Discount Rates, Labor Market Dynamics, and Income Risk*

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Abstract

Recessions are typically associated with lower firm cashflows and higher discount rates. We show that these two components have very different implications for labor income growth. Higher discount rates lead to lower worker earnings for workers at the bottom of the income distribution; these declines are primarily driven by job separations. By contrast, lower cashflow (or productivity) news is followed by declines in earnings for workers at the top of the income distribution, with most of the effect coming from the intensive margin. We build an equilibrium model of labor market search that quantitatively replicates these facts. The model matches several stylized features of the data: the level of unemployment volatility with procyclical job finding rates and counter-cyclical job destruction rates; countercyclical tail risk in labor income growth; the U-shaped sensitivity of worker earnings to aggregate output by prior income; and the cyclical evolution of income inequality.

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Recessions are associated with increases in unemployment and declines in labor force participation, with unemployment increasing significantly more than justified by declines in measured labor productivity (Shimer, 2005). Regardless of their employment status, recessions are associated with earnings losses for workers, even though average wages can rise due to shifts in worker composition (Solon, Barsky, and Parker, 1994). Further, these losses are asymmetrically distributed across workers, with workers at the bottom and at the top of the earnings distribution suffering larger earnings declines than workers in the middle (Guvenen, Ozkan, and Song, 2014; Guvenen, Schulhofer-Wohl, Song, and Yogo, 2017). Our starting point is that recessions are associated with not only declines in productivity but also increases in discount rates (risk premia)—which are often interpreted as a stand-in for financial frictions. Building on this fact and the recent work of Hall (2017) and Kehoe, Lopez, Midrigan, and Pastorino (2022), we propose, and empirically validate, a joint explanation for these facts.

Using administrative data on workers' wage earnings combined with empirical measures of discount rate and productivity (cashflow) shocks, we first document a novel stylized fact: worker earnings decline with increased discount rates or declines in productivity, but the pattern of these responses varies significantly with the worker's earnings level. In particular, we see that the wage earnings of lower-paid workers are significantly more exposed to discount rate shocks than the average worker. Importantly, these earnings losses operate primarily through the extensive margin (job separation) rather than the intensive margin (wage cuts). By contrast, we find that the earnings of the more highly paid workers are significantly more exposed to cashflow shocks than the average worker, and these earnings losses are mainly driven by the intensive rather than the extensive margin.

Motivated by this new fact, we then propose a new model with directed labor market search and aggregate productivity and discount rate shocks that quantitatively explains these patterns. The key mechanisms in the model operate through a combination of persistent worker productivity; endogenous separation decisions that are sensitive to discount rate shocks; and a preference for smoothing wages subject to constraints which follow from a two-sided limited commitment problem. In particular, changes in discount rates lead to a decline in search intensity (as in Kehoe et al., 2022) but also, as is critical for matching our evidence, to an increase in the threshold for terminating existing matches. This threshold is defined by equating the outside option of an incumbent worker with the value of staying in the match, and the former is less sensitive to discount rates than the latter for marginal workers, increasing the rate of endogenous match destruction especially among low income workers. Changes in aggregate labor productivity move the limited commitment constraints – constraints which bind more frequently for high income workers – implying that wages of top workers have higher sensitivity to productivity shocks.

Our empirical measures of discount rate and cashflow shocks builds on a voluminous literature in finance that infers these shocks from data on stock returns (Campbell and Shiller, 1988; Campbell and Vuolteenaho, 2004). Our main empirical design identifies our effects through aggregate sources of cashflow and discount rate variation interacted with a firm-level measure of exposure, which is reminiscent of a shift-share design. This design allows us to sidestep concerns about reverse causality—the alternative interpretation that employment flows drive firm discount rate and cashflow changes. An advantage of our empirical measures is that they are based on stock market data which are forward-looking and move at higher frequencies than more direct measures of productivity. Naturally, the key disadvantage of our approach is that our cashflow and discount rate proxies are indirectly inferred from the data which can obscure their economic interpretation.

To this end, we also verify that the same patterns in wage responses obtain using more direct measures of the two types of shocks. For example, when we replace the returns-based measure of cashflow news with changes in firm total factor productivity (from İmrohoroğlu and Tüzel, 2014), we also find that the earnings of higher-income workers are more exposed to cashflow shocks than the earnings of lower-income workers. In addition, we replace our measure of discount rate shocks with a more direct financial shock affecting firms: the inability to refinance their pre-existing debt during the 2008/09 financial crisis. The need to refinance maturing debt when the cost of external finance is high is likely to induce firms to prioritize short-term over long-term cashflows in a manner similar to a discount rate shock. Here, the identifying assumption is that this pre-existing variation in the maturity of long-term debt is orthogonal to the firm's current investment opportunities.We verify that the wage earnings of lower-paid workers respond more to this shock relative to the earnings of higher-paid workers, and just like our baseline result, these earnings losses are driven by concentrated earnings losses of workers who lose jobs rather than wage declines for continuing workers.

We rationalize our empirical findings using an equilibrium model of directed labor market search. The model has several features, which allow us to deliver rich predictions about the earnings responses of individual workers, job destruction, as well workers' decision to participate in the labor market. Workers in the model differ along several dimensions: their individual productivity and general human capital; their employment status; and whether they are actively searching for a job. Increases in discount rates lead to an increase in the pool of unemployed workers as firms terminate lower-surplus matches as well as an increase in the pool of workers that (somewhat persistently) decide to exit the labor force. Wage dynamics of continuing matches are determined by a preference for smooth wages subject to a constraint coming from an inability of firms to commit not to fire workers prematurely and of workers to commit not to quit if it is in their best interest to do so. The 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).

We calibrate the model to match the earnings responses to discount rate and cashflow shocks as well as average separation rates and job-finding rates across the income distribution. Overall, the model successfully reproduces the strong heterogeneity in job separation rates across workers with different income levels; workers in the bottom quartile have separation rates that are three times as large as workers in the top quartile. In contrast, in both the data and the model, job-finding rates are similar across income groups. The model is able to match these moments combined with the heterogeneous worker earnings responses to productivity and discount rate shocks as a function of income that we measure in our empirical analysis.

Our model implies that an increase in discount rates primarily affects lower-paid workers through job separations. On average, lower-paid workers are closer to the separation threshold, as income is correlated with individual worker productivity—though imperfectly. Worker productivity is correlated with the match surplus—equivalently, the value of a match is more sharply increasing in worker productivity than the value of unemployment to the worker—through a combination of several channels: first, unemployment is associated with slower growth in human capital, which is complementary to worker productivity; second, unemployment benefits do not depend on the mean-reverting component of worker productivity. As the separation threshold is sensitive to discount rates, an increase in discount rates leads to higher levels of destruction of lower-surplus matches and hence are associated with earnings losses for lower-paid workers. In addition, workers incur a cost of searching for a job; as higher discount rates also lower the benefits of job search, more workers exit the labor force as discount rates rise which contributes to a scarring effect of recessions.

Declines in labor productivity (negative cashflow news) primarily affect earnings on the intensive margin. Like most models of labor market search, we need additional assumptions to pin down the (flow) wages of continuing matches. A useful benchmark is sticky wages, in which wages of continuing matches are constant and insensitive to current productivity (see e.g. Erceg, Henderson, and Levin, 2000; Christiano, Eichenbaum, and Trabandt, 2016). We introduce two modifications to the baseline setup. First, whenever possible, firms smooth (per-period) worker wages—a stand-in for worker risk aversion. In the absence of any additional constraints, wages of continuing workers would grow at a constant rate in line with their human capital accumulation. Second, we allow for two-sided lack of commitment. Workers cannot commit to leaving existing matches when they can obtain a higher surplus in the labor market—though if they decide to inefficietly quit a match they give up unemployment benefits. Conversely, firms cannot commit to (inefficiently) terminating matches of 'overpaid' workers—the firm has to offer the worker a path of future wages that is not too high relative to the present value of output the worker produces in the match, minus a reputational cost of (inefficiently) terminating the existing match. Though no matches are inefficiently terminated in equilibrium, whenever these constraints bind (or are close to binding) it implies that wages of incumbent workers are sensitive to the current level of labor productivity, just like in models with two-sided limited commitment (Thomas and Worrall, 1988; Kocherlakota, 1996). These constraints – especially on the firm side – are more likely to bind for high-productivity workers, because for these workers the benefit to the firm of cutting their wages is larger relative to the reputational cost. As a result of these tighter bounds, wages of high-income workers are more sensitive to aggregate productivity shocks relative to their low-income counterparts. Moreover, the path dependence of different workers' contracts implies the sensitivity of earnings to these shocks can be quite heterogeneous, even for workers with similar income or productivity levels. This model feature also helps to generate a large amount of kurtosis in earnings changes, even for workers who do not separate from their current employer.

Overall, the calibrated model is reasonably successful in quantitatively replicating the features of the data that we target. In addition, the model is able to replicate several aspects of the data that are not specific targets in our calibration. For instance, the model generates realistic fluctuations in the aggregate unemployment rate, even though it is not a moment we target, therefore resolving the Shimer (2005) puzzle. To further test the model mechanism, we estimate the empirical impulse response of the unemployment rate to discount rate news and compare it to the responses in data simulated from the model. Consistent with our model, we find that positive discount rate news predicts increased future unemployment over the next two years. The model-implied responses are quantitatively consistent with these patterns, falling well within estimated confidence intervals.

In addition to employment, our model can replicate a number of stylized facts about worker wage earnings. In particular, our work can rationalize the findings of Guvenen et al. (2017), who document the response of worker earnings in recessions has a U-shape as a function of income (low- and high-income workers have higher sensitivity of wage earnings to output or the stock market). In both the model and the data, this non-monotonic pattern reflects the sum of two distinct forces: discount shocks which disproportionately move the earnings of low-wage workers and cashflow shocks which disproportionately move the earnings of high-wage workers.

Our calibrated model can also generate a realistic level of income risk: it generates distributions of earnings changes, for both stayers and movers, that are highly lepto-kurtotic even though the underlying shocks are normally distributed. These patterns emerge through the combination of two model mechanisms: first, the concentration of earnings losses among workers who experience job losses, and, second, the heterogeneous responses to shocks which endogenously arise from the dynamic wage contract. In addition to a realistic level of income risk, the model can also replicate its counter-cyclical behavior documented by Guvenen et al. (2014). In the model, income risk is counter-cyclical because an increase in discount rates decreases both output (due to lower employment) while increasing job separations as low-surplus matches are dissolved. Consistent with the model mechanism, we find in the data that increases in discount rates are associated with a higher likelihood of labor force exit, as measured by the incidence of quarters of zero W2 earnings, particularly for lower-paid workers, with magnitudes similar to the nontargeted predictions from the model. In the model, job separations lead to significant earnings losses for worker. As a result, the distribution of worker earnings growth becomes more left-skewed as output contracts, a correlation which is consistent with the data.

In addition to earnings risk, our model can also replicate the rise in income inequality in the left tail following recessions (Heathcote, Perri, and Violante, 2020). In the model, an increase in discount rates leads to a higher rate of job destruction which has highly persistent effects on (mostly low-income) workers due to the lack of human capital accumulation while unemployed. Since searching for a job involves a cost, some workers in the model can remain out of the labor force for a long time if they are sufficiently unproductive—a modeling device for a skill mismatch between workers and vacancies. In this regard, our model also implies that the duration of workers' unemployment spells increases with discount rates, and is therefore counter-cyclical.

Importantly, in addition to focusing on the unconditional moments of the data, we explore the model's ability to predict the realized fluctuations in unemployment, labor force participation, left-tail income inequality, and labor income risk by feeding in our empirical estimates of cashflow and discount rate news into the calibrated model. Though the model is missing many other factors that drive these variables in the data, it can replicate to a significant extent their realized path along the business cycle. The correlation between these model-implied series and their (detrended) empirical counterparts ranges from 0.42 to 0.45.

More broadly, our findings have implications for the redistributive effects of financial crises, which are typically associated with a marked increase in risk premia (Muir, 2017). Financial market dislocations can induce variation in the effective supply of capital to firms, which can lead to an increase in firms' discount rates. Our results indicate that low-wage workers bear the cost of these fluctuations. Our model predicts that an increase in discount rates—holding productivity shocks constant—is likely to be associated with increased earnings dispersion across workers that is likely to be persistent as some workers exit the labor force.

Our paper contributes to several strands of the literature. A large literature on labor market search has focused on trying to solve the unemployment volatility puzzle, stemming from the seminal observation of Shimer (2005) that the textbook search model (Diamond, 1982; Mortensen, 1982; Pissarides, 1985) is unable to generate a realistic level of volatility of the unemployment rate. Since then, numerous studies have proposed resolutions to this puzzle; the ones most relevant to this paper are Hall (2017); Kilic and Wachter (2018); Kehoe et al. (2022), who argue that counter-cyclical discount rates can explain why firms post fewer vacancies during recessions.[1] Closest to our work is

[1] Recent work in macroeconomics and finance has emphasized the importance of time-varying risk (or risk aversion) for generating significant aggregate fluctuations in quantities and asset prices by changing firms' discount rates. These disturbances, often modeled as changes in the stochastic discount factor, create an important channel for financial shocks to reverberate through the real economy. A partial list includes Campbell and Cochrane (1999); Bansal and

Kehoe et al. (2022), who model counter-cyclical 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—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. However, the importance of time-varying discount rates, especially quantitatively, in this context is still a subject of disagreement. Borovička and Borovičková (2018) argue that a stochastic discount factor that is consistent with observed properties of asset returns only partially alleviates the Shimer puzzle, and Martellini, Menzio, and Visschers (2021) argue that discount rate shocks can often induce counterfactual predictions for cyclicality separation rates.

We contribute to this literature along several dimensions. First and foremost, we provide direct evidence for this mechanism using detailed micro data on worker earnings and use these estimates to calibrate an equilibrium model of labor market search. Our model proposes an additional mechanism through which discount rates increase unemployment: endogenous destruction of inefficient matches, rather than relying only on lower search effort on the part of workers and firms as in Kehoe et al. (2022). The calibrated model generates sufficiently volatile unemployment—even though it is not an explicit calibration target—and therefore helps resolve the Shimer puzzle. Last, using detailed micro data allows us to study the impact of these shocks on the distribution of labor earnings across individual workers, not only along the extensive but also along the intensive margin. The model can quantitatively replicate these earnings responses for both movers and stayers through a combination of job destruction, and assumptions on the labor contract that allow for partial wage adjustments, similar in spirit to Balke and Lamadon (2022).

A voluminous literature in asset pricing explores the differential implications of cashflow versus discount rate shocks for the cross-section of asset returns (see e.g. Campbell and Vuolteenaho, 2004; Lettau and Wachter, 2007; Santos and Veronesi, 2010). A key finding in this literature is that shocks to discount rates are 'priced' in the cross-section of asset returns—that is, securities that pay off in states when discount rates are high tend to have lower returns on average. The risk premium on these shocks is often interpreted through the lens of a representative agent with a time-varying opportunity set. Our work contributes to this literature by suggesting a novel mechanism that would affect how these shocks are priced relative to cashflow (productivity) shocks through their impact on the cross-sectional distribution of worker earnings.

Our work also connects to the literature documenting the impact of financial frictions on employment (Benmelech, Bergman, and Seru, 2021; Giroud and Mueller, 2017; Benmelech, Frydman, and Papanikolaou, 2019) by documenting how these frictions impact the labor market outcomes of individual workers. In this sense, our paper is related to Caggese, Cuñat, and Metzger (2019)

Yaron (2004); Barro (2009); Wachter (2013); Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2018); Itskhoki and Mukhin (2021); Basu, Candian, Chahrour, and Valchev (2021); Kehoe et al. (2022).

who use employer-employee matched data from Sweden; they 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 high credit ratings. Caggese et al. (2019) argue theoretically that from the perspective of the firm, these workers are high-duration investments. Mitra and Xu (2020) also show theoretically how increases in discount rates lead to larger employment losses for young workers and provide empirical support using aggregate data. Our work differs from this literature along several dimensions. First, we examine a distinct source of worker heterogeneity than the duration effects considered in these papers. Second, we separately analyze the impact of discount rate and cashflow shocks and show that they have different implications for worker earnings—by contrast, the empirical design in Caggese et al. (2019) does not necessarily separate between a discount rate shock and a shock to labor productivity. Third, we provide direct estimates of the heterogeneity in earnings responses across the income distribution using granular micro data and interpret these responses through the lens of a quantitative model. Last, some of our findings are related to Baghai, Silva, Thell, and Vig (2021), who show that high-skilled workers are more likely to leave firms as they approach bankruptcy.

Last, though monetary policy is not the focus of our paper, part of the variation in discount rates that we identify could be driven by monetary policy, either directly through the risk-free rate or indirectly through a 'reaching for yield' channel (Moreira and Savov, 2017). In this respect, our empirical findings are consistent with 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 worker is more sensitive to monetary policy shocks in the United States than employment of high-income workers. Closer to us, Coglianese et al. (2022) also 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. Our findings complement these two papers by showing how broader measures of discount rate shocks affect worker earnings in the United States (a country with a different labor market structure than Sweden), while also offering a structural model of labor market search and wage determination that can quantitatively replicate these findings.

1 Worker Earnings, Cashflow and Discount Rate Shocks

We begin by documenting a new stylized fact: there is significant heterogeneity in how worker earnings respond to productivity shocks (news about cashflows) and financial shocks (news about discount rates) as a function of prior income. After describing the data in Section 1.1, we first revisit earnings exposures to aggregate market conditions across the income distribution in Section 1.2. We then decompose market returns into cashflow and discount rate news in Section 1.3, and document in Section 1.4 how wage earnings respond to these shocks as a function of workers' prior income. Section 1.5 shows that our results are similar for more direct measures of cashflow and discount rate news, and that the heterogenous responses we document are not driven by differences in employee tenure.

1.1 Data Description

We begin by describing the employer-employee linked wage earnings data that we rely on for our empirical analysis. Our main data on worker earnings are 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 data allow us to track the incomes of individual workers over time and across employers. For brevity, we briefly describe the data here and relegate all details to Appendix B.1.

Our main outcome variable is growth rate in worker earnings. We construct a measure of forward looking wage earnings growth, following Autor, Dorn, Hanson, and Song (2014) and Guvenen et al. (2014),

$$g_{i,t:t+h} \equiv w_{i,t+1,t+h} - w_{i,t-2,t}, \tag{1}$$

where w_{i,τ_1,τ_2} refers to cumulative *age-adjusted earnings* over the period from τ_1 to τ_2, defined as

$$w_{i,\tau_1,\tau_2} \equiv \log\left(\frac{\sum_{\tau=\tau_1}^{\tau_2} \text{W-2 earnings}_{i,\tau}}{\sum_{\tau=\tau_1}^{\tau_2} D(\text{age}_{i,\tau})}\right). \tag{2}$$

The term $D(\text{age}_{i,\tau})$ in the denominator of (2) is an adjustment for the average life-cycle path in worker earnings that closely follows Guvenen et al. (2014). Focusing on growth in average income over multiple horizons in (1) emphasizes persistent changes in earnings, smoothing out transitory shocks. To reduce the impact of outliers, we winsorize all worker income growth rates $g_{i,t:t+h}$ at the 1st and 99th percentile. Importantly, since we can track individuals over time, income growth in (1) may include earnings from different employers. To study how workers' exposures varies 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.

Table 1 summarizes the variables that characterize the earnings dynamics of the workers in our main LEHD sample of public firm employees between years $t = 1992$ and $t = 2019$. We summarize real earnings growth $g_{i,t:t+h}$ over various horizons, as well as the probability of a move and the probability of a zero earnings quarter 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 as a mover in all other cases (either a different main employer or no employer).

1.2 Worker Exposures to Aggregate Market Returns

We start by revisiting the U-shaped link between worker earnings growth and the stock market documented in Guvenen et al. (2017) using the panel data on individual earnings growth from the LEHD described in Section 1.1. As in Guvenen et al. (2017), we focus on heterogeneity in market exposures across the income distribution. For consistency with our main analysis, we estimate exposures to stock market *news* $N_{MKT,t}$, defined as the residual component of stock market returns after orthogonalizing with respect to state variables Ω_{t-1}. This vector Ω_{t-1} includes the lagged Treasury bill rate, the lagged term spread, the lagged aggregate market return, and the lagged market's smoothed price-earnings ratio.

We estimate the following specification:

$$g_{i,t:t+h} = \sum_s \gamma_{MKT,s}\, N_{MKT,t} \times \mathbb{1}(\theta_{i,t} = s) + \psi' X_{i,t} + \varepsilon i, t + h, \tag{3}$$

where $\theta_{i,t}$ is the within-firm income group of worker i in year t. The vector of controls $X_{i,t}$ includes a third-order polynomial in the log of average income over the past three years, a complete set of age dummies, the lagged market return interacted by income group dummies, and industry (4-digit NAICS code) by income group fixed effects. We follow Campbell (2003); Guvenen et al. (2017) and use the beginning-of-period timing convention of aligning earnings growth from year t to $t + h$ with stock returns in year t.

First, we use variation purely coming from the aggregate time series and estimate the relation between income growth and stock market returns for workers in different parts of the earnings distribution. Columns (1)–(4) of Table 2 report the results for different horizons ranging from $h = 1$ to $h = 5$ years. We find that stock market returns are significantly positively correlated with income growth on short as well as longer horizons. As in Guvenen et al. (2017), we find that aggregate risk exposures at the one-year horizon are U-shaped with respect to income levels: workers in the top 5% of the earnings distribution have the highest exposure, followed by workers below the 25th percentile. At longer horizons, market betas become monotonically decreasing in income level. Thus, lower-wage workers have more persistent exposures to aggregate stock returns than high-wage workers.

Second, we consider the pass-through from employers to employees more directly by including cross-sectional variation coming from differences in firm exposures to the stock market. We compute the systematic news component of firm stock returns as $\beta_{j,t-1} N_{MKT,t}$, where $\beta_{j,t-1}$ is the market beta of firm j's equity measured using returns up to $t - 1$. We estimate worker exposures to this systematic component:

$$g_{i,t:t+h} = \sum_s \gamma_{MKT,s}\, \beta_{j,t-1} N_{MKT,t} \times \mathbb{1}(\theta_{i,t} = s) + \psi' X_{i,j,t} + \varepsilon_{i,t+h}. \tag{4}$$

In addition to the previous set of controls, we now also include controls for the firm's market beta by worker income group.

The results from this regression specification are in columns (5)–(8) of Table 2. We see that the results are very similar to those in columns (1)–(4): the market beta of earnings by income level is U-shaped at shorter horizons and becomes monotonically decreasing in income at longer horizons.

1.3 Identifying Cashflow and Discount Rate Shocks

Here, we discuss the construction of our main measures of cashflow and discount rate shocks. We follow the finance literature and decompose the total return to the stock market into cashflow news and discount rate news (Campbell and Shiller, 1988). In particular, we start with a log-linearized expression for the log price-dividend ratio ζ:

$$\zeta_{t-1} = \kappa_{t-1} + \sum_{s=0}^{\infty} \rho^s r_{t+s} - \sum_{s=0}^{\infty} \rho^s \Delta d_{t+s}, \tag{5}$$

where r_t is the log stock return, d_t is the log dividend paid by the stock, κ is a log-linearization constant, and ρ is a discount coefficient.

We then use equation (5) to decompose unexpected stock returns into cashflow news and discount rate news:

$$\underbrace{r_t - \mathbb{E}_{t-1} r_t}_{\equiv N_{MKT,t}} = \underbrace{\Delta \mathbb{E}_t \sum_{s=0}^{\infty} \rho^s \Delta d_{t+s}}_{\equiv N_{CF,t}} - \underbrace{\Delta \mathbb{E}_t \sum_{s=1}^{\infty} \rho^s r_{t+s}}_{\equiv N_{DR,t}}. \tag{6}$$

To implement the return decomposition, we need an estimate of discount rate news. Rather than relying on identifying restrictions of a first-order VAR model (Campbell and Shiller, 1988; Campbell and Vuolteenaho, 2004) we build on the ideas in Kozak and Santosh (2020) and create a measure of discount rates shocks based on the correlation of traded market factors with future stock market returns. In particular, we consider a direct forecasting regression for the discounted sum of realized future excess returns (up to a fixed horizon S), defined by

$$\Gamma_t \equiv \sum_{s=1}^{S} \rho^s r_{t+s}. \tag{7}$$

The goal is to find a linear combination w_k of factors f_{kt} that is the best predictor of future returns on the aggregate stock market — that is the component of this period's return that captures news about discount rates. We estimate w_k by projecting Γ_t on the returns of traded factors at time t, controlling for a vector of state variables Ω_{t-1},

$$\Gamma_t = a + b\,\Omega_{t-1} + \sum_{k=1}^{N} w_k\, f_{k,t} + \eta_t. \tag{8}$$

We denote by $\widetilde{f}_{kt}$ factors that are orthogonalized w.r.t. a constant and Ω_{t-1}. To the extent that the vector Ω_{t-1} summarizes the existing prior beliefs about future returns Γ_t, the linear combination of traded factors $w_k\, f_{k,t}$ can be interpreted as news about future discount rates.

We implement this decomposition of market returns at a monthly frequency. We project the discounted sum of future returns Γ_t on six traded factors: the five Fama-French factors and the momentum factor. As in Section 1.2, in the vector of state variables Ω_{t-1}, we include the Treasury bill rate, the term spread, the aggregate market return, and the market's smoothed price-earnings ratio as of month $t-1$. We consider returns up to ten years in the future – $S = 120$ – and assume that returns after 10 years are not predictable. We follow Vuolteenaho (2002) in choosing the value $\rho = 0.967^{1/12}$. The sample period is January 1964 to December 2020.

Given the above, we then define our measures of discount rate and cashflow news as

$$N_{DR,t} \equiv \sum_{k=1}^{N} w_k \widetilde{f}_{kt} \tag{9}$$

$$N_{CF,t} \equiv N_{MKT,t} + N_{DR,t}. \tag{10}$$

Since our empirical analysis is conducted at an annual frequency, we also build analogous measures of discount rate and cashflow news at the yearly level that we use for measuring earnings exposures in the data. Figure 1 plots the annual cashflow and discount rate news terms that we obtain using the approach described above.

We present two validation checks to our approach. First, in Appendix Table A.1, we measure to what extent cashflow and discount rate shocks predict the future returns of different portfolios sorted by market betas. We use quintile portfolios from a sort on market beta from Ken French's website, and consider the discounted sum of 10-year ahead returns at a monthly frequency as in our baseline regression. We find that cashflow news does not predict future returns, while discount rate news significantly predicts future returns for all portfolios. More importantly, discount rate news is a much stronger predictor of future returns for high-beta stocks, and the last columns shows that discount rate news significantly predicts the return on a long-short portfolio of high beta minus low beta. Thus, consistent with economic intuition, discount rate news affects high-beta firms more than low-beta firms. As a second validation check, Figure A.1 shows that this predictability is not limited to our forecasting horizon of ten years; the same discount rate news component also significantly predicts future cumulative stock market returns at shorter and longer horizons.

1.4 Worker Exposures to Cashflow and Discount Rate News

We use the decomposition described above to break down the results from Section 1.2 into separate exposures to cashflow news and discount rate news. We show that worker earnings are significantly affected both by cashflow and by discount rate shocks, but there are notable differences in exposures to these two different shocks across the income distribution.

Here, we estimate

$$g_{i,t:t+h} = \sum_s (\gamma_{CF,s}\, N_{CF,t} + \gamma_{DR,s}\, N_{DR,t}) \times \mathbb{1}(\theta_{i,t} = s) + \psi' X_{i,t} + \varepsilon_{i,t+h}. \tag{11}$$

We report the estimated coefficients γ_{CF} and γ_{DR} in columns (1) through (4) of Table 3. We find that income growth significantly loads on both components of aggregate stock market returns, with the expected signs. Good cashflow news is followed by increases in labor income, whereas increased discount rates are followed by income declines.

Our main empirical finding is that the two components have markedly different implications for income growth across the earnings distribution. Exposure to cashflow news are largest for high-wage workers at the top 5% of the earnings distribution. While the point estimates are similar at short and longer horizons, statistical significance of this effect declines due to increasing standard errors. Exposures to cashflow shocks are similar for workers below the top income group and are positive but insignificant.

For discount rate news, we find the complete opposite pattern. Low-wage workers are most exposed to discount rate news. While all workers are significantly affected by discount rate news at short horizons, low-wage workers have a significantly larger exposure than the typical worker. At a horizon of two or more years, earnings exposures to discount rate news monotonically decline with income levels. In the longer term, low-wage workers face significant earnings declines when discount rates rise, while high-wage workers are unaffected.

Next, we exploit the cross-sectional variation coming from the differential exposure of employers to market returns, and estimate the following specification:

$$g_{i,t:t+h} = \sum_s (\gamma_{CF,s}\, \beta_{j,t-1} N_{CF,t} + \gamma_{DR,s}\, \beta_{j,t-1} N_{DR,t}) \times \mathbb{1}(\theta_{i,t} = s) + \psi' X_{i,j,t} + \varepsilon_{i,t+h}. \tag{12}$$

The results for this specification are reported in columns (5)–(8) of Table 3. Again, we find that cashflow shocks primarily affect the highest paid workers, whereas discount rate shocks affect wages of workers at the bottom of the earnings distribution. Due to the additional cross-sectional variation, the estimates from this specification are more precisely estimated. Overall, the results closely mimic the findings from columns (1)–(4).

We emphasize that these earnings declines we document include subsequent labor market outcomes for workers that leave the firm. That is, worker earnings can decline either because they remain employed but either work fewer hours or received a pay cut in hourly wages; they are now unemployed an receive no wage income; or they transition to a new job that pays a lower wage.

The model we describe in Section 2 has sharp predictions regarding whether the extensive or the intensive margin is the key driver of these earnings changes, an issue we revisit in the data in Section 4.1.

1.5 Additional Results and Robustness

So far, we have documented a novel stylized fact: the response of worker earnings to aggregate shocks as a function of workers' prior income is qualitatively differently depending on whether these shocks are cashflow (productivity) shocks or discount rate shocks. In particular, we see that the wage earnings of lower-paid workers are significantly more exposed to discount rate shocks than the average worker. Importantly, these earnings losses operate primarily through the extensive margin (job separation) rather than the intensive margin (wage cuts). By contrast, we find that the earnings of the more highly paid workers are significantly more exposed to aggregate cashflow (i.e. productivity) shocks than the average worker, and these earnings losses are mainly driven by the intensive rather than the extensive margin.

Next, we briefly discuss additional results and robustness checks. To conserve space, we relegate the details to Appendix B.

Direct Measures of Cashflow Shocks

Our analysis so far has relied on measures of cashflow and discount rate shocks that are inferred from data on stock returns. The advantage of these measures is that they primarily depend on aggregate sources of variation interacted with a firm-level measure of exposure reminiscent of a shift-share design. Doing so allows us to abstract away from an alternative in which employment flows drive firm discount rate and cashflow shocks. One potential disadvantage is that they are indirectly estimated which may obscure their economic interpretation. We thus revisit our analysis using a more direct measure of cashflow shocks: estimates of changes in firm total factor productivity (TFP) from İmrohoroğlu and Tüzel (2014). Appendix Table A.2 shows that we obtain quantitatively similar, though significantly more precise, estimates of worker earnings exposure to cashflow news. Appendix B.4 contains further details and additional results using this alternative measure.

Direct Measures of Discount Rate Shocks

We also estimate worker earnings responses to a more direct measure of financial shocks. In particular, we build on Almeida, Campello, Laranjeira, and Weisbenner (2011); Benmelech et al. (2021) and explore firms' need to refinance pre-existing debt during the height of the Great Recession. The identifying assumption is that this pre-existing variation in the level of maturing debt is orthogonal to the workers' marginal product during the 2008–09 period. Appendix Tables A.3, A.4, and A.5 show our findings with the details and additional results relegated to Appendix B.5.

In brief, we find that our main results on the sensitivity of wage earnings of (low-income) workers continue to hold using this alternative measure of discount rate shocks. Specifically, low-income workers in firms that needed to refinance their debt during the financial crisis experienced lower earnings, with much of the effect coming from job separations. Thus, we obtain very similar results using two very different sources of variation in the data. That is, much (though not all) of the identification of our main results in Section 1.4 comes from time-series variation. By contrast, the results in this section are obtained purely through cross-sectional variation in the share of maturing debt.

Income vs Tenure

Appendix Table A.6 shows that the income effect that we identify is distinct from a tenure effect—our results continue to hold when we rank workers on income conditional on their tenure. Thus, the effect we identify is distinct from the findings of Caggese et al. (2019).

Robustness

In addition, our main findings are largely robust to various alternative definitions of the treatment variables and to different empirical specifications. Appendix Table A.8 presents the results when we measure cashflow and discount rate news using the standard Campbell-Vuolteenaho (CV) VAR-based decomposition. We obtain qualitatively similar, though less precisely estimated coefficients, likely because the CV discount rate measure is somewhat noisier: it is less successful in differentially predicting the future returns of high- versus low-beta firms than our baseline measure (see Appendix Table A.7 vs A.1). Appendix Table A.9, we show that the results discussed above are robust to alternative versions of the stock market return decomposition in Section 1.3. Appendix Table A.10 adds time fixed effects in the worker regressions—in this case the discount rate and cashflow shocks are only identified through the cross-sectional variation in employer betas. While the point estimates become somewhat smaller, our main findings and patterns hold. Appendix Table A.11 shows that our findings continue to hold when we use separate cashflow and discount rate betas to decompose the systematic component of a firm's stock return into cashflow news and discount rate news. Last, Appendix Table A.12 shows that we obtain qualitatively similar results when we expand the sample to all workers and not just workers of public companies, using aggregate cashflow and discount rate news only.

2 Model

Next, we propose a quantitative model that is able to replicate the facts we document in Section 1, together with other (nontargeted) features of labor market and individual earnings dynamics. Specifically, we consider a Diamond-Mortenson-Pissarides (DMP) model of the labor market with directed search, where we model the stochastic discount factor of the economy using a specification from the asset pricing literature. In order to derive implications about the path of worker earnings, we propose a novel wage-setting protocol involving wage smoothing subject to constraints coming from a two-sided limited commitment problem.

2.1 Environment

Time t is discrete and runs forever. We consider an economy with a unit measure of ex-ante identical workers and a large number of firms. Each individual worker is indexed by i and is either a nonparticipant in labor markets, an unemployed job seeker, or employed by a firm. Firms employ workers to produce output, and can post vacancies to attract new workers in submarkets to be described below.

Timing

Each period in the model consists of three subperiods. First, a fraction ν of workers die and are replaced by new (unemployed) workers, and the 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. Unemployed workers who do not find a new match learn whether or not they will remain in the search pool. In addition, some of the existing matches are destroyed due to exogenous separation or because they are endogenously terminated when the surplus generated by the match becomes negative. In the third subperiod, for continuing and new matches, production is realized and wages are paid. Unemployment benefits are paid to workers that are not in a match, and nonemployed workers outside the worker search pool decide whether to pay the cost to enter the search pool for the subsequent period.

