conditions Index (NFCI), and the risk aversion index of Bekaert et al. (2022). In the second alternative, we consider the same approach applied to the remaining five measures of time-varying risk premia: Robert Shiller's CAPE Ratio, the Jurado et al. (2015) financial uncertainty index, the variance risk premium from Bekaert and Hoerova (2014), the CBOE VIX, and the Martin (2016) SVIX. We find similar effects across the three different measures of risk premium shocks, suggesting that the results are insensitive to the specific series included in the estimation. The point estimates by income group are somewhat larger for the second alternative, but the spread across different workers is consistent across specifications.

In the bottom panel of Table A.4, we consider variations to the measurement of productivity shocks. Specifically, we use TFP shocks aggregated to the 3-digit NAICS level (first four columns) and firm-level TFP shocks (last four columns) as alternatives. Reassuringly, the point estimates are very similar across the different levels of aggregation. The more granular the variation is, the more precisely these exposures are estimated. As a result, exposure to productivity shocks is highly significant when TFP growth is measured at the firm level, while exposure is only marginally statistically significant at the 3-digit NAICS level.

Fourth, Table A.5 shows that our making alternative assumptions on time aggregation leads to quantitatively similar outcomes. Specifically, in the first six columns, we line up income growth from t to $t+h$ with risk premium shocks over calendar year $t+1$, which assumes that worker earnings are paid at the end of the year. In the last six columns, we line up income growth from t to $t+h$ with risk premium shocks over calendar year t, which assumes that worker earnings are paid at the beginning of the year as in Campbell (2003). While annual income growth in year $t+1$ has a much higher correlation with financial shocks in year t than in year $t+1$, we find that the timing does not affect our long-run estimates in a material way.

Fifth, we repeat the analysis of extensive-margin effects using our shift-share design based on firm-level exposure to risk premium shocks. That is, we estimate a modified version of equation (3) where we replace the dependent variable by an indicator for job loss over the next h years: whether the worker separates from her initial employer and simultaneously experiences a decline in earnings growth below the 10th percentile. Table A.6 shows that we obtain qualitatively similar results on the likelihood of job loss to those in Table 3; that is, a 10% increase in the risk premium leads to a 0.1- to 0.2-percentage-point increase in the likelihood of job loss for those low-income workers who are employed in highly exposed firms compared to the likelihood of low-income workers employed in less exposed firms. There are no such effects for higher-paid workers.

A.6 Worker Flows from SIPP

To match the transition rates of workers between employment and nonemployment in the data, we rely on public data from the Survey of Income and Program Participation (SIPP) of the U.S. Census Bureau. The SIPP is a longitudinal 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 had major redesigns in 1996 and 2014.

We use data from the 1996, 2001, 2004, and 2008 panels of the SIPP, collectively covering nearly all months in the period from 1996 to 2013. We restrict attention to household members between ages 25 and 60 who do not own a business. We measure monthly employment status from reports in the last week of each month. Individuals are classified 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 separation and job-finding rates by worker income. To this end, we restrict attention to workers with positive wage earnings who report having a job in all weeks of the month. We sort employed workers into income groups based on wage earnings in the current month. 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 transition rates across these different income groups. We measure two types of monthly job separation rates: the employment-to-unemployment rate and the employment-to-nonparticipation rate, defined as the fraction of employed workers who transition to unemployment and nonparticipation in the next month, respectively. Monthly job-finding rates are measured as the fraction of unemployed workers who transition to employment in the next month. To compute standard errors for these moments, we cluster by SIPP panel.

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 that we focus on a symmetric equilibrium. By the one-shot deviation principle, we need only to consider a one-time deviation from 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

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

Since there is free entry of firms into labor markets, the equilibrium number of vacancies is pinned down by the zero-profit condition in (21).

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

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

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 (22).

B.2 Model Equilibrium

Our model is solved in two steps. First, we solve for equilibrium labor market allocations. Second, we solve for the optimal wage contract by finding the path of flow wages that implements the equilibrium allocations by optimally smoothing wages subject to the limited commitment constraints.

We start by defining 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 $\overline{W}_t(z) = W_t(z)/A_t$. Equilibrium labor market allocations in this model are given by the solution to the following system of equations:

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

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

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

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

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

$$\bar{\kappa}\, z = q(\theta_t(z))\left(\overline{J}_t^{MC}(z) - \overline{W}_t(z)\right) \tag{A.16}$$

$$\overline{W}_t(z) = (1 - \eta(\theta_t(z)))\overline{J}_t^O(z) + \eta(\theta_t(z))\overline{J}_t^{MC}(z). \tag{A.17}$$

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 (20) 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 we solve for the equilibrium allocations, the second step is to solve for the optimal wage contract. We again normalize the relevant objects: $\overline{w}(\Omega_{i,m,t}) = w(\Omega_{i,m,t})/A_t$, $\overline{W}^M(\Omega_{i,m,t}) = \widehat{W}^M(\Omega_{i,m,t})/A_t$, $\overline{V}_t(z, \overline{W}^M) = \widehat{V}_t(z, \widehat{W}^M)/A_t$, $\overline{\Gamma}_t^L(z) = \Gamma_t^L(z)/A_t$, and $\overline{\Gamma}_t^H(z) = \Gamma_t^H(z)/A_t$; these depend only on the aggregate state through the stationary price of risk process x_t. We find the path of wages by numerically solving the following dynamic optimization problem:

$$\overline{V}_t(z, \overline{W}^M) = \max_{\overline{w}, \{\overline{W}^{M\prime}\}} \quad \left\{(1-\chi)\,\overline{w}^{1-\gamma} + \chi\,\mathbb{E}_{t,z}\left[\Lambda_{t+1} e^{(1-\gamma)(\mu_A + \sigma_A \varepsilon_{A,t+1})}\,\mathbb{1}_{t+1}^C(z')\,\overline{V}_{t+1}(z', \overline{W}^{M\prime})^{1-\gamma}\right]\right\}^{\frac{1}{1-\gamma}} \tag{A.19}$$

$$\text{s.t.} \quad \overline{W}^M = \overline{w} + (1-\nu)(1-s)\,\mathbb{E}_{t,z}\left[\Lambda_{t+1} e^{\mu_A + \sigma_A \varepsilon_{A,t+1}}\,\mathbb{1}_{t+1}^C(z')\,\overline{W}^{M\prime}\right] \tag{A.20}$$

$$\overline{\Gamma}_{t+1}^L(z') \leq \overline{W}^{M\prime} \leq \overline{\Gamma}_{t+1}^H(z'). \tag{A.21}$$

If the limited commitment bounds are never binding, the first-order condition of this problem reduces to

$$\overline{w}^{-\gamma} = \frac{\chi}{(1-\nu)(1-s)} \left\{\frac{A_{t+1}}{A_t}\,\overline{w}'\right\}^{-\gamma}. \tag{A.22}$$

In this case, under our assumption that $\log \chi = \log(1-\nu) + \log(1-s) + \mu_A \gamma$, we obtain that wages grow deterministically at the growth rate μ_A of the economy during a match.

B.3 Calibration of the Stochastic Discount Factor

We calibrate the parameters of the stochastic discount factor to match moments of asset prices. To do so, we make the common assumption that aggregate dividends D_t represent a levered claim on aggregate productivity,

$$\Delta D_{t+1} = \mu_d + \phi \, \sigma_A \, \varepsilon_{A,t+1}, \tag{A.23}$$

where μ_d is expected dividend growth and ϕ 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 ϕ equal to 1.49. The total value of the stock market is given by the present value of aggregate dividends as specified in (8).

To calibrate the price of risk process x_t in (9), 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 -0.47 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 valuations of employment matches of 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 monthly frequency and aggregate all financial variables to annual frequency to compute annual moments. We choose μ_d, $\bar{x}$, ψ_x, σ_x, and δ to target the average price–dividend ratio, the autocorrelation of the log price–dividend 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. Table A.8 compares the resulting moments in simulated data from our calibrated model ($\mu_d = 0.001, \bar{x} = 0.384, \psi_x = 0.994, \sigma_x = 0.032, \delta = 0.431$) to the corresponding empirical statistics. The model produces an average price–dividend ratio of 20.3 that is lower than that in the data but similar to the ratios from other models of this type (Campbell and Cochrane, 1999; Lettau and Wachter, 2007). Our calibration matches the persistence of the price–dividend ratio, the distribution of aggregate stock market returns, and the stylized fact that the Sharpe ratios of risky assets are declining 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 0.35.

Figure A.11 shows that our model has realistic implications for return predictability. First, in A.11a, we run a predictive regression of future stock market returns on the level of risk premia analogous to Figure 1b, comparing the results in the 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 estimates. Second, Figure A.11b shows that the model also has realistic implications for the predictability of long-horizon returns by the level of the price–dividend ratio.

B.4 Worker Employment Dynamics

Figure A.6 plots the stationary joint distribution of individual worker productivity and employment status along the balanced growth path ($x_t = \bar{x}$). The top panel illustrates that endogenous job destruction is driven by a threshold rule defined in (35): 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. The middle panel shows that the decision to enter the unemployment pool and search for a job is similarly driven by a threshold rule defined in (36): a nonemployment worker decides to search if and only if productivity z is above $\underline{z}(x_t)$. To match average separation rates 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 income risk in our model, we start by rewriting equation (35) as

$$\log \overline{J}^{MC}(x, z^*(x)) = \log \overline{J}^{O}(x, z^*(x)). \tag{A.25}$$

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

$$z^{*\prime}(x) = -\frac{\frac{\partial}{\partial x}\log \overline{J}^{MC}(x, z^*(x)) - \frac{\partial}{\partial x}\log \overline{J}^{O}(x, z^*(x))}{\frac{\partial}{\partial z}\log \overline{J}^{MC}(x, z^*(x)) - \frac{\partial}{\partial z}\log \overline{J}^{O}(x, z^*(x))}. \tag{A.26}$$

Figure A.12 plots the partial derivatives in the numerator and denominator as a function of z and evaluated at $x = \bar{x}$. We see that, around the threshold, the derivative of the continuation value with respect to x is more negative than the derivative of the outside option. Combined with the fact that the continuation value always has a more positive derivative with respect to z than the outside option, we obtain the result that the separation threshold increases in x.

It is fairly straightforward to see why the denominator of (A.26) is positive: the output produced in a match is linear in z, while nonemployment benefits do not depend on 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 continuation 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:

$$\delta_t(z, e) = \begin{cases} A_t\, z & \text{if } e = E \\ b_t - c_t - k_t(z) & \text{if } e = U \\ b_t & \text{if } e = N. \end{cases} \tag{A.27}$$

The strip payoffs in (A.27) 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. A worker who is unemployed collects the benefit b_t 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:

$$k_t(z) = \mathbb{E}_{t,z}\left[\Lambda_{t+1}\kappa_{t+1}(z')\theta_{t+1}(z')\right]. \tag{A.28}$$

The net present value at time t of a strip with maturity T can be computed with the standard valuation equation (8), given current aggregate information $\mathcal{F}_t$ and current worker status (z, e):

$$J_t^{\delta}(z, e; T) = (1-\nu)^T\, \mathbb{E}\left[\left(\prod_{\tau=t+1}^{T} \Lambda_\tau\right) \delta_T(z_T, e_T)\,\middle|\, \mathcal{F}_t, z, e\right]. \tag{A.29}$$

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:

$$J_t^{MC}(z) = \sum_{\tau=0}^{\infty} J_t^{\delta}(z, E; t+\tau) \tag{A.30}$$

$$J_t^U(z) = \sum_{\tau=0}^{\infty} J_t^{\delta}(z, U; t+\tau) \tag{A.31}$$

$$J_t^N(z) = \sum_{\tau=0}^{\infty} J_t^{\delta}(z, N; t+\tau). \tag{A.32}$$

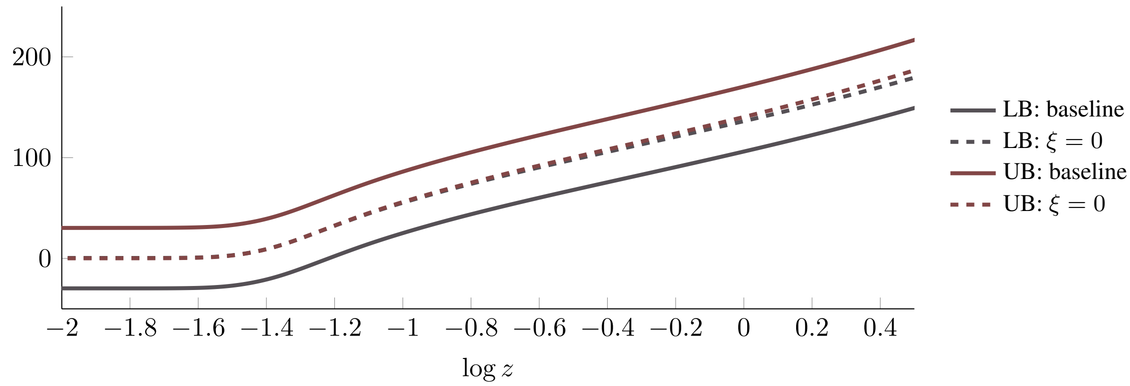
Figure **??** plots the valuation weight that the strip with payoff at horizon τ has in the total continuation value $J_t^{MC}(z)$ (i.e., $J_t^{\delta}(z, E; t+\tau)/J_t^{MC}(z)$) and in the outside option $J_t^O(z)$ (i.e., $J_t^{\delta}(z, U; \tau)/J_t^U(z)$ when $z \geq \underline{z}(x_t)$). The figure 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.

