Idiosyncratic Income Risk, Precautionary Saving, and Asset Prices

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Abstract

Households face large, imperfectly insured labor income tail risk that rises in recessions. I develop a New Keynesian asset pricing model in which higher tail risk strengthens the precautionary saving motive of households, lowering aggregate demand and firm cash flows, especially for firms facing more elastic demand. The model generates a substantial, time-varying equity premium and a premium for high-elasticity firms. The data support these predictions quantitatively. Firms with lower markups earn higher average returns and are more exposed to income risk. This exposure is priced, and income risk predicts future stock returns, especially for low-markup firms.

Keywords: idiosyncratic income risk; precautionary saving; aggregate demand; equity premium; return predictability

JEL Classification: G12, E21, E32, E44, D52

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Households face substantial idiosyncratic risk in their labor income. Events such as job displacement lead to large and persistent earnings losses (Davis and von Wachter, 2011), and households can insure only part of such shocks (Blundell, Pistaferri, and Preston, 2008). Moreover, this risk varies over the business cycle. Using administrative data, Guvenen, Ozkan, and Song (2014) show that while the variance of earnings growth rates remains stable over time, their skewness becomes substantially more negative in recessions: large income losses become more likely precisely in times of economic distress. Fluctuations in this tail risk can therefore have a large effect on how much households want to consume and save.

In this paper, I study time-varying idiosyncratic income risk as a source of aggregate demand risk that is priced in equity markets. A growing literature shows that demand risk matters for asset prices. Asset prices are highly sensitive to monetary policy (Bernanke and Kuttner, 2005), and in the cross section, firms that are more exposed to demand shocks earn higher average returns, such as firms with stickier prices (Weber, 2015) and firms facing more elastic demand (Clara, 2023). What drives these fluctuations in demand, however, remains an open question. I develop a New Keynesian general equilibrium asset pricing model in which fluctuations in income tail risk generate a strong, time-varying precautionary saving motive for households who cannot insure against this risk: when tail risk rises, aggregate demand and firm cash flows fall. With realistic macroeconomic dynamics, this channel generates a substantial and time-varying equity premium, as well as a return premium for firms facing more elastic demand. The data support these predictions. Firms with lower markups, which reflect more elastic demand, earn higher average returns, and their cash flows and returns are more exposed to fluctuations in income risk. This exposure is priced, and the level of income risk predicts future returns, especially those of low-markup firms.

The model builds on the standard New Keynesian framework and features heterogeneous households and heterogeneous firms. Asset markets are segmented. Stockholders own the firms, share idiosyncratic risks among themselves, and price all equity claims. Non-stockholders face uninsurable, countercyclical tail risk in their permanent labor income and can trade only a nominal risk-free bond in zero net supply. In equilibrium, they consume their labor income each period. The process for idiosyncratic income risk is estimated directly from the distribution of individual

earnings growth rates in administrative data (Guvenen et al., 2014). About 30% of these permanent earnings shocks pass through to the consumption of non-stockholders, in line with the estimates of Blundell et al. (2008). Firms in multiple sectors set prices subject to nominal rigidities and differ in the elasticity of demand for their goods, and nominal wages are sticky.

The central mechanism operates through aggregate demand. When income tail risk rises, non-stockholders have a stronger precautionary saving motive: they want to save more to insure themselves against large and persistent income losses. Because they cannot save more in the aggregate, aggregate demand falls instead. Fluctuations in income risk thus act as household discount factor shocks disciplined by measured income risk. With nominal rigidities, the fall in demand reduces output, and because sticky wages keep labor costs high, dividends fall by about three times as much as consumption. Stockholders are therefore exposed to income risk even though they are fully insured against it themselves. What matters for asset prices is that the marginal *consumer* bears idiosyncratic tail risk, not that the marginal *investor* does.

The model has three main implications. First, fluctuations in income risk generate a substantial equity premium. Because equity ownership is concentrated, stockholder consumption falls by more than that of non-stockholders when income risk rises, precisely when stock prices fall. In the baseline calibration, the equity premium is 6.7% per year, compared with 3.5% in the absence of income risk shocks, and the Sharpe ratio of the aggregate stock market rises from 0.20 to 0.34.

Second, firms facing more elastic demand are more exposed to income risk and earn a premium of 3.3% per year over firms facing less elastic demand. When demand falls, firms that cannot adjust their prices are left with prices that differ from those of competitors that can. This price dispersion raises the cost of production, more so in sectors where goods are close substitutes. The spread is almost entirely a premium for income risk: it falls to 0.2% in the absence of income risk shocks, and to zero when prices are flexible.

Third, the level of income risk predicts stock returns, especially for firms facing more elastic demand. A one-standard-deviation increase in income risk raises the expected excess return over the next year by 6.0 percentage points for the aggregate stock market, and by 5.4 and 11.5 percentage points for the low- and high-elasticity sectors. This predictability arises even though shocks to

income risk are homoskedastic. Because marginal utility is convex and income risk shifts the tails of the income distribution, the precautionary saving motive is convex in the level of income risk, so that demand shocks have endogenously countercyclical volatility.[1]

Taken together, these results show that empirically measured income risk is a quantitatively meaningful source of aggregate demand shocks in a New Keynesian model. The source of demand shocks in such models is often unclear. Monetary policy shocks would need to be more than an order of magnitude larger than measured monetary policy surprises to generate the volatility of stock returns in the model, and exogenous discount factor shocks (e.g., Smets and Wouters, 2007) are not directly observed. Fluctuations in income risk instead generate demand shocks of a plausible size from a process estimated from micro data, and because their effects are convex, they generate time-varying risk premia under standard preferences and homoskedastic shocks.

To test the predictions of the model directly in the data, I use two time-series measures of income tail risk. The first is a quarterly measure of time-varying skewness in permanent income growth rates, estimated from the earnings statistics reported by Guvenen et al. (2014) using the mixed-frequency approach of McKay (2017); the same measure governs income risk in the model. The second is the rate of initial claims for unemployment insurance, which Schmidt (2025) shows to be a proxy for labor market tail risk, and which is available in real time and at a monthly frequency.

To measure firm exposure to income risk, I use the tight link between demand elasticities and markups in the model: firms facing more elastic demand set lower markups. I measure markups from firms' profit margins, a special case of the production approach to markup estimation (De Loecker and Warzynski, 2012; De Loecker, Eeckhout, and Unger, 2020). This measure uses only past accounting data, so that it is available to investors when portfolios are formed. I sort firms into quintile portfolios by their average markup over the past five years. As an alternative measure of exposure, I use the durability of firms' output (Gomes, Kogan, and Yogo, 2009).

Consistent with the model, firms with low markups earn higher average returns and are more exposed to income risk. An elastic-minus-inelastic (EMI) portfolio that is long the quintile of firms

[1] In contrast, in endowment economies in which the marginal investor bears countercyclical idiosyncratic risk, return predictability requires time variation in the uncertainty about future idiosyncratic risk, that is, in higher-order moments of individual income growth rates (Constantinides and Ghosh, 2017; Schmidt, 2025).

with the lowest markups and short the quintile with the highest markups earns 3.9% per year, close to the spread of 3.3% in the model. Returns on all portfolios fall when income risk rises, and more so for firms with lower markups. The return spread is similar for value-weighted portfolios and within industries, and it holds in firm-level regressions that control for other characteristics associated with average returns. Similarly, producers of durable goods earn higher average returns than producers of services, and their returns are more exposed to income risk.

Cross-sectional asset pricing tests show that these differences in exposure are priced. First, using the EMI portfolio as a traded factor that captures demand risk, I find a positive and significant price of risk. It remains significant when controlling for the market, which becomes insignificant, and when adding the Fama–French factors and expanding the test assets to include the durability portfolios and the 25 Fama–French size and book-to-market portfolios. Second, with non-traded factors, exposures to changes in both measures of income risk carry significant prices of risk and explain nearly all of the variation in average returns across the markup-sorted portfolios. Other macroeconomic factors such as industrial production growth, consumption growth, and utilization-adjusted TFP growth do not price these portfolios, suggesting that the results do not merely reflect general differences in business cycle exposure.

In the model, these risk premia arise because the cash flows of high-elasticity firms are more exposed to the demand shocks generated by income risk. I test this cash flow channel directly. Consistent with the model, operating income and dividends fall when income risk rises, and these exposures are about three times as large for the lowest-markup firms as for the highest-markup firms. The operating income of durable-good producers is similarly much more exposed to income risk than that of producers of services and nondurables.

Finally, the level of income risk predicts stock returns. Schmidt (2025) shows that initial claims predict the return on the aggregate stock market, consistent with the model. I show that this predictability is strongly heterogeneous across firms and increases monotonically as markups decrease. A one-standard-deviation increase in initial claims is associated with a 6.4 percentage point higher return over the next year for the highest-markup quintile, compared with 12.7 percentage points for the lowest-markup quintile, close to the corresponding magnitudes of

5.4 and 11.5 percentage points in the model. Income risk therefore also predicts the EMI return, and this predictability is robust to controlling for standard predictors of stock returns and other macroeconomic indicators. Consistent with the mechanism in the model, higher income risk also predicts larger absolute returns and cash flow growth in the data, especially for low-markup firms and producers of durable goods.

Literature

This paper relates to several literatures in macroeconomics and finance. First, it contributes to the literature on asset pricing in production economies with nominal rigidities. Uhlig (2007) and Favilukis and Lin (2016) show that wage rigidities help production-based models explain asset pricing facts, and Li and Palomino (2014), Kung (2015), Campbell, Pflueger, and Viceira (2020), and Pflueger and Rinaldi (2022) study asset prices in New Keynesian models. Kekre and Lenel (2022) show that monetary policy affects risk premia by redistributing wealth across households with different risk tolerance. In these models, fluctuations in aggregate demand are driven by monetary policy shocks or by exogenous preference shocks (see also Albuquerque, Eichenbaum, Luo, and Rebelo, 2016). Empirically, however, stocks that are more exposed to monetary policy earn lower rather than higher average returns (Ozdagli and Velikov, 2020), consistent with a stabilizing role of monetary policy. I propose fluctuations in idiosyncratic income risk as an empirically disciplined source of priced demand risk.

Second, the paper relates to research on how firms' product markets shape the cross section of stock returns. Weber (2015) shows that firms with stickier prices earn higher average returns, and Clara (2023) uses Amazon product data to show that firms facing more elastic demand have lower markups and earn higher average returns. I measure demand elasticities based on average markups, which are available for a broad cross section of firms over a long sample, and show that the return premium of low-markup firms compensates for the exposure of their cash flows to income risk. A related literature studies product market competition and expected returns at the industry level, with mixed findings. Hou and Robinson (2006) find that firms in more concentrated industries earn lower returns. In contrast, Bustamante and Donangelo (2017) find that more competitive industries earn lower returns, because the threat of entry lowers the systematic

risk of incumbents, and Corhay, Kung, and Schmid (2020) find that industries with higher markups earn higher returns, because markups in concentrated industries are more exposed to entry risk. Unlike these industry-level studies, I focus on firm-level markups, and the return spread between low-markup and high-markup firms also holds within industries. Gomes et al. (2009) show that producers of durable goods earn higher returns because their cash flows are more cyclical; I show that these cash flows are particularly exposed to income risk.

Third, this paper builds on a literature in macroeconomics on the aggregate demand effects of uninsurable idiosyncratic risk. In incomplete-markets models with nominal rigidities, a stronger precautionary saving motive lowers aggregate demand.[2] Most of this literature focuses on relatively short-lived unemployment risk (see, e.g., Krueger, Mitman, and Perri, 2016), against which many households can self-insure. McKay (2017) instead estimates an income process with persistent shocks that matches administrative data and shows that fluctuations in this risk have large effects on aggregate consumption, and Berger, Dew-Becker, Schmidt, and Takahashi (2019) find substantial welfare benefits when monetary policy targets income tail risk. As in the zero-liquidity economies of Werning (2015), Ravn and Sterk (2017), and Challe (2020), the households who bear income risk in my model cannot save in the aggregate. I study the asset pricing implications of this channel and use asset prices to test it.

Fourth, the paper contributes to the literature on the asset pricing implications of uninsurable idiosyncratic risk (Mankiw, 1986; Constantinides and Duffie, 1996; Heaton and Lucas, 1996). Recent work quantifies this channel using micro data on income and consumption (Constantinides and Ghosh, 2017; Schmidt, 2025), derives uninsurable tail risk in labor earnings from optimal contracts between firms and workers (Ai and Bhandari, 2021), and relates household income risk to the common factor in firms' idiosyncratic volatility (Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2016). In these models, the marginal investor faces uninsurable countercyclical idiosyncratic risk, but a common critique is that the investors who price financial assets may not bear much of this risk. In my model, stockholders are fully insured, and income risk instead affects asset prices through the precautionary saving motive of non-stockholders and its effect on firm cash flows. This channel

[2]See, for example, Werning (2015), Challe and Ragot (2016), Ravn and Sterk (2017), Den Haan, Rendahl, and Riegler (2018), Bayer, Lütticke, Pham-Dao, and Tjaden (2019), and Challe (2020).

generates new predictions for the cross section of returns, and it implies return predictability without time variation in the uncertainty about future idiosyncratic risk.

Fifth, the model builds on asset pricing models with limited stock market participation (Basak and Cuoco, 1998; Gomes and Michaelides, 2008; Guvenen, 2009; Favilukis, 2013). Consistent with the evidence that stockholder consumption is more volatile and more correlated with stock returns than non-stockholder consumption (Mankiw and Zeldes, 1991; Attanasio, Banks, and Tanner, 2002; Vissing-Jørgensen, 2002; Aït-Sahalia, Parker, and Yogo, 2004), stockholder consumption in the model is 1.6 times as volatile as non-stockholder consumption.

Finally, this paper relates to work that links asset prices to firms' production and labor markets. A large literature relates expected returns across firms to their investment and production decisions (Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003) and to their labor leverage (Donangelo, Gourio, Kehrig, and Palacios, 2019). Conversely, fluctuations in discount rates can account for the volatility of unemployment (Hall, 2017; Kilic and Wachter, 2018; Kehoe, Lopez, Midrigan, and Pastorino, 2023), disproportionately affect lower-paid workers (Meeuwis, Papanikolaou, Rothbaum, and Schmidt, 2025), and erode the insurance that firms provide to workers, which generates countercyclical tail risk in earnings (Meeuwis, Papanikolaou, and Schmidt, 2026). Combined with the mechanism in this paper, these results suggest a feedback loop: higher risk premia raise labor income risk, which in turn lowers aggregate demand and raises risk premia.

1 Fluctuations in Idiosyncratic Labor Income Risk

Administrative data on labor earnings show that households are subject to substantial idiosyncratic tail risk, and that the amount of this risk fluctuates over the business cycle. Guvenen et al. (2014) report statistics on the cross-sectional distribution of annual labor income growth rates for millions of male U.S. workers in Social Security Administration records. While the cross-sectional standard deviation of income growth rates—controlling for life-cycle effects—is nearly acyclical, the skewness of income growth rates is highly procyclical: in recessions, the left tail of the distribution fattens and the right tail compresses, while the center of the distribution remains stable. Large income

losses are not only more likely in recessions but also highly persistent, which makes them difficult to self-insure against.

To capture macroeconomic variation in the amount of idiosyncratic labor income risk that workers face, I construct two time series. The first measure, x_t, is estimated directly from the statistics on the distribution of individual income growth rates reported by Guvenen et al. (2014). I specify a process for individual labor income in which permanent shocks are drawn from a mixture distribution whose tails shift with x_t, generating time variation in the skewness of income growth rates. Following the mixed-frequency approach of McKay (2017), I specify the income process at a quarterly frequency, aggregate simulated earnings to annual observations, and choose the parameters to match the year-by-year median, 10th percentile, and 90th percentile of the empirical distribution of 1-year, 3-year, and 5-year income growth rates. Appendix A describes the details of the income process and the simulated method of moments procedure.

To trace out the path of income risk over time, I assume that x_t is a linear combination of four quarterly labor market indicators: the share of the labor force unemployed for fewer than 15 weeks, the share of the labor force unemployed for 15 weeks or more, average weekly hours, and initial claims for unemployment as a fraction of lagged private payroll employment. The factor loadings for x_t are estimated along with the other parameters of the income process. Because the indicators are available over a longer period than the earnings moments, which cover 1978–2011, the fitted series for x_t extends from 1967 through 2019.[3] The resulting path for x_t is plotted as the solid line in Figure 1. Consistent with the finding of Guvenen et al. (2014) that negative skewness in income growth rates is countercyclical, the income tail risk measure peaks in recessions.

As a second measure of cyclical income tail risk, I use initial claims for unemployment insurance on its own. The claims measure icl_t is defined as the number of initial claims filed relative to lagged private payroll employment, so that it captures the rate of involuntary job loss in the U.S. private sector. Schmidt (2025) shows that this job loss rate comoves closely with the tails of the distribution of labor earnings growth rates and serves as a timely proxy for labor market risk. I remove a low-frequency trend from the initial claims measure and normalize it to have the same mean and

[3] I end the sample in 2019 to exclude the COVID-19 pandemic, when government interventions broke the historical link between labor market indicators and idiosyncratic income risk.

standard deviation as x_t.[4] The advantage of icl_t over x_t, which is extracted from the distribution of individual income growth rates, is that initial claims are available in real time and at a higher frequency. The dashed line of Figure 1 plots the resulting quarterly series for icl_t. The two measures move closely together: the quarterly correlation between x_t and icl_t is 0.76.[5]

2 New Keynesian Asset Pricing Model

This section sets up a tractable New Keynesian general equilibrium model with heterogeneous households, who face time-varying idiosyncratic income risk, and heterogeneous firms, which differ in their demand elasticities. Appendix B provides further details and derivations.

2.1 Households

The economy is populated by a continuum of agents of two types, $\nu \in \{s, n\}$: stockholders in the subset $\mathcal{I}_s$ and non-stockholders in $\mathcal{I}_n$. Population shares are constant, and the total population is normalized to unity, so stockholders and non-stockholders have measures δ_s and δ_n with $\delta_s + \delta_n = 1$. Both types supply labor, consume a composite of differentiated goods, and have preferences that are additively separable in consumption and labor.

Stockholders

Stockholders trade a complete set of state-contingent claims among themselves and are fully insured against idiosyncratic shocks. The representative stockholder in $\mathcal{I}_s$ solves

$$\max \quad \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_s^\tau \left[\frac{(C_{s,t+\tau} - H_{s,t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0,s} \int_0^1 \frac{L_{s,j,t+\tau}^{1+\chi_1}}{1+\chi_1} dj \right], \tag{1}$$

where $C_{s,t}$ is the stockholder's consumption of the composite good and $L_{s,j,t}$ is the labor of differentiated type j that the stockholder supplies. Preferences feature an external consumption habit $H_{s,t} =$

[4] The raw initial claims measure has a highly significant negative linear trend. To ensure that this trend does not drive the empirical results, I remove very low-frequency trends using a one-sided backward-looking HP filter with smoothing parameter 10^5. All empirical results hold without detrending.

[5] This strong correlation is not an artifact of including initial claims among the indicators underlying x_t: McKay (2017) constructs a comparable income risk series without using initial claims and reports a correlation with initial claims of 0.67.

$b_s C_{s,t-1}$ with strength b_s. The discount factor β_s also incorporates mortality risk, γ is relative risk aversion, $\chi_{0,s} > 0$ scales the disutility of labor, and χ_1 is the inverse Frisch elasticity of labor supply.

Non-Stockholders

Non-stockholders have preferences of the same form as stockholders, but they face idiosyncratic labor income risk that cannot be fully insured. Household $i \in \mathcal{I}_n$ solves

$$\max \quad \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_n^{\tau} \left[\frac{(c_{i,t+\tau} - h_{i,t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0,n} \Gamma_{i,t+\tau}^{1-\gamma} \int_0^1 \frac{l_{i,j,t+\tau}^{1+\chi_1}}{1+\chi_1} dj \right], \tag{2}$$

where $c_{i,t}$ and $l_{i,j,t}$ are the household's consumption of the composite good and hours of labor type j, respectively, and $h_{i,t} = b_n \Gamma_{i,t} C_{n,t-1}$ is an external habit, with $C_{n,t-1}$ aggregate per-capita non-stockholder consumption.

The idiosyncratic labor productivity of household i, $\Gamma_{i,t}$, is common across all labor types. A worker who supplies $l_{i,j,t}$ hours of type j thus delivers $n_{i,j,t} = \Gamma_{i,t} l_{i,j,t}$ efficiency units, paid per efficiency unit. Total labor income is the sum of worker earnings across labor types: $\int_0^1 W_{n,j,t} n_{i,j,t} dj$.[6] Note that the disutility of labor is scaled by $\Gamma_{i,t}^{1-\gamma}$, which offsets the wealth effect of idiosyncratic productivity on labor supply, and habit is scaled by $\Gamma_{i,t}$: reference points adapt to permanent changes in individual circumstances, while cyclical movements are evaluated against the recent past through $C_{n,t-1}$. The habit scaling keeps preferences well defined: given the substantial amount of idiosyncratic risk that workers face, consumption would with positive probability fall below any meaningful reference level that does not move one-for-one with $\Gamma_{i,t}$.[7] Under these assumptions, the non-stockholder's problem is homothetic in $\Gamma_{i,t}$, with individual consumption and labor income proportional to $\Gamma_{i,t}$ (see Section 2.2 and Appendix B.1). Therefore, $\Gamma_{i,t}$ directly captures the idiosyncratic income and consumption risk that a worker faces.

To account for households' partial insurance against empirically measured income shocks

[6] The literature on portfolio choice and asset pricing with idiosyncratic income risk generally treats individual labor income as exogenous. Here, labor income is endogenous in a general equilibrium production economy. Because labor supply is elastic and wages are sticky, hours are demand-determined, so that labor income responds to fluctuations in aggregate demand.

[7] An implication is that households evaluate idiosyncratic shocks with curvature γ, without habit amplification. If reference levels instead adjusted slowly to idiosyncratic shocks, the precautionary saving motive would be stronger and state-dependent, so the specification is conservative for the channel that the model emphasizes.

through channels outside the model, such as taxes and transfers or family support, I assume that transitory income shocks are fully insured, and non-stockholders bear a fraction ψ of permanent income shocks $\xi_{i,t+1}$. Idiosyncratic productivity $\Gamma_{i,t}$ in the model stands in for this uninsured component of labor income:

$$\Gamma_{i,t+1} = \Gamma_{i,t}\, e^{\psi\, \xi_{i,t+1}}. \tag{3}$$

The shock $\xi_{i,t+1}$ is a three-component mixture of ordinary shocks, large losses, and large gains, which generates tail risk in income as in the data:

$$\xi_{i,t+1} \sim \begin{cases} N(\mu_{1,t}, \sigma^2_{\xi,1}) & \text{with probability } 1 - p_2 - p_3 \\ N(\mu_{2,t}, \sigma^2_{\xi,2}) & \text{with probability } p_2 \\ N(\mu_{3,t}, \sigma^2_{\xi,3}) & \text{with probability } p_3. \end{cases} \tag{4}$$

The aggregate state x_t governs the amount of tail risk over time and follows an AR(1) process:

$$x_t = \rho_x\, x_{t-1} + \varepsilon_{x,t}, \quad \varepsilon_{x,t} \sim N(0, \sigma^2_x). \tag{5}$$

This variable shifts the conditional means of the three components of next period's permanent shock $\xi_{i,t+1}$,

$$\mu_{1,t} = \bar{\mu}_t \tag{6}$$

$$\mu_{2,t} = \bar{\mu}_t + \tilde{\mu}_2 - x_t \tag{7}$$

$$\mu_{3,t} = \bar{\mu}_t + \tilde{\mu}_3 - x_t \tag{8}$$

$$\bar{\mu}_t = -\frac{1}{\psi} \log\left((1 - p_2 - p_3)\, e^{\frac{1}{2}\psi^2 \sigma^2_{\xi,1}} + p_2\, e^{\psi(\tilde{\mu}_2 - x_t + \frac{1}{2}\psi\, \sigma^2_{\xi,2})} + p_3\, e^{\psi(\tilde{\mu}_3 - x_t + \frac{1}{2}\psi\, \sigma^2_{\xi,3})} \right). \tag{9}$$

A higher x_t lowers $\mu_{2,t}$ and $\mu_{3,t}$, increasing the negative skewness of individual income growth.

The time-varying intercept $\bar{\mu}_t$ ensures that the uninsured component has unit conditional mean, $\mathbb{E}\left[\Gamma_{i,t+1}/\Gamma_{i,t} \mid x_t\right] = 1$, so that shocks remain purely idiosyncratic given the aggregate state.[8]

Finally, I define two terms that summarize how idiosyncratic risk enters the equilibrium conditions:

$$g_{0,n}(x) \equiv \mathbb{E}[e^{-\gamma\,\psi\,\xi_{t+1}} \mid x_t = x] \tag{10}$$

$$g_{1,n}(x) \equiv \mathbb{E}[e^{(1-\gamma)\,\psi\,\xi_{t+1}} \mid x_t = x]. \tag{11}$$

These conditional expectations capture the precautionary motive that idiosyncratic risk creates.[9]

Consumption

Households consume a composite good C_t that is a nested Dixit-Stiglitz aggregate of differentiated goods produced within and across sectors. Let $C_t(k)$ denote the consumption basket of sector k. The composite good aggregates these baskets across sectors,

$$C_t = \left(\sum_k \omega_k^{\frac{1}{\eta_c}}\, C_t(k)^{\frac{\eta_c-1}{\eta_c}}\right)^{\frac{\eta_c}{\eta_c-1}}, \qquad \sum_k \omega_k = 1, \tag{12}$$

where ω_k is the expenditure weight of sector k and η_c is the elasticity of substitution across sectors. Each sector basket is in turn aggregated from a continuum of goods $C_t(k,f)$ produced by firms $f \in [0,1]$ in sector k,

$$C_t(k) = \left(\int_0^1 C_t(k,f)^{\frac{\eta_{c,k}-1}{\eta_{c,k}}}\, df\right)^{\frac{\eta_{c,k}}{\eta_{c,k}-1}}, \tag{13}$$

where $\eta_{c,k}$ is the elasticity of substitution across goods within sector k, and hence the demand elasticity faced by each firm in that sector. I assume $\eta_c \leq \eta_{c,k}$, so that goods are closer substitutes within a sector than across sectors. The aggregate and sector price indices P_t and $P_{k,t}$ are the cost-minimizing CES duals of these aggregators (Appendix B.2).