Production

Workers that are matched with a firm can produce output at a rate that depends on their permanent human capital, transitory individual productivity, as well as the aggregate state of the world. Specifically, a worker with permanent human capital h and transitory idiosyncratic productivity z produces output using the linear production technology

$$y_{i,t} = A_t \, h_{i,t} \, z_{i,t}. \tag{13}$$

The first component h of a worker's individual productivity represents the worker's permanent ability, which grows at the rate $g_{i,t}$,

$$h_{i,t+1} = \exp\left(g_{i,t}\right) \, h_{i,t}. \tag{14}$$

The growth rate of human capital depends on a worker's employment status, $g_{i,t} \in (g_O, g_E)$. This learning by doing formulation will imply that human capital grows with work experience and workers experience long-term costs from being out of a job, similar to Ljungqvist and Sargent (1998).

The second component z of a worker's individual productivity represents the worker's transitory productivity, which evolves as an AR(1) process in logs,

$$\log z_{i,t+1} = \psi_z \log z_{i,t} + (1 - \psi_z) \log \overline{z} + \sigma_z \cdot \varepsilon_{z,i,t+1}, \tag{15}$$

where $\varepsilon_{z,i,t}$ is an i.i.d. standard normal random variable. The fact that $z_{i,t}$ is mean-reverting creates scope for firms to provide some degree of insurance against idiosyncratic shocks to worker productivity and also leads to important heterogeneity in employment dynamics in the model, as we will detail below.

Newly born workers enter the economy without a job. The initial conditions for a worker born a time $t_0(i)$ are given by

$$z_{i,t_0(i)} = \overline{z}\ \exp(\sigma_z \cdot \varepsilon_{z,i,t_0(i)}) \tag{16}$$

$$h_{i,t_0(i)} = \overline{h}\ \exp(\sigma_{h0} \cdot \varepsilon_{h,i}), \tag{17}$$

where $\varepsilon_{z,i,t_0(i)}$ and $\varepsilon_{h,i}$ are i.i.d. standard normal random variables.

Finally, aggregate productivity A_t follows a random walk,

$$\Delta \log A_{t+1} = \mu_A + \sigma_A \cdot \varepsilon_{A,t+1}, \tag{18}$$

where $\varepsilon_{A,t+1} \sim N(0, 1)$. Thus, consistent with the vast majority of models in the production-based asset pricing literature, our economy will be stationary in growth rates, a feature which helps to generate realistic fluctuations in risk premia.

Financial Markets

Financial markets are complete, that is, households have access to a complete set of state-contingent securities over the aggregate shocks x_t and A_t. In addition, we assume that 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.

In order to make the role of discount rate and cashflow shocks as transparent as possible, we specify an exogenous stochastic discount factor for this economy. Doing so allows us to abstract away from household and worker preferences, since in equilibrium the intertemporal marginal rate of substitution of each agent is equated with the stochastic discount factor, so all decision makers in the economy agree on the value of all streams of risky cash flows and are risk neutral over idiosyncratic shocks.[2]

Following Lettau and Wachter (2007), the one-period stochastic discount factor Λ is given by

$$\Lambda_{t+1} = \exp\left\{-r_f - \frac{1}{2}x_t^2 - x_t\varepsilon_{A,t+1}\right\}, \tag{19}$$

where r_f is the constant real risk-free rate. Here, the market price of risk is driven by a single state variable x_t that evolves according to

$$x_{t+1} = \psi_x x_t + (1-\psi_x)\overline{x} + \sigma_x\,\varepsilon_{x,t+1}, \tag{20}$$

with $\varepsilon_{x,t} \sim N(0,1)$ corresponding to the discount rate shocks in the model. As in Lettau and Wachter (2007), we assume that $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$ are independent, and that only the productivity (cashflow) shock $\varepsilon_{A,t}$ is priced.

Worker Labor Supply

Newborn workers and workers who just separated from a previous job enter the pool of nonemployed workers. Searching for a job is costly: each nonemployed worker can decide whether to participate in labor markets by entering the unemployment pool at a cost and actively looking for a job or to stay out of the workforce. To enter the unemployment pool, a worker needs to pay an up-front search cost

$$c_t(h) = \overline{c}\,A_t\,h, \tag{21}$$

which is a stand-in for the costs of updating a resume as well as finding and applying for new jobs. Workers that pay the cost have the ability to search for several periods. More precisely, if the worker is unsuccessful in her search, with probability $1-\lambda$ she remains in the unemployment pool without incurring additional costs. With probability λ, her access to the search technology expires unless she again pays the cost $c_t(h)$ to re-enter unemployment.

This simplifying assumption implies that all workers will make labor supply decisions in order to maximize the NPV of labor earnings plus the value of unemployment, net of search costs. An equivalent interpretation is that utility costs can be converted to monetary units and that the large family aggregates them linearly across its members.

[2] The approach of deriving endogenous quantities with an exogenously-specified SDF is consistent with a voluminous literature in production-based asset pricing (see, for instance, Berk, Green, and Naik, 1999). Further, it allows us to sidestep the debate within the macroeconomics and asset pricing literature about identifying the fundamental drivers of time-varying discount rates and instead focus on implications for real activity.

All workers that are out of a job receive a flow benefit

$$b_t(h) = \overline{b}\, A_t\, h. \tag{22}$$

The flow benefits of being out of employment include not only unemployment benefits but also the value of leisure. In specifying (22), we follow Hall (2017) and Kehoe et al. (2022) by assuming that the opportunity cost of employment has a unit elasticity to aggregate productivity, which is consistent with the empirical findings of Chodorow-Reich and Karabarbounis (2016). We also assume that this opportunity cost scales with the worker's permanent human capital h, which helps keep the model tractable.

Directed Search and Matching

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

$$\kappa_t(h, z) = \overline{\kappa}\, A_t\, h\, z, \tag{23}$$

Thus, we assume that the cost of hiring workers is proportional to a worker's productivity. Together with our other assumptions this will imply that value functions are linear in permanent human capital. This assumption also ensures that the limiting employment distribution is not degenerate and that job finding rates are fairly similar across workers with different prior earnings as in the data.

Let $u_t(h, z)$ be the unemployment rate and $v_t(h, z)$ be the number of posted vacancies by firms for each type of worker. As is common in the literature, we refer to $\theta_t(h, z) \equiv v_t(h, z)/u_t(h, z)$ as labor market tightness. The number of matches in a labor market with unemployment rate u and vacancies v is $m(u, v)$. Following den Haan, Ramey, and Watson (2000), we choose

$$m(u, v) \equiv \frac{u\, v}{(u^\alpha + v^\alpha)^{\frac{1}{\alpha}}}. \tag{24}$$

The probability that a vacancy gets 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 $p(\theta) = \theta(1 + \theta^\alpha)^{-\frac{1}{\alpha}}$.

Our model allows for endogenous job destruction. Specifically, matches can be ended by the agents; this will happen in equilibrium when separation is optimal for both parties upon mutual agreement. In addition, we also let matches to be destroyed for exogenous reasons at a rate s.

2.2 Competitive Search Equilibrium

In this section, we outline conditions which determine allocations in equilibrium—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. In the subsequent section, we describe a model of wage smoothing subject to limited two-sided limited commitment constraints which pins down the complete path of state-contingent wages.

Firms and workers are exposed to search and matching frictions. In response, firms decide how many vacancies to open and of which type, characterized by the conditions for hiring a worker and an associated value of the employment contract that is offered. Each worker chooses the type of vacancy to which she will direct her search, 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 Menzio and Shi (2011). We construct a competitive search equilibrium in the spirit of Montgomery (1991) and Moen (1997).

Worker Search

Unemployed workers choose in which labor market to search for a job. Labor markets are characterized by a worker type—the duplet (h, 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 type searching for a job gets offered one type of contract with total value of employment equal to $W_t(h, z)$. That means that all unemployed workers of a particular type are searching in the same market for this employment contract. Let $\theta_t(h, z)$ be the tightness in this labor market.

We begin by characterizing the value functions capturing the worker's problem. Consider the problem of an unemployed worker who is currently searching for a job. If she receives a job offer, her outside option is to continue being out of employment. In that case, her continuation value equals

$$J_t^S(h, z) = (1 - \lambda)\, J_t^U(h, z) + \lambda\, J_t^O(h, z), \tag{25}$$

which is a weighted average of her value functions if she remains in the unemployment pool, $J^U(h, z)$, and if she returns to the nonemployment pool, $J^O(h, z)$.

A worker who begins the third subperiod in the nonemployment pool has a choice of whether to enter the next period as a nonparticipant (value $J_t^N(h, z)$) or to pay the cost $\bar{c}A_t h$ now to (re-)enter the unemployment pool for next period (value $J_t^U(h, z)$). Thus, her continuation value equals

$$J_t^O(h, z) = \max\{J_t^N(h, z),\ J_t^U(h, z) - \bar{c}A_t h\}. \tag{26}$$

A nonparticipating worker simply collects the time t unemployment benefit and, conditional on surviving to $t + 1$, begins the next period as a nonemployed worker. Thus, her continuation value is defined recursively as

$$J_t^N(h,z) = \bar{b}\, A_t\, h + (1-\nu) \times \mathbb{E}_{t,h,z}\left[\Lambda_{t+1} J_{t+1}^O(h',z')\right]. \tag{27}$$

Next, consider a worker of type (h, z) who is unemployed in period t. Her continuation value is

$$J_t^U(h,z) = \bar{b}\, A_t\, h + (1-\nu) \times \mathbb{E}_{t,h,z}\left[\Lambda_{t+1}\left\{J_{t+1}^S(h',z') + p(\theta_{t+1}(h',z'))\left(W_{t+1}(h',z') - J_{t+1}^S(h',z')\right)\right\}\right], \tag{28}$$

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

Firm Search

Labor contracts are complete: when workers begin employment, these contracts fully specify the wages that workers receive from the firm while being employed and the conditions for terminating a match, in each possible future state of the world. As a result, employment contracts offered by firms are always bilaterally efficient, i.e., they maximize the joint surplus of the match to the firm and to the worker.

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

$$J_t^{MC}(h,z) = A_t\, h\, z + (1-\nu) \times \mathbb{E}_{t,h,z}\left[\Lambda_{t+1}\left\{sJ_{t+1}^O(h',z') + (1-s)J_{t+1}^M(h',z')\right\}\right], \tag{29}$$

where

$$J_t^M(h,z) = \max\left\{J_t^{MC}(h,z),\ J_t^O(h,z)\right\} \tag{30}$$

is the current total value of a match.

A match is continued at time t if the continuing value of the match exceeds the value at nonemployment,

$$\mathbb{1}_t^C(h,z) = 1 \quad \Leftrightarrow \quad J_t^{MC}(h,z) \geq J_t^O(h,z). \tag{31}$$

When a match is terminated, the firm has no more future profits from this match, while the worker receives the value at nonemployment. As a result, the present value of a continuing match (29) consists of the current output that is produced, the present value of continuation of the match in future times when it is optimal to keep the match intact, the present value of the outside option to the worker that comes from the value of nonemployment.

Firms post vacancies and wages to target specific workers. Specifically, firms can target a specific type of worker (h, z) by posting a vacancy and offering a continuation value to the worker equal to $W_t(h, z)$ at the moment the worker is hired. The equilibrium value of $W_t(h, z)$ is pinned down by the firm's first order conditions in their vacancy posting problem together with the free entry condition,

$$q(\theta_t(h, z)) \left(J_t^{MC}(h, z) - W_t(h, z) \right) = \kappa_t(h). \tag{32}$$

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

$$W_t(h, z) = J_t^S(h, z) + \eta(\theta_t(h, z)) \left(J_t^{MC}(h, z) - J_t^S(h, z) \right). \tag{33}$$

Equation (33) states that the continuation value $W_t(h, z)$ offered to a worker of type (h, z) when that 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 when hired depends on the conditions in the labor market at the time—the elasticity of the vacancy filling rate, $\eta(\theta) \equiv -\theta\, q'(\theta)/q(\theta)$. Appendix A.1 contains further details.

Importantly, equation (33) does not pin down the path of realized worker wages. To do so we need to make additional assumptions on the type of wage contract firms offer workers in the next section.

2.3 Wage Contracts

Next, we consider wage contracts—the set of state-contingent payments made to the worker after she is hired. All that is required for the contract to be consistent with the equilibrium above is that it delivers the ex-ante contracted value $W_t(h, z)$ to the worker when she is hired. To sharpen the model's predictions about worker earnings growth, this section introduces a model of optimal wage smoothing subject to two-sided limited commitment constraints. The solution to this smoothing problem pins down how contracts between workers and firms are set.

When workers can commit not to leave their employers and firms can commit not to fire workers except at the times when it is efficient to terminate the match in equilibrium, many paths of wages can be consistent with the allocations described above. Under full commitment, firm owners could simply make a one-time payment of $W_t(h, z)$ 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 in order 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.

An inability to fully commit on both sides of the market can place some restrictions on the path of admissible wages (Thomas and Worrall, 1988). Workers cannot commit not to quit a job if doing so would be in their best interest, and in such an instance firm owners would likely have little legal recourse to claw back prior compensation. Likewise, firm managers may not be able to commit to retain workers whose contracts dictate that the present value of future compensation significantly exceeds the present value of output generated by the worker. Accordingly, we develop economically-motivated bounds on the present value of future wages during the match which ensure that neither party has an incentive to terminate the match early.

Present Value of Wages

To specify the wage contract, it is important to make the distinction between two separate components of the worker's continuation value. The first component is the value that is derived from the flow wages that are paid by the employer in the current match. Since only the worker value at origination of the contract is pinned down, wages need not be a function of the current worker state variables that pin down allocations in the competitive search equilibrium. We denote by $\Omega_{i,m,t}$ the set of relevant state variables for the wage contract of a worker i that is in an existing match m with the firm.

The worker's continuation value, defined as the net present value of wages to be paid by the current employer, is equal to

$$\widehat{W}^M(\Omega_{i,m,t}) \equiv \mathbb{E}_{t,h,z}\left[\sum_{k=0}^{\infty} \zeta^k \left\{\prod_{j=1}^{k} \Lambda_{t+j}\, \mathbb{1}^C_{t+j}(h_{i,t+j}, z_{i,t+j})\right\} w(\Omega_{i,m,t+k})\right], \tag{34}$$

where $\zeta \equiv (1-\nu)(1-s)$ and the match continuation indicator $\mathbb{1}^C$ is equal to one if the match is preserved and zero otherwise, see equation (31).

In recursive form, $\widehat{W}^M$ can be written as

$$\widehat{W}^M(\Omega_{i,m,t}) = w(\Omega_{i,m,t}) + (1-\nu) \times \mathbb{E}_{t,h,z}\Big[\Lambda_{t+1}(1-s)\, \mathbb{1}^C_{t+1}(h', z')\, \widehat{W}^M(\Omega_{i,m,t+1})\Big]. \tag{35}$$

With limited commitment, there are bounds on how this NPV of promised wages can evolve ex post. We denote these bounds by Γ^L and Γ^H:

$$\Gamma^L_t(h_{i,t}, z_{i,t}) \leq \widehat{W}^M(\Omega_{i,m,t}) \leq \Gamma^H_t(h_{i,t}, z_{i,t}). \tag{36}$$

In characterizing the bounds, we also need to consider the second component of worker value: the present value of subsequent payoffs to the worker—unemployment benefits plus the expected benefits of her new job. This value is always the same for all existing and new workers with the same productivity type. We denote this value by W^S and write it in recursive form as

$$W_t^S(h,z) = (1-\nu) \times \mathbb{E}_{t,h,z}\Big\{\Lambda_{t+1}\Big[J_{t+1}^O(h',z') \\ +(1-s)\mathbb{1}_{t+1}^C(h',z')\Big(W_{t+1}^S(h',z') - J_{t+1}^O(h',z')\Big)\Big]\Big\}. \tag{37}$$

The total worker continuation value is given by the combination of the two components:

$$\widehat{W}(\Omega_{i,m,t}) \equiv \widehat{W}^M(\Omega_{i,m,t}) + W_t^S(h_{i,t}, z_{i,t}). \tag{38}$$

This continuation value can and generically will move around during the match. The only restriction that is imposed by the equilibrium is that the continuation value of the wage contract for a new hire needs to match the promised continuation value offered to the worker given by (33). Let τ denote the time of origination of a wage contract. The wage contract needs to satisfy the restriction that at origination, the present value of wages during the match is equal to her promised continuation value minus the present value of future worker payoffs after the match is terminated. That is,

$$\widehat{W}^M(\Omega_{i,m,\tau}) = W_\tau(h_{i,\tau}, z_{i,\tau}) - W_\tau^S(h_{i,\tau}, z_{i,\tau}) \equiv W_\tau^M(h_{i,\tau}, z_{i,\tau}). \tag{39}$$

Wage Bounds

Next, we derive the bounds on wages in (36) which must hold state-by-state over the life of the contract and only depend on the aggregate variables (x_t, A_t) and the worker states $(h_{i,t}, z_{i,t})$.

Upper bound: firm IC constraint. The upper bound for the wage contract value is determined by the threat of the firm to terminate the match. When the firm does this, the net present value of future output minus wages is zero. However, it is not difficult to imagine that the decision to fire a worker off-equilibrium can create additional complications. In contrast to the endogenous separations which occur on the equilibrium paths – in which both workers and firms agree that separation is mutually beneficial – these off equilibrium threats to terminate the match early are inefficient and destroy surplus generated by the match. With this in mind, we assume that the firm accrues some additional reputational costs when terminating a match unilaterally. While we abstract away from a specific microfoundation, one can imagine that these costs stand in for potential difficulties that the firm may have in retaining current incumbent workers and attracting additional workers in the future.

Specifically, the firm needs to pay the flow reputation cost $f_t(h) = \xi A_t h$ when a worker is fired. This obligation lasts for the remaining lifetime of the worker—results are insensitive to the choice of the length of time over which these costs accrue. Thus, the NPV of these costs paid by the firm is given by

$$F_t(h) = \xi A_t h + (1-\nu) \times \mathbb{E}_{t,h}\left[\Lambda_{t+1} F_{t+1}(h')\right]. \tag{40}$$

Given these costs, the firm wants to terminate the match when its share of the surplus becomes sufficiently negative, in which case it prefers terminating the worker and incurring the firing costs:

$$J_t^{MC}(h,z) - W_t^S(h,z) - \widehat{W}^M(\Omega_{i,m,t}) < -F_t(h). \tag{41}$$

Therefore, the firm-side limited commitment constraint implies the following upper bound on wages:

$$\Gamma_t^H(h,z) = J_t^{MC}(h,z) + F_t(h) - W_t^S(h,z). \tag{42}$$

Lower bound: worker IC constraint. The lower bound for the wage contract is determined by the off-equilibrium threat of a worker to walk away from the match. When the worker quits, she enters nonemployment, and decides when to start looking for a new job. In direct analogy with the firm problem, quitting voluntarily when doing so is bilaterally inefficient imposes some flow reputation costs which also lower the worker's payoff going forward. For instance, parting on bad terms may impose some psychic costs, the loss of unemployment benefits, and/or lower the perceived level of the worker's productivity going foward. For parsimony, we model these costs symmetrically with those incurred on the firm side, which implies that

$$\Gamma_t^L(h,z) = J_t^O(h,z) - W_t^S(h,z) - F_t(h), \tag{43}$$

where these costs *loosen* the bound ex-ante by making it easier for the worker to commit, as we will discuss further in the next section after defining the smoothing problem formally.

Wage Smoothing

While the above bounds place substantial restrictions of the set of admissible wage contracts, they do not uniquely pin down wages. To do so, we assume that workers have a preference for smoothing wages to the extent possible, for a given NPV of wages.

Specifically, we assume that firms offer a wage contract with state-contingent worker (flow) compensation w_t that solves a dynamic smoothing problem, subject to the bounds in equation (36) and to a promise-keeping constraint that workers receive the NPV of wages that they were promised.

In recursive form, the constrained optimization problem that the wage contract solves is given by

$$\begin{aligned}\widehat{V}_t(h,z,\widehat{W}^M) = \max_{w,\{\widehat{W}^{M\prime}\}} \quad & \Big\{(1-\chi)w^{1-\gamma} + \chi\,\mathbb{E}_{t,h,z}\Big[\Lambda_{t+1}\,\mathbb{1}^C_{t+1}(h',z')\,\widehat{V}_{t+1}(h',z',\widehat{W}^{M\prime})^{1-\gamma}\Big]\Big\}^{\frac{1}{1-\gamma}} \\ \text{s.t.} \quad & \widehat{W}^M = w + \zeta\,\mathbb{E}_{t,h,z}\Big[\Lambda_{t+1}\,\mathbb{1}^C_{t+1}(h',z')\,\widehat{W}^{M\prime}\Big] \\ & \Gamma^L_{t+1}(h',z') \le \widehat{W}^{M\prime} \le \Gamma^H_{t+1}(h',z').\end{aligned} \tag{44}$$

Here, χ is a time discount factor, $\zeta = (1-\nu)(1-s)$ is the exogenous retention probability and $\gamma > 0$ is a preference parameter that captures the intensity of the desire to smooth wages. We further impose the restriction that

$$\chi = \zeta\, e^{(\mu_A + g_E)\,\gamma}, \tag{45}$$

which ensures that optimal wages would grow deterministically at the rate of human capital growth when the wage smoothing problem is unconstrained. The recursive formulation of the problem allows us to solve for the optimal contract in a straightforward fashion using dynamic programming methods.

Wage responses to aggregate shocks. The free parameter ξ allows us to change the amount of commitment power and, in turn, the scope for insurance within the firm arising from the model. We discipline this degree of commitment power empirically by the speed at which wages adjust to shocks. In the model, the wage per efficiency unit of labor is cointegrated with labor productivity, but the adjustment of wages to cash flow shocks can be quite sluggish and far from one-for-one even after several years.

Appendix Figure A.5 computes the upper and lower bounds which obtain along the balanced growth path of our calibrated model. Panel A illustrates how our estimates are consistent with there being a nontrivial amount of commitment power, in the sense that the bounds are considerably wider than would be the case if there are no reputational costs ($\xi = 0$). Absent these costs, wages would adjust much more rapidly — almost instantaneously — to cashflow shocks, a fact inconsistent with what we observe in the data. Wages would also adjust one for one with cashflow shocks if we were to follow another feasible alternative of equalizing wages of new hires and incumbents with the same (h, z) period-by-period.

Discount rates affect the average level of wages paid to incumbents over the life of the match for at least two reasons. The first is an "operating leverage" effect. The firm can increase a worker's compensation either by offering higher wages (expected cash flows) or safer wages. The smoothing motive means that wages will be less volatile and less exposed to systematic risks than profits from the match. As a result, the appropriate discount rate on the wage contract — the one relevant for computing $\widehat{W}^M(\Omega_{i,m,t})$ — is lower than the discount rate on a claim to the output the worker generates — the one relevant for computing $\Gamma^H_t(h', z')$. This difference between the two discount rates widens when discount rates are high, implying that average wages will need to be lower ex-ante in order to avoid hitting the firm's NPV constraint ex-post. The worker accepts a lower wage to compensate the firm for the fact that insurance against future states is now more expensive.

Second, since reputation costs have a dynamic component, the degree of commitment power declines with discount rates, as both workers and firms assign lower valuations to future reputational costs. Therefore, the additional shifter of the bound $F_t(h)$ shrinks when discount rates rise, tightening the bounds and creating less scope for risk-sharing in the model. For workers who are at or near the upper bound, higher discount rates will push the NPV of the worker's compensation downwards.

2.4 Equilibrium

An equilibrium in this model consists of a market tightness function $\theta_t(h, z)$, an employment offer function $W_t(h, z)$, value functions $J_t^k(h, z)$ with $k \in \{N, U, O, S\}$ for workers without a job, and value functions $J_t^{MC}(h, z)$ and $J_t^M(h, z)$ for (continuing) matches with a corresponding policy rule for terminating existing matches, such that (i) the offered employment value and corresponding market tightness satisfy firm optimality (33), (ii) the value functions satisfy equations (25), (26), (27), (28), (29), and (30), and (iii) the free-entry condition (32) holds.

Given our definition, the competitive equilibrium is both efficient and unique (see e.g. Kehoe et al., 2022). Thus, the symmetric equilibrium we considered above is in fact the only equilibrium. Further, we note that our assumptions on the wage contract in Section (2.3) do not affect equilibrium allocations. This assumption allows us to solve for equilibrium in a block-recursive manner, in which we first solve for allocations and then for the path of realized wages.

2.5 Discussion of Model Assumptions

We next discuss the role of specific modeling assumptions in our analysis, highlighting contrasts with other approaches from the literature.

Discount rate shocks. Recently, Hall (2017) and Kehoe et al. (2022) have emphasized the importance of time-varying discount rates for the dynamics of unemployment. To keep the analysis as transparent as possible while capturing empirically realistic fluctuations in discount rates, we work with an exogenous specification of the stochastic discount factor. Our specification of the stochastic discount factor (19) follows Lettau and Wachter (2007), who illustrate that a simple stochastic discount factor together with a productivity shock process like equations (18) to (20) can replicate many stylized facts about asset prices. That said, equation (19) implicitly assumes that the real interest rate is constant and therefore all fluctuations in discount rates in the model come from time-varying risk premia. We make this assumption to keep the model tractable. Allowing for the risk-free rate of return to vary would lead to qualitatively similar implications as fluctuations in

x_t. However, given that the volatility of the risk-free rate is an order of magnitude smaller than the volatility of risk premia in the data, we focus on the latter.

The literature has identified a number of mechanisms that generate time variation in discount rates.[3] In some of these models, discount rates are a function of the current state of the economy, while in other models they have independent sources of variation. For our purposes, we do not need to take a stance on the economic drivers behind fluctuations in discount rates. Our modeling choice of shocks to discount rates that are uncorrelated with (current) productivity shocks is in line with the baseline model of Lettau and Wachter (2007) and the low correlation documented in Campbell and Shiller (1988); Campbell and Vuolteenaho (2004). That said, even if discount rates are deterministic function of the current economic state, our model shows how they can serve as a powerful propagation mechanism. That said, this assumption is not crucial for the model implications: the dynamics of unemployment and worker earnings along the economic cycle would be similar if discount rates are a deterministic function of current and past aggregate productivity shocks.

Worker productivity and human capital accumulation. Transitory worker productivity z in the model evolves stochastically as an AR(1) process. This assumption is meant to capture the idea of a (temporary) mismatch between the skills of a worker and those required by firms. As such, it is a persistent worker-level variable whose evolution does not depend on whether the worker is employed or not. By contrast, permanent human capital h reflects general skills the worker possesses, and its rate of accumulation depends on the worker's employment status. The fact that workers out of a job lose human capital (in relative terms) increases the surplus value of a match, which is an important force behind the significant effects of discount rate shocks on unemployment and exit in the model.

Wage contract. Models with labor search typically are silent on the path of worker wages. Thus, we need additional assumptions. Our assumptions on the labor contract can be viewed as an intermediate assumption between two extremes: fully rigid wages and wages that are renegotiated every period. Our assumption that there is a "reputation" cost for unilaterally terminating a match allows the wage contract to provide a partial level of wage smoothing, similar in spirit to models with limited commitment.[4]

[3] Examples include: fluctuations in the level of uncertainty that feed into firms' cost of capital (see, e.g. Wachter, 2013; Bloom, 2014; Bansal, Kiku, Shallastovich, and Yaron, 2014); non-homothetic preferences (Campbell and Cochrane, 1999); investor heterogeneity (Chan and Kogan, 2002); temporary financial market dislocations, potentially due to a reduction in the net worth of the suppliers of capital (He and Krishnamurthy, 2013); or deviations from rational expectations (Bordalo, Gennaioli, LaPorta, and Shleifer, 2019).

[4] See, for example, Thomas and Worrall (1988); Kocherlakota (1996); Berk, Stanton, and Zechner (2010); Ai and Bhandari (2021); Balke and Lamadon (2022). 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. 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 which satisfy the initial condition and the limited commitment bounds. Nonetheless, our assumption that the contract seeks to

Our assumption that wages are not fully rigid but partially adjust to discount rate and cashflow shocks is necessary for the model to generate changes in wage earnings for workers who stay with the firm, in line with the evidence in Section 1. Importantly, our assumptions on the wage contract do not affect allocations of workers to jobs, merely the path of realized wages. This assumption is made for simplicity: wage rigidity can definitely lead to inefficient separations, but our model does not need this mechanism in order to generate a realistic level of job destruction in response to discount rate news. Allowing for the wage contract to lead to inefficient separations would imply job destruction has some sensitivity to cashflow news as well, which would only amplify the main message of the paper.

Labor supply. The model incorporates a labor supply channel: nonemployed workers must pay a fixed cost to seek employment, making their decision similar to an investment choice and sensitive to discount rate fluctuations. This cost represents the fixed expenses associated with initiating the job application process. This assumption help ensure that the size of the nonparticipant pool responds with some delay to news about labor market opportunities, consistent with what we see in the data. However, this assumption is not essential for the nonparticipation margin to respond to discount rates. Even if the cost of search were to be incurred every period, the benefits of finding a job are still back-loaded, partially due to human capital accumulation, so decision would be similarly sensitive to discount rates. In addition, this decision depends not only on the current discount rate, but also on the current tightness of the labor market. In equilibrium, even if workers were to discount the future at a constant rate, their decision to enter the search pool would still depend on discount rates because of fluctuations in the job finding rate as firms condition their vacancy postings on the current level of discount rates.

3 Model Calibration and Key Mechanisms

We next discuss the calibration and the mechanisms operating in the model.

3.1 Calibration

We calibrate the model at a monthly frequency. Some of the parameters in the model can be calibrated using a priori information—that is, existing work. We first discuss these. The remaining parameters are chosen to target specific moments of the data.

Parameters calibrated a priori. The left block of Table 4 summarizes the parameters that we calibrate based on a priori information. We choose the mortality rate ν so that the life span of a

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 it is incentive compatible (Guiso et al., 2005, 2013).

worker in the model is 30 years on average. We impose the normalizations $\overline{z} = \overline{h} = 1$ for the initial and long-run value of the transitory component z of worker productivity and the initial value of the permanent component h, respectively. Following Hagedorn and Manovskii (2008), we set the curvature α of the matching function to 0.407. For the job search problem, we assume that paying the fixed cost $\overline{c}$ implies that the worker remains in the unemployment pool for 3 months on average, which corresponds with a value of $\lambda = 1/3$.

Values for the payoff outside of employment relative to average productivity vary widely in the literature, ranging from 0.4 (Shimer, 2005) to 0.955 (Hagedorn and Manovskii, 2008). We set $\bar{b} = 1$ so that the flow value during nonemployment is 0.62 times the average worker productivity in a match along the balanced growth path, which is close to the value of leisure of 0.6 in Ljungqvist and Sargent (2017). We calibrate the worker productivity process to have a persistence of 0.9906 at the monthly frequency, following Menzio, Telyukova, and Visschers (2016). Our choice implies that the half life of a shock is approximately 6 years. We choose the wage smoothing parameter $\gamma = 1/2$, consistent with agents having a fairly modest smoothing motive (i.e., an elasticity of inter-temporal substitution equal to 2), though in practice the results are mostly insensitive to this choice.

We calibrate the asset pricing parameters based on Lettau and Wachter (2007). The real risk-free rate is 1.93% per year. For the price of risk process x_t, we set its long-run mean equal to 0.625 and set its annual persistence and volatility equal to 0.87 and 0.24, respectively. Since we calibrate the model at the monthly frequency, we convert these parameters to their monthly equivalents. We calibrate the model TFP process using the measure of Fernald (2014). We choose μ_A and σ_A to match the mean (1.2% per year) and volatility (1.9% per year) of productivity growth over the 1947–2021 period.

Last, we calibrate the process for permanent human capital using the data provided by Guvenen, Kaplan, Song, and Weidner (2022). We set the growth rate of human capital during employment to match the average annual growth rate of median log real earnings between age 25 and age 55 for the 1957–1983 cohorts, which is 1.7%. This gives the restriction $\mu_A + g_E = 0.00142$, where we note that most of the average life cycle growth in wages in the model comes from TFP growth μ_A. We leave g_U as a free parameter to help with matching the moments discussed below. We choose the dispersion in initial human capital levels σ_{h0} to match the heterogeneity in the distribution of initial earnings reported by Guvenen et al. (2022). Specifically, we target the average difference between the 25th percentile and 75th percentile of log earnings at age 25 over the period 1957–2011 by setting $\sigma_{h0} = 0.666$.

Targeted moments. All remaining model parameters are chosen to match model-implied moments to their empirical counterparts. These parameters and the chosen values are summarized in the right block of Table 4. We next discuss how these parameters are chosen and the moments in the data that help identify them.

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. 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 who are between age 25 and 60 and that 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 layoff. 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.

We choose the volatility of idiosyncratic shocks σ_z and the exogenous separation rate s to target average monthly separation rates by income groups.[5] The search cost parameter $\overline{c}$ is chosen to match the split of separations into unemployment and nonparticipation as a function of prior earnings. Monthly job finding rates are measured as the fraction of unemployed workers that transition to employment in the next month. We choose the vacancy cost parameter $\overline{\kappa}$ to target average monthly job finding rates for unemployed workers in each prior earnings group.

Last, we also target the response of worker earnings growth to cashflow and discount rate news. In a direct analogue to our empirical design, we regress income growth for employed workers on cashflow news (ε_A) and discount rate news (ε_x), interacted by dummies for the income group of a worker that is computed from current wage earnings. We focus on the two-year horizon and target the regression coefficients in column (6) of Table 3. The two remaining internally calibrated parameters ξ (reputational cost of ending a match early) and g_U (growth in h while out of the labor market) are particularly informed by targeting these ten regression coefficients.

3.2 Model Fit

We next discuss the model fit.

Targeted Moments. Overall, the model does a good job fitting the moments that we target. Figure 2 shows that both in the model and in the data, average separation rates are strongly declining in income levels, while average job finding rates are roughly constant across the distribution. Figure 3 shows that high-wage workers have a larger exposure to cashflow news while low-wage workers are most exposed to discount rate news. One thing to note here is that the model somewhat overstates the average level of the unemployment rate—8.4 in the model versus 5.7 in the data. The reason is

[5]We separately match the separation and job finding rates by worker income. To this end, we restrict attention to workers with positive wage earnings and that report having a job in all weeks of the month. We sort employed workers in income groups based on wage earnings in the current month. We sort unemployed workers in 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 (E-U) rate and the employment-to-non-participation (E-N) rate, defined as the fraction of employed workers that transition to unemployment and nonparticipation in the next month, respectively.

that we target average worker flows from the SIPP and do not have permanent exit from the labor market.

Non-targeted moments: Unemployment dynamics. Even though we do not directly target the moments of the unemployment rate, the model is able to address the Shimer (2005) puzzle, specifically the disconnect between unemployment and vacancies with labor productivity. To illustrate this point, Table 8 compares the dynamics of the unemployment rate and other key labor market indicators in the model versus the data. We see that the volatility of the monthly unemployment rate in the model is 0.78, compared to 1.24 in the data. As in the data, the employment-population ratio, the vacancy-unemployment ratio, and the job finding rate are highly procyclical, and separation into unemployment is countercyclical. Compared with the data, the model has a more volatile employment-population ratio and a less volatile vacancy-unemployment ratio and job finding rate. That said, the persistence of most variables, and the correlation with fluctuations in unemployment is comparable between the model and the data—with the exception of separation into non-employment.