Finally, we note that the payoffs in (A.27) are linear in A_t. The semi-elasticity with respect to x_t of the present value of a claim to payoff $f(z_{i,t+\tau}, e_{i,t+\tau})A_{t+\tau}$ at horizon τ is the same for each function f and is plotted in Figure A.5b. 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.

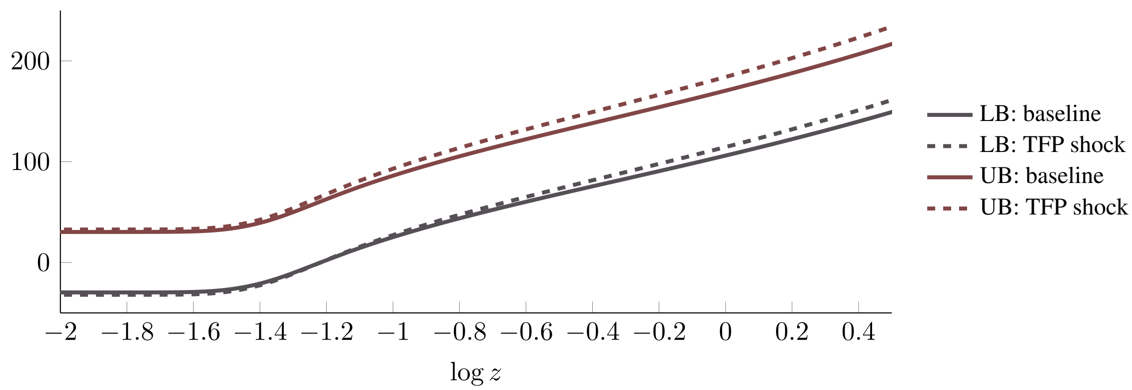
C Additional Figures and Tables

Figure A.1: Model: Wage NPV Bounds by Worker Productivity

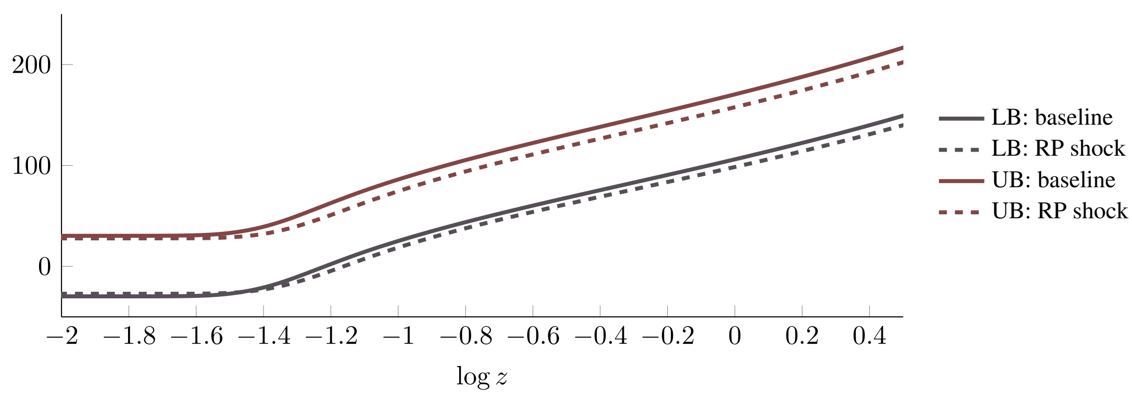
(a) Bounds in Baseline Model versus Alternative Without Reputational Costs ($\xi = 0$)



(b) Changes in Bounds Due to Aggregate Productivity Shocks



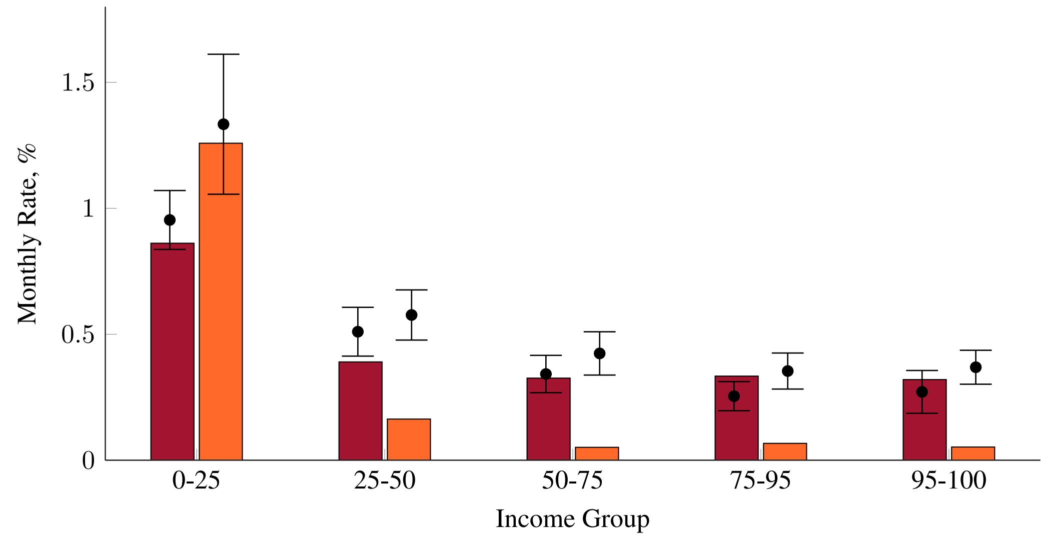
(c) Changes in Bounds Due to Risk Premium Shocks



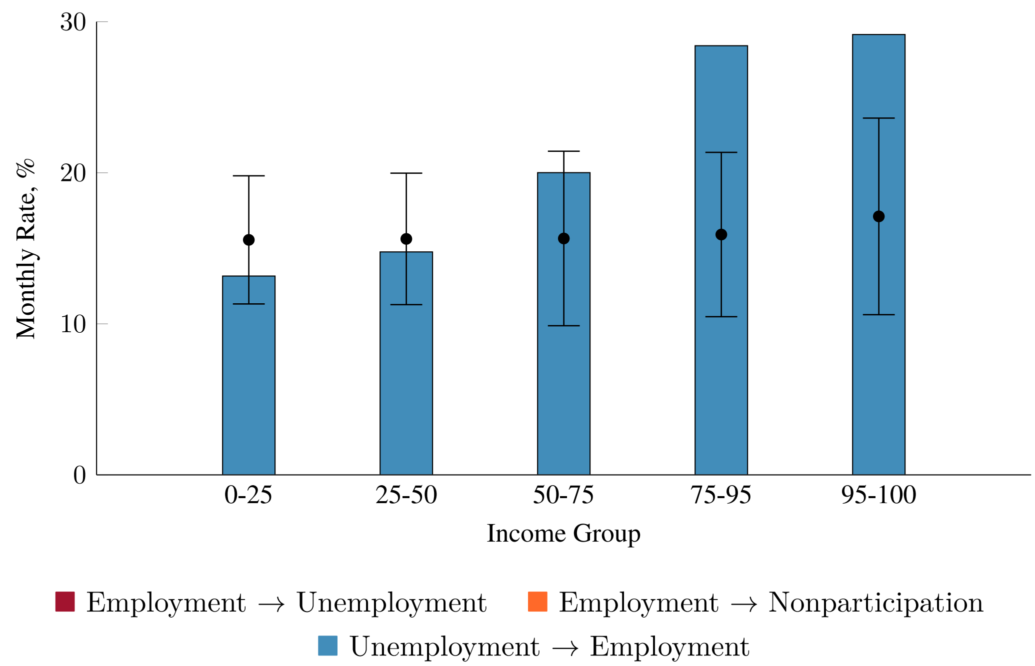
This figure plots the limited commitment bounds on the net present value (NPV) of wages in (27). The solid lines in all three panels characterize the bounds as a function of z in our baseline calibration, for $A_t = 1$ and $x_t = \bar{x}$. Panel (a) shows how the bounds change if we set $\xi = 0$ (no termination cost). Panel (b) shows how the bounds change in response to a shock of two annual standard deviations to A. Panel (c) shows how the bounds change in response to a shock of two annual standard deviations to x.

Figure A.2: Model versus Data: Worker Flows (Targeted)

(a) Average Separation Rate into Unemployment and Nonparticipation by Income Group



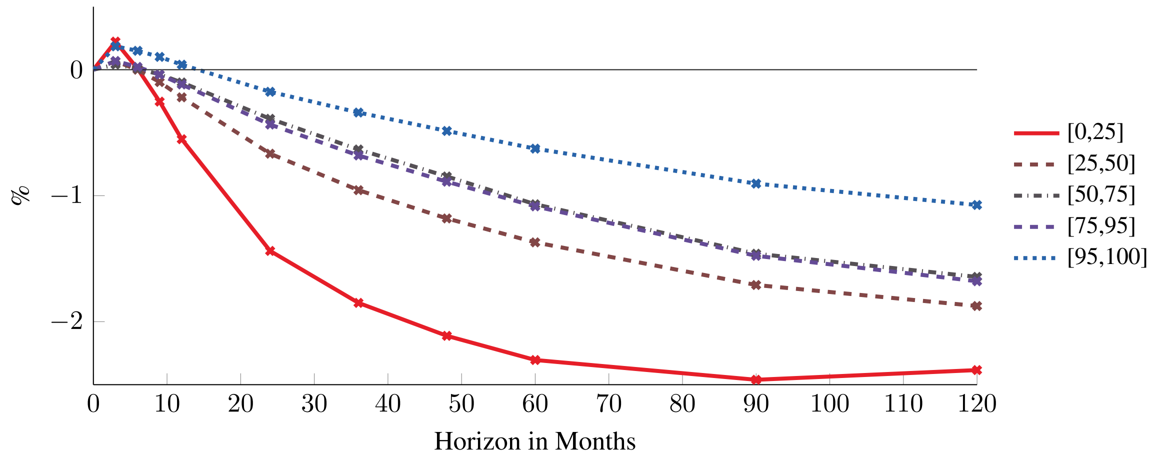
(b) Average Job-Finding Rate by Income Group



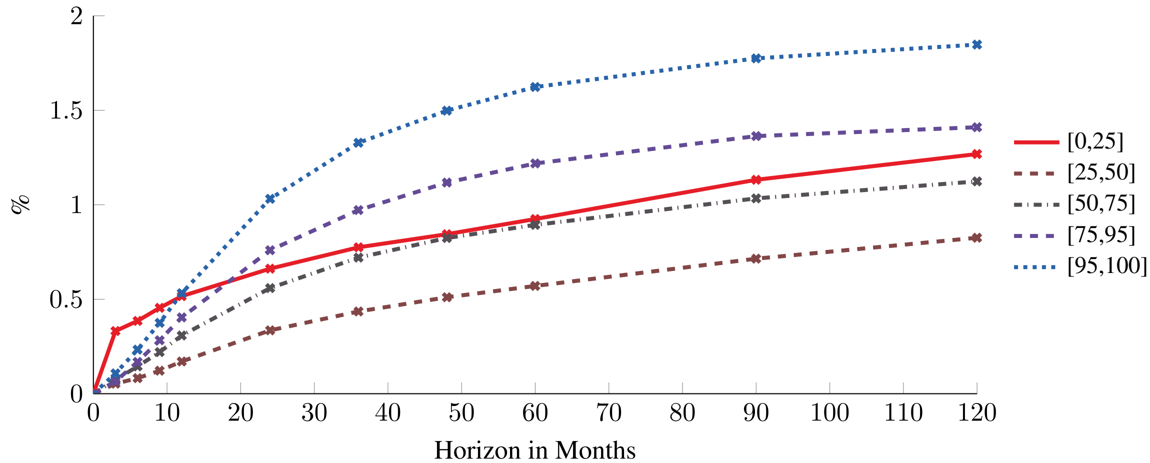
This figure compares average job separation rates into unemployment and nonparticipation (Panel (a)) and the average job-finding rate (Panel (b)) by income group in the model and in the data. The empirical counterparts are computed from public Survey of Income and Program Participation (SIPP) panel data, with standard errors clustered by panel. Incumbent workers in Panel (a) are binned into groups based on their current wage earnings. Unemployed workers in Panel (b) are binned into groups based on their earnings the last time they were employed in the prior twelve months (if applicable).