[8] Households face constant mortality risk, embedded in the time discount factor β_ν. A worker who dies is replaced by a newborn of the same type with initial productivity $\Gamma = 1$, which keeps the cross-sectional distribution of $\Gamma_{i,t}$ stationary and its mean equal to one.

[9] Stockholders face no idiosyncratic risk, so for completeness I define $\Gamma_{i,t} \equiv 1$ for $i \in \mathcal{I}_s$ and $g_{0,s} \equiv g_{1,s} \equiv 1$.

Asset Markets

Asset markets are fully segmented. Stockholders own equity in all firms and collect their dividends each period, and they trade a complete set of state-contingent claims among themselves. Non-stockholders are excluded from these markets: they can only trade a one-period risk-free nominal bond, which is in zero net supply and whose price is set by the monetary authority.

I impose full segmentation both to isolate the idiosyncratic risk channel and to keep the model tractable. Because the bond is in zero net supply, non-stockholders hold no assets in equilibrium and consume their labor income each period, so the wealth distribution is degenerate. Allowing the two groups to trade would make the entire wealth distribution a state variable and render the model intractable.

Limited participation is empirically realistic: according to the Survey of Consumer Finances (SCF), only about half of U.S. households own stocks. Full segmentation goes further by ruling out any risk sharing across agent types, but it is a reasonable approximation. Many stockholders themselves face time-varying idiosyncratic risk that cannot be fully shared through financial markets: Guvenen, Schulhofer-Wohl, Song, and Yogo (2017) find that cyclical income risk is highest at both the bottom *and the top* of the income distribution. In a model in which only non-stockholders have a precautionary motive, allowing stockholders to borrow would therefore imply a counterfactual flow of resources from non-stockholders to stockholders in recessions. For simplicity, I also assume that stockholders cannot save at the nominal risk-free rate, so that non-stockholders are always the marginal investors in the bond.[10]

2.2 Labor Market

I follow Erceg, Henderson, and Levin (2000) in modeling the labor market. Production uses a homogeneous labor bundle N_t, which firms hire in a single labor market at the aggregate wage rate W_t. A competitive labor aggregator assembles this bundle from differentiated labor services, so that wage rigidities at the level of individual labor types translate into stickiness of the aggregate wage.

[10]The implications of the model would be similar if stockholders could also save at the nominal risk-free rate. Because of their strong precautionary saving motive, non-stockholders value safe future payoffs more than stockholders do in bad times. They are therefore the natural savers, and if stockholders cannot borrow, non-stockholders would remain the marginal investors in the bond at those times.

Labor is differentiated along two dimensions. First, aggregate labor N_t is a CES aggregate of composite labor $N_{\nu,t}$ supplied by each agent type ν at the composite wage rate $W_{\nu,t}$:

$$N_t = \left(\sum_{\nu} \delta_{\nu}^{\frac{1}{\eta_n}} N_{\nu,t}^{\frac{\eta_n - 1}{\eta_n}} \right)^{\frac{\eta_n}{\eta_n - 1}}. \tag{14}$$

Second, the composite labor of each type is itself a CES aggregate of a continuum of differentiated labor types j supplied at wage $W_{\nu,j,t}$:

$$N_{\nu,t} = \left(\int_0^1 N_{\nu,j,t}^{\frac{\eta_n - 1}{\eta_n}} \, dj \right)^{\frac{\eta_n}{\eta_n - 1}}, \tag{15}$$

where for simplicity I assume the same elasticity of substitution η_n within and across agent types. The labor used in production is thus a double composite of the individual labor services supplied by the different labor types j across the different agent types ν. Cost minimization by the labor aggregator delivers downward-sloping demand curves for each labor type, and the wage indices W_t and $W_{\nu,t}$ are the corresponding cost-minimizing CES duals (Appendix B.3). Market clearing requires that the demand for each labor type equals the efficiency units supplied by the relevant agents,

$$N_{\nu,j,t} = \int_{i \in \mathcal{I}_{\nu}} n_{i,j,t} \, di, \tag{16}$$

where $n_{i,j,t}$ are the efficiency units of type j delivered by worker i, as defined above.

Nominal wages are sticky and the quantities of labor services are demand-determined. Each labor type j of each agent type ν is represented by a labor union that sets the wage rate $W_{\nu,j,t}$ optimally on behalf of the households it represents, subject to a friction à la Calvo (1983): in each period the union can reset its wage with probability $1 - \theta_w$, while with probability θ_w the wage stays at its current level.

Workers are paid per efficiency unit of labor, and I assume that the union allocates its labor demand by assigning equal hours to all of its members: $l_{i,j,t} = L_{\nu,j,t}$. This allocation maximizes members' total surplus from work measured in units of consumption, and it is standard in heterogeneous-agent New Keynesian models (e.g., Auclert, Rognlie, and Straub, 2024). Ap-

pendix B.1 shows that under equal hours, the non-stockholder's value function is homogeneous in $\Gamma_{i,t}$, and individual consumption is proportional to idiosyncratic productivity:

$$c_{i,t} = \Gamma_{i,t}\, C_{n,t}. \tag{17}$$

As a result, the marginal disutility of an extra hour relative to the marginal value of the labor income it earns is independent of $\Gamma_{i,t}$, so all members of the same agent type unanimously agree on the wage per efficiency unit that the union should set. When able to reset, the union representing labor type j for the agents $i \in \mathcal{I}_\nu$ chooses the reset wage $W^*_{\nu,j,t}$ to solve

$$\max \quad \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu\, \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}}\right)^{1-\gamma} \left[-\chi_{0,\nu}\, \frac{L_{\nu,j,t+\tau}^{1+\chi_1}}{1+\chi_1} + \lambda_{\nu,t+\tau}\, \frac{W^*_{\nu,j,t}}{P_{t+\tau}}\, L_{\nu,j,t+\tau}\right], \tag{18}$$

subject to the demand curve for labor type j, where P_t is the aggregate price index and $\lambda_{\nu,t} \equiv (C_{\nu,t} - b_\nu\, C_{\nu,t-1})^{-\gamma}$. The union sets the wage as a markup over the ratio of the marginal disutility of work to the marginal utility of consumption, internalizing that the wage chosen today governs labor demand in all future periods over which it remains fixed (Appendix B.4).

Wage rigidity is quantitatively important because it shapes the cyclicality of firm profits. An adverse shock raises marginal utility and makes households more willing to supply labor. Under flexible wages, firms' labor costs fall, cushioning profits. Sticky wages shut down this hedge: labor costs remain high precisely in bad states, so profits absorb more of the shock and fall by more than output. This amplification of dividend volatility relative to output matches the data and raises the equity premium.

2.3 Production

Each sector contains a continuum of monopolistically competitive firms. Firms face nominal price rigidities in the form of a Calvo friction: in each period a firm in sector k can reset its price with probability $1 - \theta_{p,k}$, and otherwise leaves it unchanged.

Output is demand-determined: each firm hires a homogeneous bundle of labor services to meet

demand at its posted price. Production is linear in labor, so that output of firm f in sector k is

$$Y_t(k,f) = A_t\, N_t(k,f), \tag{19}$$

where A_t is aggregate productivity and $N_t(k,f)$ is the amount of labor hired by the firm. The log of aggregate TFP follows an AR(1) process:

$$\log A_t = \rho_A\, \log A_{t-1} + \varepsilon_{A,t}, \quad \varepsilon_{A,t} \sim N(0, \sigma_A^2). \tag{20}$$

I allow for a correlation $\rho_{A,x}$ between TFP shocks $\varepsilon_{A,t}$ and income risk shocks $\varepsilon_{x,t}$.

Firms pay out their profits as dividends and set prices $P_{k,f,t}$ to maximize the present value of dividends. When a firm can reset its price, it chooses the reset price to maximize discounted dividends over the paths along which the price stays fixed (Appendix B.5). Real dividends are given by

$$D_{k,f,t} = \frac{P_{k,f,t}}{P_t}\, Y_t(k,f) - \frac{W_t}{P_t}\, N_t(k,f), \tag{21}$$

and the real market value of the firm is

$$V_{k,f,t} = \mathbb{E}_t \left[\sum_{\tau=0}^{\infty} \beta_s^{\tau}\, \frac{\lambda_{s,t+\tau}}{\lambda_{s,t}}\, D_{k,f,t+\tau} \right]. \tag{22}$$

Analogously, $V_{k,t}$ is the value of a claim to total sector-k dividends $D_{k,t}$, and V_t the value of a claim to aggregate dividends D_t.

2.4 Monetary Policy

The monetary authority sets the one-period gross nominal interest rate I_t according to a Taylor rule:

$$\log I_t = \bar{\imath} + \phi_\pi\, \pi_t + \phi_y\, \tilde{y}_t + z_t, \tag{23}$$

where $\bar{i} \equiv -\log(\beta_n\, g_{0,n}(0))$, $\pi_t \equiv \log(P_t/P_{t-1})$ is inflation, $\tilde{y}_t$ is the output gap, ϕ_π and ϕ_y are policy parameters, and z_t is an AR(1) process driven by monetary policy shocks $\varepsilon_{z,t}$:

$$z_t = \rho_z\, z_{t-1} + \varepsilon_{z,t}, \quad \varepsilon_{z,t} \sim N(0, \sigma_z^2). \tag{24}$$

The output gap is measured as aggregate output Y_t relative to productivity A_t, in deviation from its deterministic steady-state value Y: $\tilde{y}_t \equiv \log(Y_t/A_t) - \log Y$. The monetary authority therefore does not lean against movements in output that merely reflect changes in productivity.

2.5 Equilibrium

The model's equilibrium is standard. Taking prices as given, households choose consumption and savings to maximize utility; labor unions set wages to maximize the expected utility of the labor type they represent; and firms set prices to maximize firm value. The markets for consumption goods, labor, and financial assets clear, and all agents have rational expectations. Appendix B.7 summarizes the equilibrium conditions of the model.

2.6 Mechanism: Precautionary Saving and Asset Prices

The main source of risk in the model is fluctuations in non-stockholders' aggregate demand, driven by a time-varying precautionary saving motive. The Euler equation of non-stockholders, which governs their intertemporal trade-off between consumption and saving, is

$$1 = \beta_n\, g_{0,n}(x_t)\, I_t\, \mathbb{E}_t \left[\left(\frac{C_{n,t+1} - b_n\, C_{n,t}}{C_{n,t} - b_n\, C_{n,t-1}} \right)^{-\gamma} \frac{P_t}{P_{t+1}} \right]. \tag{25}$$

Idiosyncratic risk affects the consumption–saving margin through the term $g_{0,n}(x_t)$. When income risk is high, $g_{0,n}(x_t)$ is large: expected future marginal utility is high, and non-stockholders want to cut consumption today to guard against a possible future disaster in their own income. Because the bond is in zero net supply, non-stockholders cannot save more in the aggregate. Instead, aggregate demand and labor income fall until the Euler equation holds at the interest rate set by the monetary authority. Fluctuations in idiosyncratic income risk thus act as discount factor shocks to aggregate demand, disciplined directly by the data rather than specified as exogenous preference shocks.

Because of nominal rigidities, the fall in aggregate demand has real effects. Output is demand-determined, and since labor costs remain high when wages are sticky, profit margins compress as demand falls. Price dispersion adds to these effects. Goods within a sector are imperfect substitutes, so the efficient allocation has equal production across the firms in a sector. Because not all prices reset in the same period, equilibrium prices are dispersed, and more labor is needed to deliver a given composite consumption basket. Price dispersion in sector k and its aggregate counterpart are

$$DS_{p,k,t} = \int_0^1 \left(\frac{P_{k,f,t}}{P_{k,t}}\right)^{-\eta_{c,k}} df, \qquad DS_{p,t} = \sum_k \omega_k \left(\frac{P_{k,t}}{P_t}\right)^{-\eta_c} DS_{p,k,t}. \tag{26}$$

For a given level of aggregate consumption, higher price dispersion raises labor demand and lowers dividends.

The stockholders who price financial claims are fully diversified, yet they remain exposed to fluctuations in idiosyncratic income risk through the effect of aggregate demand on firm profits. What matters for asset prices is therefore that the marginal *consumer* is exposed to idiosyncratic tail risk in labor income, not necessarily the marginal *investor*.

Heterogeneity in demand elasticities turns this aggregate channel into cross-sectional differences in expected returns. To isolate the mechanism, consider claims to one-period-ahead sector dividends, and let $\widetilde{R}_{k,t+1}$ denote the return on the claim for sector k. The spread in expected returns between a high-elasticity sector H and a low-elasticity sector L is a pure cash-flow risk premium: it is determined by the covariance of relative sector dividends with the stockholders' marginal utility. Appendix B.9 shows that the difference in expected returns can be approximated as

$$\begin{aligned} \log \mathbb{E}_t \widetilde{R}_{H,t+1} - \log \mathbb{E}_t \widetilde{R}_{L,t+1} = &-(\eta_{c,H} - \eta_c) \operatorname{Cov}_t(m_{t+1}, p_{H,t+1} - p_{L,t+1}) \\ &- (1 - \eta_{c,H}) \operatorname{Cov}_t(m_{t+1}, ds_{p,H,t+1} - ds_{p,L,t+1}) \\ &- (\eta_{c,H} - \eta_{c,L}) \operatorname{Cov}_t(m_{t+1}, \log \hat{\mu}_{L,t+1}), \end{aligned} \tag{27}$$

where m_{t+1} is the log real stochastic discount factor, $p_{k,t} \equiv \log(P_{k,t}/P_t)$, $ds_{p,k,t} \equiv \log DS_{p,k,t}$, and $\hat{\mu}_{k,t} \equiv A_t P_{k,t}/(W_t DS_{p,k,t})$ is the markup of sector k: its price over the average marginal cost of

producing the sector's composite good. The three terms capture differential exposure through relative sector prices, relative price dispersion, and the level of markups.

The second term is the main driver of return spreads in the model. A rise in income risk depresses aggregate demand and moves optimal prices, but only a fraction of firms can adjust, so that posted prices within each sector spread out. This dispersion lowers sector dividends, as described above. The strength of this channel rises with demand elasticity: when goods are closer substitutes, households reallocate more strongly toward lower-priced goods. Price dispersion in the high-elasticity sector therefore rises by more in bad states, and the cash flows of high-elasticity firms fall relative to those of low-elasticity firms precisely when marginal utility is high. This difference in exposure is compensated by a risk premium. Section 3 quantifies these asset pricing implications.

3 Quantitative Model Implications

3.1 Calibration

I solve the model using a third-order approximation around the deterministic steady state. The model is calibrated at a quarterly frequency. The income risk process is estimated directly from the data, and the remaining parameters are set to standard values from the literature. Appendix Table A.2 summarizes the baseline parameterization of the model.

Preferences and Wages

According to the U.S. SCF, roughly half of households hold equity, so I set $\delta_s = \delta_n = 0.5$. The stockholder discount factor $\beta_s = 0.986$ implies an average annual real risk-free rate of 0.9% in the stochastic model, consistent with the postwar average real return on Treasury bills (Campbell, 2003), and $\beta_n = \beta_s / g_{0,n}(0)$ gives both types the same effective discount factor in the deterministic steady state. Risk aversion is $\gamma = 10$ for both types, a common value in the asset pricing literature (e.g., Bansal and Yaron, 2004; Kung, 2015). The habit weight of non-stockholders is $b_n = 0.65$ (Christiano, Eichenbaum, and Evans, 2005). Following evidence that stockholders have a higher elasticity of intertemporal substitution than non-stockholders (Vissing-Jørgensen, 2002; Guvenen, 2006), I set a

lower habit weight for stockholders, $b_s = 0.45$, since habits lower the elasticity of intertemporal substitution.

The inverse Frisch elasticity of labor supply is $\chi_1 = 1$ (Christiano et al., 2005).[11] The Calvo parameter of wage setting is $\theta_w = 0.7$, which implies an average duration of wage contracts of slightly more than three quarters. This value matches the estimate of Smets and Wouters (2007) and is broadly consistent with micro evidence on the frequency of nominal wage adjustment (Barattieri, Basu, and Gottschalk, 2014; Grigsby, Hurst, and Yildirmaz, 2021). The elasticity of substitution between labor types is $\eta_n = 12$, which implies a wage markup of 9%.

Income Risk

The parameters of the distribution of permanent income shocks $\xi_{i,t+1}$ are taken directly from the estimation of the income process discussed in Section 1 (details in Appendix A). The persistence ρ_x and volatility σ_x of income tail risk are obtained by fitting an AR(1) process to the estimated quarterly series for x_t, which yields $\rho_x = 0.883$ and $\sigma_x = 0.054$.

The assumption that transitory income shocks are fully insured is consistent with the evidence of Blundell et al. (2008), who estimate that only 5% of a transitory income shock passes through into consumption. Households can smooth such shocks by saving and borrowing outside the model, whereas permanent shocks are much harder to self-insure. The residual exposure ψ to permanent shocks to gross individual earnings captures the combined insurance from taxes and transfers, family labor supply, and other channels outside the model. I set $\psi = 0.285$, which is in line with the estimates of Blundell et al. (2008): they find a pass-through of permanent shocks into nondurable consumption of 0.22 for shocks to male earnings and 0.31 for shocks to family earnings.[12]

Production

The model has five sectors that differ in the elasticity of substitution $\eta_{c,k}$ between the goods produced within the sector. I choose $\eta_{c,k}$ so that the steady-state markups $\eta_{c,k}/(\eta_{c,k} - 1)$ of the

[11] The weighting parameters on labor disutility, $\chi_{0,s}$ and $\chi_{0,n}$, are chosen such that employment per capita is equalized for both agent types in the deterministic steady state and normalized to one.

[12] This choice of ψ is conservative, as non-stockholders are likely to be less well insured than the average household: Blundell et al. (2008) find a substantially higher pass-through of permanent shocks for households without a college education and for households with low wealth.

five sectors equal the average markups of the five markup-sorted portfolios analyzed in Section 4. These markups range from 47% to 4%, which yields elasticities $\eta_{c,k}$ of 3.1, 5.6, 8.1, 12.2, and 25.1. Each sector has an equal expenditure weight, $\omega_k = 0.2$, and I set the elasticity of substitution across sectors to $\eta_c = 2$, below the lowest within-sector elasticity.

The Calvo parameter of price setting is $\theta_{p,k} = 0.75$ in all sectors (Erceg et al., 2000), which implies an average price duration of four quarters, in line with micro evidence on the frequency of regular price changes (Nakamura and Steinsson, 2008).

The TFP process has persistence $\rho_A = 0.95$ and volatility $\sigma_A = 0.0078$, which matches the standard deviation of quarterly growth in the utilization-adjusted TFP series of Fernald (2014). Because this series is nearly uncorrelated with innovations to x_t (correlation of 0.06), I set $\rho_{A,x} = 0$, so that income risk affects output and asset prices entirely through aggregate demand.

Monetary Policy

I set the inflation coefficient of the Taylor rule to $\phi_\pi = 1.24$, based on the estimates of Rudebusch (2002), and the output gap coefficient to $\phi_y = 0.5/4$, the standard value from Taylor (1993) (see also Galí, 2015). The baseline model does not have monetary policy shocks: $\sigma_z = 0$.

3.2 Impulse Responses

Figure 2 illustrates the main mechanism of the model by plotting impulse responses to a one-standard-deviation increase in the uninsured idiosyncratic labor income risk of non-stockholders. Higher income risk raises the precautionary term $g_{0,n}(x_t)$, and aggregate demand falls. Aggregate consumption drops by 0.4% on impact and by close to 0.6% at the trough after three quarters, with the hump shape reflecting habit formation (Figure 2a). Since output is demand-determined, hours and real wages both fall by about 0.2% (Figures 2b and 2c), and inflation declines (Figure 2d).

The fall in demand hits firm profits particularly hard. Real wages fall by too little to offset the rise in price dispersion (Figure 2e), so the labor cost per unit of output rises and profit margins compress. Aggregate dividends fall by 1.7%, about three times as much as consumption (Figure 2f). As a result, stockholders face bigger drops in consumption than non-stockholders (0.7% versus 0.4%), even though the shock originates in the income risk of non-stockholders. These consumption

declines translate into large increases in marginal utility: on impact, marginal utility rises by close to 10% for stockholders and by 7% for non-stockholders (Figure 2g). Stock prices fall sharply: the aggregate stock market falls by 9.4 percentage points in the quarter of the shock (Figure 2h). In subsequent quarters, returns are above their steady-state level, reflecting higher expected returns while income risk remains elevated.

These effects are concentrated in the high-elasticity sector. When demand falls, the prices of firms that can reset move away from those of firms that cannot. When goods within a sector are close substitutes, a given price gap leads to a large reallocation of demand across firms, so that price dispersion rises by 0.7% in sector H, compared to 0.2% in sector L (Figure 2e). Higher dispersion raises the labor needed to produce a given level of sector output, so that dividends in sector H fall by 10%, while dividends in sector L fall by less than 0.5% (Figure 2f). The cash flows of high-elasticity firms thus fall the most precisely when the marginal utility of stockholders spikes. On impact, the return of sector H is -15%, compared to -9% for sector L (Figure 2h).

For comparison, Appendix Figure A.3 plots impulse responses to a one-standard-deviation positive TFP shock. Consumption rises gradually, hours fall while real wages rise, marginal utility moves by at most 2%, and stock returns respond much less than they do to the income risk shock.

3.3 Unconditional Moments

To compute model-implied moments, I simulate the model for 10,000 quarters and discard the first 100 quarters as a burn-in. In each period, I compute total sector dividends $D_{k,t}$ and the cum-dividend value $V_{k,t}$ of a claim to these dividends, so that the value-weighted return on sector k is $R_{k,t} = V_{k,t}/(V_{k,t-1} - D_{k,t-1})$. The market return R_t follows analogously from aggregate dividends D_t and the aggregate value V_t. Excess returns are measured relative to the real risk-free rate of stockholders. Asset pricing moments are annualized from quarterly returns, and macroeconomic moments are computed from annual aggregates of the simulated quarterly series.

Appendix Table A.3 compares macroeconomic moments in the model to the data. The model generates reasonable volatilities: the annual volatility of consumption growth is 1.0%, compared to 1.2% in the data, and the volatilities of hours growth, inflation, and dividend growth are somewhat lower but of similar magnitude. Because dividends are more volatile than labor income, the

consumption growth of stockholders is 1.58 times as volatile as that of non-stockholders, close to the ratio of 1.55 estimated by Mankiw and Zeldes (1991). Average markups in the simulations are close to their steady-state values and thus match those of the markup-sorted portfolios. The model understates the persistence of macroeconomic aggregates and, in particular, of valuation ratios. The annual log price-dividend ratio has an autocorrelation of 0.43 in the model, compared to 0.91 in the data. Because valuation shocks are less persistent, the log price-dividend ratio is also less volatile: its standard deviation is 0.15 in the model, compared to 0.42 in the data.

Table 1 reports annualized moments of excess stock returns. In the baseline calibration (row 1), the equity premium is 6.7% per year and the volatility of market returns is 19.6%, so that the Sharpe ratio of the aggregate stock market is 0.34. In the cross section, average returns increase with the demand elasticity that firms face (Figure 3a): the high-elasticity sector earns a return premium of 3.3% per year over the low-elasticity sector. Consistent with the impulse responses in Section 3.2, the return on the $H - L$ portfolio falls when income risk rises, with a beta of -1.24 with respect to changes in x_t.

Rows (2)–(4) show that the return spread compensates for demand risk generated by shocks to idiosyncratic income risk. Without TFP shocks (row 2), the equity premium falls to 4.8%, but the return spread remains high at 2.8%. Without income risk shocks (row 3), the equity premium falls to 3.5%, the market Sharpe ratio drops from 0.34 to 0.20, and the return spread almost disappears. Row (4) sets the correlation between TFP and income risk shocks to -0.5, which is the correlation between income risk shocks and the growth rate of measured TFP, not adjusted for factor utilization. This correlation raises the equity premium to 7.1% and slightly lowers the return spread to 2.9%.

Row (5) replaces income risk shocks with monetary policy shocks as the source of demand fluctuations. I set the persistence of monetary policy shocks to a standard value of $\rho_z = 0.9$ and choose their volatility, $\sigma_z = 0.66\%$ per quarter, to match the volatility of market returns in the baseline. This specification generates an equity premium of 4.4% and an average return spread of 1.6%. However, the return spread is much more volatile than in the baseline, so that its Sharpe ratio is only 0.06. Moreover, the required monetary policy shocks are far larger than in the data. Expressed at an annual rate, their standard deviation is 2.6 percentage points. By contrast, high-

frequency monetary policy surprises around FOMC announcements, summed within each quarter, have a standard deviation of only 0.04 percentage points in the one-year Treasury yield (Acosta, Ajello, Bauer, Loria, and Miranda-Agrippino, 2025).[13] Monetary policy news is also released outside of FOMC meetings (Neuhierl and Weber, 2019), but because central banks aim to stabilize the economy, monetary policy is more likely to offset demand shocks than to generate them. Consistent with this view, Ozdagli and Velikov (2020) show that stocks with a higher exposure to monetary policy earn lower, not higher, average returns. A time-varying precautionary saving motive, disciplined by measured income risk, is therefore a more plausible source of the demand fluctuations that drive risk premia.