3.3 Discussion of Model Mechanisms

To shed light on the model's inner workings, we next discuss the key mechanisms present, evaluated at the calibrated parameters.

Job Separations. A key mechanism in the model is endogenous job destruction in response to discount rates. Job destruction depends on a simple threshold rule, where matches where worker productivity falls below a threshold $z < z^*(x_t)$ are terminated. The separation threshold $z^*(x_t)$ is defined implicitly through the indifference condition,

$$J_t^{MC}(1, z^*(x_t)) = J_t^O(1, z^*(x_t)), \tag{46}$$

where we have exploited the model's scale invariance with respect to h. At $z^*(x_t)$, the worker is indifferent between remaining employed and becoming nonemployed, or put differently, the present value of the outside option in nonemployment exactly equals the benefits from employment. Low productivity workers are low surplus workers—that is, equivalently, $J_t^{MC}(1, z) - J_t^O(1, z)$ is strictly increasing in z—because the worker's payoff at non-employment does not depend on z.

The sensitivity of job separations to discount rates depends not only on how the separation threshold $z^*(x_t)$ varies with discount rates, but also on the distribution of worker types around the threshold. Figure A.2 illustrates how these forces interact. Specifically, the figure 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 discount rates x_t. Examining the figure, we see that an increase in discount rate leads to an increase in the separation threshold, with the end result that low-z (and likely, low-income) workers are more likely to get fired.

The separation threshold $z^*(x_t)$ is increasing in discount rates due to a duration effect. Specifically, workers face an inter-temporal trade-off associated with nonemployment: entering non-employment entails collecting a flow payoff today at the cost of a permanent reduction in future labor productivity (due to the lower growth rate in human capital h during non-employment). Thus, the payoffs in employment back-loaded relative to nonemployment, the value of the surplus for a given level of productivity $J_t^{MC}(h,z) - J_t^{O}(h,z)$ decreases with discount rates x_t, implying a higher separation threshold.

Duration of non-employment spells. The model also generates time-variation in the length of unemployment spells via two mechanisms at. First, labor market tightness and thus job finding rates fall with x_t. Second, workers are less likely to search for a job when discount rates rise. Workers trade off the possibility of finding a job (and the associated earnings which are a function of z) versus the cost of search and the benefits of non-employment. Thus, the threshold for a worker to enter the search pool $\underline{z}(x_t)$ solves

$$J_t^U(1, \underline{z}(x_t)) - \bar{c}A_t = J_t^N(1, \underline{z}(x_t)), \tag{47}$$

where workers with productivity $z < \underline{z}(x_t)$ (temporarily) exit the labor force. The threshold $\underline{z}(x_t)$ increases with discount rates for two reasons. First, the benefits of finding a job are back-loaded than the cost of searching and the non-employment benefits, so the value of search declines when discount rates rise. Second, labor market tightness, and the job finding rate both decline with discount rates x_t, which implies a lower benefit of entering the search pool.

The distribution of non-employment spells in the model is highly skewed, as we see in the top panel of Appendix Figure A.3. The bottom panel of the figure shows how the dispersion in the length of non-employment varies with the level of worker productivity, where we see that low productivity z workers experience, on average, both longer but also more volatile non-employment spells.

The average length of non-employment increases with discount rates, as we can see in Appendix Figure A.4. An increase in discount rates x affects the average duration of non-employment through two channels. First, the threshold $\underline{z}(x_t)$ for entering the search pool increases, which implies fewer workers will actively search for a job. Second, there is also a composition effect: because the termination threshold $z^*(x_t)$ increases, the average quality of the non-employment pool improves when discount rates rise.

Wage Dynamics. Our assumptions on the wage contract in Section 2.3 imply rich wage earning dynamics for continuing workers. Recall the presence of two bounds on the net present value of worker wages for continuing workers—equations (42) and (43). The existence of 'reputation' costs to inefficient termination implies that these wage bounds are wider than if these costs did not exist (the case where the wage contract is renegotiation-proof), we can see in the top panel of Appendix Figure A.5. Wages for continuing wages respond to cashflow and discount rate shocks partly because these bounds move with these shocks, as we can see in the second and third row of Appendix Figure A.5.

The sensitivity of worker earnings (for continuing workers) to cashflow and discount rate shocks largely depends on how far a worker is from these bounds, as we can see from the first and second panel of Appendix Figure A.6. Importantly, high-income workers are more likely to be close to these bounds, especially the upper bound, as we can see from the third panel. Since these constraints are more likely to bind for high-wage workers, earnings for these top workers that remain with the firm are more sensitive to cashflow (and discount rate) news.

3.4 Impulse Responses

The mechanisms discussed in the previous section interact to produce rich model dynamics. We illustrate these by discussing the impulse response of key model quantities to the underlying shocks.

Responses to aggregate productivity shocks. We first discuss the impulse response of model quantities to productivity shocks in Figure 4. By construction, the model is set up such that there is no effect of a change in aggregate productivity on employment outcomes. That is because both the flow value of unemployment and the vacancy cost are proportional to A_t. Therefore, all effects of productivity shocks on wage earnings operate along the intensive margin. Examining the figure, we see that high-income workers have a greater exposure to productivity shocks than low-income workers, as the limited commitment constraints (42) and (43) are more likely to bind for high-income workers, as we just discussed in Section 3.3.

Responses to discount rate shocks. We next turn our attention to the response of model quantities to discount rate shocks in Figure 5. An increase in discount rates x leads to an increased rate of job destruction, which leads to lower output and employment, and an increase in the rate of unemployment and non-participation. The increase in job separations is mostly affects low-income workers—recall that these workers are closer to the termination threshold, see discussion above in Section 3.3. As a result, low-income workers experience significantly larger declines in earnings than high-income workers. The change in the composition of the workforce implies that the average wage among continuing workers increases as discount rates rise—we see the model generates counter-cyclical average wages. Last, due to the dynamics of the wage contract, the earnings of continuing workers are also sensitive to discount rate shocks, with top workers having a higher exposure than workers at the bottom of the wage distribution. However, these differences are quantitatively small.

Responses to worker productivity. The model features a highly non-linear passthrough of worker productivity shocks z to worker earnings; these dynamics are partly a function of labor markets but also partly a feature of wage contract where firms smooth wages for workers. As we see in Figure 6, this passthrough coefficient, defined as the elasticity of worker earnings to z is both asymmetric and non-linear. The top panel of the figure illustrates an asymmetry between positive and negative shocks to z: negative shocks are more likely to lead to job separations and therefore proportionally larger wage losses than the wage gains associated with a positive productivity shock. The second row shocks that the degree of this asymmetry depends on a worker's prior income, since low income (low-z) workers are more likely to be separated following a negative shock to z. In the third panel we see that the passthrough to wage earnings of a negative shock to worker productivity depends on the current state of the economy—specifically the level of discount rates x as it determines the likelihood of job separation and the current tightness of the labor market. The last panel shows how these effects vary by horizon; we see that a shock to worker productivity z transmits to wage earnings with some delay; this delay is partly a feature of wage contract where firms provide some measure of smoothing to workers, and is partly a function of labor markets. Importantly, however, we see that large negative shocks have a more persistent effect on worker earnings than smaller shocks—beyond the fact that it takes longer for z to revert to its mean.

3.5 Alternative Calibrations

To illustrate the specific role of our modeling assumptions, we next compare our baseline calibration to alternatives that shut down specific mechanisms in the model. Table 9 compares key moments in the baseline model to these alternative calibrations.

First, we shut off the reputation costs of inefficiently terminating a match ($\xi = 0$). Doing so increases the sensitivity of wage earnings to productivity news, and the earnings of top workers are less sensitive than the earnings of workers in the median to 75-th percentile. Second, we remove shocks to worker productivity ($\sigma_z = 0$). In this case, there are no endogenous job separations. The volatility of unemployment is substantially lower, and there are no clear differences in the sensitivity of worker earnings to productivity or discount rate shocks across income groups. In the third alternative, we remove the z shocks but also recalibrate the volatility of discount rate shocks σ_x to match the volatility of the unemployment rate. In this case, the discount rate effects on worker earnings are counter-factually large and do not vary with worker income. Next, we remove the loss of human capital in non-employment—the rate of human capital accumulation does not differ by employment status. Now, the value of a match is substantially lower, and the extensive margin effects of discount rates become negligible once the unemployment benefit b is appropriately adjusted. In the fifth alternative we calibrate to a lower persistence of worker productivity; now, unemployment fluctuations are now even larger, but the heterogeneity by ex-ante earnings becomes smaller. Last, we assume that productivity z is match specific instead of individual specific: the persistence of z is ψ_{zE} during employment, but $\psi_{zO} = 0$ during nonemployment. In this case, the exposure of worker earnings to cashflow and discount rate news is much smaller as separations become much more frequent.

4 Model Implications and Testable Predictions

Here, we tighten the link between the model and the data. We focus our attention on both qualitative and quantitative differences between the data and the model, keeping in mind that .

4.1 Testable Predictions

We begin by testing the predictions of the model in the data.

Response of unemployment to cashflow and discount rate shocks

We first compare the effects of cashflow and discount rate news on future unemployment rates and employment-population ratios in the model and in the data. We estimate local projections of these series on our measures of discount rate and cashflow news (see, e.g. Jorda, 2005). We include controls for the current level of the series, the Treasury bill rate, the term spread, and the market's smoothed price-earnings ratio in month t.

As we see in Figure 9, a positive shock to discount rates significantly predicts an increase in the unemployment rate and a decrease in the employment-population ratio at horizons of up to 30-40 months. We then perform the same exercise in simulated data from the model. We see that the model-implied response of the unemployment rate falls within the confidence bounds of the empirical estimates. That said, we see that the model slightly overshoots on the employment-population ratio—likely because it lacks other margins which lead workers to persistently choose not to participate in the labor force. Last, we find some weak evidence that our measure of cashflow news negatively predicts employment rates in the data, however the coefficients are pretty noise and therefore we cannot reject that the response is zero—a pattern that is consistent with the model.

Worker mobility and job loss

Workers can experience wage earnings declines for several reasons: they remain with the firm but receive a wage cut (possibly because they are paid by the hour and firms reduce hours worked), they leave the firm and become unemployed for some period, or they leave the firm and obtain a new job with lower pay. Our model implies that an increase in discount rate primarily affects lower-paid workers through the extensive margin—job separations. By contrast, a fall in aggregate or firm productivity (cashflow news) primarily affects higher-paid workers through the intensive margin—incumbent workers experience slower wage earnings increases. We next examine these model implications in the data.

Worker mobility. We begin by estimating modified versions of equation (12), where now the main outcome variable captures worker mobility or proxies for job loss. Table 5 shows the results. In the first two columns of Table 5, the dependent variable is an indicator that takes the value of one if the worker is no longer employed by their time-t employer h years out. There is no significant relation between the probability of moving and cashflow news, and increased discount rates are associated with *lower* probabilities of moving for all worker types. Importantly, in the data, the main component of job exits is job-to-job transitions, which are not captured by our model.

Job Separations. Next, we construct measures of job loss. In columns (3) and (4), the dependent variable is an indicator for having at least one full quarter of zero earnings between the end of year t and the end of year $t + h$. We see that positive cashflow news only weakly affects this probability with a negative sign, and there are no significant differences by income group. Consistent with these effects, we note that in the model the effect of cashflow news on the extensive margin is precisely zero. In contrast, as in the model, increased discount rates are associated with a significant increase in the probability of zero earnings for low-wage workers, whereas the sign flips for high-wage workers. The difference between the lowest and highest income bins is significant at both horizons.

We also construct another left-tail indicator that proxies for unemployment: an indicator that takes the value of one if the worker has wage earnings at horizon h that are below the 10th percentile. We separately report outcomes for this indicator interacted by an indicator for movers versus stayers. Columns (5) and (6) of the table show that positive cashflow news is associated with a significant decline in the probability of moving and having a significant decline in earnings for high-wage workers, but the differences by income group are not significantly different from zero. In contrast, there is a strong and monotonic pattern for discount rates: increased discount rates significantly raise the probability of moving and having large wage declines for low-wage workers, and not for high-wage workers. Columns (7) and (8) show that cashflow news also affects the probability of staying with a significant decline in earnings for high-wage workers. The effects of discount rates are strongly concentrated on movers, and there are no differences in the probability of staying with large wage declines across the income distribution.

These patterns are qualitatively consistent with the model; we next explore whether the model can also *quantitatively* match these facts? Figure 7 shows that it can. The first panel plots the unconditional probability that incumbent workers have a zero-earnings quarter in the next 36 months by income bin, in the model and in the data. Even though these probabilities are not explicit calibration targets, we see that both the level of these probabilities as well as the differences across the income distribution are quantitatively consistent between the model and the data. The second and third panels reproduce column (3) of Table 5 in simulated data. In both the model and the data, workers are more likely to report zero earnings in a given quarter following a positive discount rate shock and the magnitude declines with prior income. By contrast, cashflow news have no impact on the likelihood of reporting zero earnings, just like the data.

Stayers vs Movers. Last, we examine how the pattern of cashflow and discount rate exposures of wage earnings vary across the sample of stayers vs movers, both in the data and in the model. Specifically, we separately estimate equations (11) and (12) for job stayers versus movers by interacting the treatment variables by an indicator for whether the worker stays with her initial employer over the regression window. Tables 6 and 7 shows how exposures vary across stayers and movers for discount rate and cashflow shocks, respectively.

Overall, we find that, consistent with the model, the negative effects of discount rate shocks on wage earnings operate largely through the extensive margin (are larger for movers than stayers), while the effect of cashflow news on wages is present for both groups. Examining Table 6, we see that the negative effects of discount rates are clearly concentrated on low-income workers that leave the firm. The effects of discount rates on low-wage movers is more than five times the effect on low-wage stayers, and is also two to four times the effect on high-wage movers. We see that stayers are also affected by these shocks, but significantly less so, and there is no clear differences in exposures across income groups. By contrast, Table 7 shows that the exposure of wage earnings to cashflows is not that different between movers and stayers. Importantly, high-income workers are always most affected by cashflow news, both those that stay within the firm and those that leave the firm.

As above, we also explore whether the model can replicate these facts quantitatively. Figure 8 presents the results. Since we do not have job-to-job transitions in the model, the probability of moving is positively correlated with discount rate news, opposite to the empirical effects in the first two columns of Table 5. Despite this effect, we still find that the discount rates have a large negative effect conditional on moving, while the effect of discount rates on stayers is small. With respect to cashflow news, the model predicts that the effects are similar for stayers and movers. Thus, the separately estimated coefficients for stayers versus movers in the model are mostly in line with the data.

Overall, we conclude that cashflow news affects workers across the board; the higher exposure of top earners to cashflow news is mainly driven by intensive margin effects. In contrast, discount rate shocks have a substantial extensive margin effect where the negative effects on earnings are concentrated on the left tail. Rising discount rates primarily affected low-wage workers who face an increase in the probability of being laid off as a consequence.

4.2 Worker Earnings Risk

The model has direct implications for the dynamics of labor income risk. Specifically, the link between changes in worker productivity z and worker earnings is time-varying: it depends both on the current level of z but also on the aggregate state x. Given this, we next explore whether the calibrated model can replicate these features of the data, even though they are not explicit calibration targets.

We start with the unconditional distribution of labor income growth and compare it to labor productivity in the model in Figure 10. We see that, even though changes in worker (log) productivity are normally distributed, the model can easily generate negatively skewed and highly lepto-kurtotic distributions of earnings growth. The increased tail risk in worker earnings arises in the model due to the interaction of the wage contract and the operation of the labor market. That is, the combination of idiosyncratic productivity shocks, search and matching frictions, and heterogeneity in the extent of wage smoothing across different workers in the economy, some shocks are well insulated and others lead to very large changes in earnings. The model generates levels of higher moments of earnings growth that are consistent with the estimates in Guvenen et al. (2014). For instance, the average volatility of annual income growth is 0.56, the average skewness is -1.2, and the average kurtosis is 58. For workers who stay with their same employer, the left tail is somewhat smaller, but the kurtosis is even higher (76).

In addition, the level of earnings risk varies with aggregate output, consistent with the findings of Guvenen et al. (2014). In both the data and the model, contractions in output are associated with an increase in the left tail of the distribution of income growth and a shrinking of the right tail.

Last, the model can replicate the U-shaped sensitivity of worker earnings on aggregate output as a function of prior income (Guvenen et al., 2017). Our model qualitatively matches this pattern, as we see in Figure 11. In both the model and the data, low-wage workers and high-wage workers have the largest exposures to output growth than workers in the middle of the income distribution. As we saw above, in both the data and the model, the response of the low-income workers is driven by separations, while the response of top-earners are driven by earnings changes for continuing workers.

4.3 Can the model match the observed dynamics of key labor market variables?

Next, to tighten the link between the model and the data, we feed directly into the model our empirical measures of cashflow and discount rate shocks from Section 1.3. Specifically, we standardize $N_{CF,t}$ and $N_{DR,t}$ to have zero mean and unit standard deviation, and plug these values into the model as realizations of $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$, respectively. We then accumulate these shocks into levels for A and x using their respective law of motions in the model—equations (18) and (20). Given these realizations of A_t and x_t, we then compute a number of model quantities and compare them to their empirical counterparts. We remove means from stationary series, and detrend non-stationary series with a band-pass filter.

We first examine aggregate (log) output, both in levels and in first differences. As we can see in Figure 12, the model is able to generate some of the observed output fluctuations in the data, particularly in the second half of the sample. Specifically, the correlation between output growth in the data and the time series implied by the model is 0.3 in the 1991–2019 period (vs 0.1 in the full sample). Recall the risk-free rate is constant in the model; thus, the somewhat higher correlation in the second half of the sample suggests that the fluctuations the model misses are arguably related to monetary policy—the increase in interest rates during the early 1980s and the sharp decline in rates following the Great Recession.

In Figure 13, we examine unemployment and labor force participation. For both series, the correlation between the model-implied series and their empirical counterpart is significantly positive at 0.42 over the full sample; as before, the correlation is larger in the second half of the sample, equal to 0.54 and 0.64, respectively. As before, this pattern is consistent with a smaller volatility of monetary policy shocks in the post-1990 sample.

We next examine in Figure 14 how the model-implied realization of labor income risk corresponds to its empirical counterpart. In the top panel, we focus our attention to the both the left tail: the difference between the median and the 10th percentile of earnings growth. In the bottom panel, we focus on the right tail of income risk—the difference between the 90th percentile and the median of earnings growth rates. We compare the model-implied time series with the data series from Guvenen et al. (2014). We see that, both in the model and in 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. In terms of magnitudes, we see that the model does a reasonable job capturing the observed fluctuations in income risk: the correlation between the data and the model-implied series is 0.45 and 0.30 for the left and right tail of income risk, respectively. Focusing on the second half of the sample, the correlation increases to 0.58 and 0.42, respectively.

Last, Figure 15 examines the realized path of income inequality implied by the model and compares it to the data series from Heathcote et al. (2020). The top panel calculates the level of income inequality at the bottom—time series of the ratio of the median to the 20-th percentile of earnings in both data and model. In both the data and the model, there is a strong cyclical component, consistent with the findings of Heathcote et al. (2020). The correlation between the data and the time series implied by the model is 0.54 in the full sample, and increases to 0.67 in the second half of the sample. The bottom panel plots the level of inequality at the top (the ratio of the 90-th percentile to the median). In both the model and the data, inequality at the top is essentially a-cyclical.

Overall, we see that the model can reproduce a significant fraction of the observed fluctuations in output, employment, labor income risk, and inequality. When interpreting the magnitude of these correlations, it is important to keep in mind two points. First, the model is not calibrated explicitly to match these patterns, so they should be viewed as 'out of sample' results. Second, the only data series we input into the model is our empirical decomposition of stock market returns into discount rate and cashflow shocks—and the correlation between stock returns and macroeconomic quantities is in general very low (see e.g. Campbell, 1999; Stock and Watson, 2003).

5 Conclusion

Stock markets move for two distinct reasons: because of news about firm cashflows and because of changes in discount rates. We have shown that these two components have very different implications for the earnings growth of workers. When discount rates rise, workers at the bottom of the income distribution suffer significant and persistent declines in their earnings in the following years, while workers at the top of the income distribution are much less affected. The income declines are mainly driven by job separations. On the other hand, when cashflow news is negative, high-wage workers are most affected in their earnings, with most of the effect coming from the intensive margin.

In this paper, we construct a labor search model with a canonical specification of discount rate dynamics that is able to quantitatively replicate these empirical findings. The model has several implications regarding the role of discount rates in generating unemployment fluctuations and the drivers of the low level of cyclicality of aggregate worker earnings. These implications are consistent with patterns in the data.

More broadly, our model suggests that different types of aggregate shocks can have markedly different distributional consequences. Our findings imply that monetary tightening will disproportionately affect the earnings of lower-paid workers. Similarly, low-wage workers are the ones that bear the costs of financial shocks to firms as a result of contractions in credit supply. To the extent that low-wage workers have larger MPCs than high-wage workers (Patterson, 2022), changes in discount rates may have an amplified feedback effect on aggregate output relative to a similar shock to productivity. Our results are likely to have nontrivial implications for portfolio choice. Low-wage workers may also have less of an incentive to participate in stock markets if they are more likely to be fired and to need access to liquidity during times when discount rates rise.

References

Ai, H. and A. Bhandari (2021). Asset pricing with endogenously uninsurable tail risk. *Econometrica 89*(3), 1471–1505.

Almeida, H., M. Campello, B. Laranjeira, and S. Weisbenner (2011). Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis. *Critical Finance Review 1*, 3–58.

Autor, D. H., D. Dorn, G. H. Hanson, and J. Song (2014). Trade adjustment: Worker-level evidence. *Quarterly Journal of Economics 129*(4), 1799–1860.

Baghai, R. P., R. C. Silva, V. Thell, and V. Vig (2021). Talent in distressed firms: Investigating the labor costs of financial distress. *Journal of Finance 76*(6), 2907–2961.

Balke, N. and T. Lamadon (2022). Productivity shocks, long-term contracts, and earnings dynamics. *American Economic Review 112*(7), 2139–77.

Bansal, R., D. Kiku, I. Shallastovich, and A. Yaron (2014). Volatility, the macroeconomy, and asset prices. *The Journal of Finance 69*(6), 2471–2511.

Bansal, R. and A. Yaron (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance 59*(4), 1481–1509.

Barro, R. J. (2009). Rare disasters, asset prices, and welfare costs. *American Economic Review 99*(1), 243–64.

Basu, S., G. Candian, R. Chahrour, and R. Valchev (2021). Risky Business Cycles. Boston College Working Papers in Economics 1029, Boston College Department of Economics.

Benmelech, E., N. Bergman, and A. Seru (2021). Financing Labor. *Review of Finance 25*(5), 1365–1393.

Benmelech, E., C. Frydman, and D. Papanikolaou (2019). Financial frictions and employment during the Great Depression. *Journal of Financial Economics 133*(3), 541–563.

Bergman, N. K., D. Matsa, and M. Weber (2022). Inclusive Monetary Policy: How Tight Labor Markets Facilitate Broad-Based Employment Growth. CESifo Working Paper Series 9512, CESifo.

Berk, J. B., R. C. Green, and V. Naik (1999). Optimal investment, growth options, and security returns. *The Journal of Finance 54*(5), 1553–1607.

Berk, J. B., R. Stanton, and J. Zechner (2010). Human capital, bankruptcy, and capital structure. *The Journal of Finance 65*(3), 891–926.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives 28*(2), 153–76.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. *Econometrica 86*(3), 1031–1065.

Bordalo, P., N. Gennaioli, R. LaPorta, and A. Shleifer (2019). Diagnostic expectations and stock returns. *The Journal of Finance 74*(6), 2839–2874.

Borovička, J. and K. Borovičková (2018). Risk premia and unemployment fluctuations. Working paper, New York University.

Caggese, A., V. Cuñat, and D. Metzger (2019). Firing the wrong workers: Financing constraints and labor misallocation. *Journal of Financial Economics 133*(3), 589–607.

Campbell, J. Y. (1999). Chapter 19 asset prices, consumption, and the business cycle. Volume 1 of *Handbook of Macroeconomics*, pp. 1231–1303. Elsevier.

Campbell, J. Y. (2003). Consumption-based asset pricing. In G. M. Constantinides, M. Harris, and R. M. Stulz (Eds.), *Handbook of the Economics of Finance*, pp. 803–887. Elsevier.

Campbell, J. Y. and J. H. Cochrane (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy 107*(2), 205–251.

Campbell, J. Y. and R. J. Shiller (1988). The dividend-price ratio and expectations of future dividends and discount factors. *Review of Financial Studies 1*(3), 195–228.

Campbell, J. Y. and T. Vuolteenaho (2004). Bad beta, good beta. *American Economic Review 94*(5), 1249–1275.

Chan, Y. and L. Kogan (2002). Catching up with the joneses: Heterogeneous preferences and the dynamics of asset prices. *Journal of Political Economy 110*(6), 1255–1285.

Chodorow-Reich, G. and L. Karabarbounis (2016). The cyclicality of the opportunity cost of employment. *Journal of Political Economy 124*(6), 1563–1618.

Christiano, L. J., M. S. Eichenbaum, and M. Trabandt (2016). Unemployment and business cycles. *Econometrica 84*(4), 1523–1569.

Coglianese, J., M. Olsson, and C. Patterson (2022). Monetary policy and the labor market: A quasi-experiment in sweden. Working paper, Chicago University.

den Haan, W. J., G. Ramey, and J. Watson (2000). Job destruction and propagation of shocks. *American Economic Review 90*(3), 482–498.

Diamond, P. A. (1982). Wage determination and efficiency in search equilibrium. *The Review of Economic Studies 49*(2), 217–227.

Erceg, C. J., D. W. Henderson, and A. T. Levin (2000). Optimal monetary policy with staggered wage and price contracts. *Journal of Monetary Economics 46*(2), 281–313.

Fernald, J. (2014). A quarterly, utilization-adjusted series on total factor productivity. Working paper, Federal Reserve Bank of San Francisco.

Giroud, X. and H. M. Mueller (2017). Firm leverage, consumer demand, and employment losses during the great recession. *Quarterly Journal of Economics 132*(1), 271–316.

Guiso, L., L. Pistaferri, and F. Schivardi (2005). Insurance within the firm. *Journal of Political Economy 113*(5), 1054–1087.

Guiso, L., L. Pistaferri, and F. Schivardi (2013). Credit within the firm. *Review of Economic Studies 80*(1), 211–247.

Guvenen, F., G. Kaplan, J. Song, and J. Weidner (2022). Lifetime Earnings in the United States over Six Decades. *American Economic Journal: Applied Economics 14*(4), 446–79.

Guvenen, F., S. Ozkan, and J. Song (2014). The nature of countercyclical income risk. *Journal of Political Economy 122*(3), 621–660.

Guvenen, F., S. Schulhofer-Wohl, J. Song, and M. Yogo (2017). Worker betas: Five facts about systematic earnings risk. *American Economic Review 107*(5), 398–403.

Hagedorn, M. and I. Manovskii (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review 98*(4), 1692–1706.

Hall, R. E. (2017). High discounts and high unemployment. *American Economic Review 107*(2), 305–30.

Harris, M. and B. Holmstrom (1982). A theory of wage dynamics. *The Review of Economic Studies 49*(3), 315–333.

He, Z. and A. Krishnamurthy (2013). Intermediary asset pricing. *American Economic Review 103*(2), 732–70.

Heathcote, J., F. Perri, and G. L. Violante (2020). The rise of US earnings inequality: Does the cycle drive the trend? *Review of Economic Dynamics 37*, S181–S204.

Hou, K., C. Xue, and L. Zhang (2015). Digesting anomalies: An investment approach. *Review of Financial Studies 28*(3), 650–705.

İmrohoroğlu, A. and Ş. Tüzel (2014). Firm-level productivity, risk, and return. *Management Science 60*(8), 2073–2090.

Itskhoki, O. and D. Mukhin (2021). Exchange rate disconnect in general equilibrium. *Journal of Political Economy 129*(8), 2183–2232.

Jorda, O. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review 95*(1), 161–182.

Kehoe, P. J., P. Lopez, V. Midrigan, and E. Pastorino (2022). Asset Prices and Unemployment Fluctuations: A Resolution of the Unemployment Volatility Puzzle. *The Review of Economic Studies*. rdac048.

Kilic, M. and J. A. Wachter (2018). Risk, unemployment, and the stock market: A rare-event-based explanation of labor market volatility. *Review of Financial Studies 31*(12), 4762–4814.

Kocherlakota, N. R. (1996). Implications of efficient risk sharing without commitment. *The Review of Economic Studies 63*(4), 595–609.

Kozak, S. and S. Santosh (2020). Why do discount rates vary? *Journal of Financial Economics 137*(3), 740–751.

Lettau, M. and J. A. Wachter (2007). Why is long-horizon equity less risky? a duration-based explanation of the value premium. *The Journal of Finance 62*(1), 55–92.

Ljungqvist, L. and T. J. Sargent (1998). The european unemployment dilemma. *Journal of political Economy 106*(3), 514–550.

Ljungqvist, L. and T. J. Sargent (2017). The fundamental surplus. *American Economic Review 107*(9), 2630–2665.

Martellini, P., G. Menzio, and L. Visschers (2021). Revisiting the hypothesis of high discounts and high unemployment. *The Economic Journal 131*(637), 2203–2232.

Menzio, G. and S. Shi (2011). Efficient search on the job and the business cycle. *Journal of Political Economy 119*(3), 468–510.

Menzio, G., I. A. Telyukova, and L. Visschers (2016). Directed search over the life cycle. *Review of Economic Dynamics 19*, 38–62.

Mitra, I. and Y. Xu (2020). Time-varying risk premium and unemployment risk across age groups. *Review of Financial Studies 33*(8), 3624–3673.

Moen, E. R. (1997). Competitive search equilibrium. *Journal of Political Economy 105*(2), 385–411.

Montgomery, J. D. (1991). Equilibrium wage dispersion and interindustry wage differentials. *The Quarterly Journal of Economics 106*(1), 163–179.

Moreira, A. and A. Savov (2017). The macroeconomics of shadow banking. *Journal of Finance*.

Mortensen, D. T. (1982). The matching process as a noncooperative bargaining game. *The Economics of Information and Uncertainty*, 233–258.

Muir, T. (2017). Financial Crises and Risk Premia*. *The Quarterly Journal of Economics 132*(2), 765–809.

Olley, G. S. and A. Pakes (1996). The dynamics of productivity in the telecommunications equipment. *Econometrica 64*(6), 1263–1297.

Patterson, C. (2022). The matching multiplier and the amplification of recessions. *Working Paper*.

Pissarides, C. A. (1985). Short-run equilibrium dynamics of unemployment, vacancies, and real wages. *The American Economic Review 75*(4), 676–690.

Santos, T. and P. Veronesi (2010). Habit formation, the cross section of stock returns and the cash-flow risk puzzle. *Journal of Financial Economics 98*(2), 385–413.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review 95*(1), 25–49.

Solon, G., R. Barsky, and J. A. Parker (1994). Measuring the cyclicality of real wages: How important is composition bias? *Quarterly Journal of Economics 109*(1), 1–25.

Stock, J. H. and M. Watson (2003). Forecasting output and inflation: The role of asset prices. *Journal of Economic Literature 41*(3), 788–829.

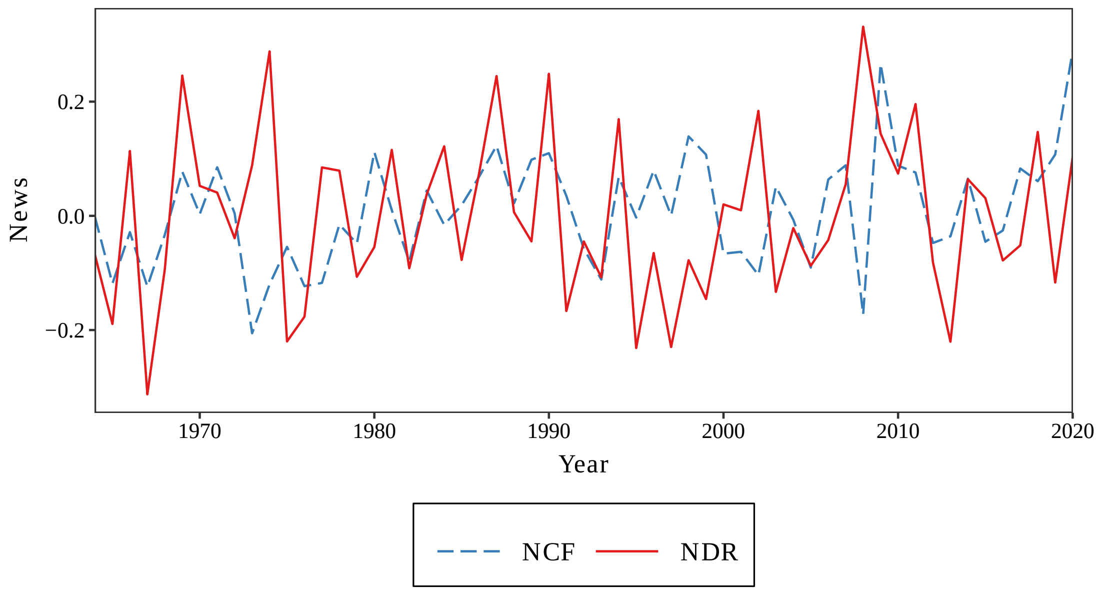
Thomas, J. and T. Worrall (1988). Self-enforcing wage contracts. *The Review of Economic Studies 55*(4), 541–553.

Vuolteenaho, T. (2002). What drives firm-level stock returns? *Journal of Finance 57*(1), 233–264.

Wachter, J. A. (2013). Can time-varying risk of rare disasters explain aggregate stock market volatility? *The Journal of Finance 68*(3), 987–1035.