Figure A.3: Model: Risk Exposure by Horizon

(a) Exposure to Risk Premium Shocks



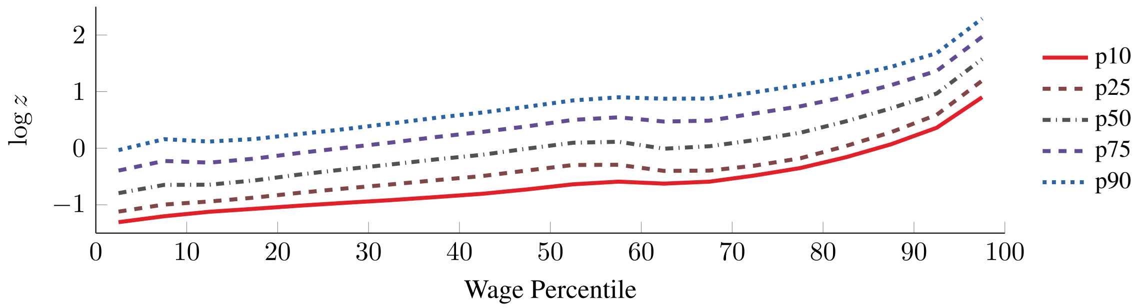
(b) Exposure to Productivity Shocks



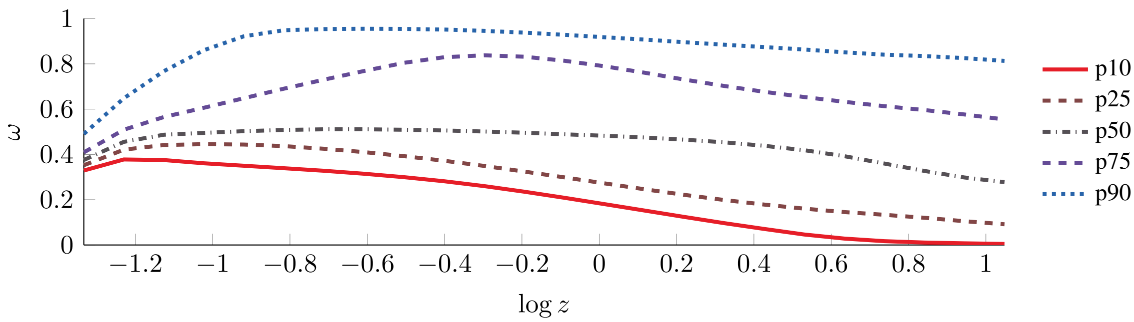
This figure plots the regression coefficients β and γ from estimates of equation (2) in the model, with cumulative income growth over various horizons h as the dependent variable. Panel (a) reports exposure to risk premium shocks by horizon, and Panel (b) reports exposure to productivity shocks by horizon. We estimate exposure across the worker earnings distribution by interacting the two shocks with indicators for the worker's prior earnings bin. Coefficients are scaled so that they correspond to a 10% shock.

Figure A.4: Model: Determinants of Worker Heterogeneity

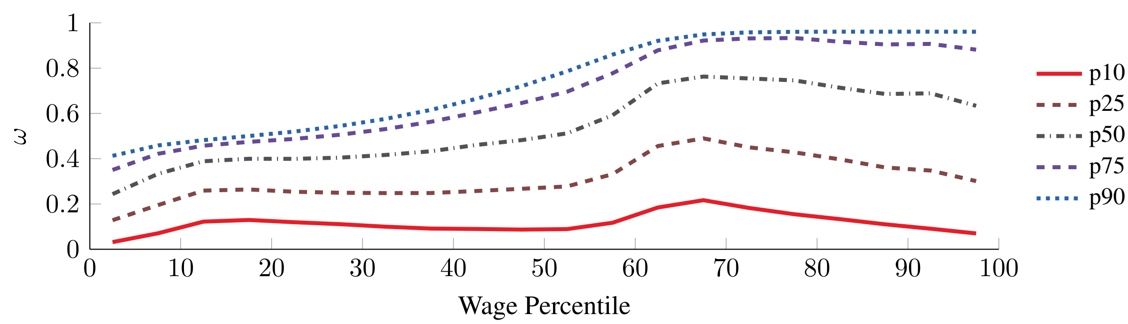
(a) Worker Productivity Conditional on Worker Wage



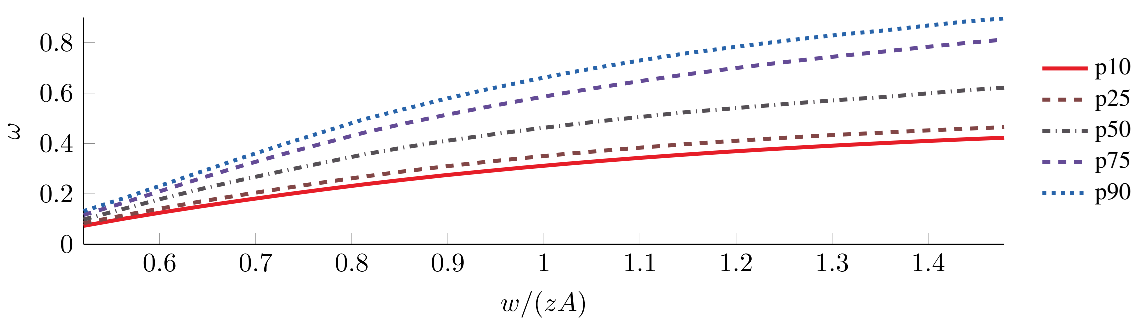
(b) Distance from Bounds Conditional on Worker Productivity



(c) Distance from Bounds Conditional on Worker Wage



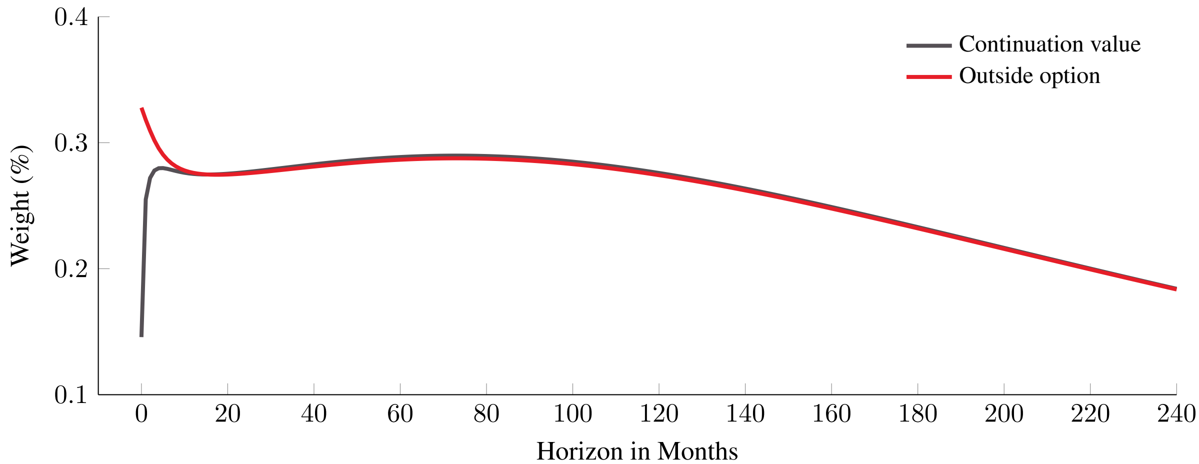
(d) Distance from Bounds Conditional on Worker Wage Relative to Productivity



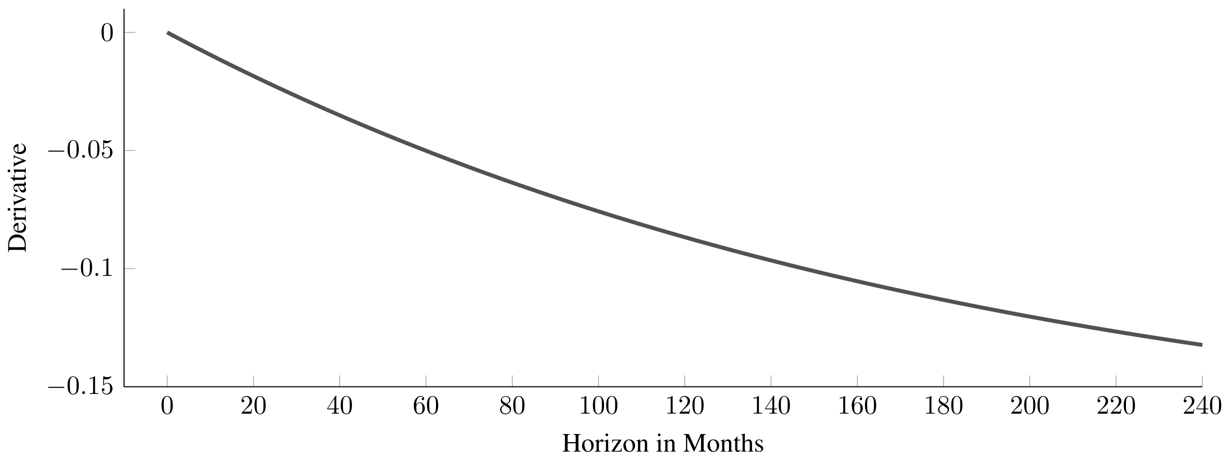
This figure plots quantiles of idiosyncratic productivity z and the position of the wage continuation value relative to the bounds $\omega \equiv \frac{\hat{W}^M - \Gamma^L}{\Gamma^H - \Gamma^L}$ as a function of current worker variables in the model.