Rows (6) and (7) show that the return spread requires nominal price rigidities. With flexible prices (row 6), the equity premium is still 5.0% because wages remain sticky, but the return spread is zero: markups are constant, so that dividends in all sectors move in proportion to aggregate demand. Row (7) replaces heterogeneity in demand elasticities by heterogeneity in price stickiness, following Weber (2015). All sectors have the same elasticity $\eta_{c,k} = 12$, and the quarterly Calvo parameters $\theta_{p,k}$ range from 0.015 to 0.895, based on the distribution of the frequency of price adjustment in Nakamura and Steinsson (2008). Firms in the stickiest sector earn a return premium of 5.1% over firms in the most flexible sector, consistent with the empirical findings of Weber (2015). As pointed out by Clara (2023), the two sources of heterogeneity have different implications for the relation between markups and expected returns. With heterogeneous price stickiness, average markups are nearly identical across sectors, ranging from 9.1% for flexible-price firms to 9.9% for sticky-price firms. With heterogeneous demand elasticities, the riskiest firms have the lowest markups: average markups range from 48% in the low-elasticity sector to 4% in the high-elasticity sector. Because the empirical analysis in Section 4 focuses on this negative relation between markups and expected returns, I take heterogeneity in demand elasticities as the main source of firm heterogeneity in the model.

Rows (8)–(18) vary key parameters one at a time. The magnitudes of risk premia depend on these parameters, but in every calibration the $H - L$ portfolio earns a positive average return

[13] Alternative measures of monetary policy surprises yield similar values of 0.04 to 0.06 percentage points (Kuttner, 2001; Bauer and Swanson, 2023).

and has a negative beta with respect to changes in income risk. The results are most sensitive to the pass-through ψ of permanent income shocks, which determines how much income risk non-stockholders bear: for values of ψ between 0.27 and 0.30, the equity premium ranges from 4.9% to 9.6%, and the return spread from 1.6% to 6.4%. A more aggressive monetary policy response to inflation or the output gap (rows 11 and 13) stabilizes demand and lowers both the equity premium and the return spread, while a weaker response (rows 10 and 12) raises them. Lower risk aversion of stockholders (row 14) lowers risk premia, while a stronger habit of stockholders (row 15) lowers the equity premium but raises the return spread. Similarly, more flexible wages (row 16) lower the equity premium but raise the return spread, and stickier wages (row 17) have the opposite effect. A higher elasticity of substitution across sectors (row 18) has little effect.

3.4 Time-Varying Risk Premia

Unlike models with linear demand shocks, such as standard monetary policy shocks, the model presented here naturally generates time-varying expected returns: the level of idiosyncratic income risk predicts future returns. In model-simulated data, I regress the cumulative excess return on sector k over the next four quarters, $R^e_{k,t\to t+4}$, on the current level of income risk:

$$R^e_{k,t\to t+4} = b_{k,0} + b_k\, x_t + \epsilon_{k,t\to t+4}, \tag{28}$$

where x_t is standardized to have a unit standard deviation. Figure 3b plots the coefficients b_k in the baseline model. Higher income risk predicts higher future returns in all sectors, and predictability increases with the demand elasticity. A one-standard-deviation increase in x_t is associated with a 5.4 percentage point higher excess return over the next year for the low-elasticity sector, compared with 11.5 percentage points for the high-elasticity sector. The return on the $H - L$ portfolio is therefore also predictable, with a coefficient of 6.1 and an R^2 of 20%. For the market return, the coefficient is 6.0 and the R^2 is 11%.

Returns are predictable even though shocks to income risk and TFP are homoskedastic. In contrast to the existing literature on idiosyncratic risk and asset prices in endowment economies, time-varying uncertainty about future idiosyncratic risk is not necessary to generate predictability. In-

stead, predictability arises from the nonlinear relation between income risk and aggregate demand, driven by fluctuations in the precautionary saving motive of non-stockholders. Figure 4 plots the precautionary saving term $g_{0,n}(x)$, together with the mean and the 10th and 90th percentiles of $g_{0,n}(x_{t+1})$ conditional on $x_t = x$. Because income risk shifts the tails of the income growth distribution and marginal utility is convex, the precautionary saving term is convex in income risk. When income risk is high, a given shock to income risk moves the precautionary saving motive by more, and the conditional distribution of $g_{0,n}(x_{t+1})$ widens. The precautionary saving channel therefore endogenously generates stochastic and countercyclical volatility of demand shocks. When income risk is high, stock returns are more volatile and covary more strongly with stockholders' marginal utility, so that expected returns rise. This effect is strongest for the high-elasticity firms that are most exposed to demand shocks.

To illustrate this channel, I regress the absolute value of future excess returns on income risk:

$$|R^e_{k,t\to t+4}| = c_{k,0} + c_k\, x_t + \epsilon_{k,t\to t+4}. \tag{29}$$

Figure 3c plots the coefficients c_k. A one-standard-deviation increase in x_t is associated with a 4.3 percentage point larger absolute excess return over the next year for the low-elasticity sector, compared with 7.4 percentage points for the high-elasticity sector. Higher income risk thus predicts higher future return volatility, and more so for firms with more elastic demand.

Predictability is a distinctive implication of the convex precautionary saving motive. Appendix Figure A.4 repeats both regressions in two alternative versions of the model. In the first, demand shocks are linear: $g_{0,n}(x)$ and $g_{1,n}(x)$ are log-linear in x. In the second, non-stockholders face no time variation in income risk, so that the precautionary saving motive is constant. In both versions, the coefficients in the return regressions are below 1 percentage point in absolute value, and higher income risk does not predict larger absolute returns. Habit preferences make effective risk aversion vary over time in all specifications, but this alone generates little predictability. Linear demand shocks, which are analogous to monetary policy shocks, thus do not generate the time-varying risk premia that arise from fluctuations in idiosyncratic income risk.

4 Empirical Analysis

In this section, I use the measures of income risk from Section 1 to test the asset pricing implications of the model: (1) exposure to fluctuations in income tail risk varies across firms due to heterogeneity in demand elasticities; (2) exposure to changes in idiosyncratic income risk is compensated by a risk premium; (3) the level of income risk predicts future equity returns; (4) return predictability is heterogeneous across firms and strongest for high-elasticity firms.

4.1 Measuring Heterogeneous Firm Exposures

Because direct measures of demand elasticities are not available for a broad cross section of firms over long periods, I use two proxies for firms' exposure to aggregate demand: their average markup, which in the model reflects the demand elasticity they face, and the durability of their output.

Markups

The main measure I employ is the firm's average markup, which the model ties tightly to the demand elasticity the firm faces. Markups of price over marginal cost are the subject of a large literature (see Basu, 2019, for a review). They are central to the debate about rising market power (Gutiérrez and Philippon, 2017; Barkai, 2020; Autor, Dorn, Katz, Patterson, and Van Reenen, 2020; De Loecker et al., 2020; Crouzet and Eberly, 2021) and to measuring the aggregate cost of markup dispersion (Baqaee and Farhi, 2020; Edmond, Midrigan, and Xu, 2023). Many of these estimates are constructed from the financial statements of publicly listed firms in Compustat.

In the model, the markup of firm f in sector k is its price over its marginal cost W_t / A_t: $\mu_{k,f,t} \equiv A_t P_{k,f,t} / W_t$. Because production is linear in labor and there are no fixed costs, marginal cost equals average cost, and real dividends are

$$D_{k,f,t} = \frac{P_{k,f,t}}{P_t} Y_t(k,f) \left(1 - \frac{1}{\mu_{k,f,t}}\right). \tag{30}$$

The markup is therefore a simple function of the firm's profit margin:

$$\mu_{k,f,t} = \left(1 - \frac{P_t D_{k,f,t}}{P_{k,f,t} Y_t(k,f)}\right)^{-1}. \tag{31}$$

With flexible prices, all firms in sector k set the markup $\eta_{c,k}/(\eta_{c,k}-1)$, which decreases in the demand elasticity $\eta_{c,k}$. With staggered price setting, markups fluctuate around this level as marginal costs move while prices remain fixed. Firms with higher average markups thus face less elastic demand.

Guided by the model, I measure firm markups in the data as

$$\mu_{f,t}^{LI} = (1 - LI_{f,t})^{-1}, \tag{32}$$

where the Lerner index $LI_{f,t}$ is the ratio of operating income before depreciation to sales. This measure is a special case of the production approach to markup estimation (Hall, 1988; De Loecker and Warzynski, 2012). For a firm that minimizes costs and takes input prices as given, the markup equals the wedge between the output elasticity of a variable input, which the firm adjusts freely each period, and that input's share in revenue. De Loecker et al. (2020) apply this approach to Compustat data with a Cobb-Douglas production function and cost of goods sold (COGS) as the variable input. Traina (2018) adds selling, general, and administrative expenses (SG&A) to the variable input. Operating income before depreciation equals sales minus COGS and SG&A. The production approach with total operating expenses as the variable input and an output elasticity of one, as in the model, therefore yields exactly $\mu_{f,t}^{LI}$ (see also Gutiérrez and Philippon, 2017).

Because markups fluctuate around their steady-state level and profit margins are subject to measurement error, I proxy for the demand elasticity a firm faces with its average markup over the current and previous four fiscal years. I take the sales-weighted harmonic mean,

$$\bar{\mu}_{f,t} = \left(\sum_{\tau=0}^{4} s_{f,t-\tau} \left(\mu_{f,t-\tau}^{LI} \right)^{-1} \right)^{-1}, \tag{33}$$

where the weight $s_{f,t-\tau}$ is the share of year $t-\tau$ in the firm's total sales over the five years. The sales-weighted harmonic mean equals the cost-weighted arithmetic mean of markups, which is the relevant average when aggregating markups across firms (Edmond et al., 2023). Over time, it is the markup implied by aggregating profits and sales over the five years. I first winsorize $\mu_{f,t}^{LI}$ at the 1st and 99th percentiles within each fiscal year, and require at least three years of data within the five-

year window. Through the lens of the model, an average markup $\bar{\mu}_{f,t}$ implies a demand elasticity of approximately $\bar{\mu}_{f,t}/(\bar{\mu}_{f,t}-1)$. This mapping requires an average markup above one, so I discard firm-years in which $\bar{\mu}_{f,t}$ is below one, that is, firms with negative cumulative operating income over the window. Because $\bar{\mu}_{f,t}$ uses only current and past accounting data, investors observe it when portfolios are formed, which is critical for asset pricing tests. Measuring output elasticities by estimating a production function, by contrast, requires either a long history or data from future years that investors did not yet have.

Empirically, the output elasticity of operating expenses need not equal one. Capital as an additional input lowers this elasticity, while overhead costs included in operating expenses raise it (Basu, 2019). Because output elasticities reflect production technology, the markup estimation literature typically allows them to differ across industries. If all firms in an industry share the same output elasticity in a given year, then $\mu^{LI}_{f,t}$ equals the true markup up to an industry-specific multiplicative factor (De Loecker et al., 2020). This factor affects the level of markups, but not the ranking of firms within an industry. Consistent with this logic, De Ridder, Grassi, and Morzenti (2026) show that the dispersion of markups across firms within sectors can be well measured with financial data. For robustness, I therefore also consider a within-industry sort of firms on $\bar{\mu}_{f,t}$.

Durability

As an alternative measure of firms' exposure to aggregate demand fluctuations, I use the durability of their output (Gomes et al., 2009). Households can shift purchases of durable goods over time, making their demand particularly sensitive to changes in relative prices (Barsky, House, and Kimball, 2007) and income shocks: durables account for a large share of households' marginal propensity to spend (Zorzi and Beraja, 2026). Producers of durables are therefore more exposed to aggregate demand shocks. Clara (2023) also estimates more elastic demand for producers of durables than for producers of nondurables.

I follow Gomes et al. (2009) in classifying industries based on the 1987 benchmark input-output accounts of the Bureau of Economic Analysis. Each industry is assigned to the component of final demand to which it contributes the most value added: personal consumption expenditures, gross private investment, government expenditures, or exports of goods and services. Consumption

industries are further split by the same rule into producers of durable goods, nondurable goods, and services. Firms are matched to industry classifications by SIC code at the most detailed level available, using the Compustat SIC code when available and the CRSP code otherwise. Wholesale, retail, and financial firms are not classified.

4.2 Portfolio Sorts and Risk Exposures

The model predicts that firms facing more elastic demand are more exposed to fluctuations in income tail risk and earn higher expected returns. To test this prediction, I sort stocks at the end of June of each year t into quintiles of the inverse average markup (IAMU) $\bar{\mu}_{f,t-1}^{-1}$, based on accounting data for fiscal years ending up to calendar year $t-1$, and hold the portfolios from July of year t to June of year $t+1$. Implied demand elasticities thus increase from the first to the fifth quintile. The sample consists of the common stocks of all nonfinancial firms in the merged CRSP–Compustat database that trade on NYSE, AMEX, or Nasdaq, have a nonmissing SIC code, and have an average markup above one. The sample period for portfolio returns is July 1965 to December 2024.

In the baseline, I focus on equal-weighted portfolio returns, for two reasons. First, market capitalization is mechanically related to markups: given sales, a higher markup implies higher profits and therefore a higher market value. Value weights thus tilt each portfolio toward its highest-markup firms, which narrows the spread in demand elasticities across portfolios. Second, firm-level markups are measured with error, and equal weighting diversifies this error across firms rather than concentrating portfolio returns on a small number of large firms. That said, value-weighted portfolios lead to similar conclusions, and I report them alongside the baseline results.

Table 2 reports average characteristics of the five portfolios. Aggregated across firms with sales weights, the average markup falls from 47% in the first quintile to 4% in the fifth, which in the model implies demand elasticities of 3.1 and 25.1, respectively. Firms in the high-elasticity portfolios are smaller, have higher book-to-market ratios, and have lower profitability and asset growth. They also have higher market betas, consistent with a greater exposure to aggregate shocks, and higher idiosyncratic volatility. Some of these characteristics are associated with higher average returns, such as small size, high book-to-market, and low asset growth (Fama and French, 1992, 2015), while others, in particular low profitability, are associated with lower average returns (Novy-Marx, 2013;

Fama and French, 2015). Consistent with the mechanical link between markups and market value, the first quintile accounts for 46% of total market capitalization, and the fifth quintile for only 4%.

Table 3 reports annualized means, volatilities, and Sharpe ratios of monthly excess returns on the five portfolios and on an elastic-minus-inelastic (EMI) portfolio that is long the fifth and short the first quintile. In Panel A, average excess returns on equal-weighted portfolios increase with $\bar{\mu}_{f,t-1}^{-1}$, from 8.6% per year for the low-elasticity portfolio to 12.6% for the high-elasticity portfolio. The monotonic relation test of Patton and Timmermann (2010) rejects a flat or decreasing pattern in average returns, with a p-value of 0.013. Volatilities also increase across quintiles. The EMI portfolio earns 3.9% per year, with a t-statistic of 2.6, and has an annual Sharpe ratio of 0.34. Panel B shows that value-weighted portfolios yield a similar EMI spread of 3.6% per year (t-statistic of 2.5).

The differences in average returns line up with exposures to income tail risk. Table 3 reports betas of portfolio returns with respect to changes in *icl*, estimated over 1967–2019, the period for which the income risk measures are available. Because icl_t averages initial claims over month t, I measure the change in income risk over a window centered on month t: $\Delta icl_t \equiv icl_{t+1} - icl_{t-1}$. This measure combines the changes under the standard end-of-period timing convention, $icl_t - icl_{t-1}$, and the beginning-of-period convention of Campbell (2003), $icl_{t+1} - icl_t$.[14] All portfolios have negative betas, which increase in magnitude from -0.18 in the first quintile to -0.33 in the fifth. The EMI portfolio has a beta of -0.15, with a standard error of 0.03. Value-weighted portfolios show a similar pattern, with an EMI beta of -0.10. Section 4.3 formally tests whether these differences in risk exposures account for the differences in average returns.

Table 3 also reports market betas and alphas with respect to the CAPM and the three-factor model of Fama and French (1993). Consistent with Table 2, market betas increase from 1.02 in the first quintile to 1.18 in the fourth and fifth. The CAPM alpha of the EMI portfolio is 2.8% per year (p-value of 0.052): market exposure accounts for 28% of the EMI spread. The three-factor model further reduces the EMI alpha to 2.0% (p-value of 0.085), due to positive loadings on the size and value factors. Together, the three factors account for 50% of the EMI spread. For value-weighted

[14] Exposures are similar when using either timing convention separately.

portfolios, the CAPM and the three-factor model account for 49% and 68% of the EMI spread, respectively, and the remaining alphas of 1.8% and 1.1% are not statistically significant.

Alternative Sorts

Industries differ in technology, cost structure, and accounting practices, which may affect measured markups independently of demand elasticities, and in other dimensions that may be associated with average returns. As discussed in Section 4.1, a within-industry sort addresses these concerns, so I also sort firms into quintiles of $\bar{\mu}_{f,t-1}^{-1}$ within each of the Fama–French 48 industries. Appendix Table A.4 shows that the results are similar to the baseline. Average equal-weighted excess returns increase monotonically from 9.0% in the first quintile to 12.7% in the fifth (Patton–Timmermann p-value of 0.003), and the EMI portfolio earns 3.7% per year, with a t-statistic of 3.2. The within-industry EMI portfolio has a lower volatility (8.9%) and a higher Sharpe ratio (0.41). The spread in exposures to income risk becomes smaller: the EMI portfolio has a beta of -0.07, roughly half of that in the unconditional sort. Part of the variation in exposures in the baseline sort thus comes from differences across industries. The spread in market betas largely disappears, so that the CAPM and three-factor alphas of the EMI portfolio, 3.4% and 2.6% per year, are larger than in the baseline and significant at the 1% level. For value-weighted portfolios, the EMI portfolio earns 2.8% per year (t-statistic of 2.1), but exposures to income risk no longer differ significantly across quintiles. Because the within-industry sort removes differences in average markups across industries, these results are distinct from the relation between industry concentration or markups and average returns documented by Hou and Robinson (2006), Bustamante and Donangelo (2017), and Corhay et al. (2020).

Appendix Table A.5 reports results for the alternative exposure measure from Section 4.1, the durability of firms' output. Following Gomes et al. (2009), I sort firms into value-weighted sector portfolios of producers of services, nondurable goods, durable goods, investment goods, and other industries, and form a durables-minus-services (DMS) portfolio. Because this classification does not require accounting data, the sample for these portfolios starts in July 1926. Over this whole period, producers of durables earn an average excess return of 10.9% per year, compared with 6.5% for producers of services, so that the DMS portfolio has an average return of 4.3% per year (t-

statistic of 2.6), in line with the premium documented by Gomes et al. (2009). Exposures to income risk line up with these differences in average returns. The beta with respect to Δicl_t is -0.29 for producers of durables, compared with -0.10 for producers of services and -0.09 for producers of nondurables. The DMS portfolio has a market beta of 0.41, which can account for a large fraction of its average return under the CAPM.

Firm-Level Regressions

To further examine the relation between markups and average returns in the cross section, I run firm-level regressions of monthly excess stock returns on $\log(\bar{\mu}_{f,t-1}^{-1})$, controlling for other firm characteristics that have been associated with average returns. Appendix Table A.6 shows that a one-standard-deviation decrease in log average markup is associated with a 1.0 percentage point higher annual return (column 1), and the coefficient is similar within industries (column 2). The coefficient remains stable at 0.8–0.9 when controlling for size, book leverage, profitability, and asset growth (column 3), momentum and short-term reversal (column 4), and market beta, idiosyncratic volatility, and turnover (column 5). Adding log market equity in column (6) lowers the coefficient to 0.5, which remains significant at the 5% level, consistent with the mechanical relation between markups and market value.

4.3 Risk Premium Estimates

Next, I use cross-sectional asset pricing tests to examine whether exposure to income tail risk is compensated by a risk premium and explains the differences in average returns across the portfolios in Section 4.2.

I estimate linear factor models in which expected excess returns are linear in factor betas. In the first stage, I estimate the betas of each test portfolio p from time-series regressions of its excess returns on a vector of risk factors F_t:

$$R_{p,t}^e = \beta_{p,0} + \beta_p' F_t + \epsilon_{p,t}. \tag{34}$$

In the second stage, I estimate the prices of risk λ from a cross-sectional regression of average

excess returns on the estimated betas:

$$\mathbb{E}_T[R^e_{p,t}] = \lambda_0 + \hat{\beta}'_p\lambda + \nu_p. \tag{35}$$

A model that prices the test assets well has significant prices of risk, small pricing errors ν_p, and a small intercept λ_0. I compute standard errors by estimating both stages jointly by GMM, which accounts for estimation error in the betas and for cross-sectional correlation in returns. I measure goodness of fit by the cross-sectional R^2 and the mean absolute pricing error (MAPE), and report the p-value of a joint test that all prices of risk are zero. Prices of risk and pricing errors are annualized and in percent.

Because of the imperfect timing of macroeconomic variables relative to returns, betas on these variables are imprecisely measured and difficult to compare with betas on return-based factors. I therefore first estimate prices of risk on traded factors using monthly returns. I use the value-weighted EMI portfolio as a traded factor that captures demand risk. In columns (1)–(3) of Table 4, Panel A, the test assets are the five equal-weighted IAMU portfolios. In column (1), the price of EMI risk is 7.4% per year (with a standard error of 2.7%), the intercept is insignificant, and the EMI factor explains 98% of the cross-sectional variation in average returns, with a MAPE of 0.17%. The CAPM in column (2) also fits these portfolios, because market betas increase across quintiles, but with higher pricing errors and only with a very large price of market risk (20.7% per year). When both factors are included in column (3), the price of EMI risk remains positive and significant, at 8.1% per year, while the price of market risk becomes negative and insignificant.

With only five test assets, a high cross-sectional R^2 is a relatively low hurdle (Lewellen, Nagel, and Shanken, 2010). In columns (4)–(8), I therefore expand the test assets to 35 portfolios by adding the five value-weighted sector portfolios sorted by durability and the 25 Fama–French portfolios sorted on size and book-to-market. On their own, neither the EMI factor nor the market explains much of the variation in average returns across all these portfolios (columns 4 and 5). Together, however, they explain 57%, and the price of EMI risk is 6.7% per year and significant (column 6). The Fama–French three-factor model in column (7) has a similar R^2 of 0.58. Adding the EMI factor in column (8) raises the R^2 to 0.68, and the price of EMI risk increases to 9.5% per year, significant

at the 1% level. Thus, the EMI factor carries a positive price of risk that is not subsumed by the market, size, and value factors.

Next, I directly estimate the price of income tail risk using the non-traded measures of income risk. The test assets are the five equal-weighted IAMU portfolios at a quarterly frequency. Average returns are computed over the full sample period 1965Q3–2024Q4, and betas are estimated over 1967–2019, the sample period of the income risk measures. As in Section 4.2, I measure changes over a centered window, $\Delta icl_t \equiv icl_{t+1} - icl_{t-1}$, and likewise for x and the other macroeconomic factors. Columns (1) and (2) of Panel B report the results. The price of risk is negative and significant for both measures, at -26.6% per year for Δicl and -20.5% for Δx. Consistent with the model, portfolios whose returns fall more when income risk rises earn higher average returns. Exposures to income risk explain 99% of the cross-sectional variation in average returns, with MAPEs of 0.18% and 0.12% and small, insignificant intercepts. The magnitudes of these prices of risk are not directly comparable to those on traded factors: noise in a non-traded factor that is unrelated to returns attenuates the betas and thereby inflates the estimated price of risk, without affecting the cross-sectional fit.

Because income risk is countercyclical, these estimates could reflect heterogeneous exposures to the business cycle more generally rather than to income risk specifically. Columns (3)–(8) of Panel B therefore replace income risk with other macroeconomic factors: TFP growth and utilization-adjusted TFP growth (Fernald, 2014), and changes in log industrial production, log real GDP, log real per capita consumption of nondurables and services, and the aggregate investment rate. Utilization-adjusted TFP, industrial production, consumption, and the investment rate do not carry significant prices of risk, and GDP is significant only at the 10% level. These factors also fit the cross section less well, with R^2s between 0.30 and 0.90 and MAPEs between 0.40% and 1.08%. The exception is measured TFP, which has a price of risk that is significant at the 5% level and an R^2 of 0.95 (column 3). Unlike its utilization-adjusted counterpart, measured TFP reflects variation in factor utilization and therefore comoves with aggregate demand. That only the unadjusted measure prices the portfolios is consistent with the demand-driven mechanism in the model.

4.4 Cash Flow Exposures

In the model, high-elasticity firms earn higher average returns because their cash flows are more affected by the aggregate demand shocks generated by fluctuations in income risk. In this section, I test this cash flow channel directly.

I measure cash flows by sales and operating income from Compustat, and by dividends from CRSP. For each portfolio formed in June of year t, I compute the growth rate of cash flows over fiscal year t, which overlaps with the holding period of the portfolio, for the same set of firms in both years. Dividends are measured over calendar years. In the baseline, I compute the log growth rate of cash flows for each firm and average it across the firms in the portfolio, in line with the equal-weighted portfolio returns. Firm-level log growth rates require positive cash flows in both years, and I winsorize them at the 1st and 99th percentiles in each year. As an alternative that does not require positive cash flows for individual firms, I also compute the log growth rate of the total cash flows of the firms in the portfolio. Because large firms account for most of total cash flows, this measure is the counterpart of value-weighted returns. To measure exposures to income risk, I regress cash flow growth from year $t-1$ to year t on the change in income risk over the same period, $\Delta x_t \equiv x_t - x_{t-1}$, where x_t is the average of x over year t.