Figures and Tables

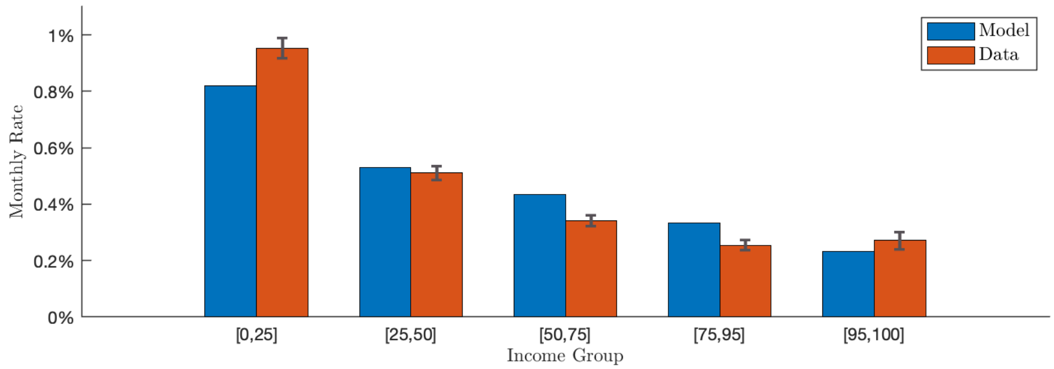
Figure 1: Annual Stock Market Return Decomposition



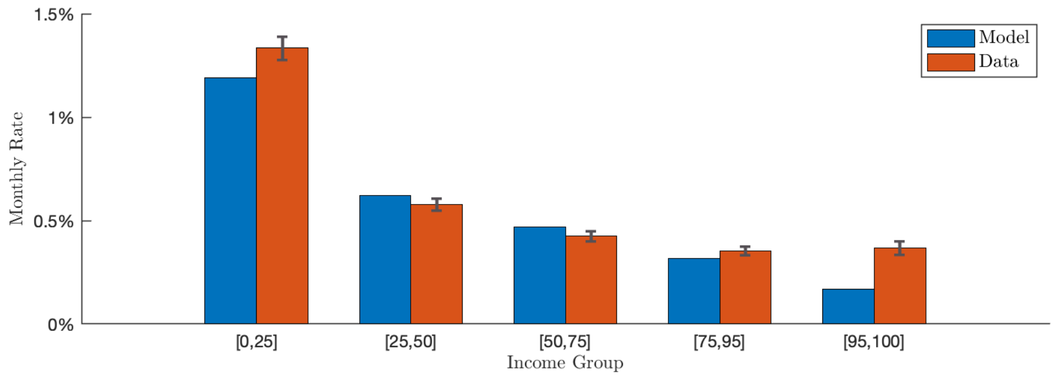
This figure plots our decomposition of annual stock market news into cashflow news ($N_{CF,t}$) and discount rate news ($N_{DR,t}$). The method for constructing these series is described in Section 1.3.

Figure 2: Moments in Model and Data: Worker Flows

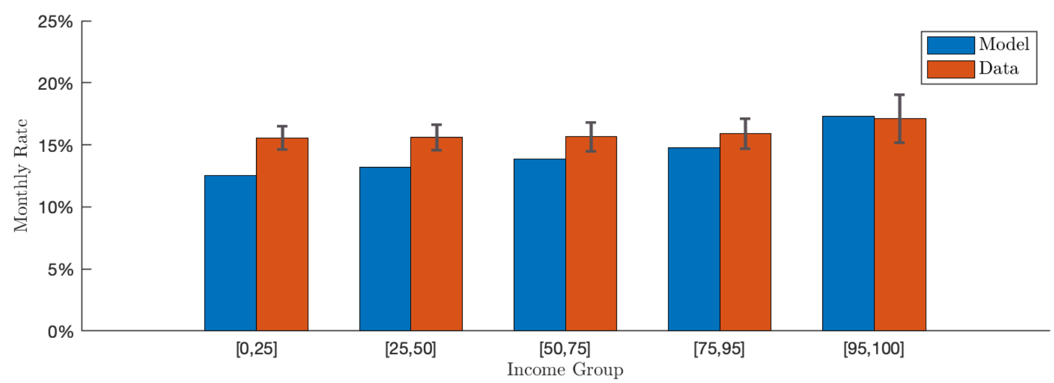
(a) Average Separation Rate into Unemployment by Income Group (Targeted)



(b) Average Separation Rate into Nonparticipation by Income Group (Targeted)



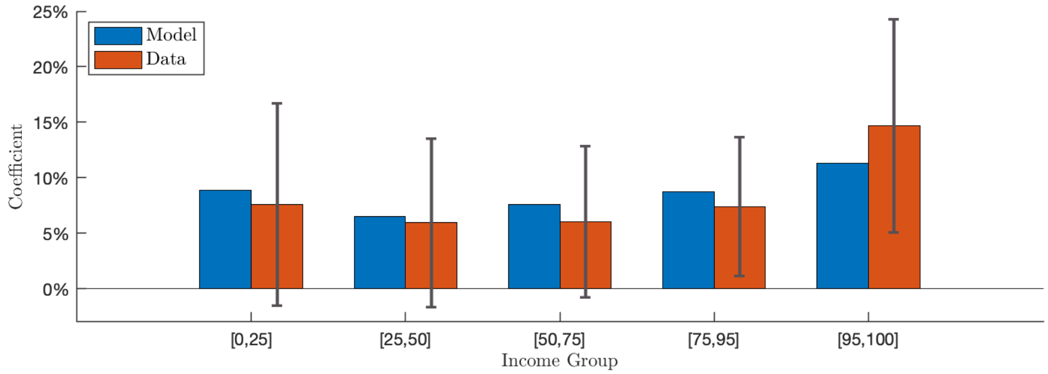
(c) Average Job Finding Rate by Income Group (Targeted)



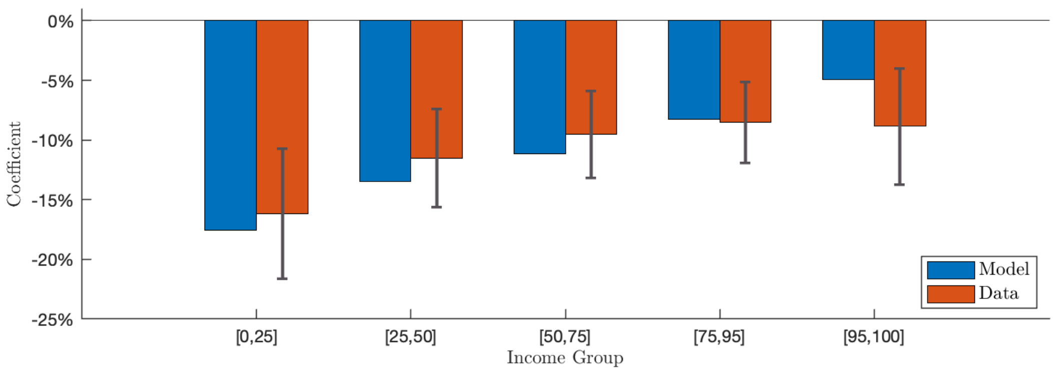
This figure compares average job separation rates into unemployment (panel a), average separation rates into nonparticipation (panel b), and the average job finding rate (panel c) by income group in the model and in the data. The empirical counterparts are computed from public Survey of Income and Program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

Figure 3: Moments in Model and Data: Regression Coefficients

(a) Coefficient of Income Growth on Cash Flow News (Targeted)

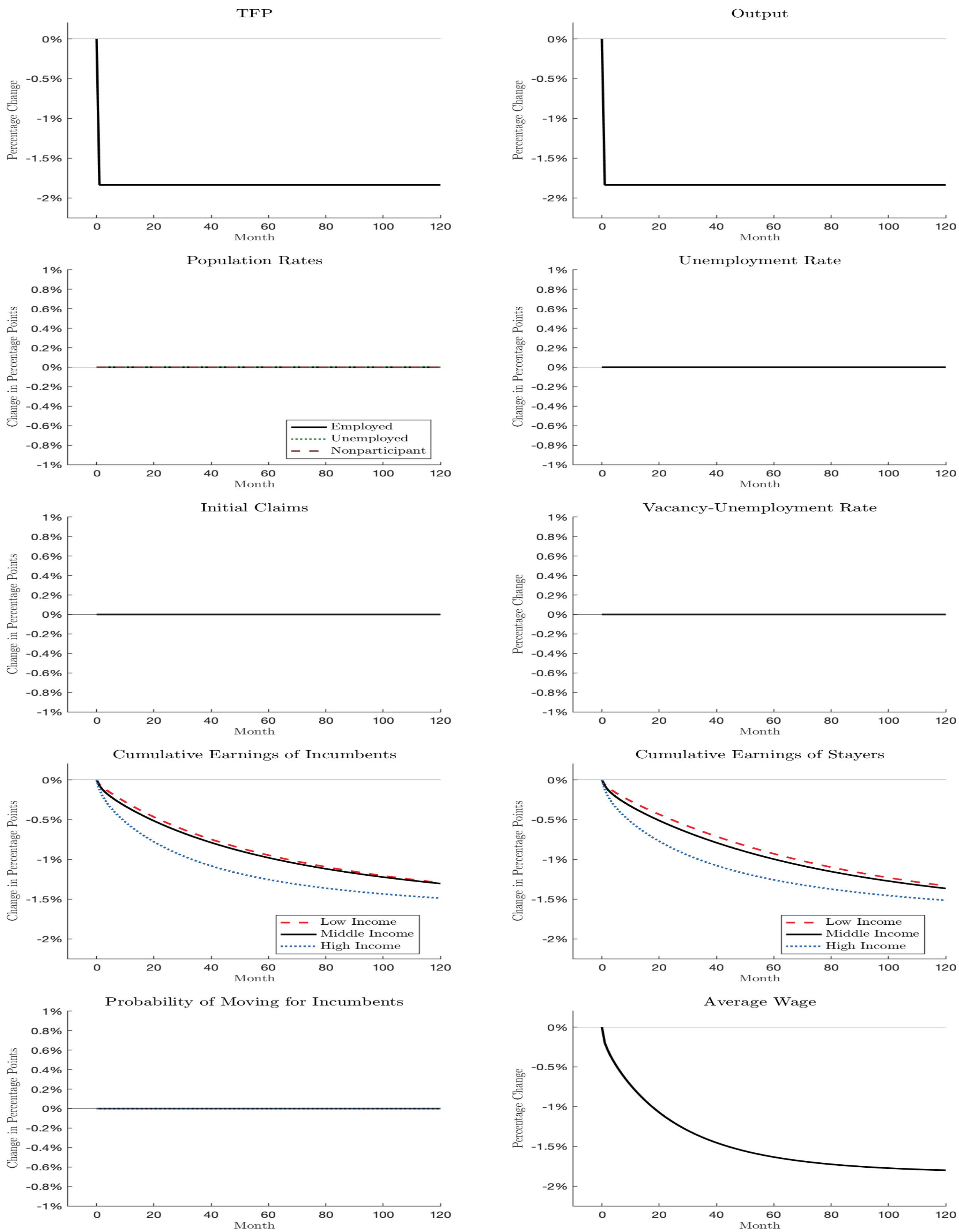


(b) Coefficient of Income Growth on Discount Rate News (Targeted)



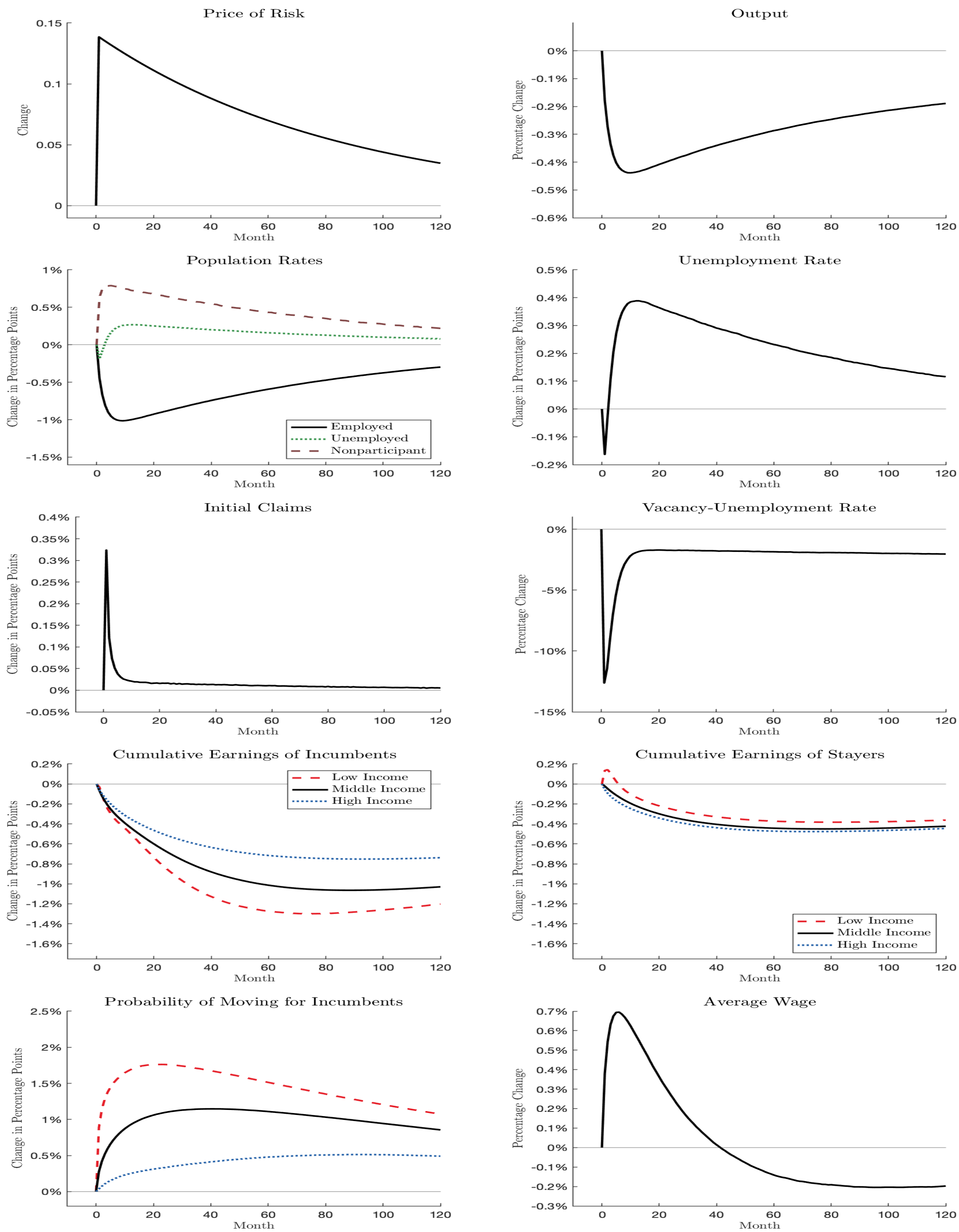
This figure compares the regression coefficients of two-year ahead worker earnings growth on cashflow news (panel a) and discount rate news (panel b) by income group in the model and in the data. These moments are targeted in our model calibration. The empirical counterparts correspond to the regression coefficients in column (6) of Table 3. In the model we compute the analogous regression coefficients, where we sort workers in income bins based on current earnings.

Figure 4: Impulse Response Functions to TFP Shock



This figure shows the impulse responses of key model quantities following a one (annual) standard deviation technology shock.

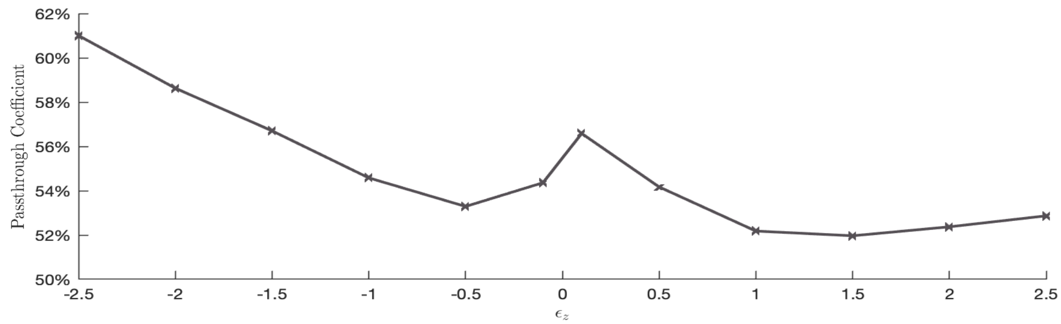
Figure 5: Impulse Response Functions to Discount Rate Shock



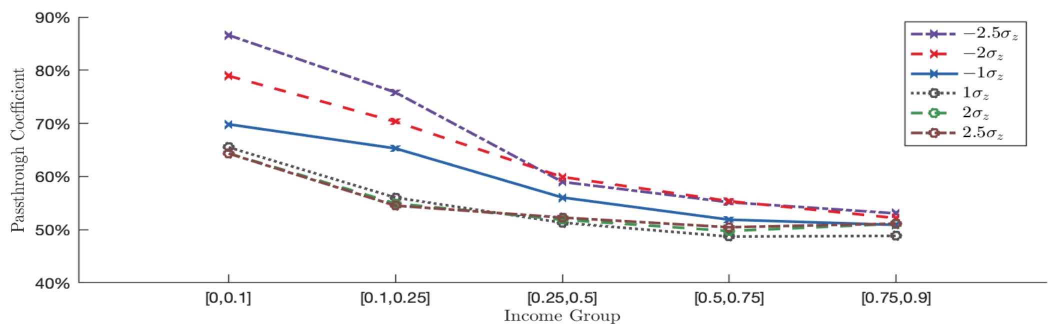
This figure shows the impulse responses of key model quantities following a one (annual) standard deviation discount rate shock.

Figure 6: Model: Asymmetric Response of Earnings to Worker Productivity

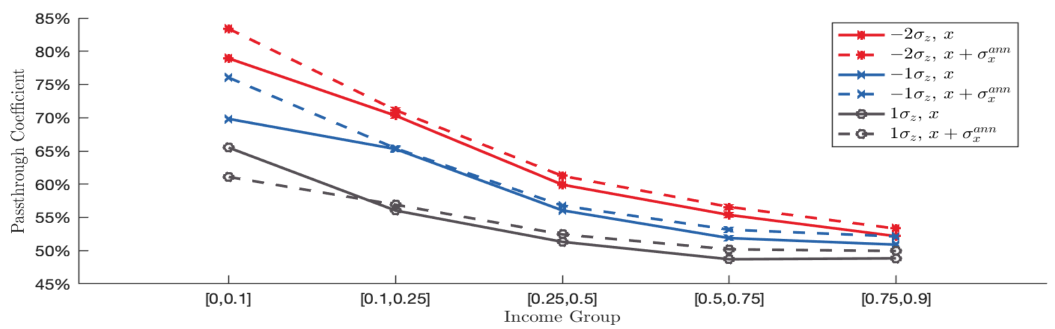
(a) By Shock Size



(b) By Income and Shock Size



(c) By Income and Aggregate State



(d) By Horizon and Shock Size

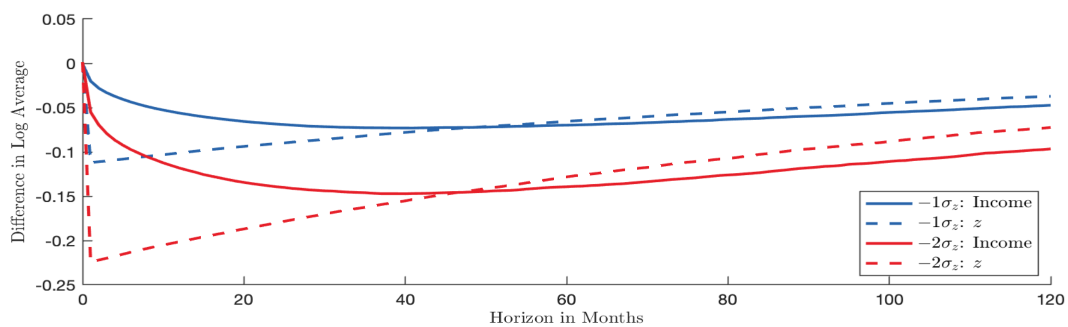
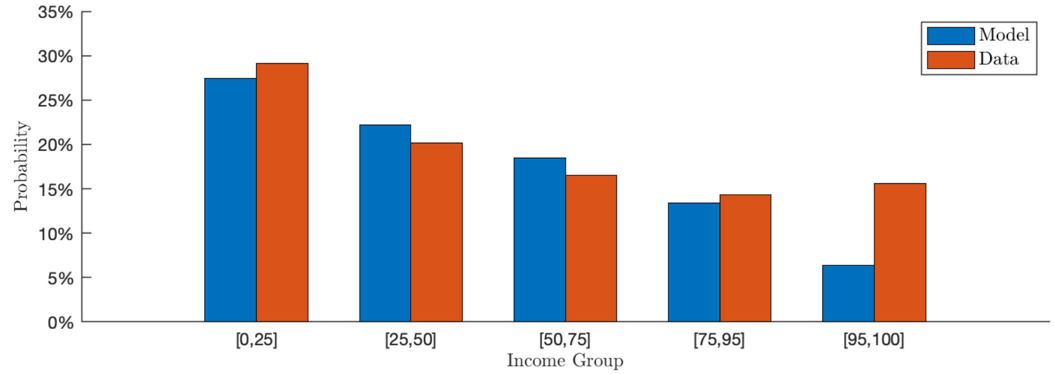


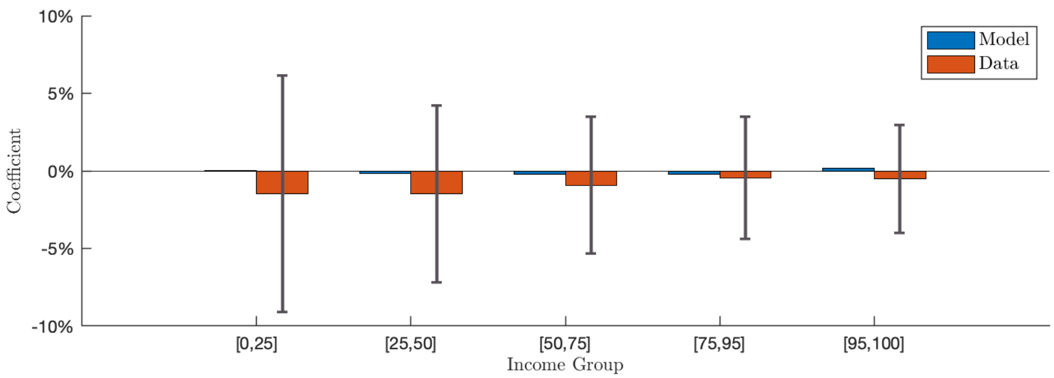
Figure illustrates the difference in the response of worker earnings starting from the ergodic distribution to a worker productivity shock z, as a function of the current level of discount rates x_t; the size of the shock; the worker's current income; or horizon. Passthrough is defined as the difference in log average income divided by the difference in log average z, both after 1 year, for everyone or by income group.

Figure 7: Moments in Model and Data: Job Separations

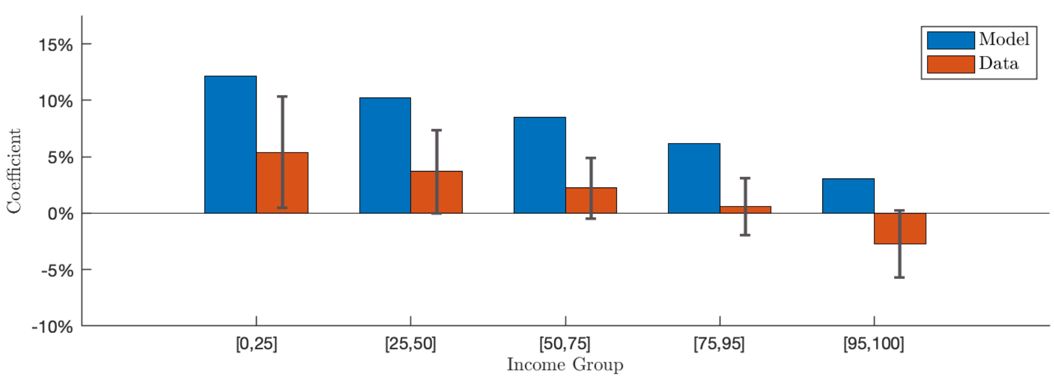
(a) Probability of a Zero-Earnings Quarter Over the Next Three Years (Non-Targeted)



(b) Coefficient of Zero-Earnings Quarter Indicator on Cashflow News by Income Group (Non-Targeted)



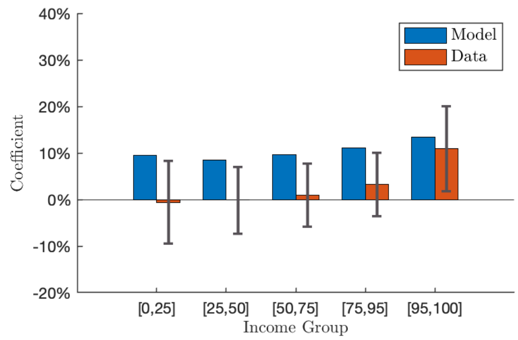
(c) Coefficient of Zero-Earnings Quarter Indicator on Discount Rate News by Income Group (Non-Targeted)



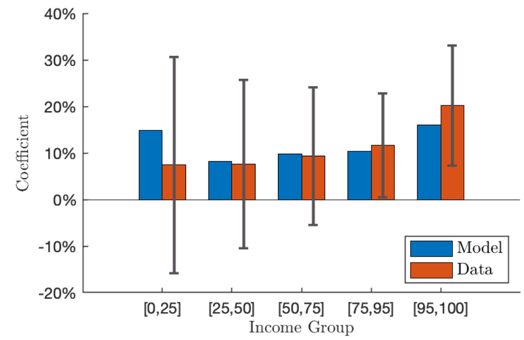
Panel (a) plots the probability of a zero-earnings quarter over the next three years. The data are from Table 1. Panels (b) and (c) of this figure compare the regression coefficients of the probability of having at least one quarter with zero earnings in the next three years on cashflow news (panel b) and discount rate news (panel c) by income group in the model and in the data. These moments are not targeted in our model calibration.

Figure 8: Moments in Model and Data: Stayers Versus Movers Regression

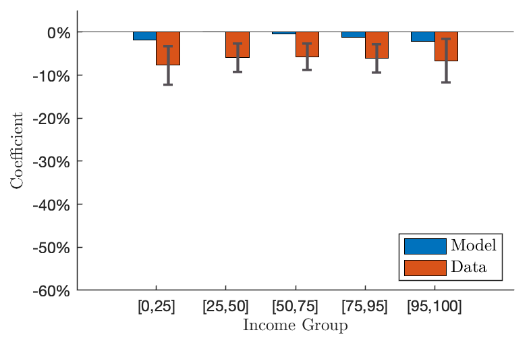
(a) Coefficient of Income Growth on Cashflow News for Stayers by Income Group (Non-Targeted)



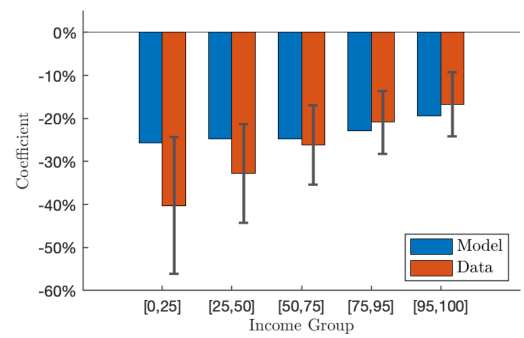
(b) Coefficient of Income Growth on Cashflow News for Movers by Income Group (Non-Targeted)



(c) Coefficient of Income Growth on Discount Rate News for Stayers by Income Group (Non-Targeted)



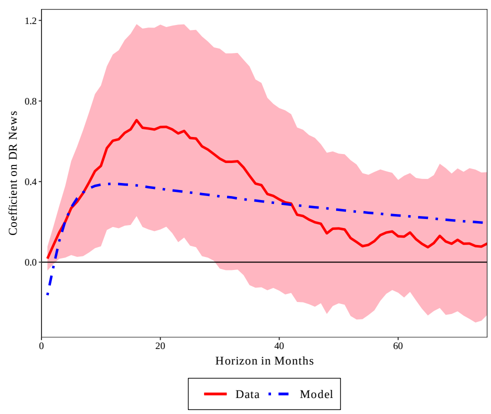
(d) Coefficient of Income Growth on Discount Rate News for Movers by Income Group (Non-Targeted)



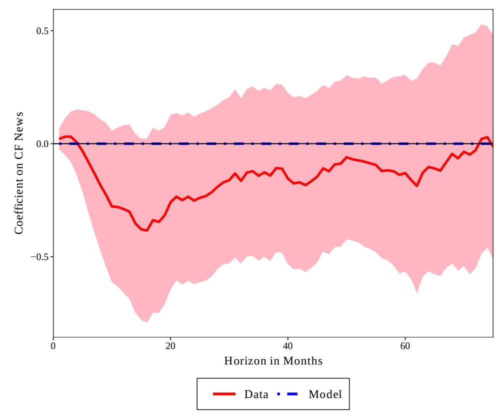
Panels (a)–(d) in this figure compare the regression coefficients of three-year income growth on cashflow news (a and b) and discount rate news (c and d), interacted by income bin indicators and also interacted by indicators for whether the worker is a stayer (a and c) or a mover (b and d) over this period. The empirical counterparts are from Tables 6 and 7. These moments are not targeted in our model calibration.

Figure 9: Impulse Responses of Unemployment Rate and Employment-Population Ratio to Discount Rate and Cashflow News

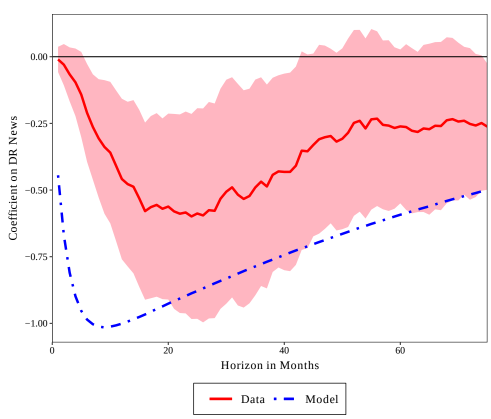
(a) Impulse Responses of Unemployment Rate to Discount Rate News



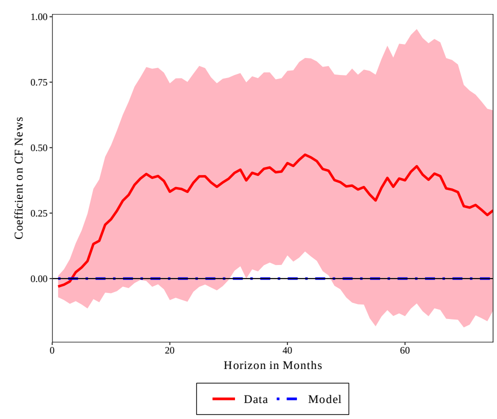
(b) Impulse Responses of Unemployment Rate to Cash Flow News



(c) Impulse Responses of Employment-Population Ratio to Discount Rate News

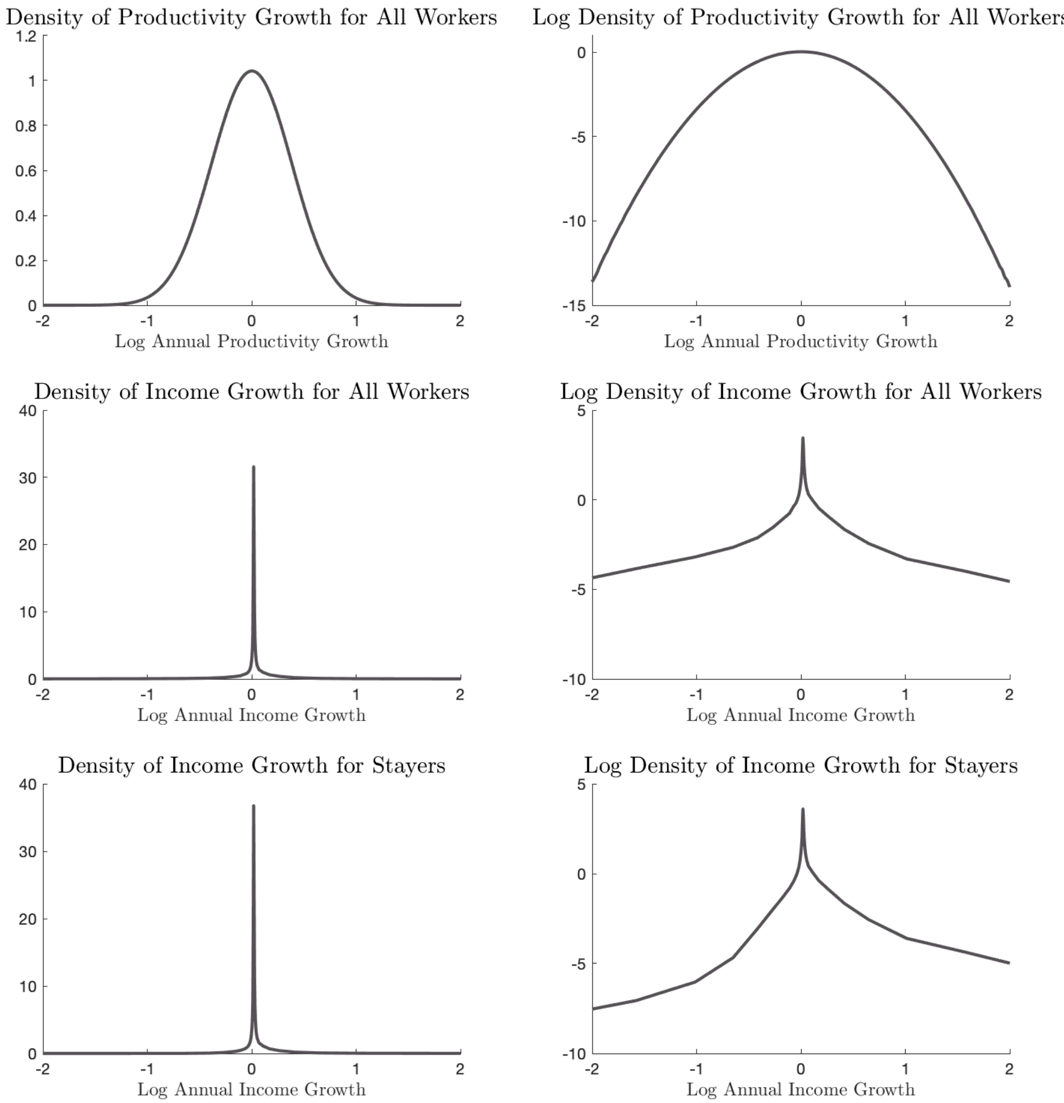


(d) Impulse Responses of Employment-Population Ratio to Cash Flow News



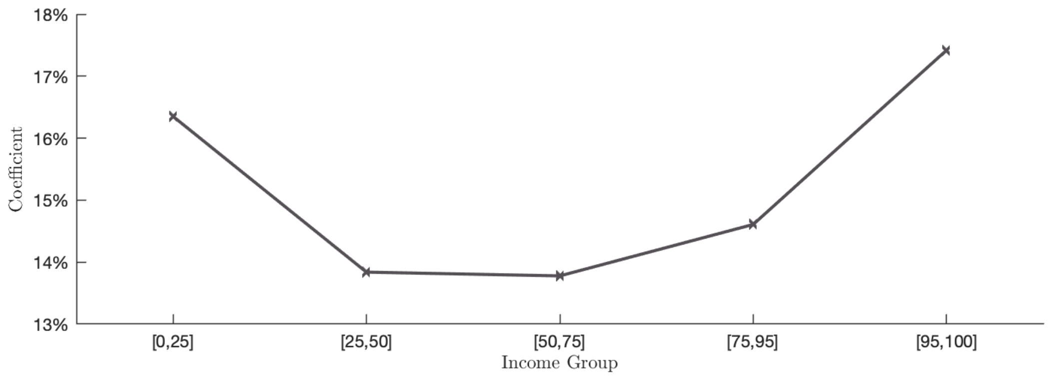
This figure plots impulse responses of the unemployment rate and employment-population ratio to discount rate and cashflow news. The impulse response is the regression coefficient on the news at $t+1$ from a regression of the series at $t+h$ on the news terms at $t+1$ and time-t controls. The vector of controls includes the current level of the variable, the Treasury bill rate, the term spread, and the market's smoothed price-earnings ratio. The shaded area represents pointwise 95% confidence bands, calculated using Newey-West standard errors, where the number of lags equals the horizon minus 1. We also report the analogous impulse responses from the model.