Figure A.5: Model: Duration of Surplus for Marginal Worker

(a) Differences in Cashflow Duration between Employment and Nonemployment

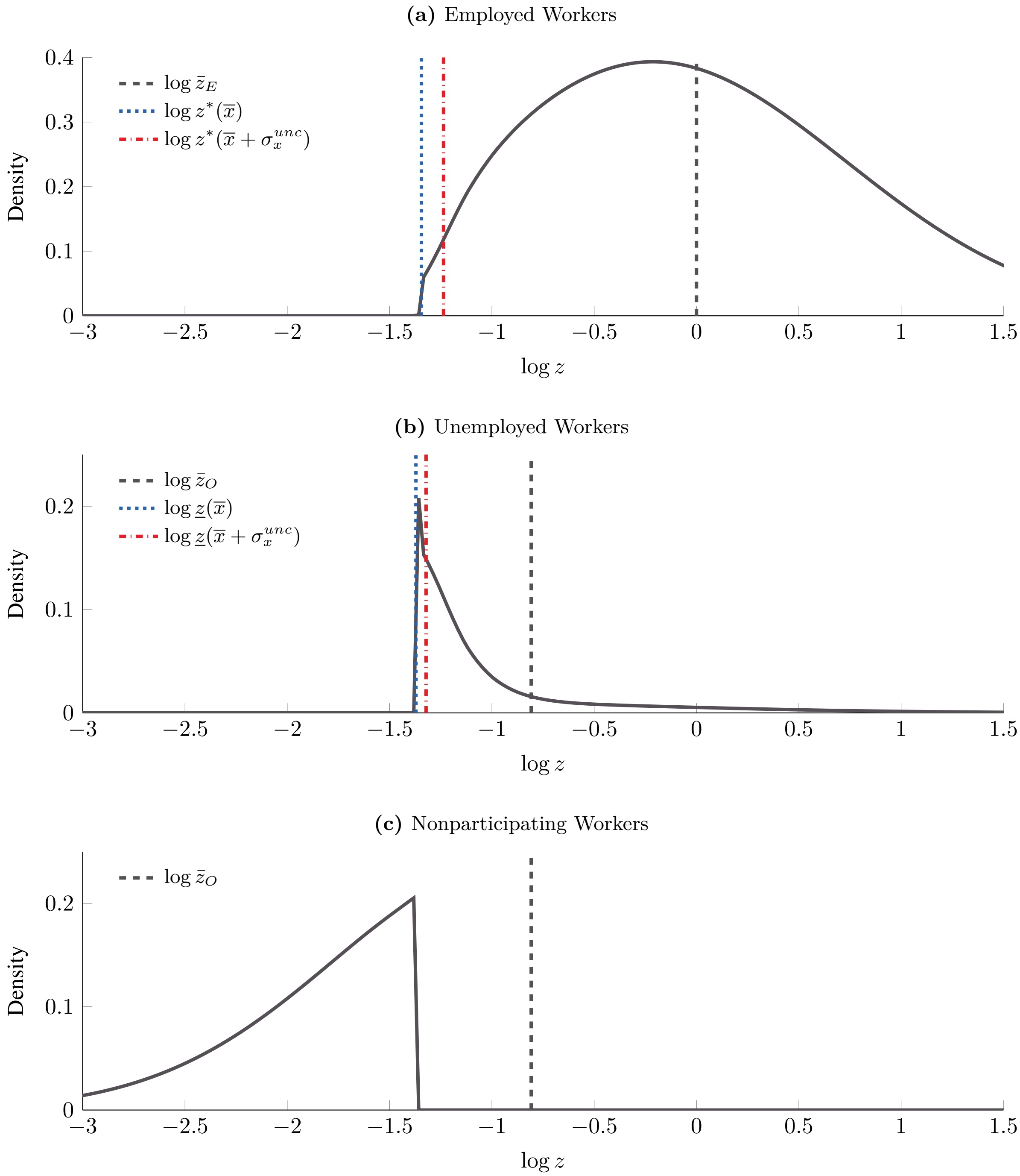


(b) Valuation Effects of Risk Premium Shock by Horizon



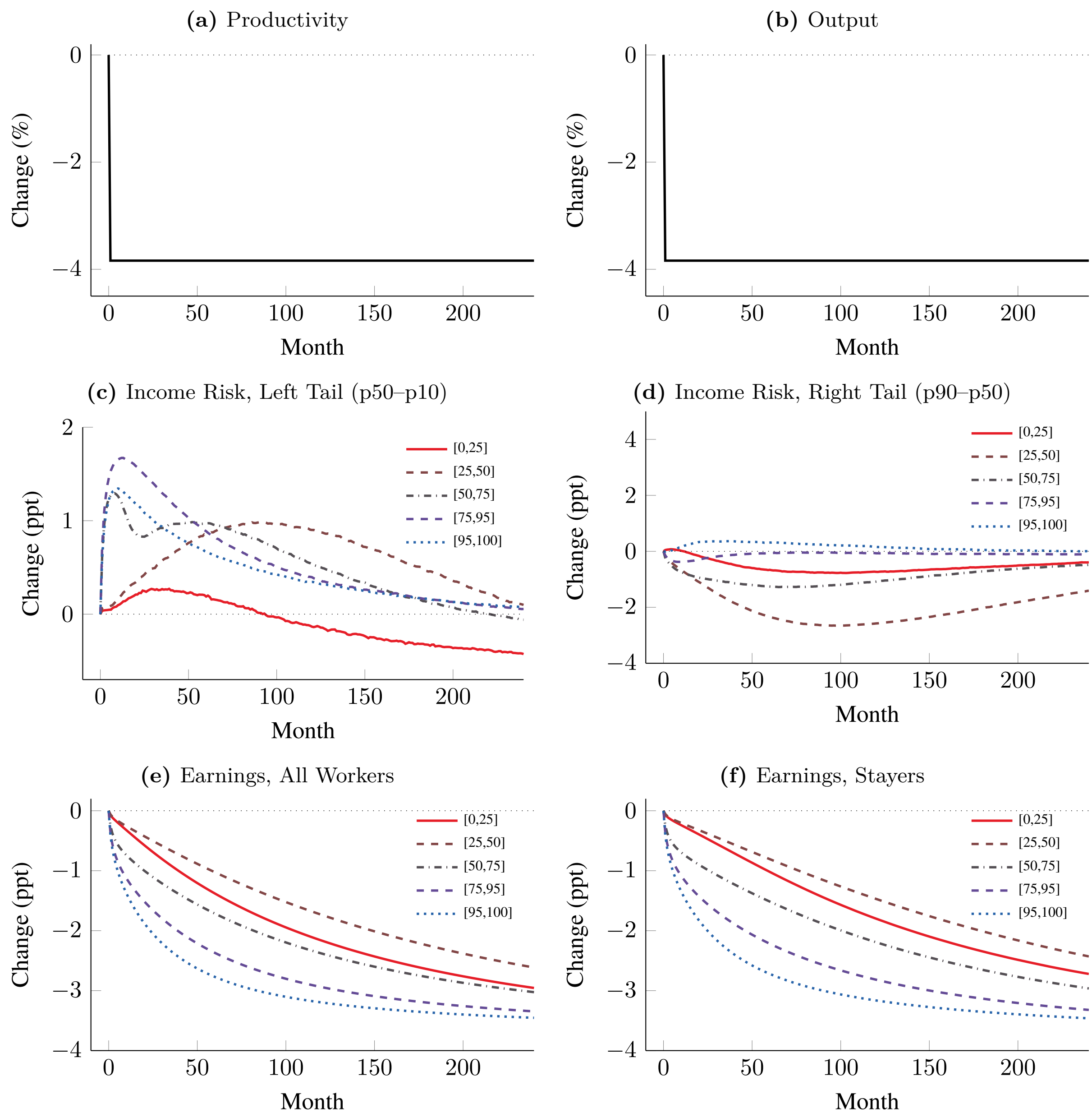
Panel (a) of this figure plots the valuation weight that the strip with payoff at horizon τ has in the total continuation value $J_t^{MC}(z)$ (i.e., $J_t^{\delta}(z, E; t+\tau)/J_t^{MC}(z)$) and in the outside option $J_t^{O}(z)$ (i.e., $J_t^{\delta}(z, U; t+\tau)/J_t^{U}(z)$ when $z \geq \underline{z}(x_t)$). The weights are for the marginal worker who is at the separation threshold when $x_t = \bar{x}$: $z = z^*(\bar{x})$. Panel (b) 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.6: Model: Joint Distribution of Employment Status and Productivity along Balanced Growth Path



This figure plots the stationary joint distribution of employment status and z along the balanced growth path. We also plot the long-run mean of z in employment, $\bar{z}_E$, and nonemployment, $\bar{z}_O$, as well as the separation threshold $z^*(x_t)$ and the job search threshold $\underline{z}(x_t)$ for $x_t = \overline{x}$ and $x_t = \overline{x} + \sigma_x^{unc}$, where σ_x^{unc} is the unconditional standard deviation of x.

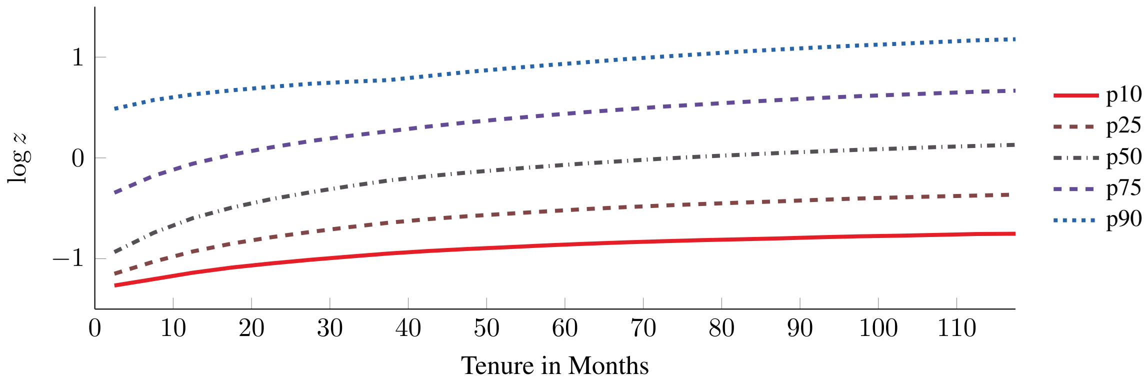
Figure A.7: Model: Impulse Responses to Productivity Shocks



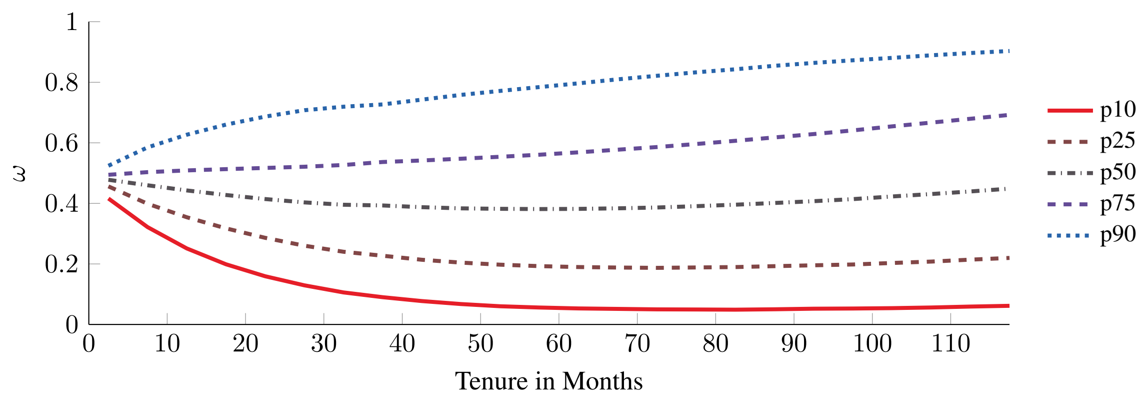
This figure shows the impulse responses of key model quantities following a negative productivity shock of one annual standard deviation.

Figure A.8: Model: Worker Characteristics by Employment Tenure

(a) Worker Productivity Conditional on Worker Tenure

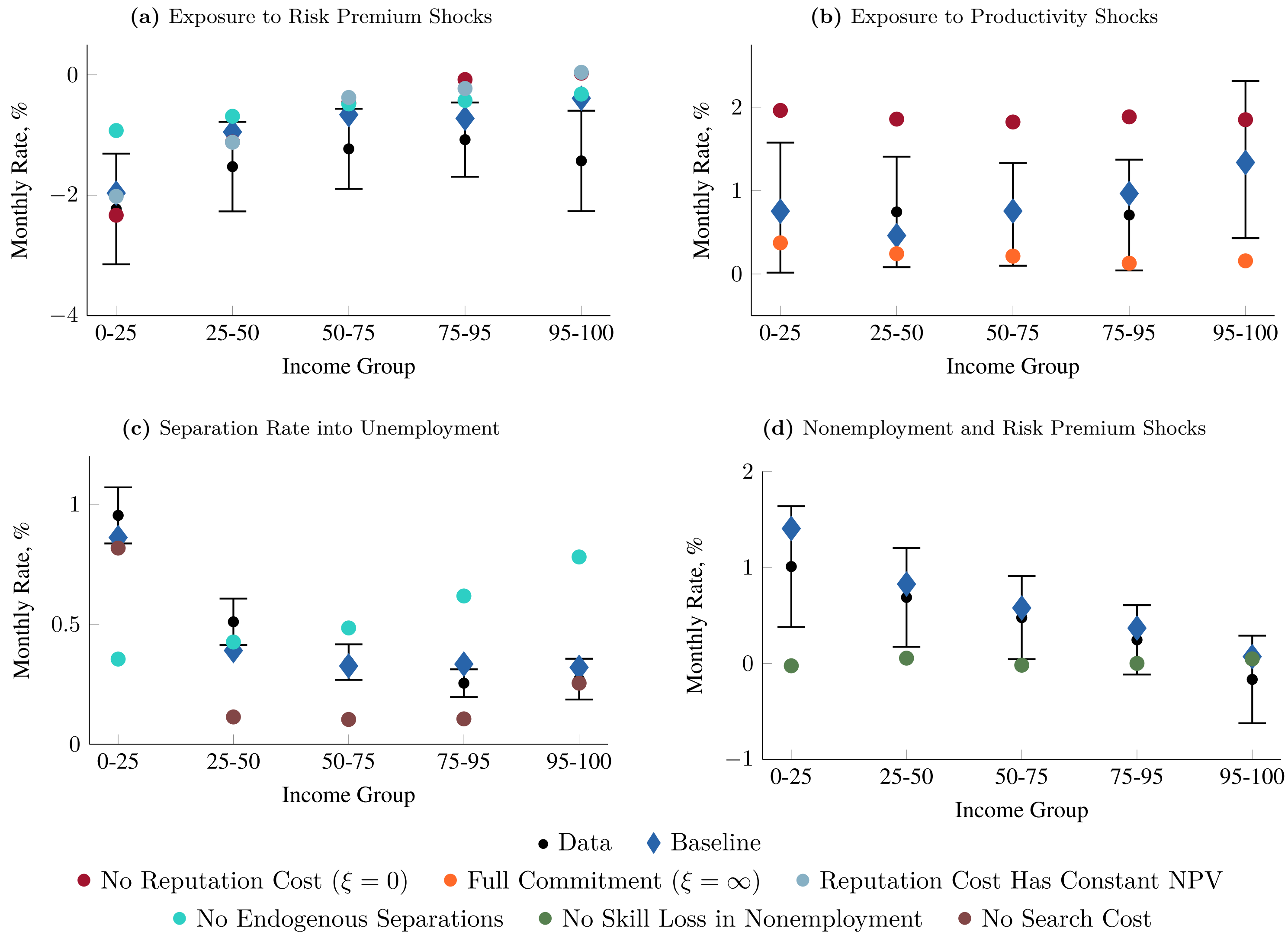


(b) Distance from Bounds Conditional on Worker Tenure



This figure plots quantiles of idiosyncratic productivity z and the position of the wage continuation value relative to the bounds $\omega \equiv \frac{\hat{W}^M - \Gamma^L}{\Gamma^H - \Gamma^L}$ as a function of worker tenure in the model.