Table 5 reports the results. Consistent with the model, cash flows tend to fall when income risk rises, and this sensitivity is stronger for high-elasticity firms. For operating income growth, the exposure increases in magnitude from -0.21 in the first quintile to -0.74 and -0.63 in the fourth and fifth quintiles, and the EMI portfolio has a significant exposure of -0.42. Sales growth of the first quintile is unrelated to changes in income risk, while the exposures of the other quintiles range from -0.13 to -0.18. Dividend growth exposures increase monotonically in magnitude from -0.10 to -0.33, and the EMI portfolio has a significant exposure of -0.22. The volatility of operating income and dividend growth also tends to increase from the first to the fifth quintile. The results are similar for growth in the total cash flows of each portfolio, reported in Appendix Table A.7.

The cash flows of the sector portfolios sorted by durability, reported in Appendix Table A.8, show a similar pattern. Consistent with Gomes et al. (2009), the operating income growth of durable-good producers is more volatile than that of service and nondurable-good producers,

with a volatility of 13.6% versus 4.8% and 6.2%. Their operating income is also substantially more exposed to income risk, with a coefficient of -1.06, compared with -0.20 for services and -0.34 for nondurables. The DMS portfolio has significant exposures of -0.86 for operating income growth, -0.31 for sales growth, and -0.24 for dividend growth.

4.5 Return Predictability

In the model, the level of income risk predicts future equity returns, and more so for firms with more elastic demand. Following the predictive regressions on model-simulated data in Section 3.4, I regress cumulative future excess returns over various horizons on the current level of income tail risk, measured by icl_t in monthly data and by x_t in quarterly data, over 1967–2019. I standardize all predictors to have a unit standard deviation and compute Newey–West standard errors with a lag length equal to the forecast horizon minus one. Table 6 reports the results for the equal-weighted IAMU quintile portfolios. Higher income risk predicts significantly higher future returns on all five portfolios. Consistent with the model, this predictability increases monotonically with demand elasticity. A one-standard-deviation increase in icl_t is associated with a 6.4 percentage point higher return over the next year for the first quintile, compared with 12.7 percentage points for the fifth quintile.

This heterogeneity in predictability implies that income risk also predicts the return on the EMI portfolio, with a significant coefficient of 6.3 and an R^2 of 16% at the one-year horizon. The EMI return is also predictable at horizons of three months and two years, and the results are similar when using x_t in quarterly data. Figure 5 plots the realized one-year EMI return together with its predicted value based on x_t: the EMI portfolio earns high returns after periods of elevated income risk, such as the recessions of the mid-1970s, early 1980s, and 2008–2009. Income risk also predicts the return on the aggregate stock market, reported in Appendix Table A.9, though more weakly. A one-standard-deviation increase in icl_t is associated with a 2.8 percentage point higher market return over the next year, which is significant at the 10% level but not at the 5% level. This predictability is consistent with Schmidt (2025), who finds stronger predictability of market returns by labor market uncertainty over a different sample period.

The durability portfolios in Appendix Table A.9 show a similar pattern. Income risk strongly

predicts the returns of durable-good producers, with a coefficient of 8.2 at the one-year horizon, but not those of service and nondurable-good producers, with coefficients of 1.5 and 0.2. The coefficient for the DMS portfolio is 6.7, with a standard error of 1.2 and an R^2 of 17%. These results hold after controlling for the durable expenditure–stock ratio, which Gomes et al. (2009) show predicts the returns of durable-good producers.

The predictability of the EMI return is not explained by other well-known predictors of stock returns. Panel A of Table 7 reports predictive regressions of the one-year-ahead EMI return on icl_t, controlling one at a time for monthly predictor variables considered by Welch and Goyal (2008). For brevity, I report the results for seven of these variables.[15] Several of these variables, such as the term spread and default yield spread, also predict the EMI return. However, the coefficient on icl_t remains between 4.6 and 6.5 and is significant at the 1% level in all specifications.

Like the risk premium estimates in Section 4.3, the predictability results are not driven by a generic relation between business cycle indicators and future stock returns. Panel B of Table 7 reports predictive regressions of the four-quarter-ahead EMI return on x_t, controlling for other macroeconomic indicators. Most of these indicators also predict the EMI return, consistent with countercyclical variation in its expected return. Nevertheless, the coefficient on x_t remains between 4.5 and 6.3 and is statistically significant in all specifications.

4.6 Time-Varying Firm Risk

In the model, return predictability comes from time variation in the quantity of risk: the volatility of demand shocks rises with the level of income risk, and firms with more elastic demand are the most exposed to these shocks (Section 3.4). In this last part of the empirical analysis, I test whether the conditional volatility of equity returns and cash flow growth varies with the level of income risk. Following Gomes et al. (2009), I regress the absolute value of future excess returns and cash flow growth on the current level of income risk, the empirical counterpart of the regression on model-simulated data in Section 3.4. I use x_t as the measure of income risk in this section; the results are

[15] The results also hold for five other monthly variables from Welch and Goyal (2008): the earnings–price ratio, book-to-market ratio, long-term yield, default return spread, and inflation.

similar using icl_t. As before, the predictor is standardized and standard errors are Newey–West with a lag length equal to the horizon minus one.

Panel A of Table 8 reports the results for one-year excess returns on the equal-weighted IAMU portfolios. A higher level of income risk predicts significantly larger absolute returns for all five portfolios, and the coefficients increase monotonically with demand elasticity, mirroring the pattern for expected returns in Table 6. A one-standard-deviation increase in x_t is associated with a 4.2 percentage point larger absolute return over the next year for the first quintile, compared with 9.1 percentage points for the fifth quintile. The difference between these two coefficients is significant at the 1% level.

Return volatility can reflect news about discount rates as well as news about cash flows. As a more direct test of the model mechanism, Panels B and C examine the volatility of cash flow growth, measured by the absolute value of one-year operating income growth and five-year dividend growth. The coefficients for operating income growth are positive for all five portfolios and roughly twice as large for the fourth and fifth quintiles (2.2 and 1.8) as for the first and second quintiles (1.1 and 0.7), though the estimate for the fifth quintile is imprecise and does not differ significantly from that for the first quintile. The coefficients for five-year dividend growth are positive and significant for all portfolios and largest for the fifth quintile, where it is significantly larger than for the first quintile.

The durability portfolios in Appendix Table A.10 show a similar pattern for returns and operating income. Income risk predicts significantly larger absolute returns and operating income growth for durable-good producers, with coefficients of 5.8 and 4.0, but not for service and nondurable-good producers. In both cases, the difference between durable-good and service producers is significant at the 1% level. The pattern is less clear for five-year dividend growth, for which the coefficient is larger for service producers than for durable-good producers. Overall, these results indicate that the stronger return predictability for high-elasticity firms and durable-good producers is accompanied by a more countercyclical volatility of their returns and cash flows, consistent with the mechanism in the model.

Conclusion

This paper shows that fluctuations in uninsurable labor income risk are an important source of the demand risk that is priced in equity markets. The households who bear income tail risk do not price financial assets, but their precautionary saving motive determines aggregate demand, and thereby the cash flows that accrue to stockholders. Because this motive is convex in income risk, the model generates a substantial equity premium, a return premium for firms facing more elastic demand, and risk premia that rise with the level of income risk. The data line up closely with these predictions, with magnitudes similar to those in the model: low-markup firms and producers of durable goods earn higher average returns, their cash flows and returns are more exposed to income risk, this exposure is priced, and income risk predicts stock returns, most strongly for these firms.

More broadly, the results suggest that the distribution of risk across households matters for asset prices even when the investors who price these assets are well insured. Because higher risk premia in turn reduce the value of employment relationships and the insurance that firms provide to workers (Meeuwis et al., 2026), the interaction between income risk and asset prices can further amplify aggregate fluctuations. Policies that insure workers against income losses in recessions may then stabilize not only aggregate demand but also risk premia, and dampen this feedback loop. Quantifying these effects is a promising direction for future research.

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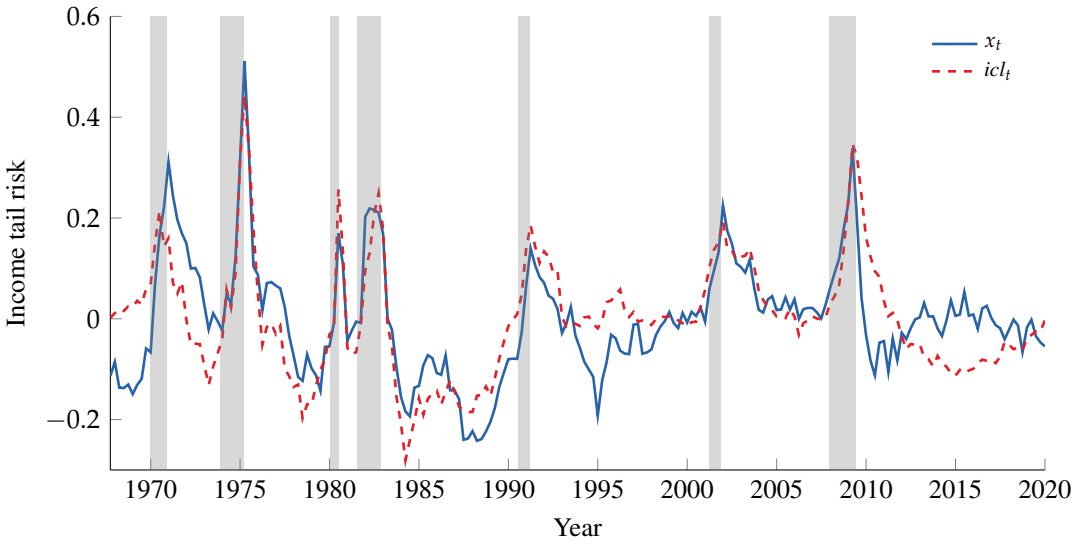
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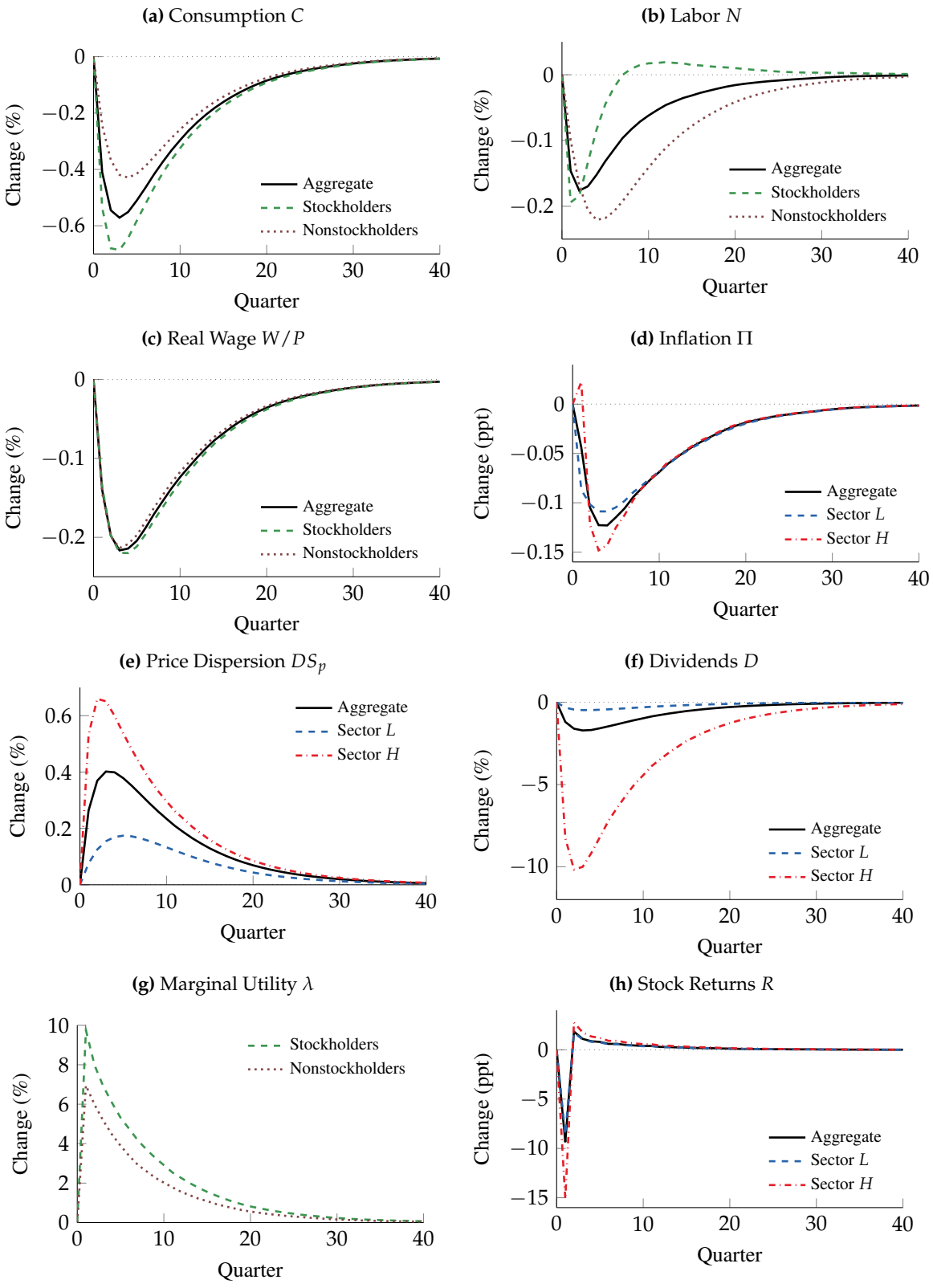
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Figure 1: Time Series of Idiosyncratic Income Risk



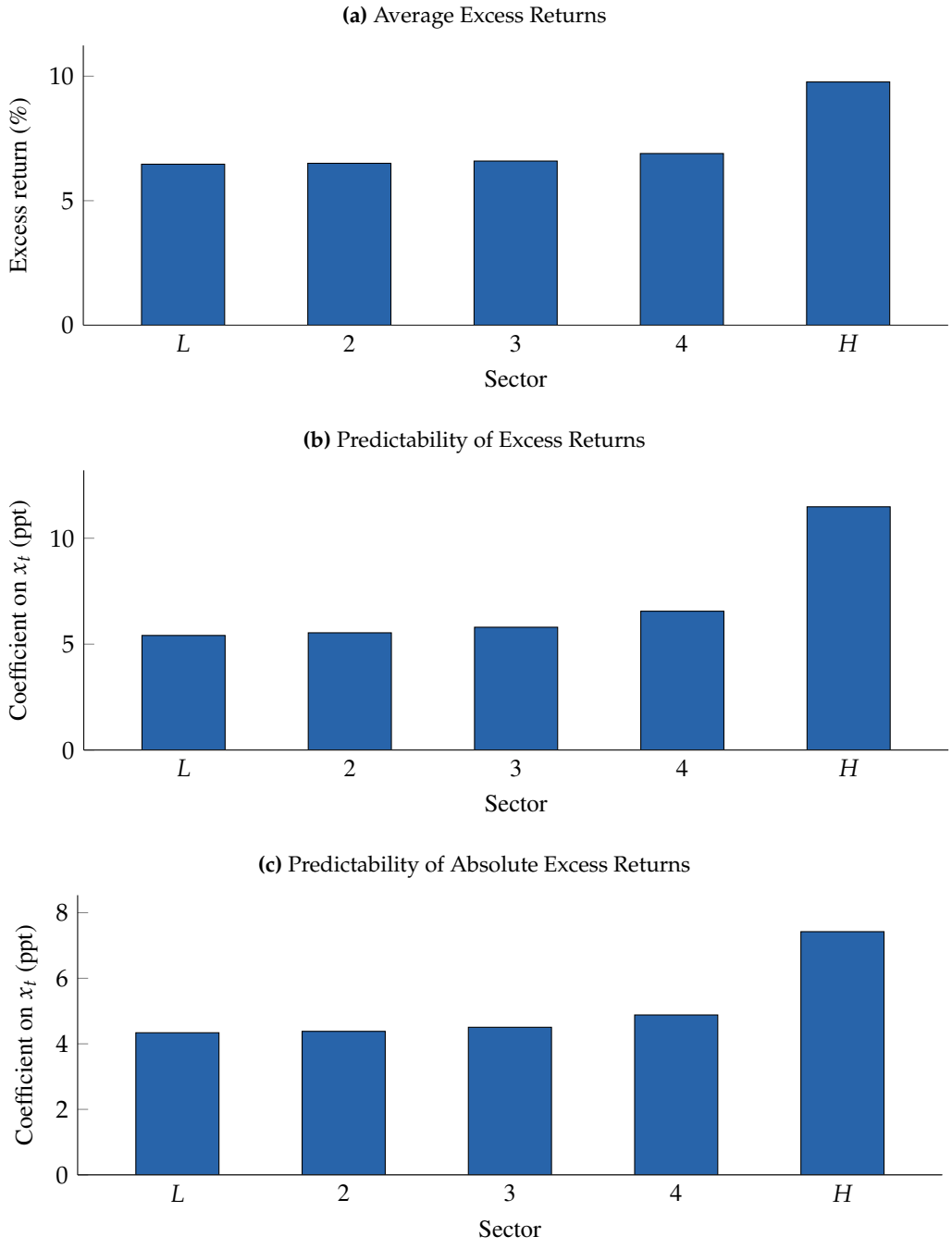
This figure plots two quarterly measures of idiosyncratic income tail risk: the tail-risk process x_t (solid line), estimated from the distribution of 1-, 3-, and 5-year income growth rates, and initial claims for unemployment insurance relative to lagged private payroll employment, icl_t (dashed line), detrended and normalized to the mean and standard deviation of x_t. Shaded areas indicate NBER recessions.

Figure 2: Impulse Responses to Idiosyncratic Income Risk Shock



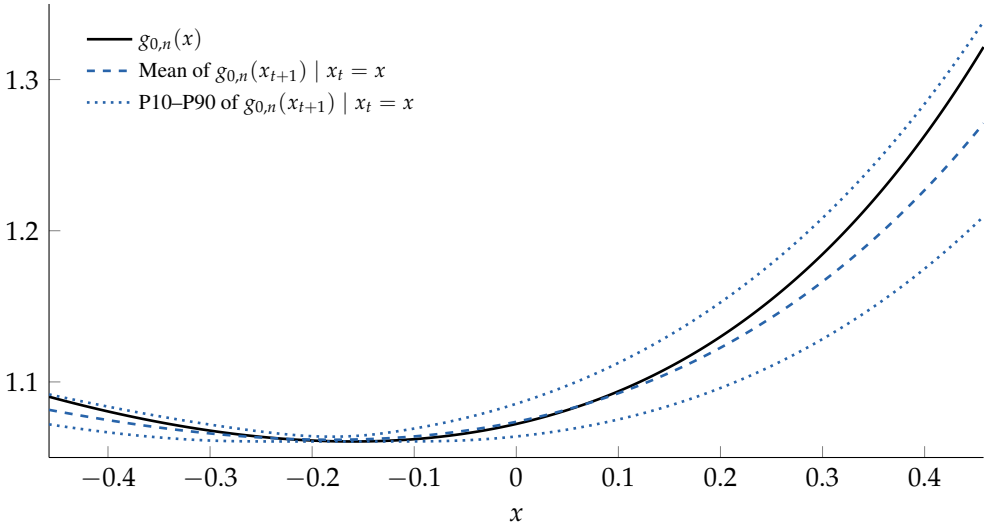
This figure plots impulse responses to a positive one-standard-deviation shock $\varepsilon_{x,t}$ to income tail risk. Sectors L and H are the sectors with the lowest and highest demand elasticity.

Figure 3: Average Returns and Predictability by Sector in the Model



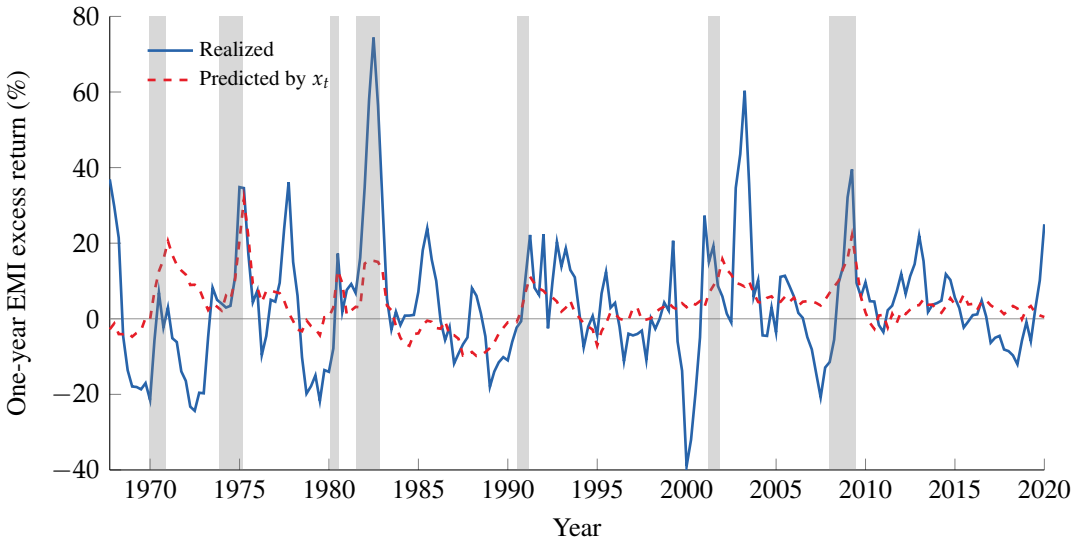
This figure reports results for the five sectors in the baseline model, ordered from the lowest (L) to the highest (H) demand elasticity $\eta_{c,k}$. Panel (a) plots annualized average excess returns. Panels (b) and (c) plot the slope coefficients from regressions of one-year excess returns and of their absolute values on income risk x_t, standardized to have a unit standard deviation.

Figure 4: Idiosyncratic Income Risk and the Precautionary Saving Motive



This figure plots the precautionary saving term $g_{0,n}(x)$ of non-stockholders as a function of income risk x, together with the mean and the 10th and 90th percentiles of next quarter's $g_{0,n}(x_{t+1})$ conditional on $x_t = x$, based on the AR(1) process for x_t. The horizontal axis spans four unconditional standard deviations of x_t on either side of its mean.

Figure 5: Income Tail Risk and Future EMI Returns



This figure plots the realized cumulative excess return on the equal-weighted EMI portfolio over the next four quarters (solid line) and its predicted value from a regression on the current level of income tail risk x_t (dashed line), in percent. The EMI portfolio is long the fifth and short the first quintile of portfolios sorted on $\bar{\mu}^{-1}_{f,t-1}$. The predictive regression is the four-quarter-ahead regression for the EMI portfolio in Panel B of Table 6. The sample period is 1967Q3–2019Q4. Shaded areas indicate NBER recessions.

Table 1: Asset Pricing Moments in the Model: Baseline and Alternative Calibrations

	Mean				Volatility		Sharpe ratio		$\beta_{\Delta x}$	
	MKT	L	H	H−L	MKT	H−L	MKT	H−L	MKT	H−L
(1) Baseline	6.71	6.47	9.77	3.30	19.64	15.38	0.34	0.21	−1.62	−1.24
Sources of fluctuations										
(2) No TFP shocks	4.79	4.59	7.35	2.76	18.19	13.67	0.26	0.20	−1.59	−1.21
(3) No income risk shocks	3.45	3.41	3.62	0.20	17.59	1.04	0.20	0.20	–	–
(4) Correlated TFP and income risk shocks	7.05	6.85	9.72	2.87	18.45	14.42	0.38	0.20	−1.55	−1.15
(5) Monetary policy shocks, no income risk shocks	4.40	4.43	6.02	1.59	19.64	28.46	0.22	0.06	–	–
Price setting										
(6) Flexible prices	5.02	5.02	5.02	0.00	15.66	0.00	0.32	–	−1.30	0.00
(7) Heterogeneous price stickiness	6.49	5.59	10.74	5.14	21.72	23.94	0.30	0.21	−1.87	−2.08
Parameters										
(8) $\psi = 0.27$	4.89	4.79	6.38	1.59	15.12	10.96	0.32	0.15	−1.24	−0.88
(9) $\psi = 0.30$	9.62	9.14	15.49	6.35	25.96	21.69	0.37	0.29	−2.12	−1.72
(10) $\phi_\pi = 1.2$	8.02	7.64	12.95	5.31	22.95	20.12	0.35	0.26	−1.85	−1.57
(11) $\phi_\pi = 1.3$	5.67	5.53	7.38	1.85	17.08	11.07	0.33	0.17	−1.39	−0.91
(12) $\phi_y = 0.25/4$	7.94	7.58	12.40	4.82	22.63	18.86	0.35	0.26	−1.80	−1.41
(13) $\phi_y = 1/4$	5.96	5.81	7.65	1.84	17.06	10.90	0.35	0.17	−1.31	−0.87
(14) $\gamma_s = 5$	5.25	5.11	7.24	2.13	15.67	13.63	0.33	0.16	−1.31	−1.10
(15) $b_s = 0.65$	5.21	4.92	8.82	3.90	21.83	15.71	0.24	0.25	−1.72	−1.24
(16) $\theta_w = 0.64$	5.68	5.35	9.53	4.18	19.18	18.24	0.30	0.23	−1.60	−1.52
(17) $\theta_w = 0.75$	7.86	7.70	10.12	2.42	20.26	12.15	0.39	0.20	−1.58	−0.89
(18) $\eta_c = 3$	6.75	6.46	9.80	3.34	20.06	15.29	0.34	0.22	−1.65	−1.23

This table reports moments of equity returns in excess of the risk-free rate of stockholders for the baseline and alternative calibrations of the model. Means and volatilities are annualized, in percent. MKT is the aggregate stock market, and L and H are the sectors with the lowest and highest demand elasticity; in row (7), L and H are the sectors with the most flexible and the stickiest prices. $\beta_{\Delta x}$ is the slope coefficient from a regression of quarterly excess returns on the change in income tail risk Δx_t. Row (4) sets $\rho_{A,x} = -0.5$, and row (5) has monetary policy shocks with $\rho_z = 0.9$ and $\sigma_z = 0.66\%$.