Figure 10: Unconditional Distributions of Annual Productivity Growth and Income Growth in the Model



This figure reports model-implied unconditional probability distributions of annual productivity growth, annual income growth for all workers, and annual income growth for stayers, where the left panel plots the densities themselves and the right panel plots the density on a logarithmic scale. We compute annual income growth as the difference between log earnings over the last twelve months and log earnings over the twelve months prior to that, and compare this to productivity growth over the last twelve months. For earnings, we restrict the sample to workers that have strictly positive earnings in both years. We also report the distribution of income growth for stayers, defined as workers that are in the same match in month $t+12$ as in month t. The left panels plot the densities on a standard scale; the right panels plot the densities on a logarithmic scale.

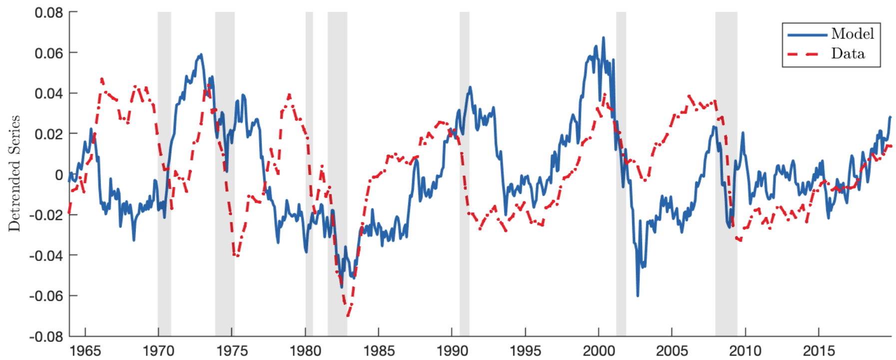
Figure 11: Coefficient of One-Year Income Growth on GDP Growth in Model



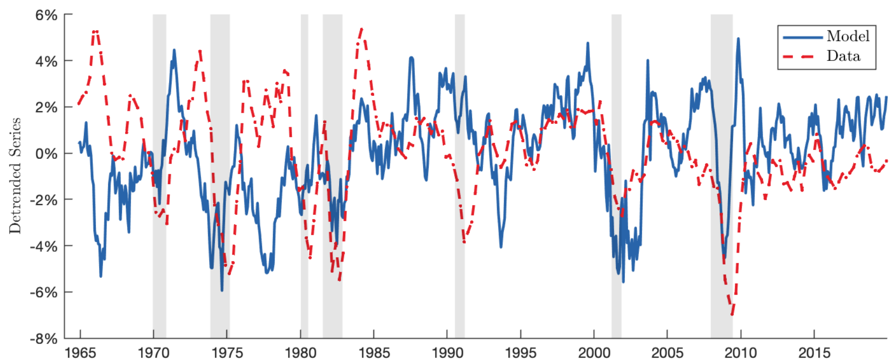
This figure reports the regression coefficient of one-year income growth on total output growth over the same twelve-month period, interacted by income bin indicators, in a large panel of worker earnings simulated from the model. Specifically, we regress annual income growth of incumbent workers on annual output growth over the same period, interacted by indicators for the five income bins. To minimize Monte Carlo error, we run this regression in a large panel of model-simulated earnings trajectories.

Figure 12: Model vs Data: Output

(a) Output



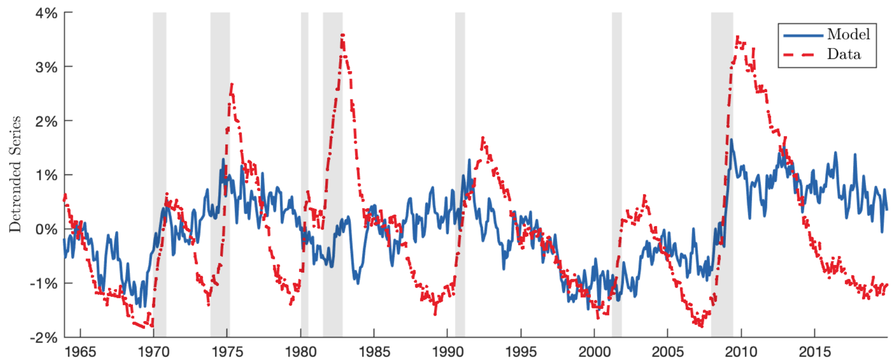
(b) Output Growth (y/y)



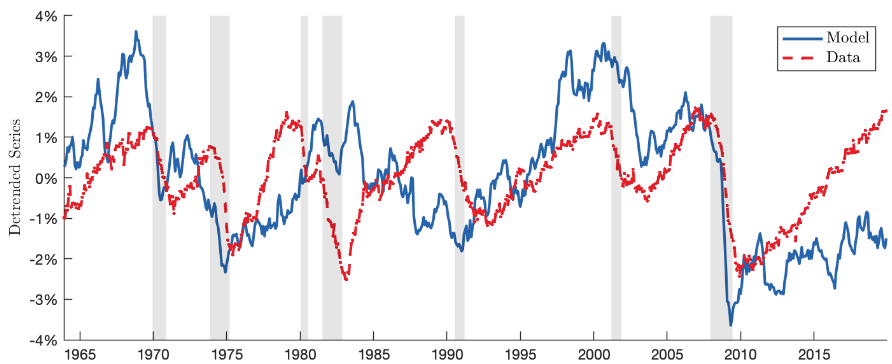
This figure compares the unemployment rate and employment-population ratio in a model simulation to the data. In the model, we directly feed in our measures of cashflow and discount rate shocks from Section 1.3 by standardizing $N_{CF,t}$ and $N_{DR,t}$ to have zero mean and unit standard deviation, and plugging these values into the model as realizations of $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$, respectively. We plot the demeaned unemployment rate from the model. The empirical counterpart is obtained by detrending the reported unemployment rate series from the Current Population Survey (CPS) through a HP filter with smoothing parameter 10^5.

Figure 13: Model vs Data: Unemployment Rate and Labor Force Participation

(a) Unemployment Rate



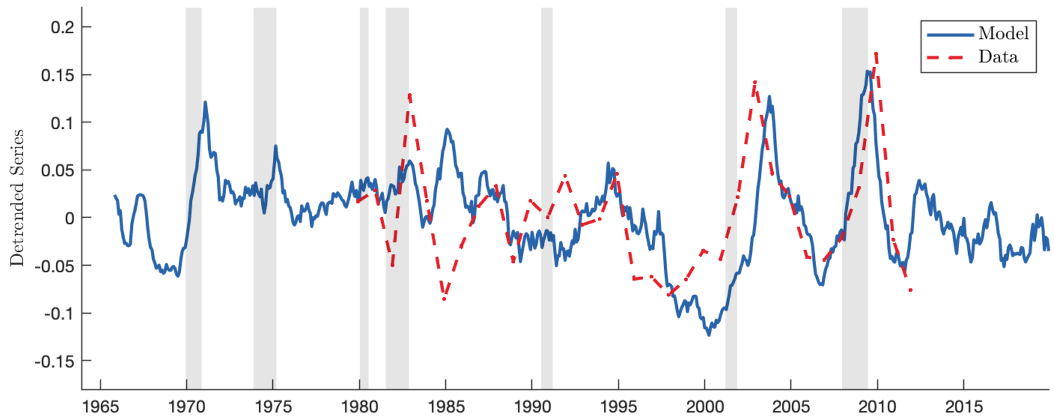
(b) Employment-Population Ratio



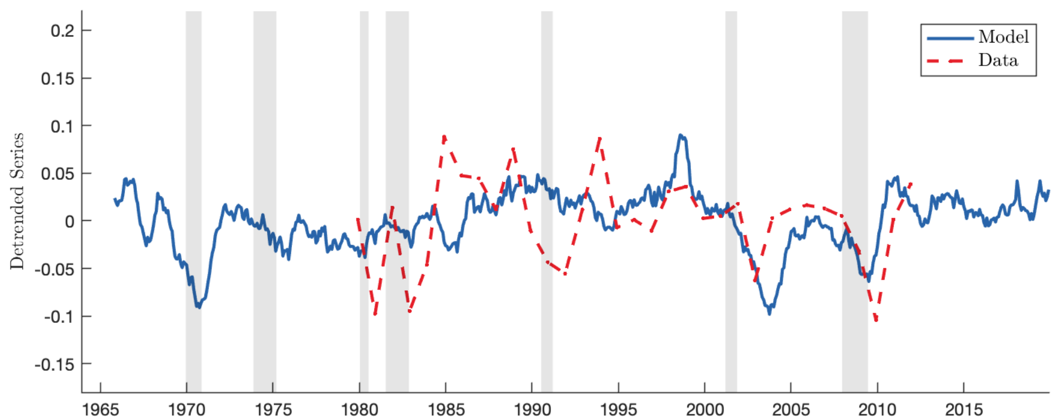
This figure compares the unemployment rate and employment-population ratio in a model simulation to the data. In the model, we directly feed in our measures of cashflow and discount rate shocks from Section 1.3 by standardizing $N_{CF,t}$ and $N_{DR,t}$ to have zero mean and unit standard deviation, and plugging these values into the model as realizations of $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$, respectively. We plot the demeaned unemployment rate from the model. The empirical counterpart is obtained by detrending the reported unemployment rate series from the Current Population Survey (CPS) through a HP filter with smoothing parameter 10^5.

Figure 14: Model vs Data: Distribution of Annual Labor Income Growth Over the Business Cycle

(a) Left tail (P50/P10)



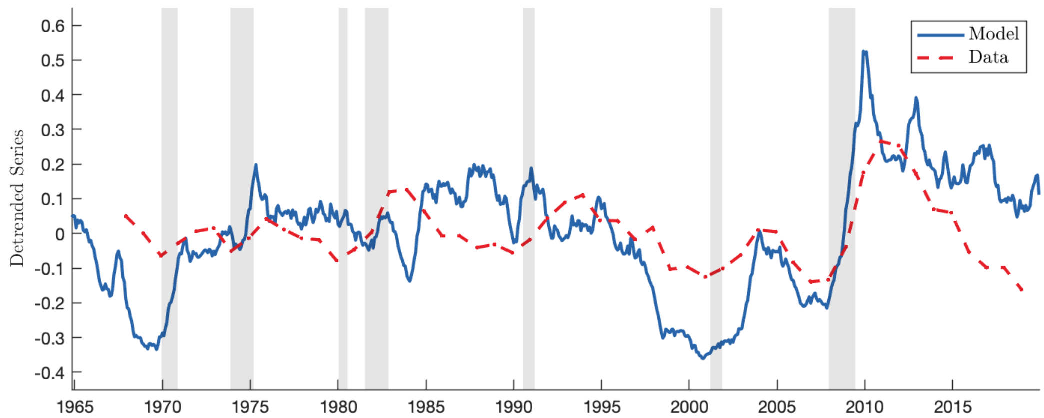
(b) Right tail (P90/P50)



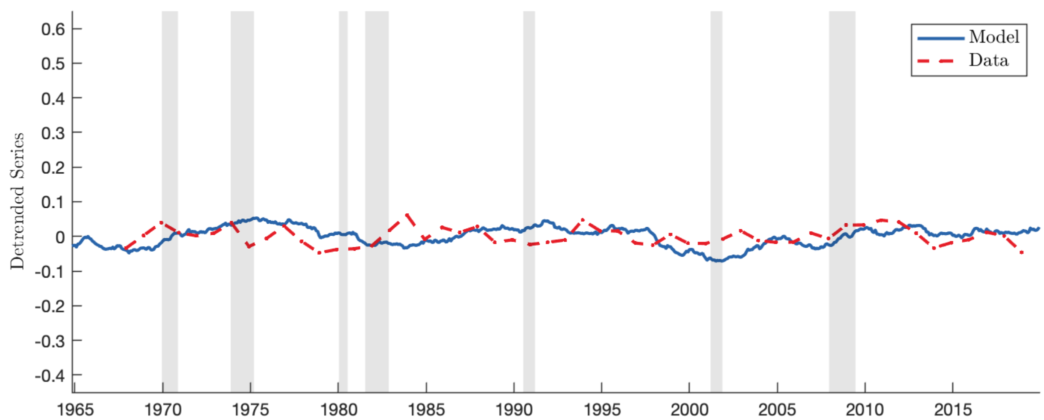
This figure compares the distribution of annual labor income growth in a model simulation to the data. In the model, we directly feed in our measures of cashflow and discount rate shocks from Section 1.3 by standardizing $N_{CF,t}$ and $N_{DR,t}$ to have zero mean and unit standard deviation, and plugging these values into the model as realizations of $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$, respectively. We then compute quantiles of individual worker earnings growth, defined as the difference in log earnings over the last twelve months and log earnings over the twelve months prior to that (conditional on positive). We plot the difference between the median and the 10th percentile (p50-p10), and the difference between the 90th percentile and the median (p90-p50). Panel (b) plots the empirical counterparts, obtained from Guvenen et al. (2014).

Figure 15: Model vs Data: Labor Income Inequality

(a) Inequality at the Bottom (P50/P20)



(b) Inequality at the Top (P90/P50)



This figure describes the cross-sectional distribution of annual labor income in a model simulation. In the model, we directly feed in our measures of cashflow and discount rate shocks from Section 1.3 by standardizing $N_{CF,t}$ and $N_{DR,t}$ to have zero mean and unit standard deviation, and plugging these values into the model as realizations of $\varepsilon_{A,t}$ and $\varepsilon_{x,t}$, respectively. We then compute quantiles of the cross-sectional distribution of individual worker earnings over the last 12 months. We plot the ratio of the median to the 20th percentile of labor income (50/20 ratio), and the ratio of the 90th percentile to the median (90/50 ratio).

Table 1: Summary Statistics for Workers in Main Sample

Variable	N ($\times 10^6$)	Mean	SD	p10	p50	p90
Income Growth $g_{i,t:t+1}$	16.0	-0.039	0.405	-0.345	0.005	0.303
Income Growth $g_{i,t:t+2}$	15.3	-0.071	0.456	-0.456	-0.002	0.301
Income Growth $g_{i,t:t+3}$	14.6	-0.102	0.502	-0.574	-0.011	0.304
Income Rank $[0, 25]$	3.7	-0.082	0.632	-0.803	0.032	0.509
Income Rank $[25, 50]$	3.7	-0.112	0.488	-0.578	-0.011	0.264
Income Rank $[50, 75]$	3.7	-0.110	0.433	-0.487	-0.023	0.215
Income Rank $[75, 95]$	2.9	-0.104	0.408	-0.448	-0.030	0.216
Income Rank $[95, 100]$	0.7	-0.105	0.485	-0.575	-0.030	0.327
Income Growth $g_{i,t:t+5}$	13.1	-0.161	0.578	-0.779	-0.034	0.310
Probability of Move$_{i,t:t+1}$	16.0	0.066				
Probability of Move$_{i,t:t+2}$	15.3	0.215				
Probability of Move$_{i,t:t+3}$	14.6	0.320				
Income Rank $[0, 25]$	3.7	0.386				
Income Rank $[25, 50]$	3.7	0.312				
Income Rank $[50, 75]$	3.7	0.294				
Income Rank $[75, 95]$	2.9	0.289				
Income Rank $[95, 100]$	0.7	0.285				
Probability of Move$_{i,t:t+5}$	13.1	0.468				
Probability of Zero$_{i,t:t+1}$	16.0	0.072				
Probability of Zero$_{i,t:t+2}$	15.3	0.140				
Probability of Zero$_{i,t:t+3}$	14.6	0.201				
Income Rank $[0, 25]$	3.7	0.291				
Income Rank $[25, 50]$	3.7	0.202				
Income Rank $[50, 75]$	3.7	0.165				
Income Rank $[75, 95]$	2.9	0.143				
Income Rank $[95, 100]$	0.7	0.156				
Probability of Zero$_{i,t:t+5}$	13.1	0.307				

This table summarizes the variables that characterize the earnings dynamics of the workers in our main LEHD sample. Income growth is defined in equations (1) and (2). Individuals are characterized as a stayer if the main employer in year $t + h$ is the same as the main employer in year t, and as a mover in all other cases. The indicator for zero earnings between t and $t + h$ takes the value of one if an individual has a quarter of zero earnings between the end of year t and the end of year $t + h$. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019.

Table 2: Income Exposures to Stock Market News

Income Growth $g_{i,t:t+h}$	Aggregate News				Market Beta × Aggregate News			
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=5$ (4)	$h=1$ (5)	$h=2$ (6)	$h=3$ (7)	$h=5$ (8)
Market News ×	0.093^{***}	0.146^{***}	0.151^{***}	0.125^{***}	0.079^{**}	0.136^{***}	0.137^{***}	0.112^{***}
Income Rank $[0, 25]$	(0.030)	(0.023)	(0.029)	(0.042)	(0.036)	(0.021)	(0.027)	(0.038)
Market News ×	0.071^{***}	0.100^{***}	0.104^{***}	0.077^{**}	0.063^{**}	0.098^{***}	0.098^{***}	0.073^{**}
Income Rank $[25, 50]$	(0.019)	(0.019)	(0.023)	(0.033)	(0.025)	(0.016)	(0.021)	(0.030)
Market News ×	0.066^{***}	0.085^{***}	0.088^{***}	0.063^{**}	0.060^{***}	0.085^{***}	0.083^{***}	0.059^{**}
Income Rank $[50, 75]$	(0.015)	(0.016)	(0.019)	(0.028)	(0.021)	(0.014)	(0.018)	(0.026)
Market News ×	0.070^{***}	0.083^{***}	0.085^{***}	0.062^{**}	0.064^{***}	0.082^{***}	0.080^{***}	0.058^{**}
Income Rank $[75, 95]$	(0.011)	(0.013)	(0.017)	(0.024)	(0.017)	(0.013)	(0.016)	(0.023)
Market News ×	0.119^{***}	0.109^{***}	0.096^{***}	0.055^{*}	0.107^{***}	0.106^{***}	0.091^{***}	0.057^{*}
Income Rank $[95, 100]$	(0.016)	(0.018)	(0.024)	(0.030)	(0.023)	(0.020)	(0.025)	(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	16.0	15.3	14.6	13.1	14.0	13.4	12.7	11.4
R^2	0.014	0.015	0.018	0.026	0.014	0.016	0.018	0.027

This table reports slope coefficients from regression estimates of equations (3) and (4) for different horizons h. In columns (1)–(4), the treatment variable is aggregate stock market news. In columns (5)–(8), the treatment variable is the employer's stock market beta multiplied by aggregate stock market news. The treatment variable is interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the lagged market return interacted by income group dummies. In columns (5)–(8), we also control for the employer beta by income group. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3: Income Exposures to Cashflow and Discount Rate News

Income Growth $g_{i,t:t+h}$	Aggregate News				Market Beta × Aggregate News			
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=5$ (4)	$h=1$ (5)	$h=2$ (6)	$h=3$ (7)	$h=5$ (8)
Cashflow News ×	0.058	0.067	0.043	0.064	0.049	0.076	0.053	0.065
Income Rank $[0, 25]$	(0.050)	(0.055)	(0.072)	(0.098)	(0.051)	(0.047)	(0.060)	(0.080)
Cashflow News ×	0.051	0.050	0.032	0.055	0.047	0.059	0.042	0.058
Income Rank $[25, 50]$	(0.038)	(0.047)	(0.060)	(0.082)	(0.038)	(0.039)	(0.050)	(0.067)
Cashflow News ×	0.054	0.052	0.037	0.060	0.053	0.060^{*}	0.045	0.062
Income Rank $[50, 75]$	(0.034)	(0.042)	(0.053)	(0.071)	(0.035)	(0.035)	(0.044)	(0.058)
Cashflow News ×	0.066^{**}	0.065^{*}	0.054	0.075	0.068^{**}	0.074^{**}	0.062	0.078
Income Rank $[75, 95]$	(0.030)	(0.038)	(0.048)	(0.062)	(0.031)	(0.032)	(0.040)	(0.051)
Cashflow News ×	0.160^{***}	0.142^{**}	0.131^{*}	0.141^{*}	0.154^{***}	0.147^{***}	0.133^{**}	0.145^{**}
Income Rank $[95, 100]$	(0.043)	(0.057)	(0.064)	(0.072)	(0.043)	(0.049)	(0.055)	(0.063)
Discount Rate News ×	-0.112^{***}	-0.186^{***}	-0.210^{***}	-0.158^{**}	-0.092^{**}	-0.162^{***}	-0.176^{***}	-0.134^{**}
Income Rank $[0, 25]$	(0.036)	(0.031)	(0.045)	(0.067)	(0.037)	(0.028)	(0.039)	(0.053)
Discount Rate News ×	-0.081^{***}	-0.126^{***}	-0.142^{***}	-0.089	-0.070^{**}	-0.115^{***}	-0.124^{***}	-0.080^{*}
Income Rank $[25, 50]$	(0.026)	(0.026)	(0.036)	(0.057)	(0.027)	(0.021)	(0.029)	(0.044)
Discount Rate News ×	-0.073^{***}	-0.102^{***}	-0.116^{***}	-0.064	-0.063^{**}	-0.095^{***}	-0.101^{***}	-0.058
Income Rank $[50, 75]$	(0.022)	(0.024)	(0.032)	(0.051)	(0.023)	(0.019)	(0.025)	(0.040)
Discount Rate News ×	-0.072^{***}	-0.092^{***}	-0.102^{***}	-0.054	-0.062^{***}	-0.085^{***}	-0.088^{***}	-0.049
Income Rank $[75, 95]$	(0.018)	(0.022)	(0.030)	(0.047)	(0.019)	(0.017)	(0.025)	(0.038)
Discount Rate News ×	-0.098^{***}	-0.093^{***}	-0.077^{*}	-0.008	-0.086^{***}	-0.088^{***}	-0.072^{**}	-0.017
Income Rank $[95, 100]$	(0.023)	(0.029)	(0.038)	(0.053)	(0.024)	(0.025)	(0.034)	(0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	16.0	15.3	14.6	13.1	14.0	13.4	12.7	11.4
R^2	0.014	0.015	0.018	0.026	0.014	0.016	0.019	0.028

This table reports slope coefficients from regression estimates of equations (11) and (12) for different horizons h. In columns (1)–(4), the treatment variables are aggregate cashflow and discount rate news. In columns (5)–(8), the treatment variables are the employer's stock market beta multiplied by aggregate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the lagged market return interacted by income group dummies. In columns (5)–(8), we also control for the employer beta by income group. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 4: Model Parameters

Fixed parameters			Calibrated parameters		
ν	Mortality	0.0028	c	Job search cost	0.013
$\overline{b}$	Unemployment flow value	1	σ_z	Volatility of z	0.113
α	Matching function elasticity	0.407	σ_{h0}	Volatility of initial h	0.666
r	Interest rate	0.0016	g_E	Growth of h in employment	0.0003
$\overline{x}$	Mean price of risk	0.361	g_O	Growth of h in nonemployment	-0.0013
ψ_x	Persistence of price of risk	0.989	s	Exogenous separation rate	0.001
σ_x	Volatility of price of risk	0.040	$\overline{\kappa}$	Vacancy posting cost	0.029
$\overline{h}$	Median initial value of h	1	ξ	Reputational cost of ending a match (off equilibrium)	0.084
$\overline{z}$	Initial value and long-run mean of z	1			
ψ_z	Persistence of z	0.991			
λ	Exit rate from unemployment into nonemployment	1/3			
γ	Wage smoothing parameter	1/2			
μ_A	Average TFP growth	0.0010			
σ_A	Volatility TFP growth	0.0054			

This table reports the parameters used to calibrate the model. The parameters on the left are fixed a priori; the parameters on the right are chosen to fit model moments to the data as described in Section 3.1.

Table 5: Cashflow and Discount Rate News and Employment Outcomes

Employment Indicator$_{i,t:t+h}$	Probability of Move		Probability of Zero		Probability of Tail Loss & Move		Probability of Tail Loss & Stay	
	$h=3$	$h=5$	$h=3$	$h=5$	$h=3$	$h=5$	$h=3$	$h=5$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cashflow News ×	-0.042	-0.042	-0.015	-0.047	-0.030	-0.021	-0.001	-0.001
Income Rank $[0, 25]$	(0.029)	(0.025)	(0.039)	(0.033)	(0.021)	(0.022)	(0.002)	(0.001)
Cashflow News ×	-0.031	-0.042^{*}	-0.015	-0.046^{*}	-0.023	-0.019	-0.002	-0.001
Income Rank $[25, 50]$	(0.023)	(0.021)	(0.029)	(0.026)	(0.016)	(0.016)	(0.001)	(0.001)
Cashflow News ×	-0.019	-0.035	-0.009	-0.037^{*}	-0.019	-0.018	-0.002	-0.001^{***}
Income Rank $[50, 75]$	(0.020)	(0.021)	(0.023)	(0.019)	(0.012)	(0.011)	(0.002)	(0.000)
Cashflow News ×	-0.005	-0.021	-0.005	-0.028^{*}	-0.018^{*}	-0.016^{*}	-0.004^{*}	-0.003^{***}
Income Rank $[75, 95]$	(0.019)	(0.019)	(0.020)	(0.016)	(0.009)	(0.008)	(0.002)	(0.001)
Cashflow News ×	0.016	-0.010	-0.005	-0.020	-0.025^{**}	-0.032^{**}	-0.025^{**}	-0.015^{**}
Income Rank $[95, 100]$	(0.019)	(0.019)	(0.018)	(0.019)	(0.011)	(0.012)	(0.010)	(0.006)
Discount Rate News ×	-0.044^{*}	-0.041^{**}	0.054^{**}	0.038	0.065^{***}	0.049^{***}	0.008^{***}	0.002^{**}
Income Rank $[0, 25]$	(0.024)	(0.017)	(0.025)	(0.026)	(0.015)	(0.013)	(0.002)	(0.001)
Discount Rate News ×	-0.040^{*}	-0.043^{**}	0.037^{*}	0.022	0.048^{***}	0.034^{***}	0.005^{***}	0.001
Income Rank $[25, 50]$	(0.021)	(0.015)	(0.019)	(0.019)	(0.011)	(0.009)	(0.001)	(0.001)
Discount Rate News ×	-0.043^{**}	-0.039^{**}	0.022	0.014	0.035^{***}	0.024^{***}	0.006^{***}	0.002^{***}
Income Rank $[50, 75]$	(0.020)	(0.014)	(0.014)	(0.013)	(0.008)	(0.007)	(0.001)	(0.000)
Discount Rate News ×	-0.048^{**}	-0.039^{***}	0.006	0.003	0.025^{***}	0.018^{***}	0.006^{***}	0.001
Income Rank $[75, 95]$	(0.019)	(0.011)	(0.013)	(0.010)	(0.006)	(0.006)	(0.002)	(0.001)
Discount Rate News ×	-0.059^{***}	-0.046^{***}	-0.027^{*}	-0.031^{**}	0.011	0.001	0.017^{***}	0.006
Income Rank $[95, 100]$	(0.020)	(0.013)	(0.015)	(0.012)	(0.008)	(0.009)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N ($\times 10^6$)	12.7	11.4	12.7	11.4	12.7	11.4	12.7	11.4
R^2	0.081	0.085	0.057	0.073	0.022	0.029	0.009	0.006

This table reports slope coefficients from regression estimates of variations to equation (12) where the outcome variable takes the form of an employment indicator. In columns (1)–(2), the outcome variable is an indicator for whether the worker no longer has the same main employer in year $t+h$ as in year t. In columns (3)–(4), the outcome variable is an indicator for having at least one quarter with zero earnings. In columns (5)–(6), the outcome variable is an indicator for having earnings growth in the bottom 10th percentile of the unconditional distribution interacted by an indicator for moving. In columns (7)–(8), the outcome variable is an indicator for having earnings growth in the bottom 10th percentile of the unconditional distribution interacted by an indicator for staying. The treatment variables are the employer's stock market beta multiplied by aggregate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the employer beta and lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6: Income Exposures to Discount Rate News: Stayers versus Movers

Income Growth $g_{i,t:t+h}$	Aggregate News $h=3$ (1)	Aggregate News $h=5$ (2)	Market Beta × Aggregate News $h=3$ (3)	Market Beta × Aggregate News $h=5$ (4)
Discount Rate News × Stayer	-0.086^{***}	-0.060^{*}	-0.077^{***}	-0.064^{***}
× Income Rank $[0, 25]$	(0.028)	(0.030)	(0.023)	(0.020)
Discount Rate News × Stayer	-0.063^{**}	-0.034	-0.058^{***}	-0.039^{*}
× Income Rank $[25, 50]$	(0.025)	(0.034)	(0.017)	(0.019)
Discount Rate News × Stayer	-0.061^{**}	-0.030	-0.057^{***}	-0.034
× Income Rank $[50, 75]$	(0.024)	(0.035)	(0.016)	(0.022)
Discount Rate News × Stayer	-0.070^{***}	-0.038	-0.061^{***}	-0.035
× Income Rank $[75, 95]$	(0.024)	(0.037)	(0.017)	(0.027)
Discount Rate News × Stayer	-0.078^{**}	-0.021	-0.066^{**}	-0.020
× Income Rank $[95, 100]$	(0.032)	(0.043)	(0.026)	(0.035)
Discount Rate News × Mover	-0.531^{***}	-0.352^{***}	-0.402^{***}	-0.264^{***}
× Income Rank $[0, 25]$	(0.099)	(0.098)	(0.081)	(0.079)
Discount Rate News × Mover	-0.434^{***}	-0.262^{***}	-0.328^{***}	-0.195^{***}
× Income Rank $[25, 50]$	(0.077)	(0.077)	(0.058)	(0.058)
Discount Rate News × Mover	-0.353^{***}	-0.198^{***}	-0.262^{***}	-0.144^{***}
× Income Rank $[50, 75]$	(0.062)	(0.065)	(0.047)	(0.048)
Discount Rate News × Mover	-0.279^{***}	-0.153^{***}	-0.209^{***}	-0.114^{***}
× Income Rank $[75, 95]$	(0.049)	(0.054)	(0.037)	(0.040)
Discount Rate News × Mover	-0.210^{***}	-0.094^{*}	-0.167^{***}	-0.074^{*}
× Income Rank $[95, 100]$	(0.046)	(0.054)	(0.038)	(0.042)
Controls	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes
N $(\times 10^6)$	14.6	13.1	12.7	11.4
R^2	0.152	0.153	0.155	0.157

This table reports slope coefficients from regression estimates of extended versions of equations (11) and (12) for different horizons h. In columns (1)–(2), the treatment variables are aggregate cashflow and discount rate news. In columns (3)–(4), the treatment variables are the employer's stock market beta multiplied by aggregate news. This table reports the estimates with respect to discount rate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own firm, and are also interacted by indicators for whether the worker is a stayer or a mover over the relevant period. 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 the lagged market return interacted by income group dummies, as well as a mover indicator interacted by income group dummies. In columns (3)–(4), we also control for the employer beta by income group. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7: Income Exposures to Cashflow News: Stayers versus Movers

Income Growth $g_{i,t:t+h}$	Aggregate News $h=3$ (1)	Aggregate News $h=5$ (2)	Market Beta × Aggregate News $h=3$ (3)	Market Beta × Aggregate News $h=5$ (4)
Cashflow News × Stayer	0.009	0.036	−0.006	0.010
× Income Rank [0, 25]	(0.061)	(0.064)	(0.045)	(0.045)
Cashflow News × Stayer	0.008	0.034	−0.001	0.014
× Income Rank [25, 50]	(0.051)	(0.057)	(0.037)	(0.041)
Cashflow News × Stayer	0.016	0.039	0.010	0.024
× Income Rank [50, 75]	(0.047)	(0.054)	(0.035)	(0.039)
Cashflow News × Stayer	0.029	0.050	0.033	0.049
× Income Rank [75, 95]	(0.046)	(0.053)	(0.035)	(0.041)
Cashflow News × Stayer	0.107*	0.117*	0.109**	0.120**
× Income Rank [95, 100]	(0.056)	(0.060)	(0.047)	(0.051)
Cashflow News × Mover	0.025	0.039	0.074	0.061
× Income Rank [0, 25]	(0.143)	(0.144)	(0.119)	(0.116)
Cashflow News × Mover	0.038	0.038	0.077	0.059
× Income Rank [25, 50]	(0.119)	(0.115)	(0.092)	(0.090)
Cashflow News × Mover	0.065	0.057	0.094	0.073
× Income Rank [50, 75]	(0.099)	(0.096)	(0.076)	(0.075)
Cashflow News × Mover	0.116	0.097	0.117*	0.095
× Income Rank [75, 95]	(0.075)	(0.076)	(0.057)	(0.058)
Cashflow News × Mover	0.219**	0.177**	0.202***	0.162**
× Income Rank [95, 100]	(0.083)	(0.079)	(0.066)	(0.064)
Controls	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes
N ($\times 10^6$)	14.6	13.1	12.7	11.4
R^2	0.152	0.153	0.155	0.157

This table reports slope coefficients from regression estimates of extended versions of equations (11) and (12) for different horizons h. In columns (1)–(2), the treatment variables are aggregate cashflow and discount rate news. In columns (3)–(4), the treatment variables are the employer's stock market beta multiplied by aggregate news. This table reports the estimates with respect to cashflow news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own firm, and are also interacted by indicators for whether the worker is a stayer or a mover over the relevant period. 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 the lagged market return interacted by income group dummies, as well as a mover indicator interacted by income group dummies. In columns (3)–(4), we also control for the employer beta by income group. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8: Macro Moments in the Model and in the Data

	Volatility		Autocorrelation		Correlation w/ Unemployment	
Variable	Model	Data	Model	Data	Model	Data
Unemployment rate	0.798	1.238	0.984	0.986	1.000	1.000
Employment-population ratio	2.084	0.959	0.997	0.977	-0.971	-0.921
Log V/U ratio	0.100	0.395	0.953	0.988	-0.837	-0.955
Separation rate into U	0.085	0.149	0.507	0.723	0.608	0.517
Separation rate into N	0.097	0.216	0.433	0.562	0.185	-0.336
Job finding rate	0.892	4.767	0.757	0.588	-0.542	-0.683

This table reports model moments of the monthly unemployment rate, employment-population ratio, log vacancy to unemployment rate, separation rates into unemployment (U) and nonparticipation (N), and job finding rate. We use the monthly unemployment rate series from the Current Population Survey (CPS) from 1948 to 2019. We remove very low-frequency trends from this series through a HP filter with monthly smoothing parameter $10^5 \times 3^4$.