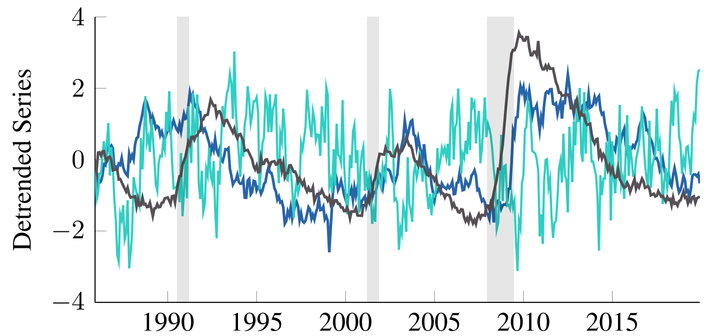
Figure A.9: Model versus Data: Alternative Calibrations



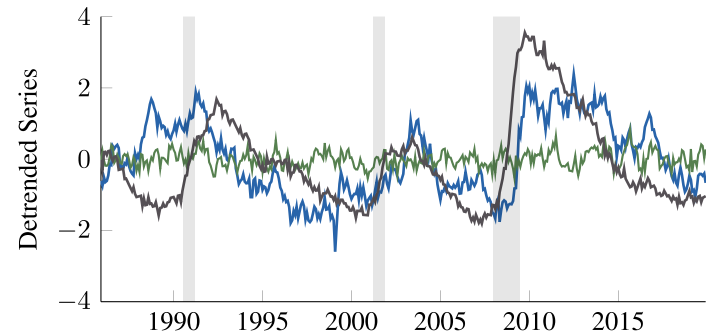
Panels (a) and (b) plot the regression coefficients β and γ from estimates of equation (2) by income group at a three-year horizon in the data, in the baseline model, and in alternative calibrations of the model. Panel (c) shows the average separation rate into unemployment, and Panel (d) plots the coefficient on risk premium shocks in a regression of the three-year probability of some nonemployment on the aggregate shocks by income group.

Figure A.10: Model versus Data: Unemployment and Income Risk under Alternative Calibrations

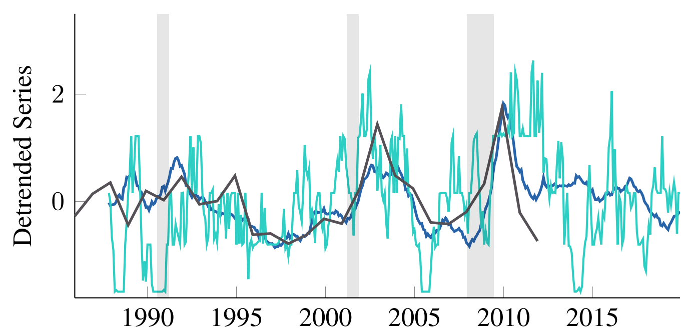
(a) Unemployment (Data versus Baseline versus No Endogenous Separations)



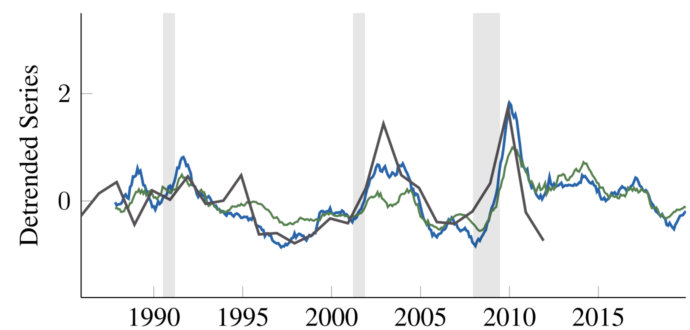
(b) Unemployment (Data versus Baseline versus No Skill Loss)



(c) Income Risk, Left Tail (Data versus Baseline versus No Endog. Separations)

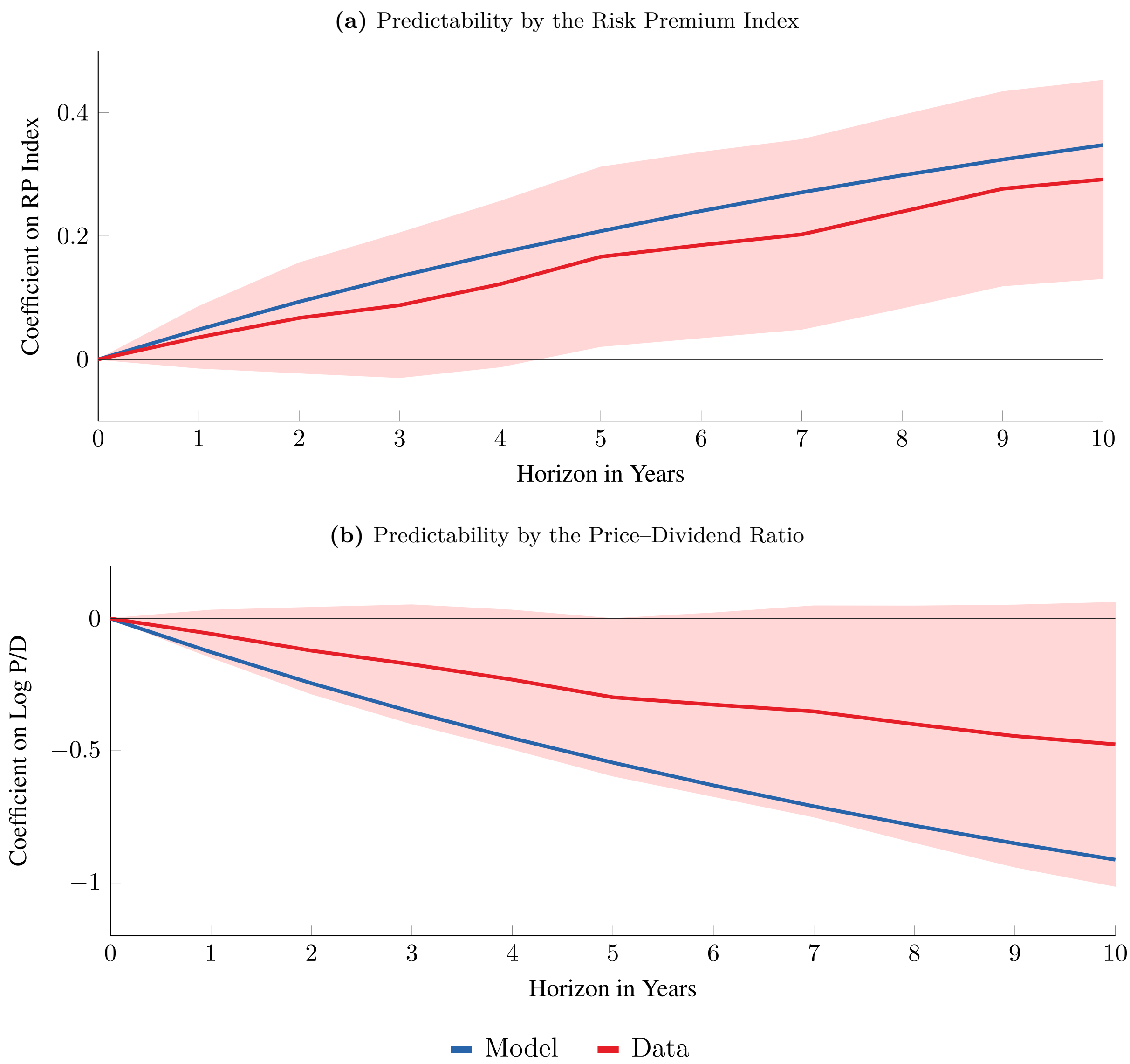


(d) Income Risk, Left Tail (Data versus Baseline versus No Skill Loss)



Panels (a) and (b) compare the unemployment rate between the data and model simulations for different calibrations. Panels (c) and (d) compare the realized paths of income risk. The empirical series are from Guvenen et al. (2014). We directly feed into the model our measures of risk premium and productivity shocks ϵ^{rp} and ϵ^{tfp} from Section 1.1, normalized to have zero mean and unit standard deviation, and accumulate these shocks into levels for A and x using equations (7) and (9). We remove the means from the stationary series and detrend the nonstationary series using a band-pass filter with quarterly smoothing parameter 10^5.

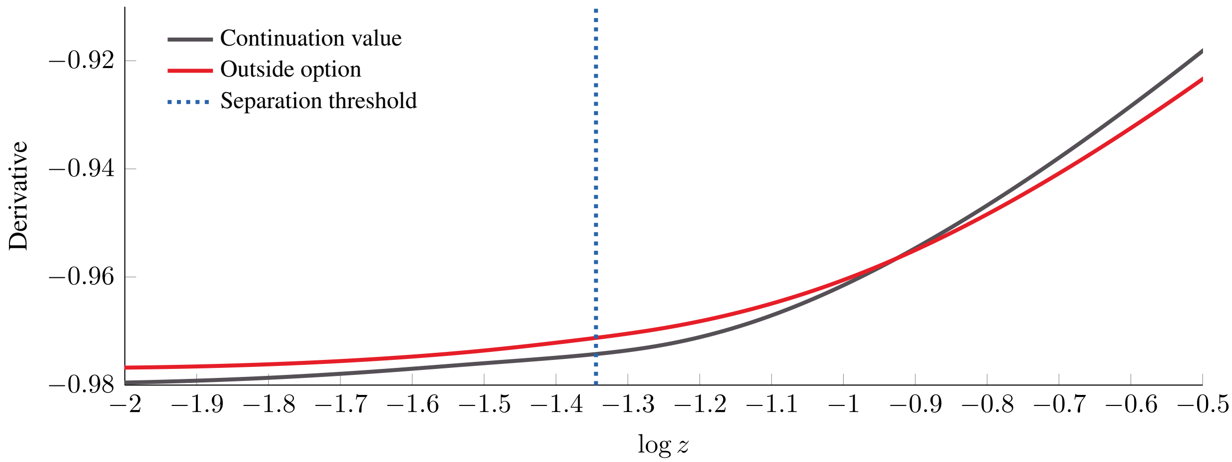
Figure A.11: Model versus Data: Predictability of Future Stock Market Returns