Table 2: Summary Statistics of Portfolios Sorted on $\bar{\mu}_{f,t-1}^{-1}$

	IAMU quintiles				
	Low	2	3	4	High
$\bar{\mu}_{f,t-1}$	1.60	1.22	1.14	1.09	1.04
$\bar{\mu}_{f,t-1}$, sales-weighted	1.47	1.22	1.14	1.09	1.04
Log assets (millions)	6.40	5.94	5.60	5.16	4.62
Book-to-market equity	0.72	0.71	0.81	0.97	1.13
Assets-to-book equity	2.59	2.41	2.53	2.72	3.13
Profitability (%)	32.5	30.2	27.5	22.6	10.5
Asset growth (%)	13.4	12.6	10.9	9.2	6.3
Market beta	1.02	1.15	1.18	1.20	1.21
Idiosyncratic volatility (%)	33.6	35.4	38.0	43.0	50.4
Market cap share (%)	45.5	26.0	14.9	9.2	4.4
Number of firms	516	516	516	516	515

This table reports time-series averages of annual cross-sectional means of firm characteristics for quintile portfolios sorted on the inverse average markup $\bar{\mu}_{f,t-1}^{-1}$ at the end of June of year t, from 1965 to 2024. Accounting variables are for the fiscal year ending in calendar year $t-1$, and book-to-market equity uses market equity at the end of December of year $t-1$. The sales-weighted $\bar{\mu}_{f,t-1}$ is the sales-weighted harmonic mean across firms. Profitability is operating income before depreciation minus interest expense, relative to book equity, and asset growth is the log growth rate of total assets. Market beta and annualized idiosyncratic volatility are estimated from CAPM regressions over the previous 60 months. Market cap share is the portfolio's share of total June market capitalization.

Table 3: Excess Returns and Exposures of Portfolios Sorted on $\bar{\mu}^{-1}_{f,t-1}$

	IAMU quintiles					
	Low	2	3	4	High	EMI
Panel A: Equal-weighted returns						
Mean (%)	8.62***	9.86***	11.03***	11.62***	12.56***	3.94***
	(2.28)	(2.52)	(2.71)	(2.86)	(3.04)	(1.52)
Volatility (%)	17.57	19.44	20.92	22.04	23.44	11.72
Sharpe ratio	0.49	0.51	0.53	0.53	0.54	0.34
$\beta_{\Delta icl}$	-0.18***	-0.26***	-0.28***	-0.31***	-0.33***	-0.15***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.03)
β_{MKT}	1.02***	1.13***	1.16***	1.18***	1.18***	0.16***
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)
α_{CAPM} (%)	1.52	2.01*	2.92**	3.38**	4.34**	2.82*
	(0.95)	(1.04)	(1.30)	(1.52)	(1.82)	(1.45)
α_{FF3} (%)	0.23	0.63	0.80	1.10	2.19**	1.96*
	(0.72)	(0.58)	(0.65)	(0.79)	(1.09)	(1.14)
Panel B: Value-weighted returns						
Mean (%)	6.96***	6.63***	7.19***	8.46***	10.53***	3.58**
	(1.86)	(2.06)	(2.33)	(2.37)	(2.53)	(1.42)
Volatility (%)	14.34	15.91	17.94	18.25	19.54	10.94
Sharpe ratio	0.48	0.42	0.40	0.46	0.54	0.33
$\beta_{\Delta icl}$	-0.13**	-0.18***	-0.22***	-0.21***	-0.23***	-0.10***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.02)
β_{MKT}	0.88***	0.98***	1.09***	1.09***	1.13***	0.25***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)
α_{CAPM} (%)	0.83	-0.22	-0.39	0.88	2.66**	1.84
	(0.51)	(0.50)	(0.71)	(0.84)	(1.07)	(1.33)
α_{FF3} (%)	1.45***	-0.25	-1.12*	0.81	2.58**	1.13
	(0.42)	(0.52)	(0.65)	(0.81)	(1.00)	(1.17)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports annualized means, volatilities, and Sharpe ratios of monthly returns in excess of the one-month Treasury bill rate for quintile portfolios sorted on $\bar{\mu}^{-1}_{f,t-1}$ at the end of June of year t and held from July of year t to June of year $t+1$. The elastic-minus-inelastic (EMI) portfolio is long the fifth and short the first quintile. $\beta_{\Delta icl}$ is the univariate beta with respect to $\Delta icl_t \equiv icl_{t+1} - icl_{t-1}$, and β_{MKT} is the CAPM beta. α_{CAPM} and α_{FF3} are annualized alphas with respect to the CAPM and the Fama–French three-factor model. The sample period is 1965M7–2024M12, and exposures to Δicl are estimated over 1967–2019. Standard errors are in parentheses.

Table 4: Risk Premium Estimates

Panel A: Monthly traded factors								
	5 IAMU			5 IAMU + 5 DUR + FF25				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EMI	7.37***		8.12**	3.41		6.67**		9.47***
	(2.65)		(3.21)	(2.48)		(2.78)		(3.13)
MKT		20.71***	-5.26		0.24	-11.77**	-1.60	-7.12*
		(7.97)	(13.01)		(4.34)	(4.62)	(3.46)	(3.67)
SMB							1.89	2.04
							(1.41)	(1.41)
HML							3.74***	3.23**
							(1.38)	(1.39)
Intercept	3.45	-12.72	12.30	6.11***	8.67**	18.77***	8.63***	13.79***
	(2.62)	(7.74)	(12.55)	(2.03)	(3.76)	(4.27)	(2.78)	(3.07)
R^2	0.98	0.84	1.00	0.18	0.00	0.57	0.58	0.68
MAPE (%)	0.17	0.46	0.07	1.39	1.73	1.08	0.97	0.96
Joint p-value	0.005	0.009	0.027	0.168	0.956	0.002	0.014	0.001
Assets	5	5	5	35	35	35	35	35
Months	714	714	714	714	714	714	714	714
Panel B: Quarterly non-traded factors								
	5 IAMU							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δicl	-26.60**							
	(13.52)							
Δx		-20.47**						
		(8.99)						
Δ TFP			3.07**					
			(1.46)					
Δ TFP (util.-adj.)				11.44				
				(14.32)				
Δ log ind. prod.					18.42			
					(19.36)			
Δ log GDP						4.93*		
						(2.94)		
Δ log consumption							3.58	
							(2.49)	
Δ investment rate								0.91
								(0.95)
Intercept	1.59	1.89	1.59	2.78	3.24	3.21	0.58	4.89
	(4.36)	(4.17)	(4.45)	(8.78)	(8.01)	(5.32)	(6.85)	(7.90)
R^2	0.99	0.99	0.95	0.63	0.75	0.90	0.89	0.30
MAPE (%)	0.18	0.12	0.29	0.73	0.68	0.40	0.52	1.08
Joint p-value	0.049	0.023	0.035	0.425	0.341	0.094	0.149	0.334
Assets	5	5	5	5	5	5	5	5
Quarters	238	238	238	238	238	238	238	238

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports risk price estimates for monthly traded factors (Panel A) and quarterly non-traded factors (Panel B). Risk prices are the slopes of a cross-sectional regression of average portfolio excess returns on betas, which are estimated in a first-stage time-series regression. The test assets are the five equal-weighted IAMU portfolios, augmented in columns (4)–(8) of Panel A with the five value-weighted durability sector portfolios (DUR) and the 25 Fama–French size and book-to-market portfolios (FF25). EMI is the value-weighted elastic-minus-inelastic portfolio. Non-traded factors are changes over a centered window, $\Delta z_t \equiv z_{t+1} - z_{t-1}$. The sample period is 1965M7–2024M12, and betas on non-traded factors are estimated over 1967–2019. Prices of risk, intercepts, and MAPEs are annualized and in percent. The joint p-value tests that all prices of risk are zero. GMM standard errors that account for estimation error in the betas are in parentheses.

Table 5: Cash Flow Growth and Exposures of Portfolios Sorted on $\bar{\mu}_{f,t-1}^{-1}$

	IAMU quintiles					
	Low	2	3	4	High	EMI
Panel A: Operating income growth						
Mean (%)	6.13	5.20	5.36	7.51	15.32	9.19
Volatility (%)	7.70	7.81	8.97	10.38	9.71	7.70
$\beta_{\Delta x}$	-0.21**	-0.46***	-0.65***	-0.74***	-0.63***	-0.42***
	(0.10)	(0.09)	(0.09)	(0.09)	(0.06)	(0.09)
R^2	0.08	0.36	0.56	0.57	0.45	0.28
Panel B: Sales growth						
Mean (%)	10.02	8.84	7.53	6.60	4.69	-5.34
Volatility (%)	6.97	5.90	6.11	6.06	5.98	4.82
$\beta_{\Delta x}$	-0.01	-0.13**	-0.17***	-0.18**	-0.18***	-0.18***
	(0.08)	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)
R^2	0.00	0.05	0.09	0.11	0.10	0.14
Panel C: Dividend growth						
Mean (%)	8.92	8.31	7.14	6.35	6.71	-2.21
Volatility (%)	6.32	7.00	8.76	9.55	10.75	6.69
$\beta_{\Delta x}$	-0.10	-0.15*	-0.22**	-0.26**	-0.33***	-0.22***
	(0.07)	(0.09)	(0.09)	(0.11)	(0.11)	(0.07)
R^2	0.02	0.05	0.08	0.08	0.09	0.10

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports annual cash flow growth rates and their exposures to income tail risk for quintile portfolios sorted on $\bar{\mu}_{f,t-1}^{-1}$ at the end of June of year t. Cash flow growth is the average log growth rate across firms in the portfolio over fiscal year t, or calendar year t for dividends. Operating income before depreciation and sales are from Compustat, and dividends are from CRSP. Firm-level growth rates require positive cash flows in both years and are winsorized at the 1st and 99th percentiles in each year. The EMI portfolio is long the fifth and short the first quintile. $\beta_{\Delta x}$ is the univariate beta with respect to $\Delta x_t \equiv x_t - x_{t-1}$, where x_t is the average of income tail risk over year t. The sample period is 1965–2024, and betas are estimated over 1968–2019. Standard errors are in parentheses.

Table 6: Return Predictability Across Portfolios Sorted on $\bar{\mu}_{f,t-1}^{-1}$

	IAMU quintiles					
	Low	2	3	4	High	EMI
Panel A: Monthly frequency						
3 months ahead						
icl_t	1.76**	2.15***	2.43***	2.60***	3.01***	1.25***
	(0.70)	(0.77)	(0.83)	(0.90)	(0.97)	(0.37)
R^2	0.03	0.04	0.04	0.04	0.05	0.04
12 months ahead						
icl_t	6.39***	8.04***	9.78***	11.10***	12.69***	6.30***
	(1.87)	(1.98)	(2.32)	(2.60)	(2.95)	(1.65)
R^2	0.11	0.14	0.17	0.18	0.18	0.16
24 months ahead						
icl_t	8.64**	9.89***	13.47***	15.80***	17.92***	9.28***
	(3.76)	(3.48)	(4.31)	(4.21)	(4.55)	(2.67)
R^2	0.09	0.11	0.15	0.17	0.17	0.13
Panel B: Quarterly frequency						
1 quarter ahead						
x_t	1.45	1.98**	2.23**	2.54**	2.79**	1.34**
	(0.93)	(1.00)	(1.09)	(1.16)	(1.30)	(0.55)
R^2	0.02	0.03	0.03	0.04	0.04	0.04
4 quarters ahead						
x_t	4.87**	7.06***	8.44***	10.37***	11.20***	6.33***
	(2.06)	(2.23)	(2.67)	(2.94)	(3.53)	(1.93)
R^2	0.06	0.10	0.12	0.14	0.13	0.16
8 quarters ahead						
x_t	6.97*	9.13**	12.29**	15.63***	16.82***	9.85***
	(3.83)	(3.98)	(5.17)	(5.23)	(6.16)	(3.60)
R^2	0.06	0.09	0.11	0.15	0.14	0.14

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports predictive regressions of cumulative future excess returns on equal-weighted quintile portfolios sorted on $\bar{\mu}_{f,t-1}^{-1}$ on the current level of income tail risk, measured by icl_t in monthly data (Panel A) and by x_t in quarterly data (Panel B). Cumulative excess returns are compounded portfolio returns minus compounded Treasury bill returns over the forecast horizon, in percent. The EMI portfolio is long the fifth and short the first quintile. The predictors are standardized to have a unit standard deviation. The sample period is 1967–2019. Newey–West standard errors with a lag length equal to the forecast horizon minus one are reported in parentheses.

Table 7: Predictability of EMI Return Spread: Controlling for Alternative Predictors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Monthly predictors							
icl_t	6.48***	6.30***	5.96***	4.55***	6.22***	6.06***	6.45***
	(1.55)	(1.75)	(1.51)	(1.21)	(1.62)	(1.65)	(1.62)
Dividend yield	3.77*						
	(2.08)						
T-bill rate		0.01					
		(1.76)					
Term spread			3.65***				
			(1.27)				
Default spread				8.17***			
				(2.49)			
Long-term return					1.03**		
					(0.48)		
Stock variance						1.54**	
						(0.65)	
Net issuing							-1.87
							(2.02)
R^2	0.20	0.16	0.22	0.25	0.16	0.16	0.16
Panel B: Quarterly predictors							
x_t	5.39***	4.52**	5.09***	5.85***	6.29***	4.78**	5.71***
	(1.60)	(1.80)	(1.75)	(1.91)	(1.93)	(1.98)	(1.80)
Unemployment rate	5.38***						
	(1.62)						
Capacity utilization		-4.34***					
		(1.64)					
Durable expenditure–stock ratio			-4.49***				
			(1.62)				
Investment–capital ratio				-3.37**			
				(1.43)			
Inflation					-2.06		
					(1.53)		
Consumer sentiment						-3.71**	
						(1.89)	
Building permits							-3.50**
							(1.56)
R^2	0.26	0.21	0.23	0.20	0.16	0.19	0.21

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports predictive regressions of the cumulative one-year-ahead return on the equal-weighted EMI portfolio on the current level of income tail risk and one alternative predictor at a time. Panel A uses monthly data, with icl_t and monthly predictors from Welch and Goyal (2008). Panel B uses quarterly data, with x_t and other macroeconomic indicators. The predictors are standardized to have a unit standard deviation. The sample period is 1967–2019. Newey–West standard errors with a lag length equal to the forecast horizon minus one are reported in parentheses.

Table 8: Predictability of Return and Cash Flow Volatility Across Portfolios Sorted on $\bar{\mu}_{f,t-1}^{-1}$

	IAMU quintiles				
	Low	2	3	4	High
Panel A: Absolute 1-year excess returns					
x_t	4.22^{***}	5.62^{***}	6.74^{***}	8.17^{***}	9.05^{***}
	(1.52)	(1.62)	(2.06)	(2.30)	(2.88)
R^2	0.10	0.14	0.16	0.18	0.16
Panel B: Absolute 1-year operating income growth					
x_t	1.05^{*}	0.69	1.25^{**}	2.24^{***}	1.81
	(0.60)	(0.66)	(0.62)	(0.84)	(1.12)
R^2	0.05	0.02	0.06	0.12	0.04
Panel C: Absolute 5-year dividend growth					
x_t	8.60^{**}	8.47^{**}	8.93^{***}	9.79^{**}	11.97^{***}
	(3.36)	(3.48)	(2.92)	(3.88)	(3.41)
R^2	0.19	0.18	0.22	0.20	0.26

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports predictive regressions of the absolute value of future excess returns and cash flow growth on the current level of income tail risk x_t for equal-weighted quintile portfolios sorted on $\bar{\mu}_{f,t-1}^{-1}$. Panel A uses cumulative four-quarter-ahead excess returns in quarterly data. Panels B and C use one-year-ahead operating income growth and cumulative five-year-ahead dividend growth in annual data, where x_t is the average of income tail risk over year t and cash flow growth is the average log growth rate across firms in the portfolio. The predictor is standardized to have a unit standard deviation. The sample period is 1967–2019. Newey–West standard errors with a lag length equal to the forecast horizon minus one are reported in parentheses.

Appendix

A Labor Income Risk over the Business Cycle

To quantify the amount of idiosyncratic income risk over time, I specify a statistical model of individual labor income and choose its parameters to match annual moments of the cross-sectional distribution of income growth rates reported by Guvenen et al. (2014). The income process is a simplified version of McKay (2017): individual income growth is subject to tail risk whose magnitude shifts with macroeconomic conditions.

A.1 Labor Income Process

Realized quarterly labor earnings $\widetilde{Y}_{i,t}$ of worker i are the product of an aggregate component $W_t\, L_t$ and two idiosyncratic components:

$$\widetilde{Y}_{i,t} = W_t\, L_t\, \Theta_{i,t}\, U_{i,t} \tag{A.1}$$

$$\Theta_{i,t+1} = \Theta_{i,t}\, e^{\xi_{i,t+1}}, \tag{A.2}$$

where $\Theta_{i,t}$ is a permanent idiosyncratic component and $U_{i,t} = e^{u_{i,t}}$ is a transitory idiosyncratic shock with a lognormal distribution, $u_{i,t} \sim N(-\frac{1}{2}\sigma_u^2, \sigma_u^2)$. For the purpose of simulating the idiosyncratic labor income process, aggregate labor income is treated as a given empirical input. In the general equilibrium model of Section 2, the aggregate wage W_t and labor supply L_t are determined endogenously by clearing the labor market.

The permanent shock $\xi_{i,t+1}$ is drawn from a mixture of three normal distributions:

$$\xi_{i,t+1} \sim \begin{cases} N(\mu_{1,t}, \sigma^2_{\xi,1}) & \text{with probability } 1 - p_2 - p_3 \\ N(\mu_{2,t}, \sigma^2_{\xi,2}) & \text{with probability } p_2 \\ N(\mu_{3,t}, \sigma^2_{\xi,3}) & \text{with probability } p_3, \end{cases} \tag{A.3}$$

where the conditional means of the three components depend on the aggregate state of the economy captured by x_t:

$$\mu_{1,t} = \bar{\mu}_t \tag{A.4}$$

$$\mu_{2,t} = \bar{\mu}_t + \tilde{\mu}_2 - x_t \tag{A.5}$$

$$\mu_{3,t} = \bar{\mu}_t + \tilde{\mu}_3 - x_t \tag{A.6}$$

$$\bar{\mu}_t = -\log\left((1 - p_2 - p_3)\, e^{\frac{1}{2}\sigma^2_{\xi,1}} + p_2\, e^{\tilde{\mu}_2 - x_t + \frac{1}{2}\sigma^2_{\xi,2}} + p_3\, e^{\tilde{\mu}_3 - x_t + \frac{1}{2}\sigma^2_{\xi,3}}\right). \tag{A.7}$$

With probability $1 - p_2 - p_3$, a worker draws an ordinary shock (the first component). The second component is a large income loss, with location parameter $\tilde{\mu}_2 < 0$, and the third component is a large gain, with location parameter $\tilde{\mu}_3 > 0$. The state variable x_t governs the amount of tail risk over the business cycle: a higher x_t lowers the conditional means $\mu_{2,t}$ and $\mu_{3,t}$ of both tail components, shifting the tails of the distribution of income growth to the left and increasing its negative skewness. The intercept $\bar{\mu}_t$ adjusts to hold the conditional mean of income growth fixed, $\mathbb{E}[e^{\xi_{i,t+1}} \mid x_t] = 1$, so that the shocks are purely idiosyncratic given the aggregate state.[16]

A.2 Measurement

To analyze idiosyncratic income risk at a higher frequency than the annual income data, I follow McKay (2017) by assuming that the latent tail-risk state x_t and aggregate income growth $\Delta \log(W_t\, L_t)$ are related to observable quarterly indicators of labor market conditions through linear measurement equations. Labor market indicators are collected from the FRED database of the Federal Reserve Bank of St. Louis and detrended with a backward-looking, one-sided Hodrick-Prescott filter with smoothing parameter 10^5 to remove very low-frequency variation, so that they reflect business-cycle rather than secular movements.

Income tail risk is specified as a linear combination of four cyclical indicators, $x_t = \phi_x' X_{x,t}$. The vector $X_{x,t}$ collects (1) the share of the labor force unemployed for fewer than 15 weeks, $(\texttt{UNEMPLOY} - \texttt{UEMP15OV})/\texttt{CLF16OV}$; (2) the share of the labor force unemployed for 15 weeks or

[16] Workers survive each quarter with probability $1 - \omega$. I set $\omega = 1/160$, so that mortality risk is 2.5% per year. A worker who dies is replaced by a newborn with initial permanent income $\Theta = 1$, which keeps the cross-sectional distribution of $\Theta_{i,t}$ stationary.

more, UEMP15OV/CLF16OV; (3) average weekly hours, PRS85006023; and (4) initial claims for unemployment insurance relative to lagged private payroll employment, ICSA/L.USPRIV.

Aggregate income growth is assumed to satisfy $\Delta \log(W_t L_t) = \phi_w' X_{w,t} - \phi_{w,x} x_t$, where $X_{w,t}$ collects (1) quarterly real GDP growth, $\log(\texttt{GDPC1}_t/\texttt{L.GDPC1})$, which is not detrended; (2) the short-term job-finding rate, $1 - \frac{(\texttt{UEMP15OV}-\texttt{UEMP27OV})/\texttt{CLF16OV}}{(\texttt{L.UNEMPLOY}-\texttt{L.UEMP15OV})/\texttt{L.CLF16OV}}$; and (3) a constant. The loading $\phi_{w,x}$ allows for a direct relationship between aggregate income growth and cyclical tail risk. For numerical convenience, I standardize the indicators and replace them with their principal components.

A.3 Parameterization

I choose the parameters of the income process by simulated method of moments, targeting moments of the income growth distribution reported by Guvenen et al. (2014) for U.S. labor earnings over the period 1978–2011. The targeted moments are the 10th, 50th, and 90th percentiles ($p10$, $p50$, $p90$) of income growth over 1-year, 3-year, and 5-year horizons. For each year and each horizon, I define the residuals as scaled deviations:

- median: $(p50_{\text{model}} - p50_{\text{data}})/p90_{\text{data}}$;
- left-tail risk: $(p50_{\text{model}} - p10_{\text{model}})/(p50_{\text{data}} - p10_{\text{data}}) - 1$;
- right-tail risk: $(p90_{\text{model}} - p50_{\text{model}})/(p90_{\text{data}} - p50_{\text{data}}) - 1$.

The parameters minimize the sum of squared residuals over all years and horizons.

I evaluate the model moments by simulation, using the same random draws for every parameter vector. For given parameter values, I simulate quarterly trajectories of aggregate income growth, the tail-risk process x_t, idiosyncratic permanent and transitory shocks, and mortality from 1967Q3 to 2019Q4 for a panel of 100,000 individuals, initializing every individual at permanent income $\Theta = 1$. I then sum the quarterly income realizations within each calendar year and compute the moments from annual incomes over 1978–2011, as in the data.[17] Following Guvenen et al. (2014), who drop earnings below a minimum threshold ($1,300 in 2005), I exclude annual incomes below $1{,}300/50{,}000 = 2.6\%$ of average annual income in the simulated cross section. Finally, I compute

[17] The parameter estimates are not sensitive to the initial income distribution, since the targeted statistics are moments of income growth rates.

the percentiles of the resulting distributions of annual income growth, mirroring the empirical moments.

The estimated parameters are the loadings of x_t and aggregate income growth on the macroeconomic indicators, ϕ_x, ϕ_w, and $\phi_{w,x}$, and the parameters of the shock distribution, σ_u, $\sigma_{\xi,1}$, $\sigma_{\xi,2}$, $\sigma_{\xi,3}$, p_2, p_3, $\tilde{\mu}_2$, and $\tilde{\mu}_3$. To limit the degrees of freedom, I restrict the two tail components to be equally likely and equally dispersed, $p_2 = p_3$ and $\sigma_{\xi,2} = \sigma_{\xi,3}$, so that they differ only in the location of their means, $\tilde{\mu}_2 < 0 < \tilde{\mu}_3$. I minimize the objective by global optimization in two steps: I first estimate the shock distribution with x_t and aggregate income growth loading only on the first principal components, and then estimate all loadings holding the shock distribution fixed.

Table A.1 reports the estimated parameters of the labor income process, and Figure A.1 compares the percentiles of the income growth distribution in the model with their empirical counterparts. The income process fits the data well, particularly at the 3- and 5-year horizons.

Variation in income risk over time is governed by the tail-risk process x_t, whose time series is discussed in Section 1. Figure A.2 illustrates how the distribution of permanent income growth depends on the macroeconomic state, plotting the log density of the permanent shock ξ for $x = -\bar{\sigma}$ (expansion) and $x = \bar{\sigma}$ (recession), where $\bar{\sigma} = 0.115$ is the unconditional standard deviation of x. When x is high, the density shifts to the left: the left tail expands, the center of the distribution is relatively stable, and the right tail shrinks. The income process thus produces idiosyncratic risk that is countercyclical and increasingly left-skewed in recessions.