Table 9: Alternative Model Specifications

	Transition Rates						Earnings Exposure			
	Average			Volatiliy			CF Coefficient		DR Coefficient	
	$E \to U$	$E \to N$	$U \to E$	U	$E \to U$	$U \to E$	$[50, 75]$	$[95, 100]$	$[0, 25]$	$[50, 75]$
Baseline	0.6	0.6	15.6	0.8	0.1	0.9	7.6	11.3	-17.6	-11.1
Alternative 1: No reputational costs ($\xi = 0$)	0.6	0.6	15.6	0.8	0.1	0.9	19.2	17.8	-21.1	-7.2
Alternative 2: No z shocks ($\sigma_z = 0, s = 0.0117, \kappa = 0.432$)	1.2	0.0	15.6	0.3	0.0	0.6	2.6	2.5	-9.1	-9.2
Alternative 3: No z shocks, matching U vol ($\sigma_z = 0, \sigma_x = 0.101, s = 0.0117, \kappa = 0.487$)	1.2	0.0	15.6	0.8	0.0	1.5	0.8	2.2	-81.9	-80.8
Alternative 4: No differential h growth ($g_O = g_E, b = 0.57, c = 0.01, \kappa = 0.027$)	0.6	0.6	15.6	0.0	0.0	0.0	7.4	11.1	-2.0	-2.4
Alternative 5: Lower persistence of z ($\psi_z = 0.97, g_O = -0.0005, c = 0.008, \kappa = 0.015$)	0.6	0.5	15.6	1.6	0.1	1.2	4.1	4.3	-20.5	-17.8
Alternative 6: Match-specific productivity z ($\psi_{zO} = 0, g_O = -0.0024, \kappa = 1.57$)	1.1	0.0	15.6	0.2	0.0	0.5	2.5	2.5	-2.8	-2.5

This table reports model moments for the baseline parameterization and alternative calibrations of the model. To compare across calibrations, we ensure that we always match the steady-state job finding rate and separation rates, and to the extent possible, separation rates into unemployment and nonparticipation. In the cases when the restricted version of the model does not have a nontrivial participation margin, we match the overall separation rate.

A Model Appendix

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

A.1 Derivation of the Labor Market Equilibrium

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 $\widetilde{W}_t(h,z)$. Let $\widetilde{\theta}_t(h,z)$ 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

$$p(\widetilde{\theta}_t(h,z))(\widetilde{W}_t(h,z) - J_t^S(h,z)) = p(\theta_t(h,z))(W_t(h,z) - J_t^S(h,z)). \tag{A.1}$$

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

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

$$\begin{aligned} J_t^V(h,z) = &-\kappa_t(h,z) + q(\theta_t(h,z))\left(J_t^{MC}(h,z) - W_t(h,z)\right) \\ &+ (1 - q(\theta_t(h,z))) \times \mathbb{E}_{t,h,z}\left[\Lambda_{t+1} \max_{\widetilde{h},\widetilde{z}} \left\{J_{t+1}^V(\widetilde{h},\widetilde{z})\right\}\right]. \end{aligned} \tag{A.2}$$

Since there is free entry of firms into labor markets, the equilibrium number of vacancies is pinned down by the zero-profit condition (32).

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

$$\begin{aligned} \max_{\widetilde{\theta},\widetilde{W}} \quad & -\kappa_t(h,z) + q(\widetilde{\theta}_t(h,z))(J_t^{MC}(h,z) - \widetilde{W}_t(h,z)) \\ \text{s.t.} \quad & p(\widetilde{\theta}_t(h,z))(\widetilde{W}_t(h,z) - J_t^S(h,z)) = p(\theta_t(h,z))(W_t(h,z) - J_t^S(h,z)). \end{aligned} \tag{A.3}$$

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

$$-q(\widetilde{\theta}_t(h,z)) = \zeta_t(h,z) \cdot p(\widetilde{\theta}_t(h,z)) \tag{A.4}$$

$$q'(\widetilde{\theta}_t(h,z))(J_t^{MC}(h,z) - \widetilde{W}_t(h,z)) = \zeta_t(h,z) \cdot p'(\widetilde{\theta}_t(h,z))(\widetilde{W}_t(h,z) - J_t^S(h,z)), \tag{A.5}$$

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

$$-\frac{q'(\theta_t(h,z))}{q(\theta_t(h,z))}(J_t^{MC}(h,z) - W_t(h,z)) = \frac{p'(\theta_t(h,z))}{p(\theta_t(h,z))}(W_t(h,z) - J_t^S(h,z)). \tag{A.6}$$

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 in equation (33).

B Additional Empirical Details and Results

Here, we include a number of additional results and robustness checks.

B.1 LEHD Sample

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 join the sample later as coverage gets more complete. By the mid- to late-1990s, the LEHD covers the majority of jobs. The last available year in our sample is 2020; only a few states drop out of the sample before 2020. 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 that are in the LEHD, coverage of private sector jobs is nearly 100 percent. 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 CPI.

The data allow us to track the incomes of individual workers over time and across employers. Our sample in year t covers individuals that are between age 25 and age 60, that live in a state in year t that is in the LEHD between years $t-2$ and $t+5$, and that 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 get assigned zero wage earnings for that year.

In addition to total earnings, we also 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. We use an internal Census mapping table from EIN to GVKEY identifiers to link firm information from Compustat to the worker earnings data.

A key focus of our analysis is on heterogeneity in treatment effects across the income distribution. We rank workers by their pre-treatment 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 build our sample by first collecting data for all U.S. workers in the LEHD, and constructing the yearly income ranks for this whole population. Then, after constructing all relevant variables, we randomly subsample 5% of all workers in each year for inclusion in our final dataset to keep the analysis computationally feasible. We exclude workers that are employed by firms with missing industry codes or that work in the 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 an employment indicator that takes the value of one if an individual has a quarter of zero earnings over a particular period. For most of our analysis, we focus on employees of publicly traded companies, for whom we have better measures of cashflow and discount rate shocks.

B.2 Robustness

Here, we show that our main findings are robust to various alternative definitions of the treatment variables and to different empirical specifications.

First, Table A.8 presents the results when we measure cashflow and discount rate news using the standard Campbell-Vuolteenaho VAR-based decomposition. With only aggregate variation in columns (1)–(4), we find similar results as in our baseline specification, although exposures to cashflow news are less precisely estimated. The results are less clear when we include cross-sectional variation from differences in firm market betas, which is consistent with our finding that this measure of discount rate news does not differentially predict future returns of high- versus low-beta firms.

In Table A.9, we show that the results discussed above are robust to alternative versions of the stock market return decomposition in Section 1.3. To measure changes in expected returns, we project the discounted sum of future returns on different sets of traded factors: the three standard Fama-French factors (market, size, and book-to-market, column 1), the three Fama-French factors and the momentum factor (column 2), the five Fama-French factors (column 3), and the five factors from the Hou, Xue, and Zhang (2015) q-factor model (column 4). We also consider alternative parameter choices: a smaller ρ of $0.95^{1/12}$ (column 5), a larger ρ of $0.99^{1/12}$ (column 6), no controls

Ω_{t-1} (column 7), and additional controls for the small value spread and credit spread (column 8). We find that while there are some differences in the point estimates of exposures to the two types of shocks, the general patterns are the same across all specifications. We conclude that our main results are robust to these alternative parameter choices.

Next, we zoom in on the cross-sectional variation through employer betas by running a specification where the industry by income bin fixed effects are interacted with year fixed effects. In that case, we are comparing outcomes for workers in the same industry, income group, and year that differ in the market beta of their employer. Table A.10 reports the results for different horizons. While the point estimates become somewhat smaller, the main findings and patterns hold even with only cross-sectional variation: high-wage workers are significantly affected by cashflow news and have the largest exposure to those shocks, and low-wage workers are significantly affected by discount rate news and have the largest exposure to those shocks.

In addition, we consider two more variation to the analysis. Table A.11 shows that our findings continue to hold when we use separate cashflow and discount rate betas to decompose the systematic component of a firm's stock return into cashflow news and discount rate news. Table A.12 reports the results when we expand the sample to all workers and not just workers of public companies, using aggregate cashflow and discount rate news only. The effects of discount rate news are nearly the same as for employees of public firms, and high-wage workers are still the most affected by cashflow news. However, the effects of cashflow news on earnings are substantially smaller for all groups, which may be because the market return is a better reflection of the employer's economic outcomes and prospects for public firms than for private firms.

B.3 Are We Picking Up Tenure or Income Effects?

One paper that is directly related to our main empirical findings is Caggese et al. (2019), who show that firms with worse credit ratings are more likely to fire short-tenured workers than long-tenured workers relative to firms with high credit ratings in response to an adverse shock to export prices. To the extent that this shock also partially captures discount rate effects, the question then is whether we are identifying a similar effect: by ranking workers based on their wage earnings, we are primarily picking up differences in worker tenure.

Table A.6 shows that this is not the case. We assign workers for whom we observe a long enough income history to one of three bins based on the tenure with their current employer—below two years, two to five years, and more than five years—and then estimate our empirical specification including controls for these bins interacted with our measures of cashflow and discount rate news. Consistent with the findings in Caggese et al. (2019), we see that low-tenure workers (the omitted group) are more affected by discount rate shocks than long-tenured workers. However, this pattern does not absorb much variation across the earnings distribution; we find that our main results hold within tenure groups. Focusing on the five-year horizon (Columns 4 and 8), we see that the differences across the income distribution have a similar order of magnitude as the differences by tenure. Interestingly, there are no differences in cashflow exposures by tenure, while high-income workers continue to have high and significant exposures to cashflow news than lower-income workers. We conclude that worker tenure is not the main worker characteristic driving our results.

B.4 Direct Measure of Cashflow Shocks

Our analysis so far has relied on measures of cashflow and discount rate shocks that are inferred from data on stock returns. The advantage of these measures is that they primarily depend on aggregate sources of variation interacted with a firm-level measure of exposure reminiscent of a shift-share design. Doing so allows us to abstract away from an alternative in which employment flows drive firm discount rate and cashflow shocks. One potential disadvantage is that they are indirectly estimated which may obscure their economic interpretation.

To this end, we next revisit our earlier analysis using a more direct measure of cashflow shocks: estimates of changes in firm total factor productivity (TFP) from İmrohoroğlu and Tüzel (2014). İmrohoroğlu and Tüzel (2014) apply the methodology of Olley and Pakes (1996) to Compustat data to compute an annual firm-specific TFP measure. We take first differences to obtain a measure of yearly firm productivity growth and then estimate the exposure of worker earnings growth rates to TFP growth by running a regression similar to (12), where we now replace the systematic cashflow component of firm stock returns by firm TFP growth.

In Table A.2, we show that worker exposures to this firm-level cashflow news measure match those to cashflow news inferred from aggregate stock returns. The relation between TFP growth and subsequent income growth is positive and strongly significant. Moreover, the pattern in exposures across the income distribution is approximately monotonic, with highest earners facing the largest exposure to TFP growth. Most of the variation in this measure is idiosyncratic, and we find the same results without and with the time component in the fixed effects by industry and income group, although in the latter case the point estimates are somewhat smaller for all income groups.

We also repeat the analysis in Section 4.1 using firm-level TFP growth as a direct measure of cashflow news. Table A.13 presents the results from regressing various employment indicators on TFP growth and discount rate news. Positive TFP news is associated with lower probabilities of moving away from the current employer—this effect does not significantly differ across income groups.

Columns (3)–(4) show that negative TFP shocks are associated with an increased probability of having a zero-earnings quarter, but the effects are significantly stronger for low-wage workers—opposite from the overall effect on income growth. Columns (5)–(8) suggest that workers on the lower end of the income distribution are mostly affected by TFP news in combination with job separations, while high-wage workers suffer the consequences of negative cashflow news also on the intensive margin.

B.5 Direct Measure of Discount Rate Shocks

Similar to the previous section, we next estimate worker earnings responses to a more direct measure of financial shocks. In particular, we build on Almeida et al. (2011); Benmelech et al. (2021) and explore firms' need to refinance pre-existing debt during the height of the Great Recession. The identifying assumption is that this pre-existing variation in the level of maturing debt is orthogonal to the workers' marginal product during the 2008–09 period. Consistent with Benmelech et al. (2021), we find that pre-existing variation in the amount of corporate debt that is due during the financial crisis is related to subsequent declines in employment. Our data allows to examine which workers inside these firms bear the consequences of rollover risk. We find stark differences in exposures consistent with the general findings from Section 1.4.

Maturing Debt Sample

Here, we provide additional details on the data that we use to study employment outcomes for firms that have a significant amount of long-term debt maturing in the Great Recession.

We collect financial information from Compustat and CRSP and match this data at the firm level to employer-employee linked data obtained through the U.S. Census Bureau. We select the sample of firms for this analysis in 2007 and measure the firm liability structure and control variables in or before 2007. We include firms in the sample that have total assets of at least one million and that have at least 50 employees. We exclude firms with a missing industry classification as well as firms in the financial sector (NAICS codes starting with 52 or 53).

Equation (A.7) defines the main treatment variable for this analysis. We impose the consistency criterion that the sum of debt maturing in two through five years is not more than the total amount of debt that matures in more than one year.

In all regressions, we control for the total leverage ratio (total debt to assets) measured in the same year as our main treatment variable. In addition, we include liquidity (cash holdings to assets), profitability, log total assets, log employment, asset maturity, and the investment rate as of 2007 as firm-level control variables. To limit the impact of outliers, all Compustat variables are winsorized at the 1% and 99% level.

Table A.14 summarizes the firms in this sample. Consistent with our empirical analysis, firms are weighted by their number of employees. We summarize the treatment variables and firm-level controls for all Compustat firms (columns 1–5) and the Compustat firms that are matched with employees that appear in the income tax data and meet the sample selection criteria for our analysis (columns 6–10).

Income Tax Data

In this section, we use data on worker earnings based on U.S. income tax data from the Internal Revenue Service (IRS). We observe complete tax filings for each worker in the U.S. population starting from 2005. In addition to the tax returns filed by taxpayers, we have wage income information for each individual worker from W-2 tax forms. Our main labor earnings measure in this data is the sum of box 1 earnings and deferred compensation on all W-2 documents of a worker. Earnings in box 1 of a W-2 form consist of wages and salaries, bonuses, exercised stock options and restricted stock units, severance pay, and fringe benefits.

We construct a sample of individual worker earnings growth in a similar fashion as the LEHD sample. We select the sample as of year $t = 2007$, which is the base year for our analysis. In this sample we include the universe of U.S. workers that work for a publicly traded company.

Maturing Debt and Firm Outcomes

We start by briefly revisiting employment outcomes for firms that have a significant amount of long-term debt maturing in the Great Recession. Compustat reports the amount of long-term debt that matures in one year through five years from the current fiscal year end date ($dd1, \dots, dd5$), in addition to the total amount of long-term debt with a maturity of at least one year ($dltt$). Following earlier papers in this literature, we measure the effects of financial frictions on real outcomes by using Compustat information on outstanding long-term debt with specific maturities to compare firms with large amounts of maturing long-term debt in the Great Recession to similar other firms. Specifically, we compute in year τ the amount of maturing debt at horizon y relative to total assets as

$$DDA_{j,\tau}(y) \equiv \frac{\text{Debt Due}_{j,\tau}(y)}{\text{Assets}_{j,\tau}}, \tag{A.7}$$

where Debt $\text{Due}_{j,\tau}(y)$ is long-term debt for firm j on the books in year τ that is set to mature in year $\tau + y$. We measure the amount of debt — relative to total assets — that matures in 2009 and therefore needs to be rolled over during the financial crisis. Importantly, we focus on long-term debt that was issued several years before the crisis. Specifically, we consider different versions of our main treatment variable with increasing measurement lag: $DDA_{j,07}(2)$, $DDA_{j,06}(3)$, $DDA_{j,05}(4)$, and $DDA_{j,04}(5)$. Using data on debt that was issued many years before the shock alleviates the concern that the timing of maturing debt is correlated with other factors that drive firm outcomes.

We begin by estimating the response of total firm payrolls to productivity growth and the amount of maturing debt in 2009,

$$\log(W_{j,07+h}) - \log(W_{j,07}) = \gamma_{TFP}\, \Delta TFP_{j,07:09} + \gamma_{DD}\, DDA_{j,09-y}(y) + \eta' Z_j + \varepsilon_{j,h}. \tag{A.8}$$

Here, $W_{j,t}$ is firm j's total wage bill in year t, $\Delta TFP_{j,07:09}$ is the change in firm-level TFP between 2007 and 2009 from the previous section, and $DDA_{j,09}(y)$ refers to our main treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The vector of controls Z_j includes the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. In addition, we control for industry fixed effects at the four-digit NAICS level.

Table A.3 presents our main firm-level analysis using income tax data that is aggregated at the firm level. The Census-based data have the advantage of more accurate payrolls, since they are based on tax filings and, importantly, have significantly broader coverage of firms' wage bills (only approximately 10% of firms in Compustat report their total wage bill).[6] The first four columns of the table focus on payroll growth over a two-year horizon. We find that firms with positive productivity growth have higher payroll growth and firms with maturing debt have lower payroll growth. Depending on the time that maturing debt is measured, a one percentage point higher amount of maturing debt relative to assets generates a decline in payrolls of 0.3 to 0.7 percent over the next two years. The last four columns show that these effects are persistent.

There is one additional thing worth noting here. Consistent with findings in Compustat data, the Census data also show a decline in the number of employees. These estimates are reported in the first four columns of Appendix Table A.16. Since we use data from tax filings, employee counts are calculated as the total number of workers that receive a tax form over the year and are therefore somewhat noisier than the current employment stock. Nevertheless, the fact that the point estimates on payroll growth and employment growth have similar magnitudes suggests that average wages at the firm level remained unchanged, a fact we confirm in the last four columns of Appendix Table A.16 by using payroll per worker growth as the outcome variable. That said, this does not necessarily mean that incumbent workers experience no wage declines. Average wages for continuing workers could remain unchanged either because wages did indeed remain constant and firms only adjusted employment; alternatively, firms did alter wages for continuing workers but changes in composition meant that average wages remained similar. We explore this possibility below.

We also replicate our analysis of firm-level outcomes in Compustat data. We estimate equation (A.8) with employment growth from Compustat as the outcome variable. We present the results in the first four columns of Table A.15. Consistent with Benmelech et al. (2021), we find a negative and significant (both statistically and economically) impact of maturing debt on firm employment, captured by the slope coefficient γ, when maturing debt is measured from the outstanding amount of four-year debt in 2005 or five-year debt in 2004. Focusing on $DDA_{05}(4)$, we find that a one percentage point increase in the ratio of maturing debt to assets leads to a 0.5 to 0.6 percent decline in employment over the next $h = 2$ years.

The next two columns of Table A.15 examine the extent to which firms reduced their leverage in response. In particular, we re-estimate equation (A.8), but now replace the dependent variable with the change in the firm's level of total debt, scaled by the pre-crisis level of assets. Controlling for initial leverage, we find that having more debt that is due to mature during the crisis leads to

[6] To mitigate the impact of extensive margin effects due to changes in employer identifiers or organizational changes, we drop firm-level payroll or employment growth rates, based on W2 data, that are below -50% or above 100%. In the Appendix, we replicate the firm-level analysis in Compustat data and show that the results hold without imposing such a filter.

deleveraging. The last two columns of Table A.15 show that firms with a significant amount of debt maturing in the crisis scaled back their operations by lowering total assets over the next two years.

Maturing Debt and Worker Outcomes

We examine how wage earnings of workers with different prior income levels varied across treated and non-treated firms,

$$g_{i,07:07+h} = \sum_s (\gamma_{TFP,s}\, \Delta TFP_{j,07:09} + \gamma_{DD,s}\, DDA_{j,09-y}(y)) \times \mathbb{1}(\theta_i = s) + \eta' Z_j + \psi' X_i + \varepsilon_{i,h}, \quad \text{(A.9)}$$

where θ_i is dummy that represents the within-firm income group of the worker. In addition to the firm-level controls Z_j, we added the vector X_i of individual-level controls that includes a third-order polynomial in the log of average income over the past three years, and age fixed effects. We also control for industry (4-digit NAICS) by within-firm income group fixed effects in all individual-level regressions.

Table A.4 report the effects of maturing debt (and productivity growth) on workers of different earnings levels. The first four columns of Table A.4 show the response to treatment of worker earnings without conditioning on income. We focus on a horizon h of three years for different versions of the treatment variable. We find that the firm-level employment effects of maturing debt translate to significant labor income effects on the average incumbent worker. The effects are highly significant even when the amount of maturing debt is measured from outstanding long-term debt long before the crisis. Not surprisingly, the point estimate generally declines with the time between the measurement date and the shock. A one percentage point increase in the amount of maturing debt to assets leads to a 0.1 to 0.2 percent decline in wage earnings for incumbent workers over the next three years.

The last four columns of Table A.4 report the effects of maturing debt on workers of different earnings levels. We see that the impact of the decline in average earnings to the financial shock is starkly concentrated on the lowest earners. Specifically, incumbent workers in treated firms who earn below the median wage income in the firm experience large and significant declines in earnings over a three-year window. Incumbent workers earning wage income above the firm median experience more modest declines, and top earners of the firm even experience no decline in earnings.

Table A.5 shows that the impact on worker earnings is quite persistent. The earnings effect for low-wage workers persists even five and ten years out: with $DDA_{05}(4)$ as the treatment variable, the long-run effect for the lowest wage workers is 0.28 percent per one percentage point increase in the amount of maturing debt to assets, and with $DDA_{04}(5)$ the long-run effect for low-wage workers is 0.13 percent.

As we compare the results of this section to the baseline results using our discount rate measure in Section 1.4, several observations are in order. First, we obtain similar results using two measures of discount rates that exploit very different sources of variation in the data. In particular, much, though not all, of the identification of our main results in Section 1.4 comes from time-series variation. By contrast, the results in this section are obtained purely through cross-sectional variation in the share of maturing debt.

In addition, we present two robustness checks for the worker-level results. First, Table A.17 re-estimates equation (A.9), but now not just by interacting treatment by the income group indicators but also the full set of firm controls such as leverage and cash holdings. The results are robust to including these more granular controls. Second, Table A.18 presents the results when we do not include ex-post measured firm TFP growth in the regressions. Again, we find the same treatment effects of the amount of maturing debt that is due to mature during the crisis.

Extensive versus Intensive Margin

Workers can experience wage earnings declines for several reasons: they remain with the firm but receive a wage cut (possibly because they are paid by the hour and firms reduce hours worked), they leave the firm and become unemployed for some period, or they leave the firm and obtain a new job with lower pay. We repeat the analysis in Section 4.1 and examine the effects of the financial shocks on employees that stay with their employer versus employees that leave the firm. In particular, we report estimates from a modified version of equation (A.9),

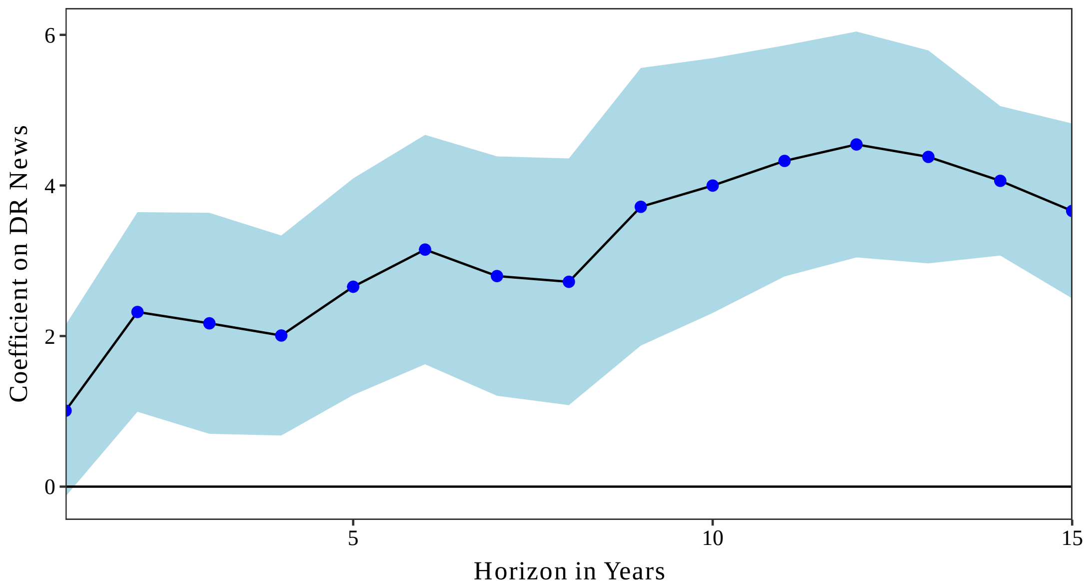
$$e_{i,07:07+h} = \sum_{s} (\gamma_{TFP,s}\, \Delta TFP_{j,07:09} + \gamma_{DD,s}\, DDA_{j,09-y}(y)) \times \mathbb{1}(\theta_i = s) + \eta' Z_j + \psi' X_i + \varepsilon_{i,h}, \quad \text{(A.10)}$$

in which now the main dependent variable is an employment indicator variable e.

In the first four columns of Table A.19, the dependent variable is an indicator that takes the value of one if worker i is employed by the pre-crisis employer h years out. We find no evidence for increased separation rates in response to our shock to firm labor demand. The lack of an effect may be due to the fact that most job separations are job-to-job transitions, which makes identifying job layoffs from all separations difficult. In the last four columns of Table A.19, the dependent variable specifically captures left-tail risk as a proxy for unemployment: an indicator that takes the value of one if worker i has earnings growth at horizon h that is less than the 10th percentile and is no longer employed by their pre-crisis employer, and zero otherwise. We find a positive relation between maturing debt and this left tail indicator for workers in the bottom half of the income distribution within their firm, not just at shorter horizons ($h = 3$) but also in the longer run ($h = 5$). The effects are strongly significant when $DDA_{05}(4)$ is the treatment variable, and positive but insignificant when $DDA_{04}(5)$ is the treatment variable.

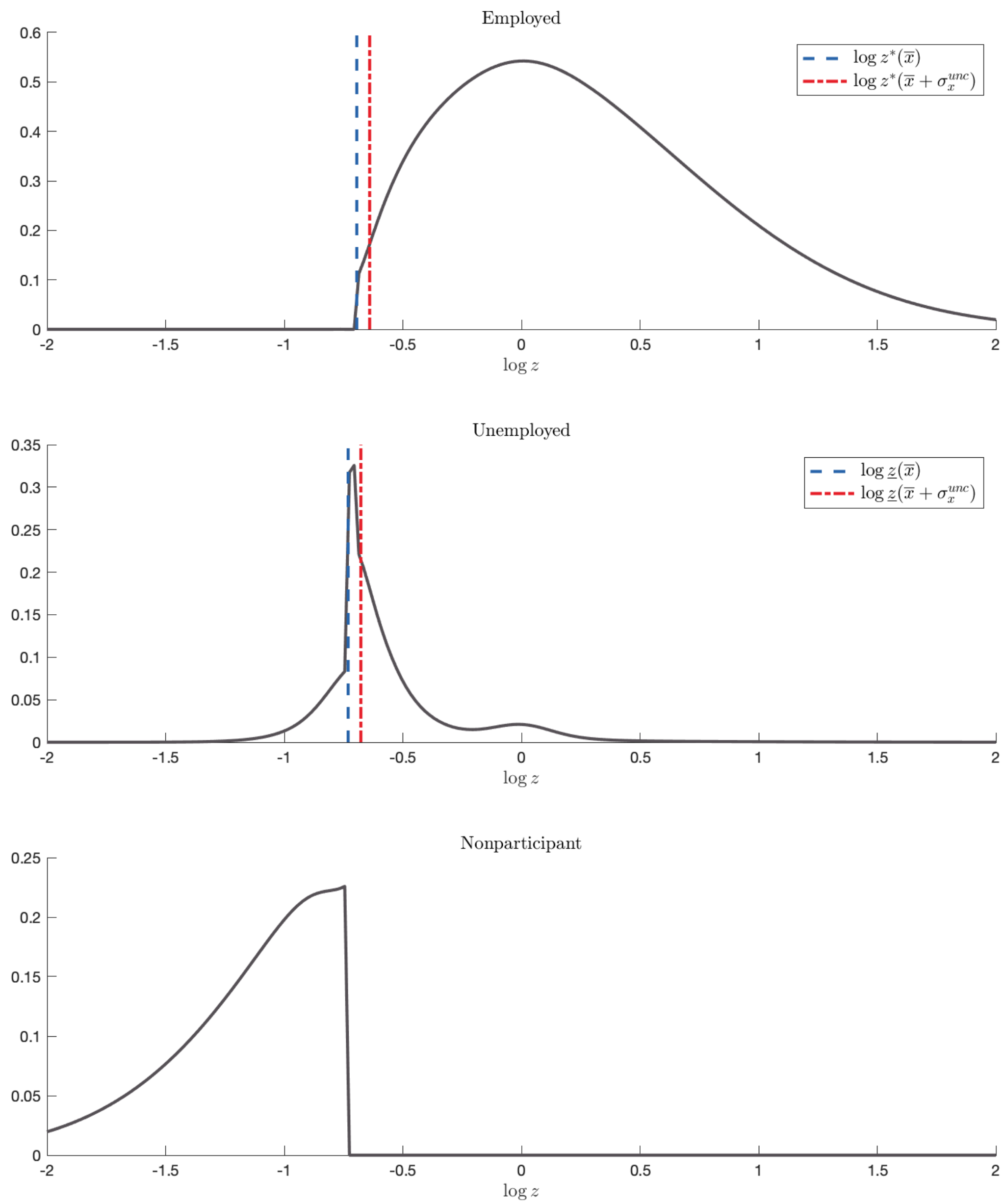
C Additional Figures and Tables

Figure A.1: Forecasting Future Stock Market Returns by Discount Rate News Measure



This figure reports estimates of predictive regressions where we project the discount sum of future stock market returns $\sum_{s=1}^{H} \rho^s r_{t+s}$ on $N_{CF,t}$, $N_{DR,t}$, and controls Ω_{t-1}. We plot the coefficients on our discount rate measure $N_{DR,t}$ at different horizons H. We set $\rho = 0.967^{1/12}$. The controls Ω_{t-1} include the Treasury bill rate, the term spread, the aggregate market return, and the market's smoothed price-earnings ratio as of month $t-1$.