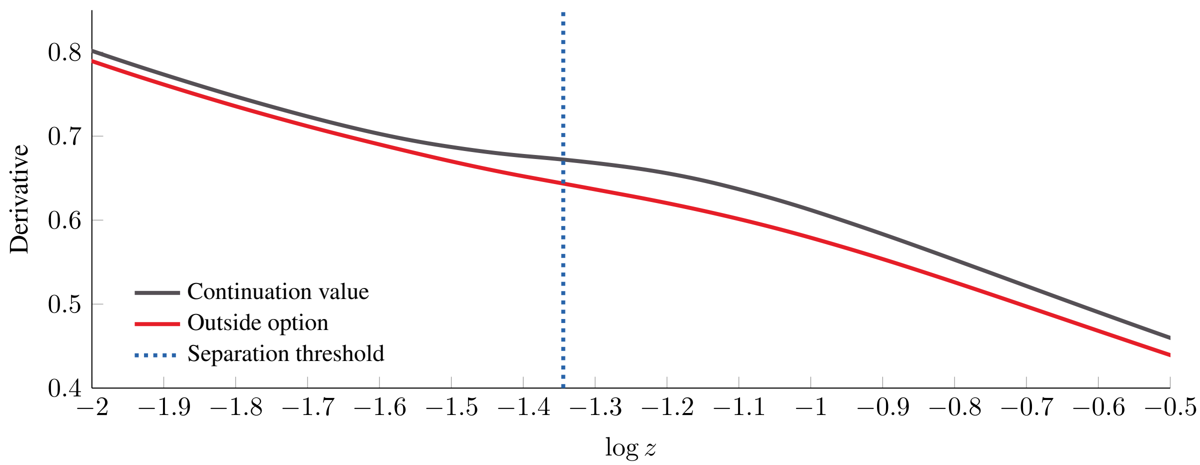
This figure reports estimates of predictive regressions where we project continuously compounded future excess stock market returns $\sum_{s=1}^{H} r^e_{t+s}$ on our risk premium index (Panel (a)) and on the log price–dividend ratio (Panel (b)) at different horizons H, in the model and in the data. The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

Figure A.12: Model: Derivatives of Worker Value Functions

(a) Derivative with Respect to Risk Premia ($\partial/\partial x$)



(b) Derivative with Respect to Worker Productivity ($\partial/\partial z$)



Panel (a) of this figure shows the partial derivatives of the worker continuation value $\log \overline{J}^{MC}(x,z)$ and the outside option $\log \overline{J}^{O}(x,z)$ with respect to x. Panel (b) plots the partial derivatives of $\log \overline{J}^{MC}(x,z)$ and $\log \overline{J}^{O}(x,z)$ with respect to z. The derivatives are plotted as a function of z, evaluated at $x = \bar{x}$.

Table A.1: Summary Statistics for Workers in Main Sample

Variable	Observations	Mean	SD	p10	p50	p90
Income Growth $g_{i,t:t+1}$	63.0m	-0.039	0.412	-0.337	0.006	0.304
Income Growth $g_{i,t:t+2}$	60.2m	-0.073	0.465	-0.456	-0.002	0.302
Income Growth $g_{i,t:t+3}$	57.3m	-0.104	0.511	-0.578	-0.011	0.305
Prior Earnings, 0–25th Percentile	14.3m	-0.087	0.642	-0.803	0.031	0.506
Prior Earnings, 25–50th Percentile	14.3m	-0.114	0.498	-0.581	-0.011	0.264
Prior Earnings, 50–75th Percentile	14.3m	-0.112	0.442	-0.492	-0.023	0.216
Prior Earnings, 75–95th Percentile	11.5m	-0.104	0.418	-0.452	-0.029	0.221
Prior Earnings, 95–100th Percentile	2.9m	-0.105	0.499	-0.582	-0.028	0.338
Income Growth $g_{i,t:t+5}$	51.3m	-0.165	0.586	-0.784	-0.035	0.310
Some Nonemployment$_{i,t:t+2}$	60.2m	0.139				
Some Nonemployment$_{i,t:t+3}$	57.3m	0.201				
Prior Earnings, 0–25th Percentile	14.3m	0.290				
Prior Earnings, 25–50th Percentile	14.3m	0.202				
Prior Earnings, 50–75th Percentile	14.3m	0.165				
Prior Earnings, 75–95th Percentile	11.5m	0.143				
Prior Earnings, 95–100th Percentile	2.9m	0.155				
Some Nonemployment$_{i,t:t+5}$	51.3m	0.307				
Move and Tail Loss$_{i,t:t+2}$	60.2m	0.068				
Move and Tail Loss$_{i,t:t+3}$	57.3m	0.087				
Prior Earnings, 0–25th Percentile	14.3m	0.119				
Prior Earnings, 25–50th Percentile	14.3m	0.088				
Prior Earnings, 50–75th Percentile	14.3m	0.074				
Prior Earnings, 75–95th Percentile	11.5m	0.065				
Prior Earnings, 95–100th Percentile	2.9m	0.072				
Move and Tail Loss$_{i,t:t+5}$	51.3m	0.096				
Age	63.0m	42.020	9.854	28	42	56
Tenure, $<$ 1 Year	50.1m	0.085				
Tenure, 1–3 Years	50.1m	0.192				
Tenure, 3–5 Years	50.1m	0.145				
Tenure, $>$ 5 Years	50.1m	0.578				

This table summarizes the variables that characterize the earnings dynamics of the workers in our main sample. Income growth is defined in equation (1). A worker is characterized as having some nonemployment 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 stayers if the main employer in year $t+h$ is the same as the main employer in year t and as movers in all other cases. A tail loss is defined by a worker's having income growth in the bottom 10%. 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.

Table A.2: Worker Exposure to Risk Premium and Productivity Shocks, All Workers

	A. Average Exposure					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
All Workers	-1.51	0.56	-1.61	0.60	-1.27	0.61
	(-4.54)	(1.74)	(-3.99)	(1.66)	(-2.77)	(1.68)

	B. By Worker Earnings (Within Firm)					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	-2.14	0.67	-2.34	0.72	-2.00	0.73
	(-5.07)	(1.68)	(-4.45)	(1.68)	(-3.21)	(1.78)
Prior Earnings, 25–50th Percentile	-1.53	0.59	-1.63	0.62	-1.29	0.64
	(-4.44)	(1.82)	(-3.91)	(1.76)	(-2.68)	(1.83)
Prior Earnings, 50–75th Percentile	-1.24	0.52	-1.31	0.54	-0.98	0.55
	(-4.12)	(1.78)	(-3.63)	(1.66)	(-2.41)	(1.64)
Prior Earnings, 75–95th Percentile	-1.05	0.49	-1.10	0.52	-0.82	0.52
	(-3.88)	(1.73)	(-3.44)	(1.59)	(-2.26)	(1.47)
Prior Earnings, 95–100th Percentile	-1.27	0.60	-1.21	0.63	-0.83	0.64
	(-4.57)	(1.55)	(-3.96)	(1.44)	(-2.66)	(1.33)
Bottom (1) – Middle (3) Earners	-0.90	0.15	-1.03	0.18	-1.02	0.19
	(-6.35)	(1.33)	(-5.53)	(1.63)	(-4.25)	(2.04)
Middle (3) – Top (5) Earners	0.02	-0.08	-0.10	-0.09	-0.15	-0.09
	(0.14)	(-0.58)	(-0.61)	(-0.61)	(-0.78)	(-0.53)
Bottom (1) – Top (5) Earners	-0.88	0.07	-1.13	0.09	-1.17	0.09
	(-4.10)	(0.52)	(-4.11)	(0.65)	(-3.14)	(0.59)
Observations	36.8m		34.6m		30.2m	
Fixed Effects	N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp	
Clustering	N4, Year		N4, Year		N4, Year	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income growth over various horizons h as the dependent variable. In Panel A, we report average worker exposure. In Panel B, we report exposure across the worker earnings distribution that we estimate by interacting the two shocks with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted by income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income bin. The sample is a 5% subsample of all U.S. workers in the LEHD who are employed by any private or public company. The sample period is 1990–2019. We report t-statistics based on standard errors double clustered by industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.3: Worker Exposure to Risk Premium and Productivity Shocks, Income Ranks Within Industry

	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	-2.08	0.89	-2.34	0.95	-2.07	0.93
	(-5.42)	(2.26)	(-4.79)	(2.21)	(-3.39)	(2.00)
Prior Earnings, 25–50th Percentile	-1.53	0.74	-1.64	0.80	-1.29	0.79
	(-5.19)	(2.46)	(-4.42)	(2.39)	(-2.92)	(2.08)
Prior Earnings, 50–75th Percentile	-1.18	0.61	-1.21	0.69	-0.87	0.71
	(-4.45)	(2.19)	(-3.65)	(2.25)	(-2.32)	(2.01)
Prior Earnings, 75–95th Percentile	-1.02	0.52	-0.96	0.60	-0.60	0.68
	(-3.73)	(1.82)	(-2.88)	(1.79)	(-1.66)	(1.70)
Prior Earnings, 95–100th Percentile	-1.80	1.01	-1.46	1.15	-0.79	1.38
	(-4.10)	(2.00)	(-3.07)	(1.92)	(-1.67)	(2.01)
Bottom (1) – Middle (3) Earners	-0.90	0.29	-1.13	0.26	-1.19	0.22
	(-5.76)	(1.56)	(-5.92)	(1.27)	(-4.45)	(0.91)
Middle (3) – Top (5) Earners	0.61	-0.41	0.26	-0.47	-0.09	-0.67
	(1.79)	(-1.10)	(0.75)	(-1.18)	(-0.24)	(-1.61)
Bottom (1) – Top (5) Earners	-0.29	-0.12	-0.88	-0.21	-1.28	-0.45
	(-0.77)	(-0.27)	(-2.14)	(-0.42)	(-2.46)	(-0.82)
Observations	60.2m		57.3m		51.3m	
Fixed Effects	N4 × Inc Grp		N4 × Inc Grp		N4 × Inc Grp	
Clustering	N4, Year		N4, Year		N4, Year	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income 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 income level relative to the levels of other workers in the same industry (instead of the same firm). The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted by income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income 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 industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.4: Worker Exposure to Risk Premium and Productivity Shocks, Alternative Measures

	A. Alternative Risk Premium Shocks							
	3 Years		5 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	-1.96	0.73	-1.76	0.68	-2.87	0.91	-2.64	0.91
	(-4.29)	(1.79)	(-3.25)	(1.51)	(-5.57)	(2.42)	(-3.39)	(2.09)
Prior Earnings, 25–50th Percentile	-1.29	0.70	-1.02	0.70	-2.06	0.83	-1.72	0.84
	(-3.62)	(2.05)	(-2.48)	(1.84)	(-4.69)	(2.54)	(-2.74)	(2.21)
Prior Earnings, 50–75th Percentile	-1.01	0.68	-0.74	0.72	-1.70	0.79	-1.36	0.83
	(-3.15)	(2.14)	(-2.03)	(1.98)	(-4.23)	(2.59)	(-2.43)	(2.29)
Prior Earnings, 75–95th Percentile	-0.88	0.68	-0.60	0.77	-1.48	0.77	-1.15	0.86
	(-3.01)	(1.98)	(-1.84)	(1.93)	(-3.95)	(2.34)	(-2.26)	(2.18)
Prior Earnings, 95–100th Percentile	-1.25	1.36	-0.65	1.58	-1.97	1.45	-1.31	1.65
	(-3.71)	(2.83)	(-2.15)	(2.77)	(-3.77)	(3.01)	(-2.22)	(2.83)
Bottom (1) – Middle (3) Earners	-0.95	0.05	-1.02	-0.04	-1.17	0.12	-1.28	0.08
	(-6.20)	(0.38)	(-4.82)	(-0.25)	(-7.01)	(1.00)	(-4.79)	(0.49)
Middle (3) – Top (5) Earners	0.24	-0.68	-0.09	-0.86	0.27	-0.66	-0.05	-0.82
	(0.79)	(-2.66)	(-0.32)	(-2.89)	(0.75)	(-2.54)	(-0.14)	(-2.70)
Bottom (1) – Top (5) Earners	-0.71	-0.63	-1.11	-0.90	-0.90	-0.54	-1.34	-0.74
	(-2.01)	(-1.98)	(-2.79)	(-2.37)	(-2.12)	(-1.68)	(-2.40)	(-1.86)
Observations	57.3m		51.3m		57.3m		51.3m	
Risk Premium Shock	Alt 1		Alt 1		Alt 2		Alt 2	