B Model Appendix

This section contains the derivations for the New Keynesian asset pricing model introduced in Section 2.

B.1 Households

Stockholders

Stockholders earn income from labor as well as firm profits, as they are the holders of firm equity. They derive utility from the consumption of the composite consumption good and can trade a

complete set of state-dependent claims among themselves. The utility maximization problem of the representative stockholder is given by

$$\begin{aligned} \max \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_s^{\tau} \left[\frac{(C_{s,t+\tau} - H_{s,t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0,s} \int_0^1 \frac{L_{s,j,t+\tau}^{1+\chi_1}}{1+\chi_1} dj \right] \\ \text{s.t.} \quad & P_t \, C_{s,t} = \int_0^1 W_{s,j,t} \, L_{s,j,t} \, dj + P_t \, \frac{D_t}{\delta_s}, \end{aligned} \tag{A.8}$$

with external habit $H_{s,t} = b_s \, C_{s,t-1}$. The budget constraint says that stockholders' consumption expenditures, $P_t \, C_{s,t}$, are equal to total labor income from differentiated labor services and dividend income per capita, after imposing market clearing for the state-contingent claims that are in zero net supply.

Let $\Lambda_{s,t}$ be the Lagrange multiplier on the budget constraint. The first-order condition with respect to consumption is

$$(C_{s,t} - b_s \, C_{s,t-1})^{-\gamma} = \Lambda_{s,t} \, P_t \equiv \lambda_{s,t}. \tag{A.9}$$

The Euler equation for any asset that is traded by the stockholders and has real return R_t is

$$1 = \mathbb{E}_t \left[M_{t+1} \, R_{t+1} \right], \tag{A.10}$$

where the real SDF M_{t+1} is defined by

$$M_{t+1} = \beta_s \frac{\lambda_{s,t+1}}{\lambda_{s,t}} = \beta_s \left(\frac{C_{s,t+1} - b_s \, C_{s,t}}{C_{s,t} - b_s \, C_{s,t-1}} \right)^{-\gamma}. \tag{A.11}$$

Non-Stockholders

Non-stockholders face incomplete markets and only have access to a one-period nominal bond with gross return I_{t-1} in period t. Since asset markets are fully segmented, non-stockholders are always the marginal holders of this asset that exists in zero net supply and has a price that is set by the monetary authority.

The problem for agent $i \in \mathcal{I}_n$ is given by

$$\begin{aligned} \max \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_n^\tau \left[\frac{(c_{i,t+\tau} - h_{i,t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0,n} \, \Gamma_{i,t+\tau}^{1-\gamma} \int_0^1 \frac{l_{i,j,t+\tau}^{1+\chi_1}}{1+\chi_1} dj \right] \\ \text{s.t.} \quad & P_t \, c_{i,t} = \Gamma_{i,t} \int_0^1 W_{n,j,t} \, l_{i,j,t} \, dj + b_{i,t-1} \, I_{t-1} - b_{i,t}, \end{aligned} \tag{A.12}$$

where $b_{i,t}$ are individual nominal bond holdings. The individual habit can be written as $h_{i,t} = \Gamma_{i,t} \, H_{n,t}$, with $H_{n,t} \equiv b_n \, C_{n,t-1}$.

Next, decompose consumption and bond holdings as $c_{i,t} = \Gamma_{i,t} \, \tilde{c}_{i,t}$ and $b_{i,t} = \Gamma_{i,t} \, \tilde{b}_{i,t}$. Per the setup of the labor market in Section 2.2, the labor union for labor type j allocates the same hours to all of its members, $l_{i,j,t} = L_{n,j,t}$. The non-stockholders' utility maximization problem can therefore be rewritten as

$$\begin{aligned} \max \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_n^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}} \right)^{1-\gamma} \left[\frac{(\tilde{c}_{i,t+\tau} - H_{n,t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0,n} \int_0^1 \frac{L_{n,j,t+\tau}^{1+\chi_1}}{1+\chi_1} dj \right] \\ \text{s.t.} \quad & P_t \, \tilde{c}_{i,t} + \tilde{b}_{i,t} = \int_0^1 W_{n,j,t} \, L_{n,j,t} \, dj + \tilde{b}_{i,t-1} \, I_{t-1} \, \frac{\Gamma_{i,t-1}}{\Gamma_{i,t}}. \end{aligned} \tag{A.13}$$

For a given normalized beginning-of-period bond position, the rescaled problem is the same for every non-stockholder: the objective depends on idiosyncratic productivity only through the future ratios $\Gamma_{i,t+\tau}/\Gamma_{i,t}$, whose conditional distribution does not depend on the level of $\Gamma_{i,t}$. Non-stockholders who enter the period with the same normalized payoff therefore choose the same normalized consumption and bond demand. Starting from zero bond holdings, all non-stockholders choose a common normalized bond position $\tilde{b}_t$. Since the bond is in zero net supply, bond market clearing implies that

$$0 = \int_{i \in \mathcal{I}_n} b_{i,t} \, di = \tilde{b}_t \int_{i \in \mathcal{I}_n} \Gamma_{i,t} \, di, \tag{A.14}$$

so that $\tilde{b}_t = 0$. The same logic holds in every period. With zero bond holdings, the rescaled budget constraint pins down a common normalized consumption level equal to per-capita non-stockholder

consumption $C_{n,t}$, so that

$$c_{i,t} = \Gamma_{i,t}\, C_{n,t}. \tag{A.15}$$

Now, let $\Lambda_{n,t}$ be the Lagrange multiplier on the budget constraint and take the first-order condition with respect to consumption:

$$(C_{n,t} - b_n\, C_{n,t-1})^{-\gamma} = \Lambda_{n,t}\, P_t \equiv \lambda_{n,t}. \tag{A.16}$$

The first-order condition with respect to bond holdings gives the Euler equation for the nominal risk-free asset:

$$1 = \beta_n\, I_t\, \mathbb{E}_t \left[\left(\frac{\Gamma_{i,t+1}}{\Gamma_{i,t}} \right)^{-\gamma} \frac{\Lambda_{n,t+1}}{\Lambda_{n,t}} \right] = \beta_n\, g_{0,n}(x_t)\, I_t\, \mathbb{E}_t \left[\frac{\Lambda_{n,t+1}}{\Lambda_{n,t}} \right]. \tag{A.17}$$

B.2 Consumption Goods

Households consume the composite good C_t. This composite good is a double Dixit-Stiglitz aggregate of the consumption goods that are produced within each sector and across sectors. Let $C_t(k)$ be the consumption basket from goods in sector k. Consumption of the composite good is given by

$$C_t = \left(\sum_k \omega_k^{\frac{1}{\eta_c}}\, C_t(k)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}}, \tag{A.18}$$

with weights ω_k over the sectors. The consumption basket from sector k is aggregated from individual consumption goods $C_t(k, f)$ of firms f:

$$C_t(k) = \left(\int_0^1 C_t(k, f)^{\frac{\eta_{c,k} - 1}{\eta_{c,k}}}\, df \right)^{\frac{\eta_{c,k}}{\eta_{c,k} - 1}}. \tag{A.19}$$

For any desired consumption level C_t of the composite good, households solve

$$\begin{aligned} \min \quad & \sum_k P_{k,t}\, C_t(k) \equiv P_t\, C_t \\ \text{s.t.} \quad & \left(\sum_k \omega_k^{\frac{1}{\eta_c}}\, C_t(k)^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} = C_t. \end{aligned} \tag{A.20}$$

The first-order condition is

$$P_{k,t} = \Omega_c\, C_t^{\frac{1}{\eta_c}}\, \omega_k^{\frac{1}{\eta_c}}\, C_t(k)^{-\frac{1}{\eta_c}}, \tag{A.21}$$

where Ω_c is the Lagrange multiplier on the composite consumption constraint. The solution is

$$C_t(k) = \omega_k \left(\frac{P_{k,t}}{P_t} \right)^{-\eta_c} C_t, \tag{A.22}$$

with price index

$$P_t = \left(\sum_k \omega_k\, P_{k,t}^{1-\eta_c} \right)^{\frac{1}{1-\eta_c}}. \tag{A.23}$$

Analogously, at the sector level,

$$C_t(k,f) = \left(\frac{P_{k,f,t}}{P_{k,t}} \right)^{-\eta_{c,k}} C_t(k) \tag{A.24}$$

$$P_{k,t} = \left(\int_0^1 P_{k,f,t}^{1-\eta_{c,k}}\, df \right)^{\frac{1}{1-\eta_{c,k}}}. \tag{A.25}$$

B.3 Labor Demand

A competitive labor aggregator combines labor services from individual agent and labor types, hired at the posted wages $W_{\nu,j,t}$, into homogeneous labor that is used as an input in the production function by firms. The problem for the labor aggregator of hiring across agent types can be written as

$$\begin{aligned} \min \quad & \sum_\nu W_{\nu,t}\, N_{\nu,t} \equiv W_t\, N_t \\ \text{s.t.} \quad & \left(\sum_\nu \delta_\nu^{\frac{1}{\eta_n}}\, N_{\nu,t}^{\frac{\eta_n - 1}{\eta_n}} \right)^{\frac{\eta_n}{\eta_n - 1}} = N_t. \end{aligned} \tag{A.26}$$

The first-order condition of this problem is

$$W_{\nu,t} = \Omega_w \, N_t^{\frac{1}{\eta_n}} \, \delta_\nu^{\frac{1}{\eta_n}} \, N_{\nu,t}^{-\frac{1}{\eta_n}}, \tag{A.27}$$

where Ω_w is the Lagrange multiplier on the labor quantity constraint. The solution is

$$N_{\nu,t} = \delta_\nu \left(\frac{W_{\nu,t}}{W_t} \right)^{-\eta_n} N_t, \tag{A.28}$$

with aggregate wage index

$$W_t = \left(\sum_\nu \delta_\nu \, W_{\nu,t}^{1-\eta_n} \right)^{\frac{1}{1-\eta_n}}. \tag{A.29}$$

Similarly, within agent type,

$$\begin{aligned} N_{\nu,j,t} &= \left(\frac{W_{\nu,j,t}}{W_{\nu,t}} \right)^{-\eta_n} N_{\nu,t} \\ W_{\nu,t} &= \left(\int_0^1 W_{\nu,j,t}^{1-\eta_n} \, dj \right)^{\frac{1}{1-\eta_n}}. \end{aligned} \tag{A.30}$$

B.4 Wage Setting

Labor is demand driven: hours for labor type j by agent type ν are fulfilled at the posted wage rate $W_{\nu,j,t}$ to meet total labor demand. As a consequence, under equal hours, the hours supplied by workers of type ν for labor type j are

$$L_{\nu,j,t} = \frac{1}{\delta_\nu} N_{\nu,j,t} = \left(\frac{W_{\nu,j,t}}{W_{\nu,t}} \right)^{-\eta_n} \left(\frac{W_{\nu,t}}{W_t} \right)^{-\eta_n} N_t, \tag{A.31}$$

so that the total efficiency units supplied by agent type ν for labor type j, $\int_{i \in \mathcal{I}_\nu} \Gamma_{i,t} \, L_{\nu,j,t} \, di$, meet the demand $N_{\nu,j,t}$.

All unions of agent type ν that reset their wage in period t face the same problem and therefore choose the same reset wage, $W_{\nu,j,t}^* = W_{\nu,t}^*$. The maximization problem for the labor union in setting the reset wage $W_{\nu,t}^*$ is

$$\max \quad \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \, \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}} \right)^{1-\gamma} \left[-\chi_{0,\nu} \, \frac{L_{\nu,j,t+\tau}^{1+\chi_1}}{1+\chi_1} + \lambda_{\nu,t+\tau} \, \frac{W_{\nu,t}^*}{P_{t+\tau}} \, L_{\nu,j,t+\tau} \right] \tag{A.32}$$

$$\text{s.t.} \quad L_{\nu,j,t+\tau} = \left(\frac{W^*_{\nu,t}}{W_{\nu,t+\tau}}\right)^{-\eta_n} \left(\frac{W_{\nu,t+\tau}}{W_{t+\tau}}\right)^{-\eta_n} N_{t+\tau}, \tag{A.33}$$

with first-order condition

$$\begin{aligned}
0 &= \eta_n \, \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \, \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}}\right)^{1-\gamma} \chi_{0,\nu} \left(\frac{W^*_{\nu,t}}{W_{\nu,t+\tau}}\right)^{-\eta_n(1+\chi_1)} \left(\frac{W_{\nu,t+\tau}}{W_{t+\tau}}\right)^{-\eta_n(1+\chi_1)} \frac{N_{t+\tau}^{1+\chi_1}}{W^*_{\nu,t}} \\
&\quad + (1-\eta_n) \, \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \, \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}}\right)^{1-\gamma} \lambda_{\nu,t+\tau} \left(\frac{W^*_{\nu,t}}{W_{\nu,t+\tau}}\right)^{-\eta_n} \left(\frac{W_{\nu,t+\tau}}{W_{t+\tau}}\right)^{-\eta_n} \frac{N_{t+\tau}}{P_{t+\tau}} \\
&\Leftrightarrow \\
&\frac{\eta_n}{\eta_n - 1} \frac{\chi_{0,\nu}}{\lambda_{\nu,t}} \left(\frac{W_t}{P_t}\right)^{\eta_n \chi_1} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \, \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}}\right)^{1-\gamma} \left(\frac{W_{t+\tau}}{W_t}\right)^{\eta_n(1+\chi_1)} N_{t+\tau}^{1+\chi_1} \\
&= \left(\frac{W^*_{\nu,t}}{P_t}\right)^{1+\eta_n\chi_1} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \, \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{i,t}}\right)^{1-\gamma} \frac{\lambda_{\nu,t+\tau}}{\lambda_{\nu,t}} \left(\frac{W_{t+\tau}}{W_t}\right)^{\eta_n} \frac{P_t}{P_{t+\tau}} N_{t+\tau}.
\end{aligned} \tag{A.34}$$

Hence, the optimal reset wage is given by

$$\left(\frac{W^*_{\nu,t}}{P_t}\right)^{1+\eta_n\chi_1} = \frac{\eta_n}{\eta_n - 1} \frac{\chi_{0,\nu}}{\lambda_{\nu,t}} \left(\frac{W_t}{P_t}\right)^{\eta_n\chi_1} \frac{F_{w,\nu,t}}{K_{w,\nu,t}} \tag{A.35}$$

$$F_{w,\nu,t} = N_t^{1+\chi_1} + \beta_\nu \, \theta_w \, g_{1,\nu}(x_t) \, \mathbb{E}_t \left[\left(\frac{W_{t+1}}{W_t}\right)^{\eta_n(1+\chi_1)} F_{w,\nu,t+1} \right] \tag{A.36}$$

$$K_{w,\nu,t} = N_t + \beta_\nu \, \theta_w \, g_{1,\nu}(x_t) \, \mathbb{E}_t \left[\frac{\lambda_{\nu,t+1}}{\lambda_{\nu,t}} \left(\frac{W_{t+1}}{W_t}\right)^{\eta_n} \frac{P_t}{P_{t+1}} K_{w,\nu,t+1} \right]. \tag{A.37}$$

Since the unions that reset their wage in a given period are a random sample of all unions, the law of motion for the real wage is given by

$$\left(\frac{W_{\nu,t}}{P_t}\right)^{1-\eta_n} = (1-\theta_w) \left(\frac{W^*_{\nu,t}}{P_t}\right)^{1-\eta_n} + \theta_w \left(\frac{W_{\nu,t-1}}{P_{t-1}}\right)^{1-\eta_n} \left(\frac{P_t}{P_{t-1}}\right)^{\eta_n - 1}. \tag{A.38}$$

B.5 Price Setting

Firms choose their prices to maximize the value of the firm, which is the net present value of future dividends. Since the firms are owned by the stockholders, the stochastic discount factor that prices claims to firm dividends is given by the marginal utility of stockholders. Real firm dividends are

given by

$$
\begin{aligned}
D_{k,f,t} &= \frac{P_{k,f,t}}{P_t} Y_t(k,f) - \frac{W_t}{P_t} N_t(k,f) \\
&= \omega_k C_t \left[\left(\frac{P_{k,f,t}}{P_{k,t}} \right)^{1-\eta_{c,k}} \left(\frac{P_{k,t}}{P_t} \right)^{1-\eta_c} - \frac{W_t}{P_t} \frac{1}{A_t} \left(\frac{P_{k,f,t}}{P_{k,t}} \right)^{-\eta_{c,k}} \left(\frac{P_{k,t}}{P_t} \right)^{-\eta_c} \right] \\
&= \omega_k C_t \left[\left(\frac{P_{k,f,t}}{P_t} \right)^{1-\eta_{c,k}} \left(\frac{P_{k,t}}{P_t} \right)^{\eta_{c,k}-\eta_c} - \frac{W_t}{P_t} \frac{1}{A_t} \left(\frac{P_{k,f,t}}{P_t} \right)^{-\eta_{c,k}} \left(\frac{P_{k,t}}{P_t} \right)^{\eta_{c,k}-\eta_c} \right].
\end{aligned} \tag{A.39}
$$

When getting the chance to update their price, firms in sector k choose the reset price $P^*_{k,t}$ to maximize the present value of future dividends over the periods in which the price remains fixed:

$$
\begin{aligned}
\max_{P^*_{k,t}} \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_s \theta_{p,k})^\tau \frac{\lambda_{s,t+\tau}}{\lambda_{s,t}} C_{t+\tau} \left[\left(\frac{P^*_{k,t}}{P_{t+\tau}} \right)^{1-\eta_{c,k}} \left(\frac{P_{k,t+\tau}}{P_{t+\tau}} \right)^{\eta_{c,k}-\eta_c} \right. \\
& \left. - \frac{W_{t+\tau}}{P_{t+\tau}} \frac{1}{A_{t+\tau}} \left(\frac{P^*_{k,t}}{P_{t+\tau}} \right)^{-\eta_{c,k}} \left(\frac{P_{k,t+\tau}}{P_{t+\tau}} \right)^{\eta_{c,k}-\eta_c} \right],
\end{aligned} \tag{A.40}
$$

with first-order condition

$$
\begin{aligned}
& \frac{P^*_{k,t}}{P_t} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_s \theta_{p,k})^\tau \frac{\lambda_{s,t+\tau}}{\lambda_{s,t}} \left(\frac{P_t}{P_{t+\tau}} \right)^{1-\eta_{c,k}} \left(\frac{P_{k,t+\tau}}{P_{t+\tau}} \right)^{\eta_{c,k}-\eta_c} C_{t+\tau} \\
& \quad = \frac{\eta_{c,k}}{\eta_{c,k}-1} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_s \theta_{p,k})^\tau \frac{\lambda_{s,t+\tau}}{\lambda_{s,t}} \left(\frac{P_t}{P_{t+\tau}} \right)^{-\eta_{c,k}} \frac{W_{t+\tau}}{P_{t+\tau}} \frac{1}{A_{t+\tau}} \left(\frac{P_{k,t+\tau}}{P_{t+\tau}} \right)^{\eta_{c,k}-\eta_c} C_{t+\tau}.
\end{aligned} \tag{A.41}
$$

It follows that the optimal reset price $P^*_{k,t}$ is given by

$$
\frac{P^*_{k,t}}{P_t} = \frac{\eta_{c,k}}{\eta_{c,k}-1} \frac{F_{p,k,t}}{K_{p,k,t}} \tag{A.42}
$$

$$
F_{p,k,t} = \frac{W_t}{P_t} \frac{1}{A_t} \left(\frac{P_{k,t}}{P_t} \right)^{\eta_{c,k}-\eta_c} C_t + \beta_s \theta_{p,k} \mathbb{E}_t \left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}} \left(\frac{P_t}{P_{t+1}} \right)^{-\eta_{c,k}} F_{p,k,t+1} \right] \tag{A.43}
$$

$$
K_{p,k,t} = \left(\frac{P_{k,t}}{P_t} \right)^{\eta_{c,k}-\eta_c} C_t + \beta_s \theta_{p,k} \mathbb{E}_t \left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}} \left(\frac{P_t}{P_{t+1}} \right)^{1-\eta_{c,k}} K_{p,k,t+1} \right]. \tag{A.44}
$$

The law of motion for the relative price of sector k is

$$
\left(\frac{P_{k,t}}{P_t} \right)^{1-\eta_{c,k}} = (1-\theta_{p,k}) \left(\frac{P^*_{k,t}}{P_t} \right)^{1-\eta_{c,k}} + \theta_{p,k} \left(\frac{P_{k,t-1}}{P_{t-1}} \right)^{1-\eta_{c,k}} \left(\frac{P_t}{P_{t-1}} \right)^{\eta_{c,k}-1}. \tag{A.45}
$$

B.6 Aggregates

This section derives quantities and market values at the sector and aggregate level.

First, total labor demand in sector k is

$$N_t(k) = \int_0^1 N_t(k,f)\,df = \frac{1}{A_t}\int_0^1 Y_t(k,f)\,df = \frac{C_t(k)}{A_t}\underbrace{\int_0^1 \left(\frac{P_{k,f,t}}{P_{k,t}}\right)^{-\eta_{c,k}} df}_{DS_{p,k,t}}, \tag{A.46}$$

where price dispersion is

$$DS_{p,k,t} = (1-\theta_{p,k})\left(\frac{P^*_{k,t}}{P_{k,t}}\right)^{-\eta_{c,k}} + \theta_{p,k}\,DS_{p,k,t-1}\left(\frac{P_{k,t}}{P_{k,t-1}}\right)^{\eta_{c,k}}. \tag{A.47}$$

The total dividend in sector k is

$$D_{k,t} = \int_0^1 D_{k,f,t}\,df = \omega_k\left(\frac{P_{k,t}}{P_t}\right)^{1-\eta_c} C_t\left[1 - \underbrace{\frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{k,t}}{P_t}\right)^{-1} DS_{p,k,t}}_{\hat{\mu}_{k,t}^{-1}}\right]. \tag{A.48}$$

Note that $\hat{\mu}_{k,t}$ is the markup of sector k. The price of a claim to total dividends in sector k is given by

$$V_{k,t} = \mathbb{E}_t\left[\sum_{\tau=0}^{\infty}\beta_s^\tau\frac{\lambda_{s,t+\tau}}{\lambda_{s,t}}D_{k,t+\tau}\right] = D_{k,t} + \beta_s\,\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}}V_{k,t+1}\right]. \tag{A.49}$$

Next, turning to aggregates across sectors, total labor demand is given by

$$N_t = \sum_k N_t(k) = \frac{C_t}{A_t}\underbrace{\sum_k \omega_k\left(\frac{P_{k,t}}{P_t}\right)^{-\eta_c} DS_{p,k,t}}_{DS_{p,t}}. \tag{A.50}$$

Since N_t is an aggregate of differentiated labor services, it differs from total hours worked. Using the hours $L_{\nu,j,t}$ supplied by workers of type ν from Section B.4, aggregate hours per capita are

$$L_t = \sum_\nu \delta_\nu \int_0^1 L_{\nu,j,t}\,dj = \sum_\nu N_{\nu,t}\underbrace{\int_0^1\left(\frac{W_{\nu,j,t}}{W_{\nu,t}}\right)^{-\eta_n} dj}_{DS_{w,\nu,t}}, \tag{A.51}$$

where wage dispersion within agent type ν is

$$DS_{w,\nu,t} = (1-\theta_w)\left(\frac{W^*_{\nu,t}}{W_{\nu,t}}\right)^{-\eta_n} + \theta_w\, DS_{w,\nu,t-1}\left(\frac{W_{\nu,t}}{W_{\nu,t-1}}\right)^{\eta_n}. \tag{A.52}$$

Aggregate dividends are

$$D_t = \sum_k D_{k,t} = C_t\left[1 - \underbrace{\frac{W_t}{P_t}\frac{1}{A_t}\, DS_{p,t}}_{\hat{\mu}_t^{-1}}\right], \tag{A.53}$$

where $\hat{\mu}_t$ is the aggregate markup. The price of a claim to aggregate dividends is

$$V_t = D_t + \beta_s\, \mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}}\, V_{t+1}\right]. \tag{A.54}$$

Finally, clearing the markets for consumption goods yields the following equilibrium relations:

$$C_t = \delta_s\, C_{s,t} + \delta_n\, C_{n,t} = Y_t \tag{A.55}$$

$$C_{s,t} = \int_0^1 \frac{W_{s,j,t}}{P_t} L_{s,j,t}\, dj + \frac{D_t}{\delta_s} = \left(\frac{W_{s,t}}{P_t}\right)^{1-\eta_n}\left(\frac{W_t}{P_t}\right)^{\eta_n} N_t + \frac{D_t}{\delta_s} \tag{A.56}$$

$$C_{n,t} = \int_0^1 \frac{W_{n,j,t}}{P_t} L_{n,j,t}\, dj = \left(\frac{W_{n,t}}{P_t}\right)^{1-\eta_n}\left(\frac{W_t}{P_t}\right)^{\eta_n} N_t. \tag{A.57}$$

B.7 Equilibrium Conditions

This section summarizes all equilibrium conditions.