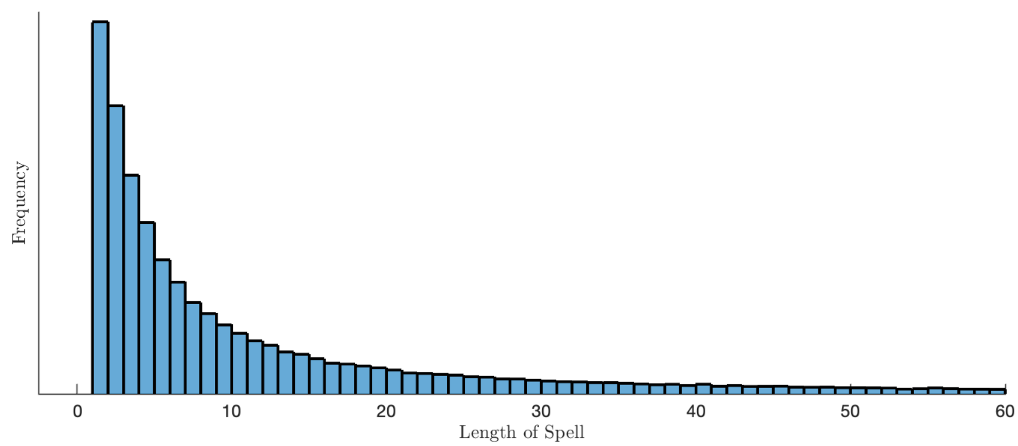
Figure A.2: Joint Distribution of Employment Status and Idiosyncratic Transitory Productivity z



This figure plots the stationary joint distribution of employment status and z along the balanced growth path. In the top panel, we plot the separation threshold $z^*(x_t)$. In the second panel, we plot the job search threshold $\underline{z}(x_t)$. We also plot how these thresholds change as a function of discount rates, 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.3: Nonemployment Spells in Steady State

(a) Distribution of Spell Length



(b) Conditional Distribution of spell length as a function of z at start of spell

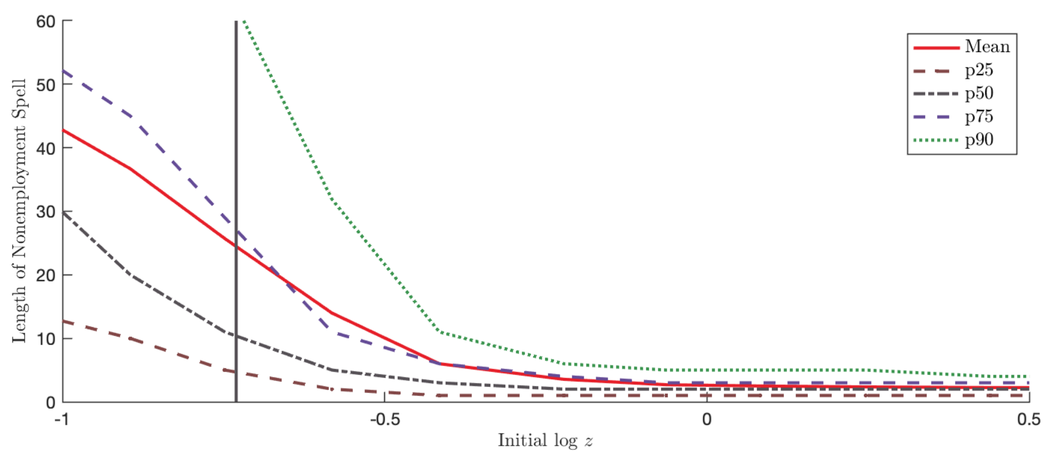


Figure A.4: Non-employment Length and Discount Rate Shocks

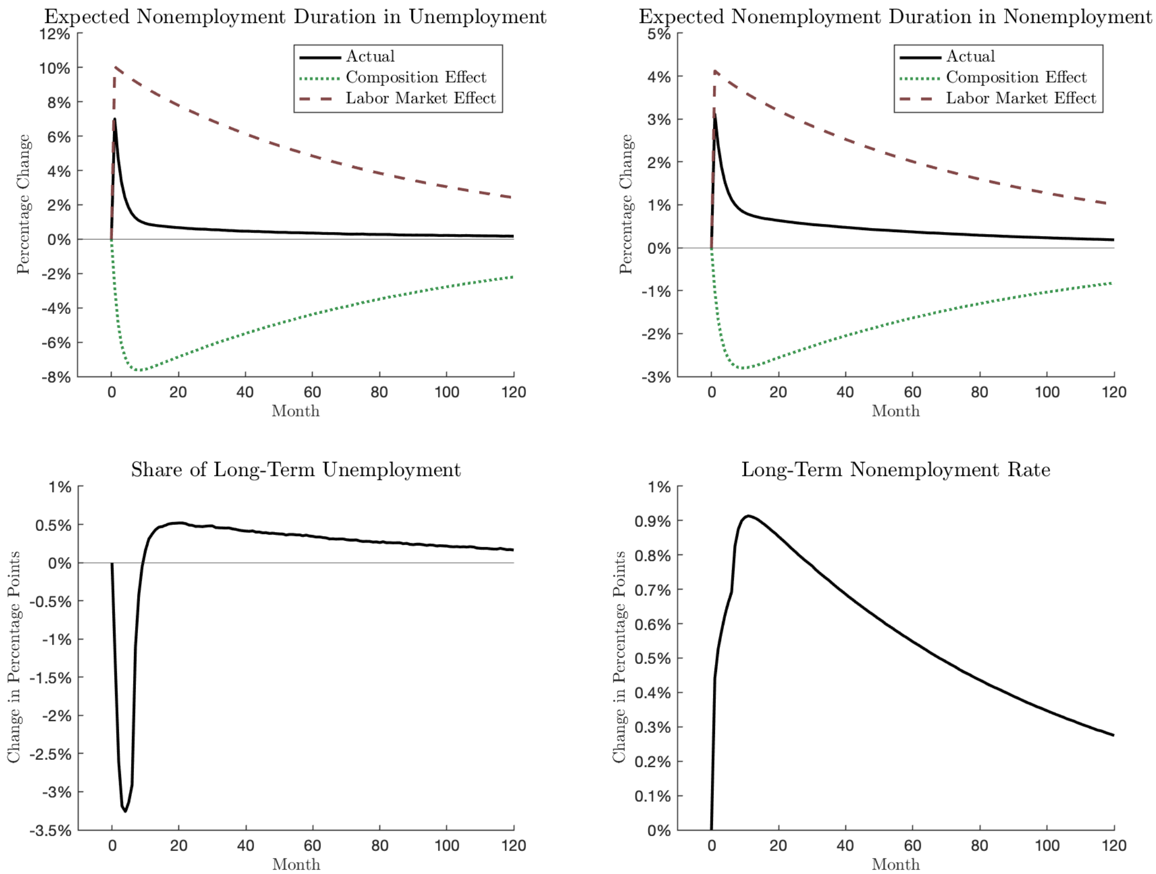
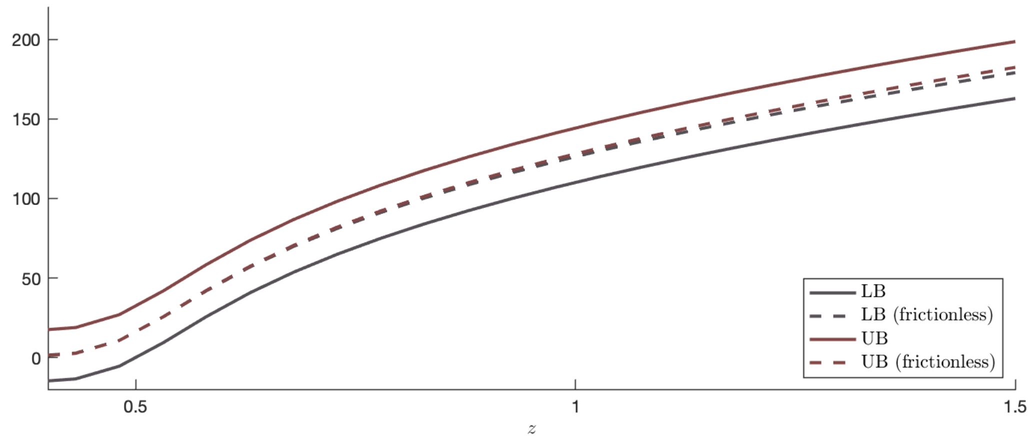
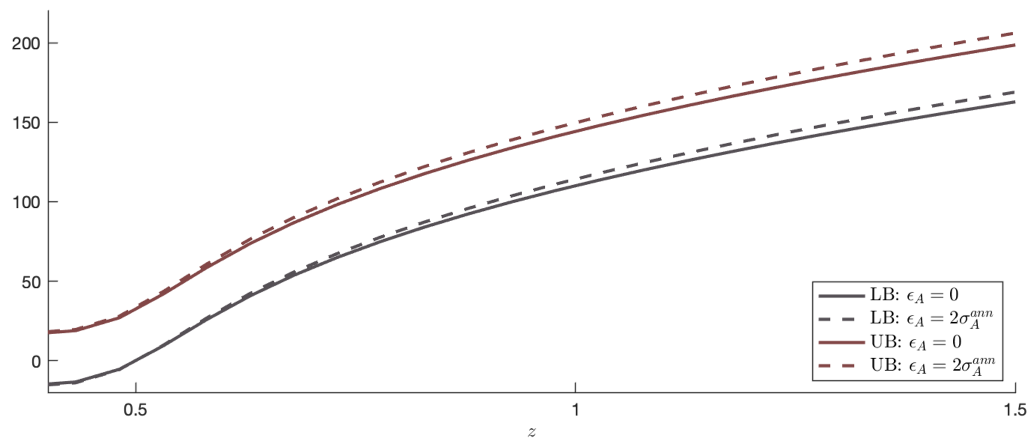


Figure A.5: Wage NPV Bounds Given z Along Balanced Growth Path

(a) Bounds in baseline model vs alternative without reputational costs ($\xi = 0$)



(b) Changes in Bounds from Cashflow News



(c) Changes in Bounds from Cashflow News

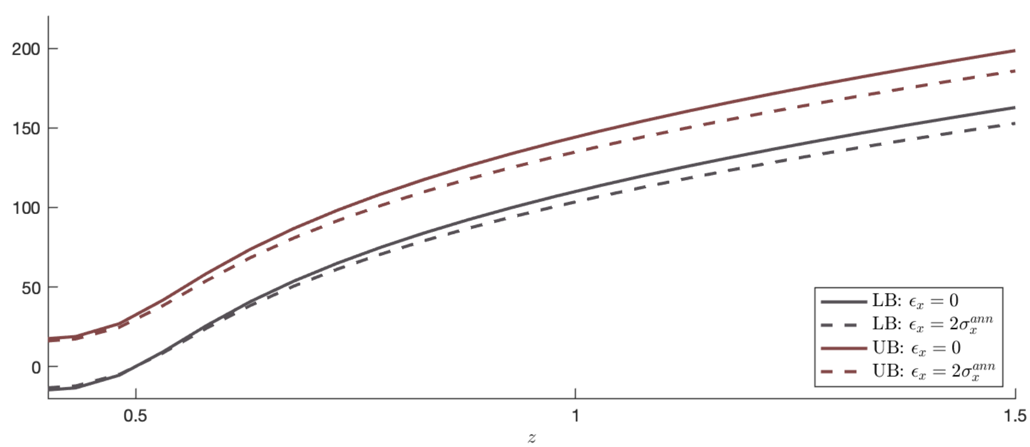
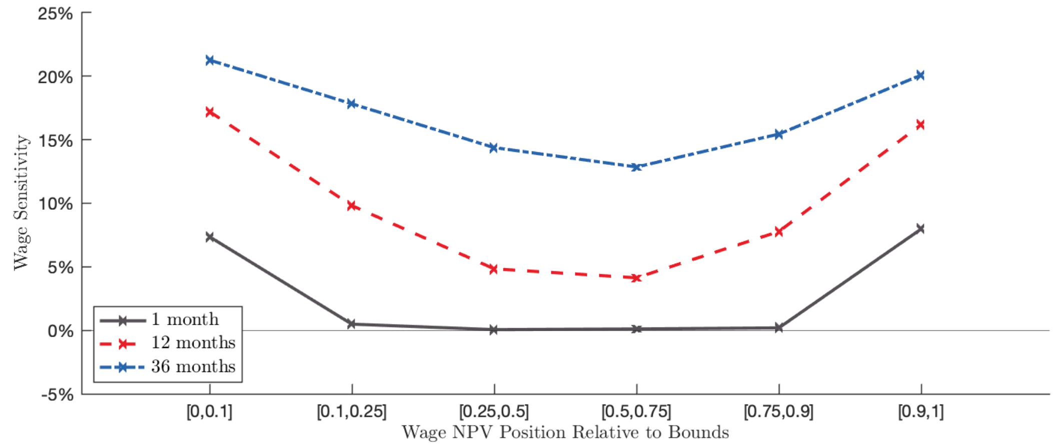
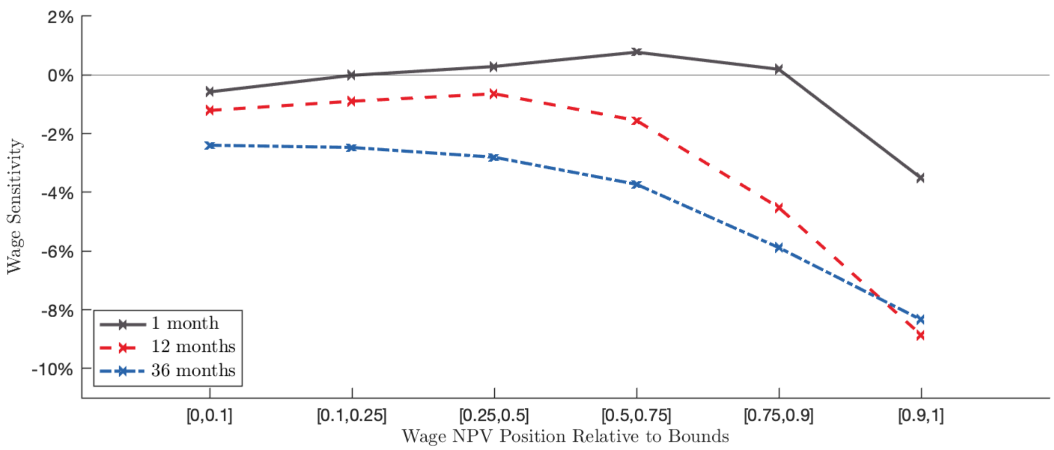


Figure A.6: Dynamics of the Wage Contract

(a) Wage Sensitivity to Cashflow News



(b) Wage Sensitivity to Discount Rate News



(c) Cumulative Distribution of Wage NPV Relative to Bounds

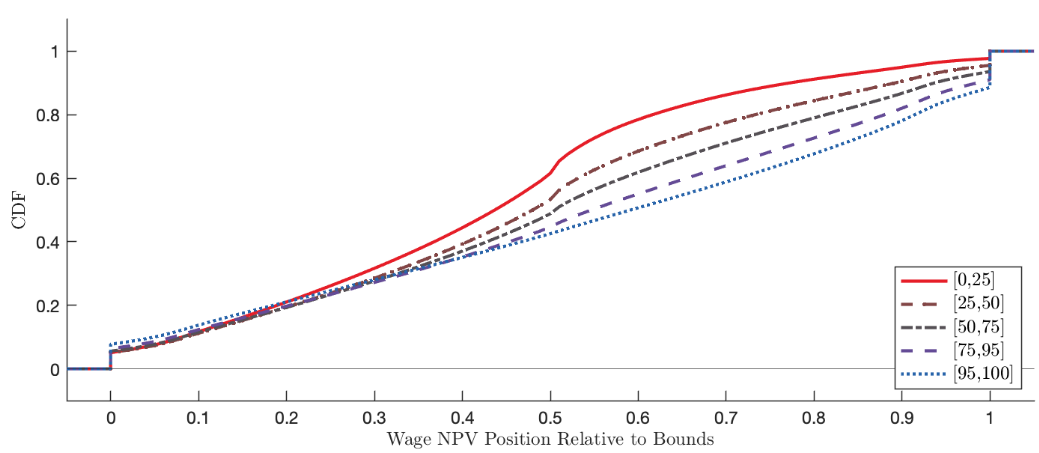


Table A.1: Forecasting Future Stock Returns with Cashflow and Discount Rate News

	Market Beta Portfolio					
	(1)	(2)	(3)	(4)	(5)	(5)–(1)
Cashflow News	−0.839	0.835	−0.172	0.902	0.017	0.856
	(1.147)	(1.292)	(1.112)	(1.569)	(2.243)	(2.171)
Discount Rate News	2.378***	2.342***	3.758***	4.834***	7.478***	5.100***
	(0.649)	(0.873)	(0.676)	(0.707)	(0.647)	(0.711)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R2	0.020	0.010	0.028	0.030	0.039	0.026

This table reports estimates of predictive regressions where we project the discount sum of future returns $\sum_{s=1}^{S} \rho^s r_{t+s}$ on $N_{CF,t}$, $N_{DR,t}$, and controls Ω_{t-1}. We report the coefficients on our baseline news measures. We consider the returns on five portfolios sorted by their stock market beta from Ken French's website. The parameters are $S = 120$ and $\rho = 0.967^{1/12}$. The controls Ω_{t-1} include the Treasury bill rate, the term spread, the aggregate market return, and the market's smoothed price-earnings ratio as of month $t-1$.

Table A.2: Income Exposures to Firm-Level Total Factor Productivity Changes

Income Growth $g_{i,t:t+h}$	$h=1$		$h=2$		$h=3$		$h=5$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP Growth ×	0.041^{***}	0.024^{***}	0.057^{***}	0.030^{***}	0.065^{***}	0.035^{***}	0.074^{***}	0.040^{***}
Income Rank $[0,25]$	(0.014)	(0.007)	(0.016)	(0.007)	(0.017)	(0.008)	(0.019)	(0.009)
TFP Growth ×	0.051^{***}	0.025^{***}	0.066^{***}	0.032^{***}	0.075^{***}	0.039^{***}	0.088^{***}	0.048^{***}
Income Rank $[25,50]$	(0.016)	(0.006)	(0.016)	(0.005)	(0.017)	(0.006)	(0.020)	(0.008)
TFP Growth ×	0.047^{***}	0.027^{***}	0.064^{***}	0.036^{***}	0.071^{***}	0.041^{***}	0.080^{***}	0.044^{***}
Income Rank $[50,75]$	(0.011)	(0.004)	(0.012)	(0.005)	(0.013)	(0.005)	(0.015)	(0.006)
TFP Growth ×	0.048^{***}	0.029^{***}	0.066^{***}	0.042^{***}	0.071^{***}	0.045^{***}	0.081^{***}	0.049^{***}
Income Rank $[75,95]$	(0.010)	(0.006)	(0.011)	(0.006)	(0.012)	(0.007)	(0.013)	(0.007)
TFP Growth ×	0.102^{***}	0.069^{***}	0.128^{***}	0.095^{***}	0.131^{***}	0.095^{***}	0.134^{***}	0.090^{***}
Income Rank $[95,100]$	(0.017)	(0.012)	(0.017)	(0.012)	(0.019)	(0.013)	(0.021)	(0.013)
Discount Rate News ×	-0.113^{***}	-0.066^{***}	-0.154^{***}	-0.071^{***}	-0.168^{***}	-0.060^{***}	-0.125^{**}	-0.048^{***}
Income Rank $[0,25]$	(0.035)	(0.013)	(0.035)	(0.014)	(0.043)	(0.015)	(0.056)	(0.016)
Discount Rate News ×	-0.081^{***}	-0.058^{***}	-0.108^{***}	-0.062^{***}	-0.116^{***}	-0.050^{***}	-0.071	-0.033^{**}
Income Rank $[25,50]$	(0.028)	(0.011)	(0.026)	(0.012)	(0.030)	(0.013)	(0.045)	(0.013)
Discount Rate News ×	-0.069^{**}	-0.048^{***}	-0.087^{***}	-0.051^{***}	-0.091^{***}	-0.037^{***}	-0.047	-0.023^{**}
Income Rank $[50,75]$	(0.026)	(0.010)	(0.023)	(0.010)	(0.027)	(0.011)	(0.041)	(0.011)
Discount Rate News ×	-0.064^{**}	-0.047^{***}	-0.076^{***}	-0.050^{***}	-0.080^{***}	-0.034^{***}	-0.039	-0.018
Income Rank $[75,95]$	(0.025)	(0.010)	(0.023)	(0.011)	(0.027)	(0.012)	(0.040)	(0.012)
Discount Rate News ×	-0.080^{*}	-0.027	-0.072^{**}	-0.020	-0.058	0.004	-0.002	0.013
Income Rank $[95,100]$	(0.040)	(0.019)	(0.034)	(0.020)	(0.040)	(0.022)	(0.050)	(0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes		Yes		Yes		Yes	
NAICS4 × Inc. bin × Year FE		Yes		Yes		Yes		Yes
N $(\times 10^6)$	11.1	11.1	11.1	11.1	10.6	10.6	9.5	9.5
R^2	0.014	0.029	0.016	0.031	0.020	0.035	0.030	0.046

This table reports slope coefficients from regression estimates of equation (12) for different horizons h and with different fixed effects. Cashflow news is measured by the annual change in estimated firm total factor productivity (TFP) from İmrohoroğlu and Tüzel (2014). Discount rate is measured as the employer market beta interacted by aggregate discount rate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the employer market beta and the lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.3: Maturing Debt in Great Recession and Firm Payroll Growth

	$h = 2$				$h = 3$		$h = 5$	
Payroll Growth$_{j,07:07+h}$	$DDA_{07}(2)$ (1)	$DDA_{06}(3)$ (2)	$DDA_{05}(4)$ (3)	$DDA_{04}(5)$ (4)	$DDA_{05}(4)$ (5)	$DDA_{04}(5)$ (6)	$DDA_{05}(4)$ (7)	$DDA_{04}(5)$ (8)
TFP Growth	0.167***	0.175***	0.148***	0.166***	0.170***	0.172***	0.220***	0.256***
	(0.033)	(0.033)	(0.034)	(0.036)	(0.041)	(0.044)	(0.060)	(0.062)
$\frac{\text{Debt due}}{\text{Assets}}$	−0.711***	−0.329*	−0.626***	−0.384***	−0.615***	−0.383**	−1.011***	−0.489**
	(0.258)	(0.196)	(0.174)	(0.146)	(0.234)	(0.172)	(0.269)	(0.238)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,000	2,000	2,000	1,900	1,800	1,700	1,500	1,400
R^2	0.528	0.516	0.520	0.498	0.461	0.451	0.480	0.464

This table reports slope coefficients from regression estimates of equation (A.8) for different versions of the treatment variable and for different horizons h. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The payroll data are constructed by aggregating the tax records of all public firm employees at the firm level. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.4: Maturing Debt in Great Recession and Individual Labor Income Growth

Income Growth $g_{i,07:10}$	$DDA_{07}(2)$ (1)	$DDA_{06}(3)$ (2)	$DDA_{05}(4)$ (3)	$DDA_{04}(5)$ (4)	$DDA_{07}(2)$ (5)	$DDA_{06}(3)$ (6)	$DDA_{05}(4)$ (7)	$DDA_{04}(5)$ (8)
TFP Growth	0.021	0.013	0.006	0.007				
	(0.024)	(0.023)	(0.026)	(0.028)				
TFP Growth ×					−0.015	−0.025	−0.040	−0.043
Income Rank $[0, 25]$					(0.045)	(0.044)	(0.049)	(0.051)
TFP Growth ×					0.022	0.009	0.003	0.004
Income Rank $[25, 50]$					(0.021)	(0.019)	(0.021)	(0.023)
TFP Growth ×					0.027	0.018	0.015	0.017
Income Rank $[50, 75]$					(0.020)	(0.019)	(0.021)	(0.022)
TFP Growth ×					0.037^{**}	0.033^{**}	0.031^{*}	0.032^{*}
Income Rank $[75, 95]$					(0.017)	(0.016)	(0.018)	(0.019)
TFP Growth ×					0.111^{***}	0.111^{***}	0.112^{***}	0.110^{***}
Income Rank $[95, 100]$					(0.025)	(0.024)	(0.028)	(0.028)
$\frac{\text{Debt due}}{\text{Assets}}$	-0.218^{**}	-0.165^{**}	-0.157^{***}	-0.102^{**}				
	(0.109)	(0.076)	(0.054)	(0.045)				
$\frac{\text{Debt due}}{\text{Assets}}$ ×					-0.495^{***}	-0.365^{***}	-0.261^{***}	-0.128^{**}
Income Rank $[0, 25]$					(0.187)	(0.132)	(0.079)	(0.060)
$\frac{\text{Debt due}}{\text{Assets}}$ ×					-0.186^{*}	-0.130^{*}	-0.151^{**}	-0.099^{**}
Income Rank $[25, 50]$					(0.100)	(0.074)	(0.061)	(0.050)
$\frac{\text{Debt due}}{\text{Assets}}$ ×					-0.156^{*}	−0.086	-0.136^{**}	-0.099^{**}
Income Rank $[50, 75]$					(0.089)	(0.069)	(0.055)	(0.050)
$\frac{\text{Debt due}}{\text{Assets}}$ ×					−0.055	−0.065	-0.109^{**}	-0.091^{**}
Income Rank $[75, 95]$					(0.084)	(0.065)	(0.054)	(0.046)
$\frac{\text{Debt due}}{\text{Assets}}$ ×					0.047	−0.132	0.031	−0.038
Income Rank $[95, 100]$					(0.125)	(0.121)	(0.078)	(0.079)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	14.9	14.8	14.3	14.5	14.9	14.8	14.3	14.5
R^2	0.037	0.036	0.037	0.036	0.037	0.036	0.037	0.036

This table reports slope coefficients from regression estimates of equation (A.9) for different versions of the treatment variable. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The firm controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The worker controls include a third-order polynomial in the log of average income over the past three years and a complete set of age dummies. The sample consists of the tax records of all public firm employees. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.5: Maturing Debt in Great Recession and Individual Labor Income Growth – by Horizon

Income Growth $g_{i,07:07+h}$	$DDA_{05}(4)$				$DDA_{04}(5)$			
	$h=1$	$h=2$	$h=5$	$h=10$	$h=1$	$h=2$	$h=5$	$h=10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP Growth $\times$	-0.031	-0.033	-0.045	-0.046	-0.030	-0.034	-0.048	-0.047
Income Rank $[0,25]$	(0.039)	(0.046)	(0.050)	(0.051)	(0.042)	(0.048)	(0.053)	(0.054)
TFP Growth $\times$	-0.014	-0.001	0.013	0.024	-0.012	0.000	0.015	0.027
Income Rank $[25,50]$	(0.021)	(0.022)	(0.019)	(0.019)	(0.022)	(0.023)	(0.021)	(0.021)
TFP Growth $\times$	-0.007	0.010	0.028	0.039^{**}	-0.004	0.012	0.030	0.042^{**}
Income Rank $[50,75]$	(0.019)	(0.021)	(0.019)	(0.017)	(0.020)	(0.023)	(0.020)	(0.018)
TFP Growth $\times$	0.010	0.031^{*}	0.044^{**}	0.046^{***}	0.012	0.032^{*}	0.045^{**}	0.047^{***}
Income Rank $[75,95]$	(0.015)	(0.018)	(0.018)	(0.017)	(0.015)	(0.018)	(0.019)	(0.018)
TFP Growth $\times$	0.078^{***}	0.102^{***}	0.120^{***}	0.095^{***}	0.079^{***}	0.101^{***}	0.119^{***}	0.093^{***}
Income Rank $[95,100]$	(0.021)	(0.027)	(0.028)	(0.032)	(0.022)	(0.028)	(0.029)	(0.032)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.142^{**}	-0.246^{***}	-0.271^{***}	-0.279^{***}	-0.060	-0.120^{**}	-0.132^{**}	-0.132^{*}
Income Rank $[0,25]$	(0.059)	(0.072)	(0.085)	(0.097)	(0.053)	(0.056)	(0.064)	(0.076)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.107^{**}	-0.160^{***}	-0.118^{*}	-0.062	-0.080^{*}	-0.112^{**}	-0.072	-0.037
Income Rank $[25,50]$	(0.049)	(0.057)	(0.065)	(0.079)	(0.043)	(0.047)	(0.053)	(0.064)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.092^{**}	-0.144^{***}	-0.097^{*}	-0.045	-0.102^{**}	-0.124^{***}	-0.061	-0.021
Income Rank $[50,75]$	(0.042)	(0.052)	(0.058)	(0.073)	(0.041)	(0.047)	(0.053)	(0.063)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.061	-0.112^{**}	-0.089	-0.048	-0.089^{**}	-0.102^{**}	-0.082^{*}	-0.081
Income Rank $[75,95]$	(0.051)	(0.052)	(0.058)	(0.074)	(0.043)	(0.045)	(0.049)	(0.064)
$\frac{\text{Debt due}}{\text{Assets}} \times$	0.131	0.056	0.000	0.018	-0.044	-0.040	-0.068	-0.114
Income Rank $[95,100]$	(0.086)	(0.078)	(0.082)	(0.097)	(0.071)	(0.080)	(0.072)	(0.083)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 $\times$ Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N ($\times 10^6$)	14.3	14.3	14.3	14.3	14.5	14.5	14.5	14.5
R^2	0.027	0.033	0.045	0.070	0.026	0.032	0.045	0.070

This table reports slope coefficients from regression estimates of equation (A.9) at different horizons and for different versions of the treatment variable. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The firm controls include the firm's leverage ratio (also measured at $2009-y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The worker controls include a third-order polynomial in the log of average income over the past three years and a complete set of age dummies. The sample consists of the tax records of all public firm employees. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.6: Income Exposures to Cashflow and Discount Rate News – by Income and Tenure

Income Growth $g_{i,t:t+h}$	Aggregate News				Market Beta × Aggregate News			
	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=5$ (4)	$h=1$ (5)	$h=2$ (6)	$h=3$ (7)	$h=5$ (8)
Cashflow News ×	0.077	0.089	0.057	0.094	0.054	0.087	0.060	0.085
Income Rank $[0, 25]$	(0.069)	(0.075)	(0.102)	(0.139)	(0.072)	(0.067)	(0.086)	(0.112)
Cashflow News ×	0.074	0.078	0.051	0.092	0.055	0.074	0.052	0.082
Income Rank $[25, 50]$	(0.057)	(0.068)	(0.092)	(0.124)	(0.059)	(0.059)	(0.076)	(0.099)
Cashflow News ×	0.076	0.078	0.053	0.092	0.062	0.075	0.054	0.084
Income Rank $[50, 75]$	(0.053)	(0.064)	(0.085)	(0.113)	(0.056)	(0.055)	(0.070)	(0.090)
Cashflow News ×	0.088^{*}	0.088	0.067	0.103	0.077	0.086	0.069	0.099
Income Rank $[75, 95]$	(0.050)	(0.062)	(0.082)	(0.105)	(0.052)	(0.053)	(0.066)	(0.082)
Cashflow News ×	0.183^{**}	0.162^{*}	0.142	0.174	0.163^{**}	0.157^{**}	0.138^{*}	0.168^{*}
Income Rank $[95, 100]$	(0.066)	(0.082)	(0.098)	(0.112)	(0.065)	(0.068)	(0.079)	(0.090)
Cashflow News ×	−0.028	−0.035	−0.035	−0.046	−0.012	−0.021	−0.021	−0.032
Tenure $[2, 5]$	(0.029)	(0.035)	(0.043)	(0.052)	(0.026)	(0.030)	(0.036)	(0.042)
Cashflow News ×	−0.027	−0.035	−0.022	−0.034	−0.015	−0.022	−0.015	−0.026
Tenure > 5	(0.029)	(0.033)	(0.043)	(0.051)	(0.026)	(0.029)	(0.035)	(0.042)
Discount Rate News ×	-0.145^{**}	-0.250^{***}	-0.273^{***}	-0.200^{*}	-0.114^{**}	-0.205^{***}	-0.215^{***}	-0.164^{*}
Income Rank $[0, 25]$	(0.053)	(0.048)	(0.072)	(0.101)	(0.054)	(0.046)	(0.064)	(0.080)
Discount Rate News ×	-0.135^{***}	-0.216^{***}	-0.236^{***}	-0.164^{*}	-0.108^{**}	-0.180^{***}	-0.188^{***}	-0.138^{*}
Income Rank $[25, 50]$	(0.042)	(0.042)	(0.063)	(0.090)	(0.043)	(0.038)	(0.054)	(0.069)
Discount Rate News ×	-0.129^{***}	-0.195^{***}	-0.211^{***}	−0.140	-0.104^{**}	-0.163^{***}	-0.168^{***}	-0.118^{*}
Income Rank $[50, 75]$	(0.038)	(0.040)	(0.058)	(0.083)	(0.039)	(0.035)	(0.049)	(0.063)
Discount Rate News ×	-0.132^{***}	-0.187^{***}	-0.200^{***}	−0.132	-0.106^{***}	-0.154^{***}	-0.156^{***}	-0.110^{*}
Income Rank $[75, 95]$	(0.035)	(0.039)	(0.056)	(0.079)	(0.036)	(0.034)	(0.048)	(0.061)
Discount Rate News ×	-0.164^{***}	-0.192^{***}	-0.178^{**}	−0.088	-0.134^{***}	-0.160^{***}	-0.142^{**}	−0.079
Income Rank $[95, 100]$	(0.045)	(0.049)	(0.066)	(0.084)	(0.044)	(0.042)	(0.056)	(0.067)
Discount Rate News ×	0.029	0.051^{*}	0.049	0.036	0.019	0.033	0.029	0.025
Tenure $[2, 5]$	(0.024)	(0.028)	(0.036)	(0.040)	(0.021)	(0.024)	(0.031)	(0.032)
Discount Rate News ×	0.088^{***}	0.130^{***}	0.138^{***}	0.114^{**}	0.067^{***}	0.098^{***}	0.102^{***}	0.093^{**}
Tenure > 5	(0.025)	(0.027)	(0.036)	(0.040)	(0.022)	(0.025)	(0.033)	(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Tenure bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	12.9	12.2	11.5	10.2	11.4	10.8	10.2	9.0
R^2	0.021	0.022	0.024	0.032	0.021	0.022	0.025	0.034

This table reports slope coefficients from regression estimates of equations (11) and (12) for different horizons h. In columns (1)–(4), the treatment variables are aggregate cashflow and discount rate news. In columns (5)–(8), the treatment variables are the employer's stock market beta multiplied by aggregate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own firm. We also interact the treatment variables by indicators for worker employment tenure bins computed for workers for whom we observe an income history of more than five years. 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 the lagged market return interacted by income group dummies. In columns (5)–(8), we also control for the employer beta by income group. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
${}^{*}p < 0.1$; ${}^{**}p < 0.05$; ${}^{***}p < 0.01$.

Table A.7: Forecasting Future Stock Returns with Cashflow and Discount Rate News – Campbell-Vuolteenaho Decomposition

	Market Beta Portfolio					
	(1)	(2)	(3)	(4)	(5)	(5)–(1)
Cashflow News	0.725	0.686	-0.748	-2.076	-4.843^{*}	-5.568^{**}
	(0.835)	(1.556)	(1.247)	(1.721)	(2.487)	(2.465)
Discount Rate News	3.537^{***}	2.529^{*}	3.780^{***}	3.609^{***}	5.414^{***}	1.877
	(1.331)	(1.436)	(1.107)	(1.392)	(2.088)	(2.323)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R2	0.025	0.006	0.023	0.019	0.035	0.029

This table reports estimates of predictive regressions where we project the discount sum of future returns $\sum_{s=1}^{S} \rho^s r_{t+s}$ on $N_{CF,t}$, $N_{DR,t}$, and controls Ω_{t-1}. Here, we use the VAR-based approach from Campbell and Vuolteenaho (2004) as alternative news measures. We consider the returns on five portfolios sorted by their stock market beta from Ken French's website. The parameters are $S = 120$ and $\rho = 0.967^{1/12}$. The controls Ω_{t-1} include the Treasury bill rate, the term spread, the aggregate market return, and the market's smoothed price-earnings ratio as of month $t - 1$.