	B. Alternative TFP Growth Measures							
	3 Years		5 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	-2.26	0.51	-1.96	0.41	-2.14	0.59	-1.80	0.63
	(-4.75)	(1.07)	(-3.34)	(0.72)	(-4.69)	(3.89)	(-3.20)	(3.71)
Prior Earnings, 25–50th Percentile	-1.55	0.49	-1.20	0.43	-1.43	0.61	-1.05	0.69
	(-4.04)	(1.23)	(-2.68)	(0.90)	(-3.91)	(4.03)	(-2.47)	(4.13)
Prior Earnings, 50–75th Percentile	-1.26	0.49	-0.91	0.47	-1.14	0.61	-0.78	0.69
	(-3.66)	(1.31)	(-2.33)	(1.04)	(-3.45)	(4.43)	(-2.07)	(4.52)
Prior Earnings, 75–95th Percentile	-1.10	0.49	-0.76	0.58	-0.98	0.63	-0.63	0.73
	(-3.43)	(1.23)	(-2.10)	(1.21)	(-3.30)	(4.06)	(-1.89)	(4.20)
Prior Earnings, 95–100th Percentile	-1.46	1.09	-0.83	1.38	-1.31	1.23	-0.69	1.34
	(-3.24)	(1.90)	(-1.97)	(2.04)	(-3.48)	(5.55)	(-2.01)	(5.27)
Bottom (1) – Middle (3) Earners	-1.01	0.02	-1.04	-0.06	-1.00	-0.02	-1.02	-0.06
	(-6.70)	(0.11)	(-4.74)	(-0.30)	(-7.02)	(-0.39)	(-4.86)	(-1.45)
Middle (3) – Top (5) Earners	0.21	-0.60	-0.09	-0.91	0.17	-0.62	-0.08	-0.66
	(0.63)	(-2.10)	(-0.28)	(-2.78)	(0.60)	(-4.09)	(-0.31)	(-3.82)
Bottom (1) – Top (5) Earners	-0.80	-0.59	-1.13	-0.97	-0.83	-0.64	-1.10	-0.71
	(-2.23)	(-1.70)	(-2.58)	(-2.28)	(-2.56)	(-4.28)	(-2.72)	(-4.34)
Observations	57.3m		51.3m		50.5m		45.1m	
TFP Growth	NAICS3 TFP		NAICS3 TFP		Firm TFP		Firm TFP	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income growth over various horizons h as the dependent variable, using alternative measures of risk premium shocks (Panel A) and productivity shocks (Panel B). See Section A.5 for details. The sample and controls are the same as in our baseline specification. We report t-statistics based on standard errors double clustered by industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.5: Worker Exposure to Risk Premium and Productivity Shocks, Alternative Timing Assumptions

	Worker Earnings Timing											
	End of Period						Beginning of Period					
	2 Years		3 Years		5 Years		2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP	RP	TFP	RP	TFP	RP	TFP
Prior Earnings, 0–25th Percentile	-1.15	0.83	-1.57	0.92	-1.37	1.07	-1.62	0.79	-1.62	0.86	-1.22	0.78
	(-4.20)	(1.99)	(-5.13)	(2.04)	(-3.27)	(2.17)	(-6.32)	(2.02)	(-4.51)	(1.99)	(-2.74)	(1.68)
Prior Earnings, 25–50th Percentile	-0.86	0.78	-1.14	0.88	-0.83	1.05	-1.14	0.71	-1.06	0.78	-0.67	0.74
	(-3.74)	(2.22)	(-4.43)	(2.34)	(-2.58)	(2.55)	(-5.34)	(2.17)	(-3.73)	(2.21)	(-2.00)	(1.97)
Prior Earnings, 50–75th Percentile	-0.74	0.72	-0.95	0.83	-0.63	1.01	-0.94	0.65	-0.84	0.74	-0.49	0.74
	(-3.41)	(2.30)	(-4.01)	(2.50)	(-2.15)	(2.75)	(-4.80)	(2.20)	(-3.26)	(2.29)	(-1.63)	(2.08)
Prior Earnings, 75–95th Percentile	-0.70	0.69	-0.84	0.82	-0.53	1.03	-0.84	0.63	-0.72	0.73	-0.38	0.79
	(-3.29)	(2.35)	(-3.86)	(2.50)	(-1.91)	(2.76)	(-4.55)	(2.07)	(-2.98)	(2.11)	(-1.39)	(2.03)
Prior Earnings, 95–100th Percentile	-1.15	1.48	-1.14	1.66	-0.65	1.96	-1.12	1.27	-0.83	1.42	-0.26	1.60
	(-3.79)	(3.67)	(-3.76)	(3.62)	(-2.07)	(3.63)	(-3.92)	(3.03)	(-2.62)	(2.94)	(-0.88)	(2.88)
Bottom (1) – Middle (3) Earners	-0.40	0.12	-0.62	0.09	-0.74	0.06	-0.68	0.15	-0.78	0.12	-0.74	0.04
	(-5.63)	(0.88)	(-7.29)	(0.57)	(-5.51)	(0.28)	(-8.04)	(1.15)	(-6.62)	(0.78)	(-4.27)	(0.23)
Middle (3) – Top (5) Earners	0.41	-0.76	0.19	-0.82	0.03	-0.95	0.18	-0.63	-0.01	-0.68	-0.23	-0.86
	(1.67)	(-3.75)	(0.75)	(-3.43)	(0.11)	(-3.26)	(0.79)	(-2.83)	(-0.05)	(-2.75)	(-1.23)	(-2.97)
Bottom (1) – Top (5) Earners	0.00	-0.65	-0.44	-0.73	-0.71	-0.89	-0.49	-0.48	-0.79	-0.56	-0.97	-0.82
	(0.01)	(-2.41)	(-1.68)	(-2.21)	(-2.33)	(-2.11)	(-2.05)	(-1.86)	(-3.03)	(-1.79)	(-3.12)	(-2.01)
Observations	60.2m		57.3m		51.3m		60.2m		57.3m		51.3m	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income growth over various horizons h as the dependent variable, using two variations to the timing of risk premium shocks: measured over calendar year $t+1$ (first six columns) or over calendar year t (last six columns). We report exposure across the worker earnings distribution that we estimate by interacting the two shocks with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged risk premium index interacted by income group dummies, and fixed effects for the worker's industry I, defined at the 4-digit NAICS level, interacted with her income 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 industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.6: Worker Probability of Job Loss, Shift-Share Design

	Measure of Firm Exposure to Risk Premium Shocks						
	Stock Return Exposure to Market	Stock Return Exposure to RP	Maturing Debt Next 2 Years	Cash to Assets	Firm Size	Distance to Default	Whited–Wu Index
	RP	RP	RP	RP	RP	RP	RP
Prior Earnings, 0–25th Percentile $\times \chi_f$	0.08	0.11	0.12	0.23	0.13	0.20	0.15
	(1.78)	(2.57)	(2.63)	(3.03)	(2.46)	(4.27)	(2.65)
Prior Earnings, 25–50th Percentile $\times \chi_f$	0.05	0.08	0.05	0.26	0.11	0.23	0.15
	(1.16)	(2.06)	(0.90)	(3.64)	(2.22)	(4.99)	(2.97)
Prior Earnings, 50–75th Percentile $\times \chi_f$	0.06	0.11	0.02	0.19	0.13	0.20	0.17
	(1.88)	(3.28)	(0.34)	(2.95)	(2.83)	(4.48)	(3.40)
Prior Earnings, 75–95th Percentile $\times \chi_f$	0.07	0.07	0.05	0.12	0.09	0.13	0.12
	(2.37)	(2.50)	(1.32)	(2.03)	(2.11)	(3.45)	(2.71)
Prior Earnings, 95–100th Percentile $\times \chi_f$	0.05	0.06	0.08	0.04	0.00	0.09	0.03
	(1.06)	(1.19)	(1.70)	(0.51)	(0.01)	(1.91)	(0.62)
Bottom (1) – Middle (3) Earners	0.02	0.01	0.10	0.04	0.00	0.00	-0.01
	(0.50)	(0.23)	(2.71)	(0.80)	(0.10)	(0.11)	(-0.40)
Middle (3) – Top (5) Earners	0.01	0.04	-0.06	0.15	0.13	0.11	0.14
	(0.30)	(0.84)	(-1.41)	(1.96)	(2.39)	(2.90)	(2.46)
Bottom (1) – Top (5) Earners	0.03	0.05	0.04	0.19	0.13	0.11	0.12
	(0.52)	(0.80)	(0.87)	(2.08)	(2.00)	(2.74)	(1.81)
Observations	49.7m	49.1m	47.8m	56.4m	56.4m	52.4m	55.9m
Fixed Effects	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc	N4 × Y × Inc
Clustering	N4, Year	N4, Year	N4, Year	N4, Year	N4, Year	N4, Year	N4, Year

This table reports the regression coefficient β from estimates of equation (3) for various measures of firm-level exposure $\chi_{f,t}$, where we replace the dependent variable with an indicator for job loss over the next three years: 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 that we estimate by interacting $\chi_{f,t} \times \epsilon^{rp}_{t+1}$ with indicators for the worker's prior income level relative to the levels of other workers in the same firm. The controls include a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, and fixed effects for the worker's industry I (4-digit NAICS) by year t, interacted with her income 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 clustered by firm in parentheses. The exposure measures χ_f are standardized to have unit cross-sectional standard deviation and coefficients are scaled so that they correspond to a 10% shock.

Table A.7: Model: Parameter Values

A. Fixed Parameters		
μ_A	Average TFP growth	0.0018
σ_A	Volatility of TFP growth	0.011
$\rho_{A,x}$	Correlation between TFP and RP shock	-0.468
r	Interest rate	0.0016
$\bar{z}_E$	Long-run mean of z in employment	1
ψ_z	Persistence of z	0.991
σ_{z0}	Volatility of initial z	0.666
ν	Mortality rate	0.0028
α	Matching function elasticity	0.407
$\bar{b}$	Unemployment flow value	0.6
γ	Wage smoothing parameter	0.5
B. Parameters Calibrated to Asset Prices		
$\bar{x}$	Average price of risk	0.384
ψ_x	Persistence of price of risk	0.994
σ_x	Volatility of price of risk	0.032
δ	Relative price of RP shock	0.431
C. Parameters Calibrated to Worker Data		
s	Exogenous separation rate	0.0030
$\bar{c}(\bar{\theta}(\bar{z}_O))^{\lambda}$	Level of job search cost at $x_t = \bar{x}$	0.0060
λ	Dependence of search cost on market tightness	2.28
$\bar{\kappa}$	Vacancy posting cost	0.094
$\bar{z}_O$	Long-run mean of z in nonemployment	0.446
σ_z	Volatility of z	0.128
ξ	Reputational cost of ending a match (off equilibrium)	0.171

This table reports the parameter values in our baseline calibration of the model. The parameters in Panel A are fixed a priori, the parameters in Panel B are calibrated to asset pricing moments, and the parameters in Panel C are chosen to fit worker employment and income growth moments to the data, as described in Section 2.5. We report all parameters at monthly frequency.

Table A.8: Model versus Data: Asset Pricing Moments

	Model	Data
Targeted:		
Average P/D	20.3	33.4
Autocorrelation of log P/D	0.91	0.90
Duration of market	21.5	20
Average excess market return	7.1%	7.9%
Volatility of excess market return	19.7%	20.0%
Average excess long-run strip return	7.6%	6.6%
Volatility of excess long-run strip return	30.7%	34.7%
Nontargeted:		
Volatility of log P/D	0.38	0.48
Sharpe ratio of market	0.36	0.40
Autocorrelation of excess market return	-0.03	0.01
Sharpe ratio of long-run strip	0.25	0.19

This table reports annual moments of the price–dividend ratio (P/D), aggregate stock market, and long-run strip in the data and in our model simulations. The empirical moments are over the sample period 1929–2019. For the long-run strip, we use the long-duration portfolio from Gormsen and Lazarus (2023), who sort stocks into decile portfolios based on ex ante duration. In the model, the stock market is a claim to the stream of aggregate dividends (A.23). The long-run strip is a claim to the aggregate dividend in 59 years (the realized empirical duration).