Household consumption and saving:

$$\lambda_{\nu,t} = (C_{\nu,t} - b_\nu\, C_{\nu,t-1})^{-\gamma} \qquad \nu \in \{s,n\} \tag{A.58}$$

$$1 = \beta_n\, g_{0,n}(x_t)\, I_t\, \mathbb{E}_t\left[\frac{\lambda_{n,t+1}}{\lambda_{n,t}}\, e^{-\pi_{t+1}}\right] \tag{A.59}$$

$$C_{s,t} = \frac{W_{s,t}}{P_t}\,\frac{N_{s,t}}{\delta_s} + \frac{D_t}{\delta_s} \tag{A.60}$$

$$C_{n,t} = \frac{W_{n,t}}{P_t}\,\frac{N_{n,t}}{\delta_n} \tag{A.61}$$

Demand and price indices for consumption goods and labor services:

$$C_t(k) = \omega_k \left(\frac{P_{k,t}}{P_t}\right)^{-\eta_c} C_t \qquad \forall\, k \tag{A.62}$$

$$1 = \left(\sum_k \omega_k \left(\frac{P_{k,t}}{P_t}\right)^{1-\eta_c}\right)^{\frac{1}{1-\eta_c}} \tag{A.63}$$

$$N_{\nu,t} = \delta_\nu \left(\frac{W_{\nu,t}}{P_t}\right)^{-\eta_n} \left(\frac{W_t}{P_t}\right)^{\eta_n} N_t \qquad \nu \in \{s,n\} \tag{A.64}$$

$$\frac{W_t}{P_t} = \left(\sum_\nu \delta_\nu \left(\frac{W_{\nu,t}}{P_t}\right)^{1-\eta_n}\right)^{\frac{1}{1-\eta_n}} \tag{A.65}$$

Wage setting for agent type $\nu \in \{s,n\}$:

$$\left(\frac{W^*_{\nu,t}}{P_t}\right)^{1+\eta_n\chi_1} = \frac{\eta_n}{\eta_n - 1}\frac{\chi_{0,\nu}}{\lambda_{\nu,t}} \left(\frac{W_t}{P_t}\right)^{\eta_n\chi_1} \frac{F_{w,\nu,t}}{K_{w,\nu,t}} \tag{A.66}$$

$$F_{w,\nu,t} = N_t^{1+\chi_1} + \beta_\nu\, \theta_w\, g_{1,\nu}(x_t)\, \mathbb{E}_t\left[\left(\frac{P_t}{W_t}\frac{W_{t+1}}{P_{t+1}}\, e^{\pi_{t+1}}\right)^{\eta_n(1+\chi_1)} F_{w,\nu,t+1}\right] \tag{A.67}$$

$$K_{w,\nu,t} = N_t + \beta_\nu\, \theta_w\, g_{1,\nu}(x_t)\, \mathbb{E}_t\left[\frac{\lambda_{\nu,t+1}}{\lambda_{\nu,t}} \left(\frac{P_t}{W_t}\frac{W_{t+1}}{P_{t+1}}\right)^{\eta_n} e^{\pi_{t+1}(\eta_n - 1)}\, K_{w,\nu,t+1}\right] \tag{A.68}$$

$$\left(\frac{W_{\nu,t}}{P_t}\right)^{1-\eta_n} = (1-\theta_w)\left(\frac{W^*_{\nu,t}}{P_t}\right)^{1-\eta_n} + \theta_w \left(\frac{W_{\nu,t-1}}{P_{t-1}}\right)^{1-\eta_n} e^{\pi_t(\eta_n - 1)} \tag{A.69}$$

$$DS_{w,\nu,t} = (1-\theta_w)\left(\frac{W^*_{\nu,t}}{W_{\nu,t}}\right)^{-\eta_n} + \theta_w\, DS_{w,\nu,t-1}\, e^{\pi_t\eta_n} \left(\frac{W_{\nu,t}}{P_t}\right)^{\eta_n} \left(\frac{W_{\nu,t-1}}{P_{t-1}}\right)^{-\eta_n} \tag{A.70}$$

Price setting for sector k:

$$\frac{P^*_{k,t}}{P_t} = \frac{\eta_{c,k}}{\eta_{c,k} - 1}\frac{F_{p,k,t}}{K_{p,k,t}} \tag{A.71}$$

$$F_{p,k,t} = \frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{k,t}}{P_t}\right)^{\eta_{c,k}-\eta_c} C_t + \beta_s\, \theta_{p,k}\, \mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}}\, e^{\pi_{t+1}\eta_{c,k}}\, F_{p,k,t+1}\right] \tag{A.72}$$

$$K_{p,k,t} = \left(\frac{P_{k,t}}{P_t}\right)^{\eta_{c,k}-\eta_c} C_t + \beta_s\, \theta_{p,k}\, \mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}}\, e^{\pi_{t+1}(\eta_{c,k}-1)}\, K_{p,k,t+1}\right] \tag{A.73}$$

$$\left(\frac{P_{k,t}}{P_t}\right)^{1-\eta_{c,k}} = (1-\theta_{p,k})\left(\frac{P^*_{k,t}}{P_t}\right)^{1-\eta_{c,k}} + \theta_{p,k}\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{1-\eta_{c,k}} e^{\pi_t(\eta_{c,k}-1)} \tag{A.74}$$

$$DS_{p,k,t} = (1-\theta_{p,k})\left(\frac{P^*_{k,t}}{P_{k,t}}\right)^{-\eta_{c,k}} + \theta_{p,k}\, DS_{p,k,t-1}\, e^{\pi_t\eta_{c,k}} \left(\frac{P_{k,t}}{P_t}\right)^{\eta_{c,k}} \left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{-\eta_{c,k}} \tag{A.75}$$

Market clearing for consumption goods:

$$DS_{p,t} = \sum_k \omega_k \left(\frac{P_{k,t}}{P_t}\right)^{-\eta_c} DS_{p,k,t} \tag{A.76}$$

$$Y_t = A_t \, N_t \, DS_{p,t}^{-1} \tag{A.77}$$

$$C_t = \delta_s \, C_{s,t} + \delta_n \, C_{n,t} = Y_t \tag{A.78}$$

Aggregate hours:

$$L_t = \sum_\nu N_{\nu,t} \, DS_{w,\nu,t} \tag{A.79}$$

Dividends and total equity values:

$$D_{k,t} = \omega_k \left(\frac{P_{k,t}}{P_t}\right)^{1-\eta_c} C_t \left[1 - \frac{W_t}{P_t} \frac{1}{A_t} \left(\frac{P_{k,t}}{P_t}\right)^{-1} DS_{p,k,t}\right] \qquad \forall \, k \tag{A.80}$$

$$V_{k,t} = D_{k,t} + \beta_s \, \mathbb{E}_t \left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}} \, V_{k,t+1}\right] \qquad \forall \, k \tag{A.81}$$

$$D_t = C_t \left[1 - \frac{W_t}{P_t} \frac{1}{A_t} \, DS_{p,t}\right] \tag{A.82}$$

$$V_t = D_t + \beta_s \, \mathbb{E}_t \left[\frac{\lambda_{s,t+1}}{\lambda_{s,t}} \, V_{t+1}\right] \tag{A.83}$$

Exogenous processes and monetary policy rule:

$$\log A_t = \rho_A \, \log A_{t-1} + \varepsilon_{A,t} \tag{A.84}$$

$$x_t = \rho_x \, x_{t-1} + \varepsilon_{x,t} \tag{A.85}$$

$$\log I_t = -\log(\beta_n \, g_{0,n}(0)) + \phi_\pi \, \pi_t + \phi_y \, (\log(Y_t / A_t) - \log Y) + z_t \tag{A.86}$$

$$z_t = \rho_z \, z_{t-1} + \varepsilon_{z,t}. \tag{A.87}$$

B.8 Deterministic Steady State

The deterministic steady state is described by the following system of equations:

$$\frac{P_k}{P} = \frac{\eta_{c,k}}{\eta_{c,k}-1}\frac{W}{P} \qquad \forall\, k \tag{A.88}$$

$$DS_p = \sum_k \omega_k \left(\frac{P_k}{P}\right)^{-\eta_c} \tag{A.89}$$

$$N_\nu = \delta_\nu \left(\frac{W_\nu}{P}\right)^{-\eta_n} \left(\frac{W}{P}\right)^{\eta_n} N \qquad \nu \in \{s,n\} \tag{A.90}$$

$$C_n = \frac{W_n}{P}\frac{N_n}{\delta_n}, \qquad C_s = \frac{1}{\delta_s}\left(\frac{N}{DS_p} - \delta_n C_n\right) \tag{A.91}$$

$$\lambda_\nu = (C_\nu(1-b_\nu))^{-\gamma} \qquad \nu \in \{s,n\} \tag{A.92}$$

$$\left(\frac{W_\nu}{P}\right)^{1+\eta_n\chi_1} = \frac{\eta_n}{\eta_n-1}\frac{\chi_{0,\nu}}{\lambda_\nu}\left(\frac{W}{P}\right)^{\eta_n\chi_1} N^{\chi_1} \qquad \nu \in \{s,n\} \tag{A.93}$$

$$\frac{W}{P} = \left(\delta_s\left(\frac{W_s}{P}\right)^{1-\eta_n} + \delta_n\left(\frac{W_n}{P}\right)^{1-\eta_n}\right)^{\frac{1}{1-\eta_n}} \tag{A.94}$$

$$1 = \sum_k \omega_k \left(\frac{P_k}{P}\right)^{1-\eta_c} \tag{A.95}$$

For given values of $W/P, W_s/P, W_n/P$, and N, (A.88)–(A.92) can be used to obtain relative prices and marginal utility. The values of those four unknowns then follow from solving the four nonlinear equations (A.93)–(A.95). Given those steady state values, the other steady-state values are straightforward:

$$\pi = 0 \tag{A.96}$$

$$F_{w,\nu} = \frac{N^{1+\chi_1}}{1-\beta_\nu\,\theta_w\,g_{1,\nu}(0)}, \qquad K_{w,\nu} = \frac{N}{1-\beta_\nu\,\theta_w\,g_{1,\nu}(0)} \qquad \nu \in \{s,n\} \tag{A.97}$$

$$\frac{W_\nu^*}{P} = \frac{W_\nu}{P}, \qquad DS_{w,\nu} = 1 \qquad \nu \in \{s,n\} \tag{A.98}$$

$$F_{p,k} = \frac{\frac{W}{P}\left(\frac{P_k}{P}\right)^{\eta_{c,k}-\eta_c} C}{1-\beta_s\,\theta_{p,k}}, \qquad K_{p,k} = \frac{\left(\frac{P_k}{P}\right)^{\eta_{c,k}-\eta_c} C}{1-\beta_s\,\theta_{p,k}} \qquad \forall\, k \tag{A.99}$$

$$\frac{P_k^*}{P} = \frac{P_k}{P}, \qquad DS_{p,k} = 1 \qquad \forall\, k \tag{A.100}$$

$$C = Y = N\,DS_p^{-1}, \qquad C(k) = \omega_k \left(\frac{P_k}{P}\right)^{-\eta_c} C \quad \forall\, k \tag{A.101}$$

$$L = N_s + N_n \tag{A.102}$$

$$D_k = \omega_k \left(\frac{P_k}{P}\right)^{1-\eta_c} C \left[1 - \frac{W}{P}\left(\frac{P_k}{P}\right)^{-1}\right], \qquad V_k = \frac{D_k}{1-\beta_s} \qquad \forall\, k \tag{A.103}$$

$$D = C\left[1 - \frac{W}{P}\,DS_p\right], \qquad V = \frac{D}{1-\beta_s}. \tag{A.104}$$

B.9 Asset Returns

To illustrate the forces that drive cross-sectional differences in expected returns, I derive an approximation for the pricing of claims to one-period-ahead sector dividends, following Li and Palomino (2014). I compare two sectors that differ in the elasticity of demand their firms face: a high-elasticity sector H and a low-elasticity sector L. Let $\widetilde{R}_{k,t+1}$ be the return on the claim to sector k's next-period dividends.

Any real return R spanned by traded assets satisfies the fundamental asset pricing relation

$$1 = \mathbb{E}_t[M_{t+1}R_{t+1}]. \tag{A.105}$$

Assume for expositional purposes that the SDF and asset returns are conditionally jointly lognormal, so that

$$\mathbb{E}_t[r_{t+1}] + \frac{1}{2}\mathrm{Var}_t[r_{t+1}] - r_{f,t} = -\mathrm{Cov}_t(m_{t+1}, r_{t+1}), \tag{A.106}$$

where $m_{t+1} \equiv \log M_{t+1}$, $r_{t+1} \equiv \log R_{t+1}$, and $r_{f,t}$ is the continuously compounded real risk-free rate between t and $t+1$. The claim that only pays next period's sector dividend has log return $\widetilde{r}_{k,t+1} = d_{k,t+1} - \log \widetilde{V}_{k,t}$, where the price $\widetilde{V}_{k,t}$ is known at t. Differencing the pricing relation across the two sectors gives

$$\log \mathbb{E}_t \widetilde{R}_{H,t+1} - \log \mathbb{E}_t \widetilde{R}_{L,t+1} = -\mathrm{Cov}_t(m_{t+1}, \widetilde{r}_{H,t+1} - \widetilde{r}_{L,t+1}) = -\mathrm{Cov}_t(m_{t+1}, d_{H,t+1} - d_{L,t+1}). \tag{A.107}$$

The cross-sectional return spread thus depends only on how the dividends of the high-elasticity sector, relative to the low-elasticity sector, covary with marginal utility.

To unpack this covariance, define $p_{k,t} \equiv \log(P_{k,t}/P_t)$. Using (A.48), the difference in log dividends is

$$d_{H,t} - d_{L,t} = \log \omega_H - \log \omega_L + (1-\eta_c)(p_{H,t} - p_{L,t}) + \log(1-\hat{\mu}_{H,t}^{-1}) - \log(1-\hat{\mu}_{L,t}^{-1}). \tag{A.108}$$

Log-linearizing the markup term around the steady state gives

$$\log(1-\hat{\mu}_{k,t}^{-1}) \approx \log(1-\hat{\mu}_k^{-1}) + (\eta_{c,k}-1)\,(\log \hat{\mu}_{k,t} - \log \hat{\mu}_k), \tag{A.109}$$

where $\hat{\mu}_k = \eta_{c,k}/(\eta_{c,k}-1)$ is the steady-state markup, so that $1/(\hat{\mu}_k - 1) = \eta_{c,k} - 1$. Finally, let $ds_{p,k,t} \equiv \log DS_{p,k,t}$. The markup definition in (A.48) implies $\log \hat{\mu}_{k,t} = \log(A_t\, P_t/W_t) + p_{k,t} - ds_{p,k,t}$, so that the two sector markups are related by $\log \hat{\mu}_{H,t} = \log \hat{\mu}_{L,t} + (p_{H,t} - p_{L,t}) - (ds_{p,H,t} - ds_{p,L,t})$. Substituting and dropping constants from the covariances, the return spread becomes

$$\begin{aligned}
\log \mathbb{E}_t \widetilde{R}_{H,t+1} - \log \mathbb{E}_t \widetilde{R}_{L,t+1} &= -(1-\eta_c)\,\mathrm{Cov}_t(m_{t+1}, p_{H,t+1} - p_{L,t+1}) - (\eta_{c,H}-1)\,\mathrm{Cov}_t(m_{t+1}, \log \hat{\mu}_{H,t+1}) \\
&\quad + (\eta_{c,L}-1)\,\mathrm{Cov}_t(m_{t+1}, \log \hat{\mu}_{L,t+1}) \\
&= -(\eta_{c,H} - \eta_c)\,\mathrm{Cov}_t(m_{t+1}, p_{H,t+1} - p_{L,t+1}) \\
&\quad - (1-\eta_{c,H})\,\mathrm{Cov}_t(m_{t+1}, ds_{p,H,t+1} - ds_{p,L,t+1}) \\
&\quad - (\eta_{c,H} - \eta_{c,L})\,\mathrm{Cov}_t(m_{t+1}, \log \hat{\mu}_{L,t+1}).
\end{aligned} \tag{A.110}$$

C Data Construction

This section describes the data used in the empirical analysis, in addition to the labor market indicators used to estimate the income risk process (Appendix A). Macroeconomic time series are from FRED unless noted otherwise.

C.1 Macroeconomic Data

Consumption and inflation. Aggregate consumption is real per capita consumption expenditures on nondurable goods and services. I chain the real quantity indices of nondurables (DNDGRA3Q086SBEA) and services (DSERRA3Q086SBEA) with a Törnqvist index, using nominal expenditure shares (PCND, PCESV), and divide by population (B230RC0Q173SBEA). Inflation is the growth rate of the corresponding implied price deflator.

Hours. Hours worked per capita are average weekly hours in the nonfarm business sector (PRS85006023) times civilian employment (CLF16OV minus UNEMPLOY), divided by population.

Durable expenditure–stock ratio. Following Gomes et al. (2009), the durable expenditure–stock ratio is real expenditures on consumer durables (A795RX0Q048SBEA times population) relative to the real stock of consumer durables at the end of the previous quarter. The real stock is the annual current-cost net stock of consumer durables (K1CTOTL1CD000) deflated by the implicit price deflator for durable goods (DDURRD3Q086SBEA). I interpolate the stock to a quarterly frequency by perpetual inventory, with a depreciation rate that is constant within each year and matches the year-end stocks.

Other indicators. Additional series are real GDP (GDPC1), industrial production (INDPRO), capacity utilization (TCU), the unemployment rate (UNRATE), the University of Michigan consumer sentiment index (UMCSENT), and building permits for new private housing units (PERMIT). TFP growth and utilization-adjusted TFP growth are from Fernald (2014).

C.2 Financial Data

Stock returns. Monthly stock returns, prices, shares outstanding, trading volume, and SIC codes are from CRSP, for common stocks (share codes 10 and 11) traded on NYSE, AMEX, and Nasdaq (exchange codes 1–3). Returns are adjusted for delisting returns. Dividends are computed from the difference between returns with and without dividends.

Accounting data. Annual accounting data are from Compustat, merged to CRSP through the CRSP–Compustat link table. Book equity is stockholders' equity plus deferred taxes and investment tax credit, minus the redemption, liquidation, or par value of preferred stock, in that order of availability.

Firm characteristics. Size is log total assets or log market equity at the end of June, and book leverage is the log ratio of total assets to book equity. Profitability is operating income before depreciation minus interest expense, relative to book equity, and asset growth is the log growth rate of total assets. Market beta and idiosyncratic volatility are estimated from rolling CAPM regressions of monthly excess returns over the previous 60 months, requiring at least 36 months. Turnover is the average ratio of monthly trading volume to shares outstanding over the previous 12 months, requiring at least six months, with Nasdaq volume adjusted for double counting of dealer trades. Accounting variables are winsorized at the 1st and 99th percentiles in each fiscal year, and momentum, turnover, market beta, and idiosyncratic volatility in each month.

Factors and predictors. The Fama–French factors, the one-month Treasury bill rate, the 25 portfolios sorted on size and book-to-market, and the 48 industry definitions are from Kenneth French's data library. The return predictors in Panel A of Table 7, as well as the investment–capital ratio and CPI inflation in Panel B, are from the data of Welch and Goyal (2008), updated through 2024. Annual dividend growth and the price–dividend ratio of the aggregate stock market in Table A.3 are for the S&P 500 index from the same source, with dividends deflated by the consumption deflator for nondurables and services.

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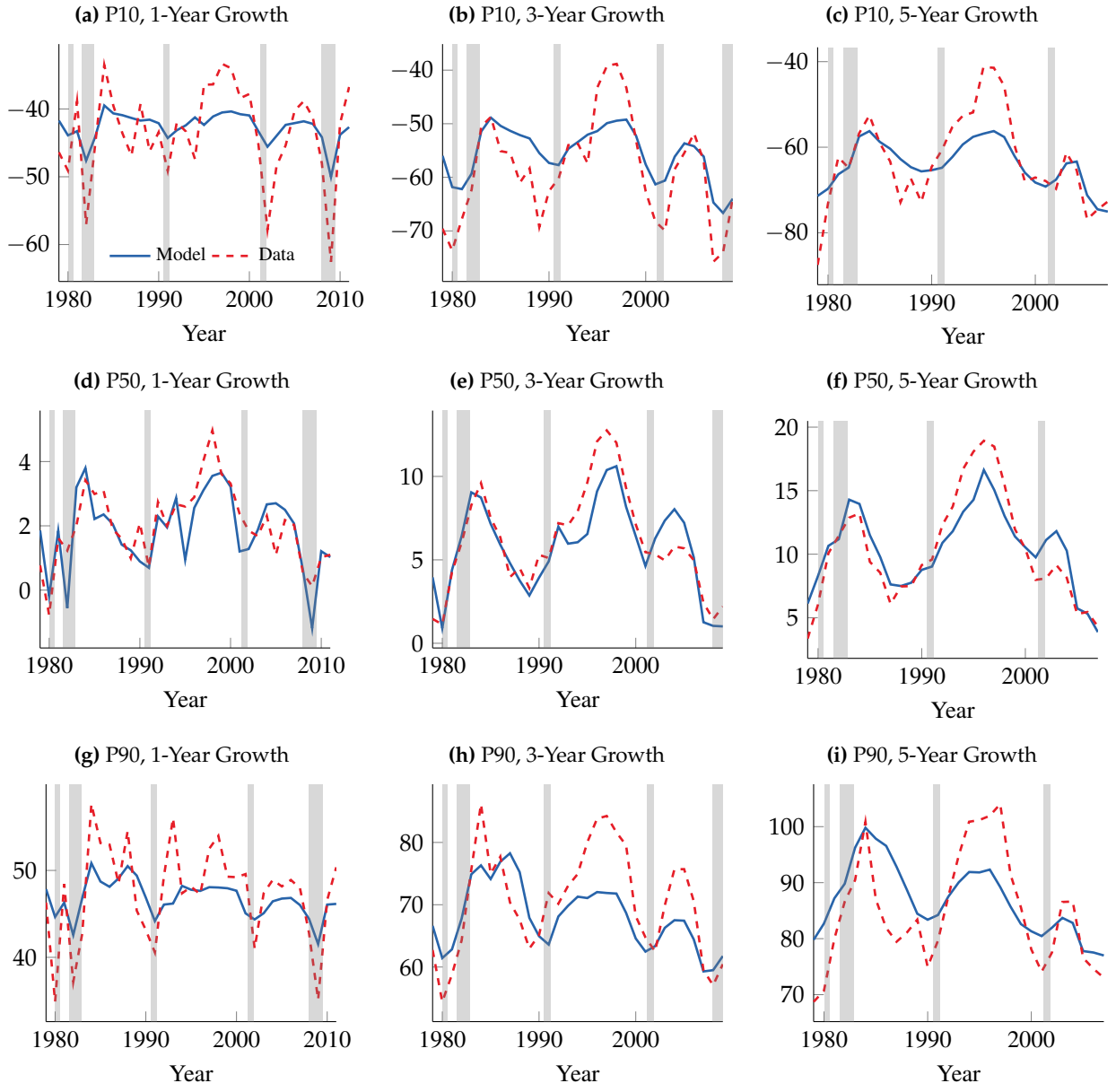
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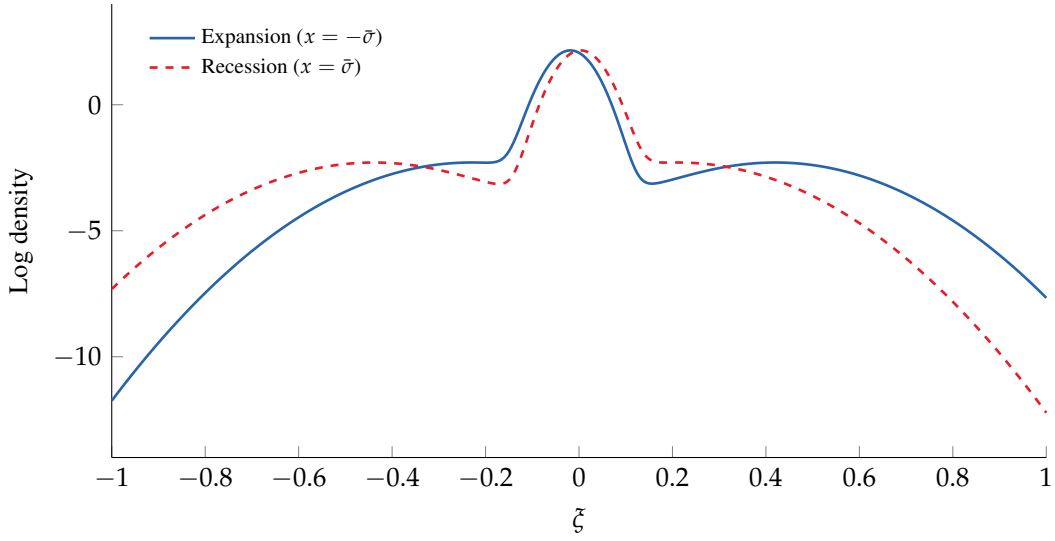
Welch, I. and A. Goyal (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies 21*(4), 1455–1508.