Table A.8: Income Exposures to Cashflow and Discount Rate News – Campbell-Vuolteenaho Decomposition

Income Growth $g_{i,t:t+h}$	Aggregate News				Market Beta $\times$ Aggregate News			
	$h=1$	$h=2$	$h=3$	$h=5$	$h=1$	$h=2$	$h=3$	$h=5$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cashflow News $\times$	0.007	0.085	0.161	0.309	0.020	0.083	0.136	0.244
Income Rank $[0,25]$	(0.101)	(0.123)	(0.167)	(0.230)	(0.089)	(0.105)	(0.142)	(0.190)
Cashflow News $\times$	0.035	0.096	0.144	0.262	0.030	0.078	0.112	0.196
Income Rank $[25,50]$	(0.081)	(0.105)	(0.140)	(0.198)	(0.075)	(0.090)	(0.119)	(0.164)
Cashflow News $\times$	0.026	0.074	0.104	0.205	0.020	0.056	0.077	0.148
Income Rank $[50,75]$	(0.075)	(0.097)	(0.126)	(0.178)	(0.071)	(0.084)	(0.109)	(0.149)
Cashflow News $\times$	0.023	0.068	0.091	0.177	0.017	0.046	0.062	0.123
Income Rank $[75,95]$	(0.068)	(0.091)	(0.117)	(0.161)	(0.068)	(0.082)	(0.106)	(0.137)
Cashflow News $\times$	0.167^{*}	0.214^{*}	0.249^{*}	0.322^{*}	0.120	0.151	0.170	0.218
Income Rank $[95,100]$	(0.094)	(0.115)	(0.134)	(0.159)	(0.096)	(0.107)	(0.124)	(0.142)
Discount Rate News $\times$	-0.109^{**}	-0.176^{***}	-0.176^{***}	-0.128^{**}	-0.085^{*}	-0.160^{***}	-0.158^{***}	-0.117^{***}
Income Rank $[0,25]$	(0.040)	(0.029)	(0.037)	(0.048)	(0.045)	(0.023)	(0.030)	(0.041)
Discount Rate News $\times$	-0.085^{***}	-0.121^{***}	-0.122^{***}	-0.076^{*}	-0.071^{**}	-0.118^{***}	-0.117^{***}	-0.077^{**}
Income Rank $[25,50]$	(0.025)	(0.023)	(0.028)	(0.038)	(0.030)	(0.017)	(0.022)	(0.032)
Discount Rate News $\times$	-0.082^{***}	-0.106^{***}	-0.108^{***}	-0.065^{*}	-0.071^{***}	-0.105^{***}	-0.104^{***}	-0.067^{**}
Income Rank $[50,75]$	(0.020)	(0.020)	(0.025)	(0.034)	(0.025)	(0.015)	(0.020)	(0.029)
Discount Rate News $\times$	-0.086^{***}	-0.102^{***}	-0.104^{***}	-0.065^{*}	-0.076^{***}	-0.101^{***}	-0.100^{***}	-0.067^{**}
Income Rank $[75,95]$	(0.015)	(0.018)	(0.023)	(0.032)	(0.020)	(0.015)	(0.021)	(0.030)
Discount Rate News $\times$	-0.120^{***}	-0.108^{***}	-0.089^{**}	-0.031	-0.109^{***}	-0.111^{***}	-0.092^{**}	-0.047
Income Rank $[95,100]$	(0.021)	(0.028)	(0.038)	(0.047)	(0.028)	(0.029)	(0.038)	(0.046)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 $\times$ Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	16.0	15.3	14.6	13.1	14.0	13.4	12.7	11.4
R^2	0.014	0.016	0.018	0.027	0.014	0.016	0.019	0.028

This table reports slope coefficients from regression estimates of equations (11) and (12) for different horizons h. For this table, we measure cashflow news and discount rate news by using the Campbell-Vuolteenaho approach. In columns (1)–(4), the treatment variables are aggregate cashflow and discount rate news. In columns (5)–(8), the treatment variables are the employer's stock market beta multiplied by aggregate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the lagged market return interacted by income group dummies. In columns (5)–(8), we also control for the employer beta by income group. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.9: Income Exposures to Cashflow and Discount Rate News – Alternative Definitions

Income Growth $g_{i,t:t+3}$	FF3F (1)	FF3F+ Mom (2)	FF5F (3)	q-F (4)	$\rho = 0.95^{\frac{1}{12}}$ (5)	$\rho = 0.99^{\frac{1}{12}}$ (6)	$\widetilde{\Omega} = \emptyset$ (7)	$\widetilde{\Omega} = \{\Omega, CS, SVS\}$ (8)
Cashflow News ×	0.175	0.075	0.142	0.059	0.048	0.061	0.124^{***}	0.034
Income Rank $[0, 25]$	(0.112)	(0.054)	(0.101)	(0.107)	(0.061)	(0.058)	(0.027)	(0.071)
Cashflow News ×	0.130	0.053	0.119	0.030	0.037	0.049	0.096^{***}	0.030
Income Rank $[25, 50]$	(0.093)	(0.046)	(0.081)	(0.089)	(0.051)	(0.048)	(0.021)	(0.057)
Cashflow News ×	0.126	0.051	0.125^{*}	0.016	0.041	0.051	0.084^{***}	0.031
Income Rank $[50, 75]$	(0.081)	(0.040)	(0.071)	(0.079)	(0.045)	(0.042)	(0.019)	(0.054)
Cashflow News ×	0.138^{*}	0.065^{*}	0.141^{**}	0.024	0.058	0.067^{*}	0.084^{***}	0.040
Income Rank $[75, 95]$	(0.073)	(0.037)	(0.065)	(0.073)	(0.041)	(0.039)	(0.018)	(0.050)
Cashflow News ×	0.227^{*}	0.134^{**}	0.225^{**}	0.118	0.130^{**}	0.137^{**}	0.119^{***}	0.104
Income Rank $[95, 100]$	(0.112)	(0.056)	(0.098)	(0.109)	(0.057)	(0.053)	(0.030)	(0.061)
Discount Rate News ×	-0.120^{*}	-0.170^{***}	-0.135^{***}	-0.187^{***}	-0.186^{***}	-0.164^{***}	-0.242^{***}	-0.203^{***}
Income Rank $[0, 25]$	(0.059)	(0.039)	(0.047)	(0.057)	(0.043)	(0.035)	(0.060)	(0.041)
Discount Rate News ×	-0.084^{*}	-0.122^{***}	-0.090^{**}	-0.142^{***}	-0.132^{***}	-0.115^{***}	-0.169^{***}	-0.149^{***}
Income Rank $[25, 50]$	(0.049)	(0.031)	(0.037)	(0.047)	(0.032)	(0.026)	(0.051)	(0.030)
Discount Rate News ×	−0.065	-0.100^{***}	-0.068^{*}	-0.126^{***}	-0.107^{***}	-0.095^{***}	-0.140^{***}	-0.124^{***}
Income Rank $[50, 75]$	(0.044)	(0.027)	(0.033)	(0.040)	(0.028)	(0.022)	(0.047)	(0.026)
Discount Rate News ×	−0.055	-0.088^{***}	-0.057^{*}	-0.115^{***}	-0.092^{***}	-0.084^{***}	-0.120^{***}	-0.110^{***}
Income Rank $[75, 95]$	(0.040)	(0.026)	(0.031)	(0.037)	(0.028)	(0.021)	(0.043)	(0.026)
Discount Rate News ×	−0.034	-0.068^{*}	−0.042	−0.074	-0.070^{*}	-0.075^{**}	-0.130^{*}	-0.098^{**}
Income Rank $[95, 100]$	(0.051)	(0.035)	(0.043)	(0.058)	(0.038)	(0.029)	(0.073)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	12.7	12.7	12.7	12.7	12.7	12.7	12.7	12.7
R^2	0.018	0.018	0.018	0.019	0.019	0.019	0.019	0.019

This table reports slope coefficients from regression estimates of equation (12) at a three-year horizon. For this table, we measure cashflow news and discount rate news using variations to our main measure. In columns (1)–(4), we project the discounted sum of future returns on different sets of traded factors: the three standard Fama-French factors (market, size, and book-to-market), the three Fama-French factors and the momentum factor, the five Fama-French factors, and the five factors from the Hou et al. (2015) q-factor model. In columns (5)–(8), we consider alternative parameter choices: a smaller ρ of $0.95^{1/12}$, a larger ρ of $0.99^{1/12}$, no controls Ω_{t-1}, and additional controls for the small value spread and credit spread. The treatment variables are the employer market beta interacted by aggregate discount rate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the employer market beta and the lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.10: Income Exposures to Cashflow and Discount Rate News – Time Fixed Effects

Income Growth $g_{i,t:t+h}$	$h = 1$ (1)	$h = 2$ (2)	$h = 3$ (3)	$h = 5$ (4)
Cashflow News $\times$	0.002	0.036^{**}	0.033^{**}	0.039^{**}
Income Rank $[0, 25]$	(0.015)	(0.014)	(0.015)	(0.017)
Cashflow News $\times$	0.013	0.037^{***}	0.037^{***}	0.048^{***}
Income Rank $[25, 50]$	(0.012)	(0.011)	(0.011)	(0.012)
Cashflow News $\times$	0.024^{**}	0.042^{***}	0.043^{***}	0.055^{***}
Income Rank $[50, 75]$	(0.011)	(0.010)	(0.010)	(0.012)
Cashflow News $\times$	0.025^{*}	0.039^{***}	0.038^{***}	0.048^{***}
Income Rank $[75, 95]$	(0.014)	(0.012)	(0.012)	(0.013)
Cashflow News $\times$	0.068^{***}	0.073^{***}	0.071^{***}	0.091^{***}
Income Rank $[95, 100]$	(0.023)	(0.021)	(0.022)	(0.025)
Discount Rate News $\times$	-0.040^{***}	-0.059^{***}	-0.046^{***}	-0.037^{***}
Income Rank $[0, 25]$	(0.013)	(0.012)	(0.013)	(0.014)
Discount Rate News $\times$	-0.038^{***}	-0.052^{***}	-0.038^{***}	-0.026^{**}
Income Rank $[25, 50]$	(0.010)	(0.010)	(0.011)	(0.011)
Discount Rate News $\times$	-0.031^{***}	-0.042^{***}	-0.027^{***}	-0.016
Income Rank $[50, 75]$	(0.009)	(0.009)	(0.010)	(0.010)
Discount Rate News $\times$	-0.028^{***}	-0.042^{***}	-0.025^{**}	-0.013
Income Rank $[75, 95]$	(0.010)	(0.010)	(0.010)	(0.011)
Discount Rate News $\times$	-0.022	-0.029	-0.003	0.006
Income Rank $[95, 100]$	(0.017)	(0.018)	(0.020)	(0.021)
Controls	Yes	Yes	Yes	Yes
NAICS4 $\times$ Inc. bin $\times$ Year FE	Yes	Yes	Yes	Yes
N $(\times 10^6)$	14.0	13.4	12.7	11.4
R^2	0.030	0.030	0.034	0.043

This table reports slope coefficients from regression estimates of equation (12) for different horizons h and with the inclusion of time fixed effects. The treatment variables are the employer market beta interacted by aggregate discount rate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the employer market beta and the lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.11: Income Exposures to Cashflow and Discount Rate News – Two-Factor Betas

Income Growth $g_{i,t:t+h}$	$h=1$		$h=2$		$h=3$		$h=5$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cashflow News ×	0.039	0.009	0.062	0.026^{**}	0.043	0.024^{**}	0.057	0.038^{***}
Income Rank $[0,25]$	(0.047)	(0.011)	(0.043)	(0.010)	(0.054)	(0.011)	(0.070)	(0.012)
Cashflow News ×	0.038	0.010	0.048	0.019^{**}	0.034	0.019^{**}	0.050	0.029^{***}
Income Rank $[25,50]$	(0.035)	(0.008)	(0.035)	(0.007)	(0.044)	(0.008)	(0.057)	(0.009)
Cashflow News ×	0.044	0.013	0.051	0.021^{***}	0.039	0.023^{***}	0.057	0.035^{***}
Income Rank $[50,75]$	(0.032)	(0.008)	(0.032)	(0.007)	(0.039)	(0.008)	(0.050)	(0.009)
Cashflow News ×	0.056^{*}	0.012	0.060^{**}	0.017^{**}	0.050	0.016^{*}	0.069	0.025^{***}
Income Rank $[75,95]$	(0.029)	(0.010)	(0.029)	(0.008)	(0.035)	(0.009)	(0.044)	(0.009)
Cashflow News ×	0.133^{***}	0.040^{**}	0.127^{***}	0.050^{***}	0.117^{**}	0.055^{***}	0.135^{**}	0.076^{***}
Income Rank $[95,100]$	(0.039)	(0.017)	(0.042)	(0.016)	(0.047)	(0.016)	(0.052)	(0.018)
Discount Rate News ×	-0.088^{**}	-0.034^{***}	-0.158^{***}	-0.054^{***}	-0.171^{***}	-0.042^{***}	-0.131^{**}	-0.033^{**}
Income Rank $[0,25]$	(0.037)	(0.011)	(0.028)	(0.011)	(0.039)	(0.012)	(0.051)	(0.013)
Discount Rate News ×	-0.068^{**}	-0.038^{***}	-0.113^{***}	-0.054^{***}	-0.122^{***}	-0.041^{***}	-0.079^{*}	-0.028^{***}
Income Rank $[25,50]$	(0.027)	(0.010)	(0.021)	(0.010)	(0.029)	(0.010)	(0.042)	(0.011)
Discount Rate News ×	-0.062^{**}	-0.030^{***}	-0.094^{***}	-0.041^{***}	-0.099^{***}	-0.026^{***}	-0.058	-0.014
Income Rank $[50,75]$	(0.024)	(0.009)	(0.019)	(0.009)	(0.024)	(0.010)	(0.037)	(0.010)
Discount Rate News ×	-0.062^{***}	-0.031^{***}	-0.084^{***}	-0.044^{***}	-0.088^{***}	-0.029^{***}	-0.051	-0.018^{*}
Income Rank $[75,95]$	(0.020)	(0.010)	(0.017)	(0.009)	(0.024)	(0.010)	(0.036)	(0.010)
Discount Rate News ×	-0.085^{***}	-0.032^{*}	-0.087^{***}	-0.038^{**}	-0.071^{**}	-0.016	-0.018	-0.005
Income Rank $[95,100]$	(0.027)	(0.017)	(0.026)	(0.018)	(0.034)	(0.019)	(0.044)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes		Yes		Yes		Yes	
NAICS4 × Inc. bin × Year FE		Yes		Yes		Yes		Yes
N $(\times 10^6)$	14.0	14.0	13.4	13.4	12.7	12.7	11.4	11.4
R^2	0.014	0.030	0.016	0.030	0.019	0.034	0.028	0.044

This table reports slope coefficients from regression estimates of equation (12) for different horizons h, with and without time fixed effects. The treatment variables are the employer cashflow beta times aggregate cashflow news and the employer discount rate beta times aggregate discount rate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the employer 2-factor betas and the lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors in the odd columns are double clustered by employer and year. Standard errors in the even columns are clustered by employer.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.12: Income Exposures to Cashflow and Discount Rate News – All Workers

Income Growth $g_{i,t:t+h}$	$h=1$ (1)	$h=2$ (2)	$h=3$ (3)	$h=5$ (4)	$h=1$ (5)	$h=2$ (6)	$h=3$ (7)	$h=5$ (8)
Market News ×	0.072^{**}	0.126^{***}	0.135^{***}	0.118^{***}				
Income Rank $[0, 25]$	(0.033)	(0.023)	(0.029)	(0.042)				
Market News ×	0.055^{***}	0.086^{***}	0.094^{***}	0.076^{**}				
Income Rank $[25, 50]$	(0.020)	(0.019)	(0.023)	(0.033)				
Market News ×	0.048^{***}	0.070^{***}	0.077^{***}	0.060^{**}				
Income Rank $[50, 75]$	(0.015)	(0.016)	(0.019)	(0.028)				
Market News ×	0.049^{***}	0.065^{***}	0.071^{***}	0.057^{**}				
Income Rank $[75, 95]$	(0.012)	(0.013)	(0.016)	(0.023)				
Market News ×	0.073^{***}	0.077^{***}	0.076^{***}	0.054^{**}				
Income Rank $[95, 100]$	(0.010)	(0.011)	(0.015)	(0.024)				
Cashflow News ×					0.029	0.035	0.009	0.029
Income Rank $[0, 25]$					(0.053)	(0.053)	(0.068)	(0.093)
Cashflow News ×					0.024	0.020	−0.001	0.018
Income Rank $[25, 50]$					(0.040)	(0.045)	(0.055)	(0.074)
Cashflow News ×					0.021	0.015	−0.002	0.016
Income Rank $[50, 75]$					(0.035)	(0.039)	(0.048)	(0.064)
Cashflow News ×					0.025	0.019	0.007	0.025
Income Rank $[75, 95]$					(0.030)	(0.034)	(0.042)	(0.055)
Cashflow News ×					0.066^{**}	0.054	0.042	0.052
Income Rank $[95, 100]$					(0.029)	(0.036)	(0.044)	(0.056)
Discount Rate News ×					-0.094^{**}	-0.172^{***}	-0.203^{***}	-0.166^{**}
Income Rank $[0, 25]$					(0.038)	(0.030)	(0.042)	(0.060)
Discount Rate News ×					-0.071^{**}	-0.120^{***}	-0.145^{***}	-0.107^{**}
Income Rank $[25, 50]$					(0.027)	(0.026)	(0.033)	(0.049)
Discount Rate News ×					-0.062^{**}	-0.097^{***}	-0.119^{***}	-0.083^{*}
Income Rank $[50, 75]$					(0.023)	(0.023)	(0.029)	(0.044)
Discount Rate News ×					-0.062^{***}	-0.088^{***}	-0.106^{***}	-0.074^{*}
Income Rank $[75, 95]$					(0.019)	(0.020)	(0.026)	(0.039)
Discount Rate News ×					-0.077^{***}	-0.088^{***}	-0.095^{***}	−0.055
Income Rank $[95, 100]$					(0.016)	(0.019)	(0.027)	(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	51.4	48.9	46.3	41.2	51.4	48.9	46.3	41.2
R^2	0.013	0.015	0.017	0.024	0.013	0.015	0.017	0.024

This table reports slope coefficients from regression estimates of equations (3) and (11) for different horizons h. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD (and not only public firm employees). The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.13: Firm-Level Total Factor Productivity Changes and Employment Outcomes

Employment Indicator$_{i,t:t+h}$	Probability of Move		Probability of Zero		Probability of Tail Loss & Move		Probability of Tail Loss & Stay	
	$h=3$ (1)	$h=5$ (2)	$h=3$ (3)	$h=5$ (4)	$h=3$ (5)	$h=5$ (6)	$h=3$ (7)	$h=5$ (8)
TFP Growth ×	-0.047^{***}	-0.050^{***}	-0.039^{***}	-0.040^{***}	-0.025^{***}	-0.025^{***}	-0.002	0.000
Income Rank $[0,25]$	(0.012)	(0.011)	(0.010)	(0.010)	(0.008)	(0.007)	(0.001)	(0.001)
TFP Growth ×	-0.072^{***}	-0.075^{***}	-0.048^{***}	-0.049^{***}	-0.030^{***}	-0.033^{***}	-0.002	0.000
Income Rank $[25,50]$	(0.024)	(0.021)	(0.011)	(0.011)	(0.010)	(0.009)	(0.003)	(0.001)
TFP Growth ×	-0.072^{**}	-0.077^{***}	-0.037^{***}	-0.040^{***}	-0.023^{***}	-0.025^{***}	-0.003^{*}	0.000
Income Rank $[50,75]$	(0.028)	(0.024)	(0.008)	(0.010)	(0.007)	(0.006)	(0.002)	(0.001)
TFP Growth ×	-0.066^{**}	-0.071^{***}	-0.020^{***}	-0.025^{***}	-0.017^{***}	-0.019^{***}	-0.003^{***}	-0.001
Income Rank $[75,95]$	(0.024)	(0.022)	(0.006)	(0.007)	(0.005)	(0.004)	(0.001)	(0.001)
TFP Growth ×	-0.058^{***}	-0.063^{***}	-0.014^{*}	-0.018^{**}	-0.022^{***}	-0.029^{***}	-0.019^{***}	-0.006^{**}
Income Rank $[95,100]$	(0.011)	(0.011)	(0.008)	(0.008)	(0.005)	(0.006)	(0.003)	(0.002)
Discount Rate News ×	-0.042^{*}	-0.045^{***}	0.050^{*}	0.031	0.062^{***}	0.046^{***}	0.007^{***}	0.002^{*}
Income Rank $[0,25]$	(0.023)	(0.015)	(0.025)	(0.026)	(0.017)	(0.015)	(0.002)	(0.001)
Discount Rate News ×	-0.039^{*}	-0.047^{***}	0.031^{*}	0.015	0.045^{***}	0.031^{***}	0.005^{***}	0.001
Income Rank $[25,50]$	(0.020)	(0.012)	(0.018)	(0.019)	(0.012)	(0.010)	(0.001)	(0.001)
Discount Rate News ×	-0.044^{**}	-0.044^{***}	0.014	0.005	0.031^{***}	0.020^{**}	0.005^{***}	0.002^{**}
Income Rank $[50,75]$	(0.018)	(0.011)	(0.013)	(0.012)	(0.008)	(0.007)	(0.001)	(0.001)
Discount Rate News ×	-0.049^{**}	-0.045^{***}	-0.001	-0.004	0.022^{***}	0.014^{**}	0.005^{***}	0.001
Income Rank $[75,95]$	(0.018)	(0.011)	(0.012)	(0.008)	(0.007)	(0.006)	(0.002)	(0.001)
Discount Rate News ×	-0.060^{***}	-0.054^{***}	-0.031^{**}	-0.036^{***}	0.008	-0.002	0.015^{*}	0.005
Income Rank $[95,100]$	(0.019)	(0.014)	(0.015)	(0.011)	(0.008)	(0.010)	(0.007)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N ($\times 10^6$)	10.6	9.5	10.6	9.5	10.6	9.5	10.6	9.5
R^2	0.074	0.080	0.055	0.072	0.023	0.031	0.010	0.006

This table reports slope coefficients from regression estimates of variations to equation (12) where the outcome variable takes the form of an employment indicator. In columns (1)–(2), the outcome variable is an indicator for whether the worker no longer has the same main employer in year $t+h$ as in year t. In columns (3)–(4), the outcome variable is an indicator for having at least one quarter with zero earnings. In columns (5)–(6), the outcome variable is an indicator for having earnings growth in the bottom 10th percentile of the unconditional distribution interacted by an indicator for moving. In columns (7)–(8), the outcome variable is an indicator for having earnings growth in the bottom 10th percentile of the unconditional distribution interacted by an indicator for staying. Cashflow news is measured by the annual change in estimated firm total factor productivity (TFP) from İmrohoroğlu and Tüzel (2014). Discount rate is measured as the employer market beta interacted by aggregate discount rate news. The treatment variables are interacted by income bin indicators that are constructed by sorting workers based on income within their own 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 the employer beta and lagged market return interacted by income group dummies. The sample is a 5% subsample of all U.S. workers in the LEHD that are employed by public companies. The sample period is 1992–2019. Standard errors are double clustered by employer and year and are displayed in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A.14: Summary Statistics for Public Firms in Maturing Debt Sample

	All Compustat Firms					Matched Firms				
Variable	N	Avg	SD	p10	p90	N	Avg	SD	p10	p90
TFP Growth	4,700	-0.106	0.209	-0.278	0.099	3,400	-0.121	0.202	-0.264	0.071
$DDA_{07}(2)$	3,500	0.021	0.029	0	0.053	2,600	0.019	0.029	0	0.048
$DDA_{06}(3)$	3,400	0.021	0.03	0	0.052	2,600	0.020	0.031	0	0.049
$DDA_{05}(4)$	3,300	0.02	0.035	0	0.045	2,600	0.020	0.037	0	0.044
$DDA_{04}(5)$	3,100	0.023	0.041	0	0.053	2,400	0.024	0.044	0	0.058
$\frac{\text{Debt}}{\text{Assets}}$	4,600	0.254	0.172	0.044	0.45	3,400	0.255	0.184	0.038	0.474
$\frac{\text{Cash}}{\text{Assets}}$	4,700	0.097	0.1	0.013	0.219	3,400	0.093	0.101	0.012	0.221
Profitability	4,500	0.169	0.091	0.081	0.285	3,400	0.165	0.089	0.077	0.282
Log assets	4,700	23.15	1.67	20.78	25.05	3,400	22.78	1.71	20.49	25.05
Log employment	4,700	10.84	1.36	8.89	12.09	3,400	10.73	1.42	8.72	12.09
Asset maturity	4,600	14.62	7.03	7.37	22.44	3,400	14.07	6.36	7.14	21.11
$\frac{\text{Investment}}{\text{Capital}}$	4,500	0.075	0.059	0.021	0.139	3,400	0.069	0.058	0.019	0.123

This table summarizes Compustat firm-level variables in our sample of public firms around the Great Recession. On the left, we summarize all firms in Compustat that meet our sample selection criteria. On the right, we summarize the firms that are matched to payroll information that we construct from individual worker tax records. TFP growth is from İmrohoroğlu and Tüzel (2014) and is measured from 2007 to 2009. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The remaining firm variables are measured as of 2007.

Table A.15: Maturing Debt in Great Recession and Compustat Firm Outcomes over Two-Year Horizon

	Employment Growth$_{j,07:09}$				$\frac{\text{Change in LT Debt}_{j,07:09}}{\text{Assets}_{j,07}}$		Asset Growth$_{j,07:09}$	
	$DDA_{07}(2)$	$DDA_{06}(3)$	$DDA_{05}(4)$	$DDA_{04}(5)$	$DDA_{05}(4)$	$DDA_{04}(5)$	$DDA_{05}(4)$	$DDA_{04}(5)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP Growth	0.083***	0.076**	0.054*	0.055	0.020	0.007	0.147***	0.133***
	(0.031)	(0.033)	(0.031)	(0.035)	(0.029)	(0.029)	(0.050)	(0.051)
$\frac{\text{Debt due}}{\text{Assets}}$	−0.389	0.003	−0.605***	−0.472***	−0.264**	−0.158*	−0.565***	−0.278*
	(0.291)	(0.229)	(0.194)	(0.165)	(0.114)	(0.087)	(0.214)	(0.162)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,900	2,900	2,800	2,600	2,900	2,700	2,900	2,700
R^2	0.395	0.381	0.471	0.413	0.34	0.33	0.442	0.418

This table reports slope coefficients from regression estimates of equation (A.8) for different versions of the treatment variable and for different Compustat firm outcomes as the dependent variables. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.16: Maturing Debt in Great Recession and Firm Employment Outcomes

	Employment Growth$_{j,07:07+h}$				Payroll per Worker Growth$_{j,07:07+h}$			
	$DDA_{05}(4)$		$DDA_{04}(5)$		$DDA_{05}(4)$		$DDA_{04}(5)$	
	$h = 2$	$h = 5$	$h = 2$	$h = 5$	$h = 2$	$h = 5$	$h = 2$	$h = 5$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP Growth	0.076***	0.152***	0.090***	0.157**	0.105***	0.119***	0.109***	0.129***
	(0.025)	(0.058)	(0.026)	(0.062)	(0.019)	(0.038)	(0.021)	(0.041)
$\frac{\text{Debt due}}{\text{Assets}}$	−0.310*	−0.980***	−0.275*	−0.548**	−0.113	0.061	−0.041	0.110
	(0.161)	(0.251)	(0.141)	(0.241)	(0.130)	(0.137)	(0.093)	(0.126)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,000	1,500	1,900	1,400	2,000	1,400	1,900	1,400
R^2	0.582	0.497	0.556	0.485	0.536	0.423	0.530	0.442

This table reports slope coefficients from regression estimates of equation (A.8) for different versions of the treatment variable and for different horizons h. The dependent variable is either growth in the number of firm employees with positive earnings over the year (columns 1–4) or growth is payroll per worker (payroll growth minus employment growth, columns 5–8). $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The payroll data are constructed by aggregating the tax records of all public firm employees at the firm level. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.17: Maturing Debt in Great Recession and Individual Labor Income Growth – Extended Controls

Income Growth $g_{i,07:07+h}$	$DDA_{07}(2)$		$DDA_{06}(3)$		$DDA_{05}(4)$		$DDA_{04}(5)$	
	$h=3$ (1)	$h=5$ (2)	$h=3$ (3)	$h=5$ (4)	$h=3$ (5)	$h=5$ (6)	$h=3$ (7)	$h=5$ (8)
TFP Growth ×	-0.017	-0.015	-0.027	-0.027	-0.040	-0.044	-0.044	-0.049
Income Rank $[0, 25]$	(0.045)	(0.047)	(0.044)	(0.046)	(0.049)	(0.051)	(0.051)	(0.053)
TFP Growth ×	0.023	0.039^{*}	0.010	0.023	0.003	0.013	0.004	0.015
Income Rank $[25, 50]$	(0.021)	(0.020)	(0.019)	(0.019)	(0.021)	(0.019)	(0.023)	(0.021)
TFP Growth ×	0.028	0.045^{**}	0.019	0.034^{*}	0.016	0.028	0.018	0.031
Income Rank $[50, 75]$	(0.019)	(0.019)	(0.018)	(0.018)	(0.021)	(0.019)	(0.022)	(0.020)
TFP Growth ×	0.037^{**}	0.052^{***}	0.033^{**}	0.046^{***}	0.032^{*}	0.043^{**}	0.033^{*}	0.046^{**}
Income Rank $[75, 95]$	(0.017)	(0.017)	(0.016)	(0.016)	(0.018)	(0.018)	(0.019)	(0.019)
TFP Growth ×	0.108^{***}	0.120^{***}	0.107^{***}	0.117^{***}	0.110^{***}	0.117^{***}	0.110^{***}	0.118^{***}
Income Rank $[95, 100]$	(0.025)	(0.026)	(0.024)	(0.025)	(0.027)	(0.028)	(0.028)	(0.029)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	-0.486^{***}	-0.507^{***}	-0.331^{***}	-0.342^{***}	-0.268^{***}	-0.276^{***}	-0.127^{**}	-0.123^{**}
Income Rank $[0, 25]$	(0.182)	(0.195)	(0.118)	(0.127)	(0.079)	(0.084)	(0.059)	(0.063)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	-0.178^{*}	-0.138	-0.132^{*}	-0.090	-0.141^{**}	-0.110	-0.098^{*}	-0.073
Income Rank $[25, 50]$	(0.103)	(0.110)	(0.077)	(0.085)	(0.064)	(0.069)	(0.052)	(0.055)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	-0.162^{*}	-0.127	-0.094	-0.055	-0.128^{**}	-0.091	-0.095^{*}	-0.058
Income Rank $[50, 75]$	(0.092)	(0.094)	(0.072)	(0.073)	(0.058)	(0.062)	(0.052)	(0.055)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	-0.076	-0.028	-0.089	-0.045	-0.120^{**}	-0.100^{*}	-0.090^{**}	-0.089^{*}
Income Rank $[75, 95]$	(0.084)	(0.088)	(0.068)	(0.070)	(0.054)	(0.058)	(0.046)	(0.048)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	0.072	0.128	-0.150	-0.065	0.015	-0.006	-0.072	-0.096
Income Rank $[95, 100]$	(0.130)	(0.132)	(0.121)	(0.113)	(0.084)	(0.084)	(0.073)	(0.070)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N $(\times 10^6)$	14.9	14.9	14.8	14.8	14.3	14.3	14.5	14.5
R^2	0.037	0.045	0.036	0.044	0.037	0.045	0.036	0.045

This table reports slope coefficients from regression estimates of equation (A.9) for different versions of the treatment variable. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The firm controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The worker controls include a third-order polynomial in the log of average income over the past three years and a complete set of age dummies. All firm controls are also interacted by worker income bin dummies. The sample consists of the tax records of all public firm employees. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.18: Maturing Debt in Great Recession and Individual Labor Income Growth – Without TFP

Income Growth $g_{i,07:07+h}$	$DDA_{07}(2)$		$DDA_{06}(3)$		$DDA_{05}(4)$		$DDA_{04}(5)$	
	$h=3$ (1)	$h=5$ (2)	$h=3$ (3)	$h=5$ (4)	$h=3$ (5)	$h=5$ (6)	$h=3$ (7)	$h=5$ (8)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.506^{**}	-0.534^{**}	-0.374^{**}	-0.396^{**}	-0.260^{***}	-0.268^{***}	-0.130^{**}	-0.133^{**}
Income Rank $[0, 25]$	(0.211)	(0.225)	(0.150)	(0.162)	(0.080)	(0.086)	(0.063)	(0.067)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.176^{*}	-0.128	-0.128^{*}	-0.076	-0.150^{**}	-0.118^{*}	-0.098^{*}	-0.070
Income Rank $[25, 50]$	(0.098)	(0.103)	(0.074)	(0.081)	(0.061)	(0.065)	(0.050)	(0.053)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.143^{*}	-0.094	-0.081	-0.030	-0.136^{**}	-0.097^{*}	-0.097^{*}	-0.057
Income Rank $[50, 75]$	(0.086)	(0.087)	(0.069)	(0.070)	(0.055)	(0.059)	(0.050)	(0.053)
$\frac{\text{Debt due}}{\text{Assets}} \times$	-0.036	0.023	-0.054	-0.003	-0.110^{**}	-0.090	-0.088^{*}	-0.078
Income Rank $[75, 95]$	(0.076)	(0.080)	(0.063)	(0.068)	(0.054)	(0.058)	(0.046)	(0.049)
$\frac{\text{Debt due}}{\text{Assets}} \times$	0.108	0.161	-0.094	-0.024	0.027	-0.003	-0.031	-0.059
Income Rank $[95, 100]$	(0.105)	(0.110)	(0.117)	(0.114)	(0.076)	(0.082)	(0.081)	(0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N ($\times 10^6$)	14.9	14.9	14.8	14.8	14.3	14.3	14.5	14.5
R^2	0.037	0.045	0.036	0.044	0.037	0.045	0.036	0.044

This table reports slope coefficients from regression estimates of equation (A.9) for different versions of the treatment variable. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The firm controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The worker controls include a third-order polynomial in the log of average income over the past three years and a complete set of age dummies. The sample consists of the tax records of all public firm employees. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.19: Maturing Debt in Great Recession and Individual Employment Indicators

Employment Indicator$_{i,07:07+h}$	Probability of Move				Probability of Tail Loss			
	$DDA_{05}(4)$		$DDA_{04}(5)$		$DDA_{05}(4)$		$DDA_{04}(5)$	
	$h=3$ (1)	$h=5$ (2)	$h=3$ (3)	$h=5$ (4)	$h=3$ (5)	$h=5$ (6)	$h=3$ (7)	$h=5$ (8)
TFP Growth ×	−0.006	−0.021	−0.002	−0.018	0.009	0.006	0.010	0.007
Income Rank $[0, 25]$	(0.019)	(0.020)	(0.019)	(0.021)	(0.010)	(0.010)	(0.010)	(0.010)
TFP Growth ×	−0.018	−0.028	−0.012	−0.022	0.006	0.002	0.006	0.002
Income Rank $[25, 50]$	(0.019)	(0.020)	(0.020)	(0.021)	(0.007)	(0.006)	(0.008)	(0.007)
TFP Growth ×	−0.019	−0.030	−0.012	−0.024	0.003	−0.001	0.004	−0.002
Income Rank $[50, 75]$	(0.020)	(0.022)	(0.021)	(0.023)	(0.007)	(0.006)	(0.008)	(0.006)
TFP Growth ×	−0.019	-0.039^{*}	−0.010	−0.030	0.001	−0.002	0.001	−0.002
Income Rank $[75, 95]$	(0.020)	(0.023)	(0.021)	(0.024)	(0.005)	(0.004)	(0.005)	(0.005)
TFP Growth ×	-0.035^{**}	-0.058^{**}	-0.029^{*}	-0.056^{**}	-0.015^{**}	-0.016^{**}	-0.013^{**}	-0.015^{**}
Income Rank $[95, 100]$	(0.017)	(0.024)	(0.018)	(0.025)	(0.006)	(0.007)	(0.006)	(0.007)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	−0.058	−0.020	−0.059	−0.146	0.098^{***}	0.085^{***}	0.041	0.038
Income Rank $[0, 25]$	(0.093)	(0.104)	(0.093)	(0.095)	(0.031)	(0.027)	(0.025)	(0.024)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	-0.153^{*}	−0.151	−0.066	−0.150	0.061^{**}	0.040^{*}	0.024	0.019
Income Rank $[25, 50]$	(0.085)	(0.102)	(0.086)	(0.094)	(0.025)	(0.023)	(0.019)	(0.018)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	-0.177^{**}	−0.170	−0.081	−0.159	0.050^{**}	0.018	0.008	−0.001
Income Rank $[50, 75]$	(0.079)	(0.108)	(0.081)	(0.097)	(0.022)	(0.019)	(0.017)	(0.017)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	−0.107	−0.062	−0.057	−0.124	0.015	−0.002	−0.007	−0.009
Income Rank $[75, 95]$	(0.085)	(0.118)	(0.080)	(0.099)	(0.017)	(0.015)	(0.015)	(0.014)
$\frac{\text{Debt due}}{\text{Assets}}$ ×	0.015	0.118	−0.031	−0.081	−0.013	0.001	−0.015	−0.001
Income Rank $[95, 100]$	(0.112)	(0.152)	(0.097)	(0.118)	(0.026)	(0.024)	(0.023)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS4 × Income bin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N ($\times 10^6$)	14.3	14.3	14.5	14.5	14.3	14.3	14.5	14.5
R^2	0.093	0.101	0.091	0.096	0.031	0.035	0.030	0.034

This table reports slope coefficients from regression estimates of variations to equation (A.9) where the outcome variable takes the form of an employment indicator, for different versions of the treatment variable and different horizons. In columns (1)–(4), the outcome variable is an indicator for whether the worker no longer has the same main employer in year $t+h$ as in year t. In columns (5)–(8), the outcome variable is an indicator for having earnings growth in the bottom 10th percentile of the unconditional distribution. $DDA_{j,09}(y)$ refers to the treatment variable defined in equation (A.7): the amount of maturing debt in 2009 relative to book assets, measured y years before maturity. The firm controls include the firm's leverage ratio (also measured at $2009 - y$), as well as liquidity, profitability, book assets (in logs), prior employment (in logs), and asset maturity, all measured in 2007. The worker controls include a third-order polynomial in the log of average income over the past three years and a complete set of age dummies. The sample consists of the tax records of all public firm employees. The base year for the analysis is 2007. Standard errors are clustered by employer and are displayed in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.