Table A.9: Worker Exposure to Risk Premium and Productivity Shocks, by Job Tenure and Income

	A. Worker Tenure					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Shorter Tenure (<1 Year)	-2.96	0.82	-3.06	0.80	-2.45	0.65
	(-6.80)	(1.62)	(-5.47)	(1.47)	(-3.79)	(1.08)
Tenure, 1–3 Years	-2.21	0.72	-2.30	0.74	-1.82	0.67
	(-5.80)	(1.96)	(-4.65)	(1.80)	(-3.28)	(1.39)
Tenure, 3–5 Years	-1.51	0.96	-1.55	0.98	-1.10	0.91
	(-5.18)	(3.13)	(-4.20)	(2.92)	(-2.67)	(2.35)
Longer Tenure (>5 Years)	-1.02	0.73	-1.00	0.78	-0.61	0.81
	(-4.04)	(2.65)	(-3.24)	(2.64)	(-1.78)	(2.35)
Shorter – Longer Tenure	-1.94	0.09	-2.06	0.01	-1.83	-0.16
	(-7.45)	(0.25)	(-6.79)	(0.04)	(-5.50)	(-0.43)
Observations	47.6m		45.0m		39.5m	

	B. Worker Tenure and Relative Income					
	2 Years		3 Years		5 Years	
	RP	TFP	RP	TFP	RP	TFP
Shorter Tenure (<1 Year)	*Omitted Category*					
Tenure, 1–3 Years	0.70	-0.09	0.70	-0.06	0.55	-0.00
	(4.75)	(-0.42)	(4.85)	(-0.28)	(3.54)	(-0.00)
Tenure, 3–5 Years	1.37	0.15	1.39	0.17	1.21	0.23
	(5.81)	(0.52)	(5.37)	(0.60)	(4.84)	(0.81)
Longer Tenure (>5 Years)	1.84	-0.09	1.92	-0.03	1.68	0.12
	(7.18)	(-0.25)	(6.60)	(-0.08)	(5.51)	(0.31)
Prior Earnings, 0–25th Percentile	-3.24	0.87	-3.43	0.83	-2.84	0.64
	(-6.95)	(1.62)	(-5.63)	(1.45)	(-3.91)	(1.01)
Prior Earnings, 25–50th Percentile	-2.87	0.82	-2.98	0.80	-2.36	0.64
	(-6.63)	(1.63)	(-5.34)	(1.48)	(-3.68)	(1.09)
Prior Earnings, 50–75th Percentile	-2.68	0.74	-2.73	0.75	-2.12	0.62
	(-6.49)	(1.54)	(-5.22)	(1.42)	(-3.57)	(1.07)
Prior Earnings, 75–95th Percentile	-2.61	0.71	-2.62	0.73	-2.00	0.66
	(-6.48)	(1.48)	(-5.19)	(1.33)	(-3.58)	(1.07)
Prior Earnings, 95–100th Percentile	-3.22	1.30	-2.96	1.36	-2.04	1.43
	(-6.22)	(2.12)	(-5.08)	(1.92)	(-3.68)	(1.78)
Bottom (1) – Middle (3) Earners	-0.55	0.14	-0.70	0.08	-0.71	0.01
	(-7.29)	(1.09)	(-6.72)	(0.55)	(-4.79)	(0.08)
Middle (3) – Top (5) Earners	0.54	-0.56	0.23	-0.62	-0.09	-0.81
	(1.83)	(-2.35)	(0.86)	(-2.23)	(-0.36)	(-2.51)
Bottom (1) – Top (5) Earners	-0.02	-0.42	-0.47	-0.53	-0.80	-0.79
	(-0.07)	(-1.50)	(-1.80)	(-1.51)	(-2.56)	(-1.85)
Observations	47.6m		45.0m		39.5m	

This table reports the regression coefficients β and γ from estimates of equation (2) with cumulative income 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 and controls are the same as in our baseline specification. We report t-statistics based on standard errors double clustered by industry and year in parentheses. Coefficients are scaled so that they correspond to a 10% shock.

Table A.10: Model: Parameter Values, Alternative Calibrations

Parameter	Interpretation	Base	Alt1	Alt2	Alt3	Alt4	Alt5	Alt6	Alt7
s	Exogenous separation rate	0.0030	0.0029	0.0036	0.0126	0.0015	0.0007	0.0033	0.0031
$\bar{c}(\bar{\theta}(\bar{z}_O))^{\lambda}$	Job search cost at $x_t = \bar{x}$	0.0060	0.0062	0.0103	10.37	0.0029	0	0.0065	0.0068
λ	Dependence of search cost on market tightness	2.28	2.30	3.99	0.26	5.01	0	0	2.40
$\bar{\kappa}$	Vacancy posting cost	0.094	0.080	0.046	1.711	0.027	0.0001	0.099	0.069
$\bar{z}_O$	Long-run mean of z in nonemployment	0.446	0.449	0.538	0.476	1	0.636	0.351	0.472
σ_z	Volatility of z	0.128	0.122	0.134	0.1	0.071	0.042	0.146	0.129
ξ	Reputational cost of ending a match (off equilibrium)	0.171	0	∞	∞	0.219	0.154	0.167	26.22 (once)

This table compares the parameter values in our baseline calibration and alternative calibrations of the model. Alt1: no reputation cost ($\xi = 0$); Alt2: full commitment ($\xi = \infty$); Alt3: no endogenous separations; Alt4: no skill loss in nonemployment; Alt5: no search cost; Alt6: search cost proportional to A; Alt7: reputation cost has constant NPV. The parameters are chosen to fit the same set of worker employment and income growth moments (see Table A.11). We report all parameters at monthly frequency. The parameters in gray are fixed.

Table A.11: Model versus Data: Targeted Moments, Alternative Calibrations

Moment	Data	Base	Alt1	Alt2	Alt3	Alt4	Alt5	Alt6	Alt7
Unemployment rate, mean	5.7	6.1	5.8	5.8	6.0	6.2	7.2	5.7	6.0
Unemployment rate, vol	1.2	1.3	1.2	1.3	1.3	0.3	0.9	0.9	1.2
E → U rate, 0–25th percentile	1.0	0.9	0.9	0.7	0.4	1.1	0.8	1.1	0.9
E → U rate, 25–50th percentile	0.5	0.4	0.3	0.5	0.4	0.4	0.1	0.4	0.4
E → U rate, 50–75th percentile	0.3	0.3	0.3	0.4	0.5	0.3	0.1	0.4	0.3
E → U rate, 75–95th percentile	0.3	0.3	0.3	0.4	0.6	0.3	0.1	0.4	0.4
E → U rate, 95–100th percentile	0.3	0.3	0.3	0.4	0.8	0.5	0.3	0.3	0.3
E → N rate, 0–25th percentile	1.3	1.3	1.1	0.9	0.9	0.8	0.0	1.1	1.3
E → N rate, 25–50th percentile	0.6	0.2	0.1	0.8	0.8	0.2	0.0	0.1	0.2
E → N rate, 50–75th percentile	0.4	0.1	0.1	0.5	0.8	0.1	0.0	0.0	0.1
E → N rate, 75–95th percentile	0.4	0.1	0.2	0.2	0.6	0.1	0.0	0.0	0.1
E → N rate, 95–100th percentile	0.4	0.1	0.6	0.1	0.4	0.3	0.0	0.0	0.1
U → E rate, 0–25th percentile	15.6	13.2	16.3	22.6	23.4	12.2	13.9	13.4	14.8
U → E rate, 25–50th percentile	15.6	14.8	16.6	21.2	23.0	12.6	14.8	14.7	16.5
U → E rate, 50–75th percentile	15.7	20.0	17.0	23.2	23.0	15.0	17.0	20.5	21.2
U → E rate, 75–95th percentile	15.9	28.4	28.6	28.6	22.9	19.1	30.2	30.8	29.1
U → E rate, 95–100th percentile	17.1	29.2	32.8	33.9	11.6	17.0	32.2	33.4	28.3
2-yr Exposure to TFP, 0–25th percentile	7.6	6.2	18.6	3.3	-0.3	5.1	6.2	7.1	8.2
2-yr Exposure to TFP, 25–50th percentile	7.0	3.6	16.3	1.8	1.2	3.8	4.6	4.3	3.7
2-yr Exposure to TFP, 50–75th percentile	6.4	5.9	15.5	1.6	-0.7	3.2	5.4	6.9	6.1
2-yr Exposure to TFP, 75–95th percentile	6.2	7.5	15.4	0.9	1.6	6.5	8.1	8.6	8.3
2-yr Exposure to TFP, 95–100th percentile	12.2	10.3	15.2	1.1	5.9	9.4	13.8	11.5	11.5
3-yr Exposure to TFP, 0–25th percentile	8.0	7.5	19.6	3.7	0.7	6.3	7.0	8.3	9.6
3-yr Exposure to TFP, 25–50th percentile	7.4	4.6	18.6	2.4	1.7	4.4	5.4	5.5	4.8
3-yr Exposure to TFP, 50–75th percentile	7.1	7.5	18.2	2.1	-0.4	4.1	6.2	8.8	8.0
3-yr Exposure to TFP, 75–95th percentile	7.1	9.6	18.8	1.3	1.9	7.6	9.0	11.1	10.9
3-yr Exposure to TFP, 95–100th percentile	13.7	13.4	18.5	1.6	9.2	11.0	14.9	14.8	14.7
5-yr Exposure to TFP, 0–25th percentile	7.5	9.4	18.9	4.6	1.7	8.1	8.1	9.2	11.2
5-yr Exposure to TFP, 25–50th percentile	7.4	6.1	19.9	3.3	1.3	5.4	6.3	7.6	6.6
5-yr Exposure to TFP, 50–75th percentile	7.4	9.5	19.9	2.8	0.0	5.5	7.0	11.0	10.4
5-yr Exposure to TFP, 75–95th percentile	7.9	12.3	21.4	2.0	1.7	8.4	9.5	13.9	14.0
5-yr Exposure to TFP, 95–100th percentile	15.7	16.6	21.3	2.4	11.2	12.7	15.8	18.1	18.1
2-yr Exposure to RP, 0–25th percentile	-20.2	-15.7	-17.6	-12.9	-6.6	-8.4	-13.4	-14.7	-16.9
2-yr Exposure to RP, 25–50th percentile	-14.4	-6.8	-7.7	-8.4	-4.3	-4.8	-4.9	-6.4	-8.4
2-yr Exposure to RP, 50–75th percentile	-12.0	-4.3	-2.5	-6.3	-2.8	-2.4	-3.6	-5.0	-1.8
2-yr Exposure to RP, 75–95th percentile	-11.0	-4.9	0.2	-5.2	-1.3	-2.2	-3.7	-4.3	-0.9
2-yr Exposure to RP, 95–100th percentile	-17.0	-2.3	1.1	-3.0	-2.8	-3.6	-4.2	-2.0	1.1
3-yr Exposure to RP, 0–25th percentile	-22.3	-19.6	-23.3	-16.8	-9.3	-12.5	-16.9	-18.5	-20.2
3-yr Exposure to RP, 25–50th percentile	-15.2	-9.5	-11.2	-11.3	-6.9	-8.0	-7.4	-9.3	-11.2
3-yr Exposure to RP, 50–75th percentile	-12.3	-6.6	-4.7	-9.0	-4.8	-4.0	-5.2	-7.5	-3.8
3-yr Exposure to RP, 75–95th percentile	-10.8	-7.2	-0.8	-7.4	-4.3	-3.5	-4.6	-6.6	-2.3
3-yr Exposure to RP, 95–100th percentile	-14.3	-3.9	0.3	-4.8	-3.2	-5.0	-4.8	-3.5	0.4
5-yr Exposure to RP, 0–25th percentile	-19.1	-23.5	-27.7	-20.9	-13.3	-19.1	-22.9	-23.4	-23.3
5-yr Exposure to RP, 25–50th percentile	-11.7	-13.2	-14.7	-15.4	-11.4	-13.6	-11.8	-13.2	-14.5
5-yr Exposure to RP, 50–75th percentile	-8.8	-10.5	-7.7	-12.8	-7.4	-7.2	-8.4	-11.5	-7.0
5-yr Exposure to RP, 75–95th percentile	-7.4	-11.0	-2.4	-11.1	-9.7	-6.5	-6.7	-10.4	-4.6
5-yr Exposure to RP, 95–100th percentile	-8.1	-6.3	-0.9	-8.2	-7.6	-7.8	-6.0	-5.7	-0.8

This table compares targeted moments between the data and the model, comparing across the baseline and alternative calibrations. Alt1: no reputation cost ($\xi = 0$); Alt2: full commitment ($\xi = \infty$); Alt3: no endogenous separations; Alt4: no skill loss in nonemployment; Alt5: no search cost; Alt6: search cost proportional to A; Alt7: reputation cost has constant NPV.

Table A.12: Risk Premium Series

					Correlation of AR(1) Residual With	
Series	Start Date	End Date	Sign	AR(1)	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.13: Months with Largest Risk Premium Shocks

Month	RP Shock	Market	ΔVIX	ΔCS
2008:10	26.82	-17.23	20.50	2.39
2020:03	22.23	-13.38	13.43	1.86
1998:08	19.06	-16.08	19.48	0.64
2008:09	17.73	-9.24	18.74	1.00
1987:10	14.12	-23.24		0.13

This table lists the five months with the largest risk premium shocks and the realized excess stock market return, the change in the VIX, and the change in credit spreads during these months. All numbers are in percentages.