Figure A.1: Percentiles of Income Growth Rates: Model vs. Data



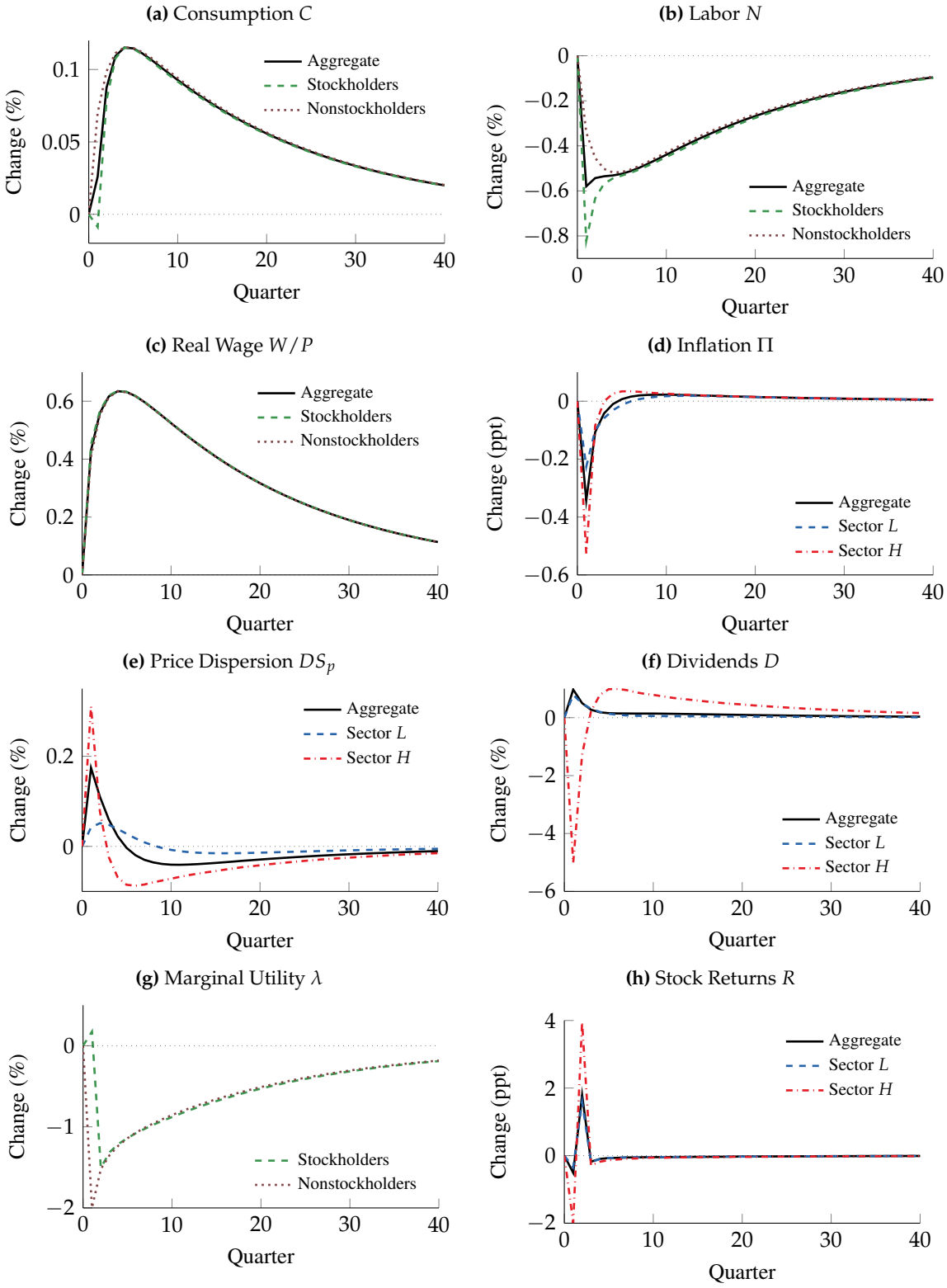
This figure compares percentiles of 1-, 3-, and 5-year labor income growth rates in the estimated income process with their empirical counterparts from Guvenen et al. (2014). Growth rates are log changes, in percent. Shaded areas indicate NBER recessions.

Figure A.2: Density of Permanent Idiosyncratic Income Shock



This figure plots the log density of the quarterly permanent income shock ξ for $x = -\bar{\sigma}$ (expansion) and $x = \bar{\sigma}$ (recession), where $\bar{\sigma} = 0.115$ is the unconditional standard deviation of x_t.

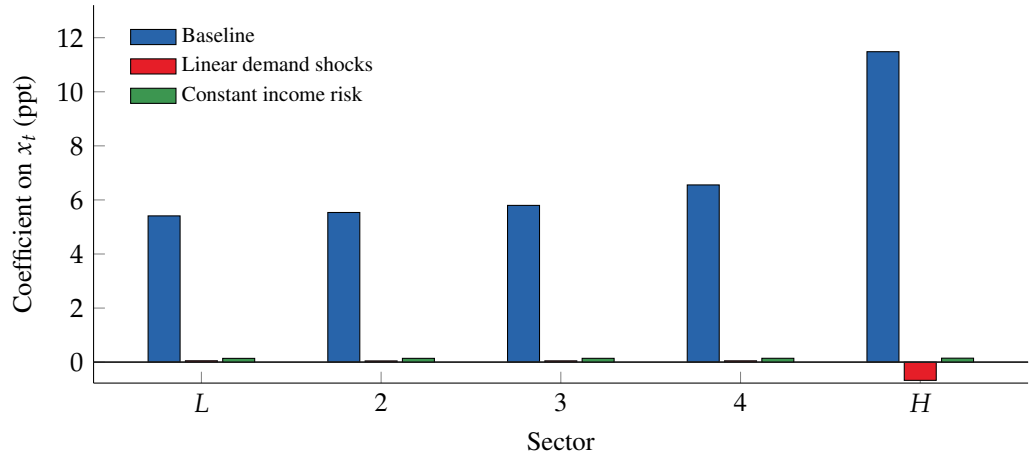
Figure A.3: Impulse Responses to TFP Shock



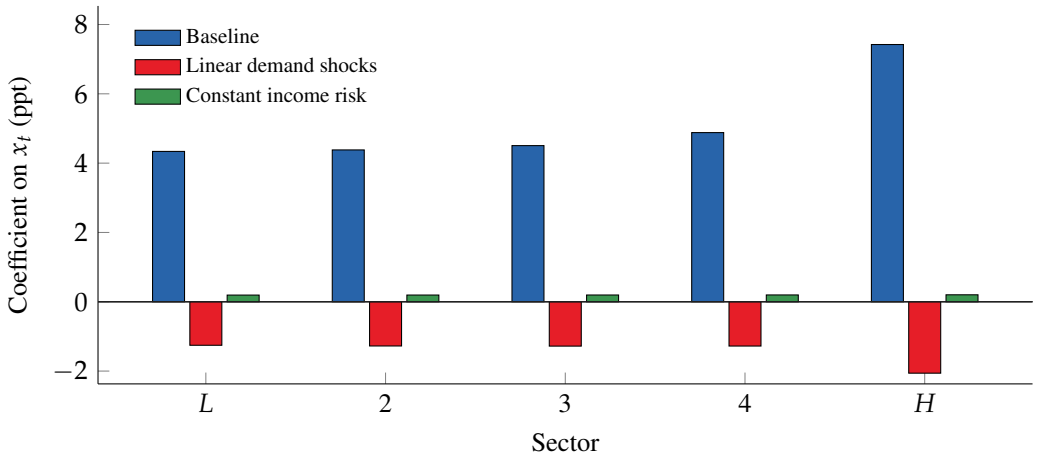
This figure plots impulse responses to a positive one-standard-deviation TFP shock $\varepsilon_{A,t}$. Sectors L and H are the sectors with the lowest and highest demand elasticity.

Figure A.4: Predictability by Sector in Alternative Models

(a) Predictability of Excess Returns



(b) Predictability of Absolute Excess Returns



This figure compares return predictability across the five sectors, ordered from the lowest (L) to the highest (H) demand elasticity, in the baseline model and two alternative versions. With linear demand shocks, $\log g_{0,n}(x)$ and $\log g_{1,n}(x)$ are linear in x. With constant income risk, $g_{0,n}(x)$ and $g_{1,n}(x)$ do not vary with x. All other parameters are as in the baseline. Panels (a) and (b) plot the slope coefficients from regressions of one-year excess returns and of their absolute values on income risk x_t, standardized to have a unit standard deviation.

Table A.1: Estimated Income Process Parameters

Symbol	Description	Value
σ_u	Volatility of transitory component	0.402
$\sigma_{\xi,1}$	Typical volatility of permanent component	0.042
$\sigma_{\xi,2} = \sigma_{\xi,3}$	Tail volatility of permanent component	0.177
$p_2 = p_3$	Probability of tail event	0.045
$\tilde{\mu}_2$	Location of left tail	-0.328
$\tilde{\mu}_3$	Location of right tail	0.324

This table reports the estimated parameters of the distribution of quarterly idiosyncratic income shocks. Appendix A describes the estimation.

Table A.2: Model Calibration

Symbol	Description	Value
Preferences and wages		
δ_s	Population share of stockholders	0.5
β_s	Time discount factor of stockholders	0.986
β_n	Time discount factor of non-stockholders	$\beta_s / g_{0,n}(0)$
γ	Relative risk aversion	10
b_s	Habit weight of stockholders	0.45
b_n	Habit weight of non-stockholders	0.65
χ_1	Inverse Frisch elasticity of labor supply	1
η_n	Elasticity of substitution across labor types	12
θ_w	Calvo parameter of wage setting	0.7
Income risk		
ψ	Pass-through of permanent income shocks	0.285
ρ_x	Persistence of income tail risk	0.883
σ_x	Volatility of shocks to income tail risk	0.054
Production		
ω_k	Expenditure weight of sector k	0.2
η_c	Elasticity of substitution across sectors	2
$\eta_{c,1}$	Elasticity of substitution within sector 1	3.13
$\eta_{c,2}$	Elasticity of substitution within sector 2	5.60
$\eta_{c,3}$	Elasticity of substitution within sector 3	8.07
$\eta_{c,4}$	Elasticity of substitution within sector 4	12.16
$\eta_{c,5}$	Elasticity of substitution within sector 5	25.07
$\theta_{p,k}$	Calvo parameter of price setting	0.75
ρ_A	Persistence of TFP	0.95
σ_A	Volatility of TFP shocks	0.0078
$\rho_{A,x}$	Correlation of TFP and income tail risk shocks	0
Monetary policy		
ϕ_π	Taylor rule coefficient on inflation	1.24
ϕ_y	Taylor rule coefficient on output gap	0.5/4
σ_z	Volatility of monetary policy shocks	0

This table reports the baseline parameter values of the model, calibrated at a quarterly frequency, as described in Section 3.

Table A.3: Macroeconomic Moments: Model vs. Data

	Model	Data
Consumption growth		
σ (%)	0.98	1.19
AC1	0.16	0.45
σ_s/σ_n	1.58	1.55
Hours growth		
σ (%)	1.10	1.76
AC1	0.17	0.26
Inflation		
σ (%)	1.50	2.31
AC1	0.59	0.82
Dividend growth		
σ (%)	3.18	6.09
AC1	0.13	0.52
Log P/D ratio		
σ	0.15	0.42
AC1	0.43	0.91
Average markup		
Sector 1	1.48	1.47
Sector 2	1.22	1.22
Sector 3	1.14	1.14
Sector 4	1.09	1.09
Sector 5	1.04	1.04

This table presents statistics for key macroeconomic variables in the model and in the data. The model is calibrated at a quarterly frequency, and all statistics are computed from annualized series. AC1 is the first-order autocorrelation, and σ_s/σ_n is the volatility of consumption growth of stockholders relative to non-stockholders, with the empirical value based on the estimates of Mankiw and Zeldes (1991). Average markups in the data are those of the markup-sorted portfolios in Table 2.

Table A.4: Excess Returns and Exposures of Portfolios Sorted on $\bar{\mu}^{-1}_{f,t-1}$ by Industry

	IAMU within-industry quintiles					
	Low	2	3	4	High	EMI
Panel A: Equal-weighted returns						
Mean (%)	8.96***	10.26***	10.72***	11.22***	12.66***	3.70***
	(2.46)	(2.54)	(2.64)	(2.74)	(2.95)	(1.16)
Volatility (%)	18.97	19.59	20.35	21.11	22.73	8.94
Sharpe ratio	0.47	0.52	0.53	0.53	0.56	0.41
$\beta_{\Delta icl}$	-0.24***	-0.26***	-0.27***	-0.29***	-0.31***	-0.07***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.02)
β_{MKT}	1.11***	1.12***	1.14***	1.15***	1.15***	0.05*
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)
α_{CAPM} (%)	1.23	2.41**	2.80**	3.22**	4.62***	3.39***
	(0.97)	(1.09)	(1.25)	(1.40)	(1.75)	(1.15)
α_{FF3} (%)	-0.09	0.71	0.78	1.10	2.54**	2.63***
	(0.59)	(0.58)	(0.63)	(0.74)	(1.06)	(0.94)
Panel B: Value-weighted returns						
Mean (%)	6.96***	6.90***	7.20***	7.40***	9.79***	2.83**
	(2.04)	(1.98)	(2.04)	(2.16)	(2.36)	(1.35)
Volatility (%)	15.77	15.25	15.71	16.68	18.22	10.44
Sharpe ratio	0.44	0.45	0.46	0.44	0.54	0.27
$\beta_{\Delta icl}$	-0.18***	-0.15***	-0.17***	-0.18***	-0.14**	0.04
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.03)
β_{MKT}	0.97***	0.94***	0.96***	0.99***	1.04***	0.07**
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
α_{CAPM} (%)	0.19	0.32	0.51	0.48	2.55**	2.37*
	(0.53)	(0.47)	(0.59)	(0.78)	(1.06)	(1.35)
α_{FF3} (%)	0.95**	0.34	0.37	-0.14	2.36**	1.41
	(0.46)	(0.47)	(0.60)	(0.76)	(1.05)	(1.29)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports statistics for quintile portfolios sorted on $\bar{\mu}^{-1}_{f,t-1}$ within each of the Fama–French 48 industries. The EMI portfolio is long the fifth and short the first quintile. The sample period is 1965M7–2024M12, and exposures to Δicl are estimated over 1967–2019. Standard errors are in parentheses.

Table A.5: Excess Returns and Exposures of Portfolios Sorted by Sector Durability

	Sector portfolios					
	Services	Nondurables	Durables	Investment	Other	DMS
Mean (%)	6.54***	8.55***	10.86***	8.89***	9.14***	4.31***
	(1.70)	(1.66)	(2.64)	(2.41)	(2.04)	(1.64)
Volatility (%)	16.92	16.46	26.16	23.92	20.21	16.32
Sharpe ratio	0.39	0.52	0.41	0.37	0.45	0.26
$\beta_{\Delta icl}$	-0.10**	-0.09*	-0.29***	-0.24***	-0.24***	-0.19***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.03)
β_{MKT}	0.85***	0.82***	1.26***	1.23***	1.05***	0.41***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.05)
α_{CAPM} (%)	-0.47	1.78***	0.50	-1.25	0.44	0.96
	(0.63)	(0.65)	(1.16)	(0.77)	(0.55)	(1.38)
α_{FF3} (%)	-0.84	1.76***	0.29	-1.42*	1.01**	1.12
	(0.60)	(0.63)	(1.18)	(0.74)	(0.48)	(1.38)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports statistics for value-weighted sector portfolios of producers of services, nondurable goods, durable goods, investment goods, and other industries, classified following Gomes et al. (2009). The durables-minus-services (DMS) portfolio is long producers of durable goods and short producers of services. The sample period is 1926M7–2024M12, and exposures to Δicl are estimated over 1967–2019. Standard errors are in parentheses.

Table A.6: Firm-Level Regressions of Returns on Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\bar{\mu}_{f,t-1}^{-1})$	0.99**	0.89**	0.76***	0.78***	0.87***	0.54**
	(0.49)	(0.35)	(0.24)	(0.24)	(0.24)	(0.25)
Log assets			-1.59**	-1.64**	-0.40	9.80***
			(0.81)	(0.81)	(0.68)	(1.68)
Log assets-to-book			-0.83*	-0.88*	-0.87*	-2.79***
			(0.50)	(0.50)	(0.48)	(0.40)
Profitability			3.40***	3.37***	3.70***	5.82***
			(0.81)	(0.80)	(0.71)	(0.68)
Asset growth			-5.77***	-5.90***	-4.84***	-3.98***
			(0.53)	(0.54)	(0.50)	(0.44)
Momentum				2.58**	2.36**	3.28***
				(1.00)	(1.04)	(1.01)
Short-term reversal				-11.81***	-11.73***	-11.73***
				(1.06)	(1.07)	(1.07)
Market beta					0.90	0.92
					(0.61)	(0.61)
Idiosyncratic volatility					0.52	-0.17
					(1.07)	(1.05)
Log turnover					-3.34***	-2.30***
					(0.80)	(0.80)
Log ME						-11.22***
						(1.97)
Time FE	Yes	No	No	No	No	No
Industry × time FE	No	Yes	Yes	Yes	Yes	Yes
Observations	1,777,450	1,769,605	1,725,496	1,719,993	1,481,013	1,480,800
R^2	0.131	0.180	0.183	0.186	0.192	0.193

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports firm-level panel regressions of monthly stock returns in excess of the one-month Treasury bill rate on the log inverse average markup $\log(\bar{\mu}_{f,t-1}^{-1})$ and other firm characteristics. Characteristics measured at the end of June of year t are matched to returns from July of year t to June of year $t+1$, except for momentum (the cumulative return over months -12 to -2) and short-term reversal (the return in month -1), which are updated monthly. All regressors are standardized, and coefficients are in percent per year. Industries are the Fama–French 48 industries. The sample period is 1965M7–2024M12. Standard errors clustered by month are in parentheses.

Table A.7: Aggregate Cash Flow Growth and Exposures of Portfolios Sorted on $\bar{\mu}^{-1}_{f,t-1}$

	IAMU quintiles					
	Low	2	3	4	High	EMI
Panel A: Growth in total operating income						
Mean (%)	6.62	5.98	5.75	9.80	15.23	8.61
Volatility (%)	7.25	11.06	11.72	12.34	12.38	12.21
$\beta_{\Delta x}$	-0.08	-0.52***	-0.61***	-0.63***	-0.74***	-0.66***
	(0.09)	(0.13)	(0.08)	(0.11)	(0.10)	(0.13)
R^2	0.01	0.26	0.36	0.50	0.41	0.30
Panel B: Growth in total sales						
Mean (%)	8.66	6.82	5.65	7.55	7.13	-1.53
Volatility (%)	6.11	7.44	6.79	5.30	5.71	4.18
$\beta_{\Delta x}$	0.05	-0.09	-0.15**	-0.06	-0.06	-0.11*
	(0.09)	(0.09)	(0.07)	(0.08)	(0.05)	(0.06)
R^2	0.01	0.01	0.05	0.01	0.01	0.07
Panel C: Growth in total dividends						
Mean (%)	7.40	6.43	6.05	7.58	8.41	1.02
Volatility (%)	8.08	6.14	8.79	13.13	35.41	34.60
$\beta_{\Delta x}$	-0.03	-0.17*	-0.29**	-0.39**	-0.48	-0.45
	(0.09)	(0.10)	(0.15)	(0.16)	(0.38)	(0.36)
R^2	0.00	0.07	0.10	0.09	0.02	0.01

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports annual growth rates of total cash flows and their exposures to income tail risk for quintile portfolios sorted on $\bar{\mu}^{-1}_{f,t-1}$ at the end of June of year t. Cash flow growth is the log growth rate of the total cash flows of the firms in the portfolio over fiscal year t, or calendar year t for dividends, for the same firms in both years. Operating income before depreciation and sales are from Compustat, and dividends are from CRSP. The EMI portfolio is long the fifth and short the first quintile. $\beta_{\Delta x}$ is the univariate beta with respect to $\Delta x_t \equiv x_t - x_{t-1}$, where x_t is the average of income tail risk over year t. The sample period is 1965–2024, and betas are estimated over 1968–2019. Standard errors are in parentheses.

Table A.8: Cash Flow Growth and Exposures of Portfolios Sorted by Sector Durability

	Sector portfolios					
	Services	Nondurables	Durables	Investment	Other	DMS
Panel A: Operating income growth						
Mean (%)	9.48	7.43	5.69	9.43	9.20	-3.80
Volatility (%)	4.79	6.15	13.57	13.66	8.80	11.17
$\beta_{\Delta x}$	-0.20***	-0.34***	-1.06***	-0.72***	-0.55***	-0.86***
	(0.04)	(0.07)	(0.12)	(0.17)	(0.08)	(0.11)
R^2	0.18	0.36	0.57	0.27	0.43	0.53
Panel B: Sales growth						
Mean (%)	10.85	9.91	7.31	8.80	9.31	-3.54
Volatility (%)	6.54	4.72	6.88	8.57	6.06	6.09
$\beta_{\Delta x}$	-0.01	-0.07	-0.32***	-0.18*	-0.18***	-0.31***
	(0.05)	(0.06)	(0.06)	(0.10)	(0.06)	(0.06)
R^2	0.00	0.03	0.23	0.04	0.09	0.31
Panel C: Dividend growth						
Mean (%)	7.59	7.20	6.18	8.01	8.38	-1.41
Volatility (%)	7.31	6.47	11.55	9.04	8.40	7.97
$\beta_{\Delta x}$	-0.19***	-0.18***	-0.42***	-0.13	-0.19**	-0.24***
	(0.06)	(0.06)	(0.11)	(0.14)	(0.09)	(0.08)
R^2	0.08	0.08	0.13	0.02	0.05	0.08

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports annual cash flow growth rates and their exposures to income tail risk for sector portfolios sorted by durability. Cash flow growth is the average log growth rate across firms in the portfolio over fiscal year t, or calendar year t for dividends. Operating income before depreciation and sales are from Compustat, and dividends are from CRSP. Firm-level growth rates require positive cash flows in both years and are winsorized at the 1st and 99th percentiles in each year. The DMS portfolio is long producers of durable goods and short producers of services. $\beta_{\Delta x}$ is the univariate beta with respect to $\Delta x_t \equiv x_t - x_{t-1}$, where x_t is the average of income tail risk over year t. The sample period is 1963–2024, and betas are estimated over 1968–2019. Standard errors are in parentheses.

Table A.9: Return Predictability Across Portfolios Sorted by Sector Durability

		Sector portfolios					
	Market	Services	Nondurables	Durables	Investment	Other	DMS
Panel A: Monthly frequency							
3 months ahead							
icl_t	0.74	0.26	0.23	1.96**	1.17	1.28*	1.70***
	(0.58)	(0.50)	(0.47)	(0.76)	(0.73)	(0.69)	(0.41)
R^2	0.01	0.00	0.00	0.03	0.01	0.02	0.07
12 months ahead							
icl_t	2.79*	1.54	0.23	8.22***	4.91***	4.43**	6.68***
	(1.68)	(1.84)	(1.51)	(2.46)	(1.87)	(1.99)	(1.15)
R^2	0.03	0.01	0.00	0.11	0.05	0.05	0.17
24 months ahead							
icl_t	1.90	2.07	-2.40	9.82**	6.11*	2.42	7.74***
	(2.88)	(3.60)	(3.24)	(4.38)	(3.30)	(3.03)	(2.08)
R^2	0.01	0.01	0.01	0.05	0.03	0.01	0.05
Panel B: Quarterly frequency							
1 quarter ahead							
x_t	0.66	0.23	0.17	1.56*	1.05	1.14	1.32***
	(0.73)	(0.64)	(0.64)	(0.94)	(0.88)	(0.85)	(0.48)
R^2	0.01	0.00	0.00	0.02	0.01	0.01	0.04
4 quarters ahead							
x_t	1.77	0.64	-1.01	5.93**	4.16**	3.39	5.28***
	(1.84)	(1.94)	(1.66)	(2.76)	(1.97)	(2.22)	(1.45)
R^2	0.01	0.00	0.00	0.05	0.03	0.03	0.09
8 quarters ahead							
x_t	-0.15	0.34	-4.84	5.20	5.17	0.31	4.86*
	(2.89)	(3.34)	(3.05)	(4.86)	(3.30)	(3.15)	(2.94)
R^2	0.00	0.00	0.04	0.01	0.02	0.00	0.02

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports predictive regressions of cumulative future excess returns on the market portfolio and on value-weighted sector portfolios sorted by durability on the current level of income tail risk, measured by icl_t in monthly data (Panel A) and by x_t in quarterly data (Panel B). Cumulative excess returns are compounded portfolio returns minus compounded Treasury bill returns over the forecast horizon, in percent. The DMS portfolio is long producers of durable goods and short producers of services. The predictors are standardized to have a unit standard deviation. The sample period is 1967–2019. Newey–West standard errors with a lag length equal to the forecast horizon minus one are reported in parentheses.

Table A.10: Predictability of Return and Cash Flow Volatility Across Portfolios Sorted by Sector Durability

	Sector portfolios				
	Services	Nondurables	Durables	Investment	Other
Panel A: Absolute 1-year excess returns					
x_t	1.15	-1.07	5.80***	3.43***	3.64***
	(1.06)	(0.88)	(1.94)	(1.28)	(1.24)
R^2	0.01	0.01	0.09	0.05	0.08
Panel B: Absolute 1-year operating income growth					
x_t	0.12	0.86	4.03***	1.75	0.60
	(0.55)	(0.66)	(1.18)	(1.12)	(0.87)
R^2	0.00	0.04	0.22	0.04	0.01
Panel C: Absolute 5-year dividend growth					
x_t	9.23***	5.50*	4.80	11.33***	10.53***
	(2.63)	(3.24)	(3.21)	(4.30)	(3.68)
R^2	0.22	0.12	0.06	0.21	0.22

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

This table reports predictive regressions of the absolute value of future excess returns and cash flow growth on the current level of income tail risk x_t for sector portfolios sorted by durability. Panel A uses cumulative four-quarter-ahead excess returns on value-weighted portfolios in quarterly data. Panels B and C use one-year-ahead operating income growth and cumulative five-year-ahead dividend growth in annual data, where x_t is the average of income tail risk over year t and cash flow growth is the average log growth rate across firms in the portfolio. The predictor is standardized to have a unit standard deviation. The sample period is 1967–2019. Newey–West standard errors with a lag length equal to the forecast horizon minus one are reported in parentheses.