Idiosyncratic Income Risk, Precautionary Saving, and Asset Prices

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Abstract

Households are subject to substantial tail risk in individual labor income, and the amount of income risk fluctuates over the business cycle. This paper proposes a New Keynesian production-based asset pricing model where idiosyncratic labor income risk is a key source of priced risk in equity markets. Uninsured income tail risk drives the aggregate demand for consumption goods through a time-varying precautionary saving motive, generating cyclicality in firm cash flows. In the cross section, firms facing more elastic demand are more exposed to fluctuations in idiosyncratic tail risk. This risk exposure is compensated by a significant and countercyclical risk premium in equity returns. Empirical findings support the predictions of the model.

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1 Introduction

Households are subject to sources of risk that extend beyond aggregate risks. Private events such as job displacement can have large and persistent effects on household earnings. These events are hard to insurance against (Blundell, Pistaferri, and Preston, 2008). Exposure to idiosyncratic tail risks can therefore drastically change the consumption and saving decision of market participants. Recent empirical studies show strong state dependency in the amount of tail risk at the individual level: the skewness of earnings growth rates is procyclical (Guvenen, Ozkan, and Song, 2014), and recessions are times when the cross-sectional distribution of income growth displays particularly severe left-tail risk. This cyclicality implies that workers face additional risks coming from individual exposures in times of economic distress.

In this paper, I propose time-varying idiosyncratic risk in labor income as a key driver of asset prices and macroeconomic quantities in a production-based economy. A growing literature documents the importance of aggregate demand-based risks for asset prices. Asset prices are highly responsive to changes in monetary policy (Bernanke and Kuttner, 2005), and nominal rigidities can give rise to a substantial equity premium in equilibrium models (Li and Palomino, 2014). In the cross section of stocks, recent work shows that *exposure* to demand shocks is compensated with a risk premium: Weber (2015) finds that firms with more sticky prices earn higher average returns, and Clara (2019) finds that heterogeneity in demand elasticities is priced across stocks. An open question is what the *source* of demand fluctuations is that drives asset prices. I build a general equilibrium macroeconomic model where the aggregate demand for consumption goods is driven by a time-varying precautionary saving motive due to uninsured income risks. The direct effects of income tail risk are on the marginal consumer – not necessarily the marginal investor – that trades off consumption versus saving. Demand fluctuations due to income tail risk generate cyclicality in firm cash flows. This risk exposure, that is heterogeneous across firms, is compensated by a significant and countercyclical risk premium in equity returns. Empirical asset pricing tests show support for this channel.

The model features heterogeneous agents and heterogeneous firms and builds on the basic multi-sector New Keynesian model from Carvalho (2006) where firms face nominal rigidities in price setting. Asset markets are segmented and agents face idiosyncratic permanent shocks to labor income. Stockholders own shares of the output-producing firms and have access to a complete market that allows for full risk sharing of non-systematic shocks. Non-stockholders cannot diversify idiosyncratic risks in their labor income and are subject to countercyclical tail risk in individual income growth rates. They do not participate in equity markets and only trade nominal risk-free bonds in zero net supply, so that they are hand-to-mouth in equilibrium. While these non-stockholders do not price returns on traded assets, their consumption demand is important for the profits of the firms that are distributed to the stockholders.

In the model, asset prices fluctuate with changes in idiosyncratic income tail risk over time. Increased background risk calls for an increase in savings to self-insure against the shocks that are ex-post concentrated on a small number of non-stockholders, and leads uninsured households to reduce present consumption. Faced with a reduced demand, optimal firm prices change. Since the prices of consumption goods are rigid, output falls and price dispersion rises. As a result, firm earnings are sensitive to changes in individual tail risk. The model has four main implications.

First, not all firms are affected equally by income risk fluctuations: exposure to demand shocks varies across firms. Firms are heterogeneous in the elasticity of demand for the consumption good that they produce. In sectors where demand is highly elastic, optimal prices change by more in response to demand shocks. Nominal rigidities then imply that prices are more dispersed in these sectors. Firms with more elastic demand are therefore more exposed to fluctuations in the amount of idiosyncratic income risk and have more volatile cash flows.

Second, firm exposure to variation in idiosyncratic income risk over the business cycle is priced. Since equity holdings are concentrated among a limited part of the population, the consumption of stockholders is significantly affected by reduced firm profits as a result of lower aggregate demand when idiosyncratic income risk rises. With external habit preferences to generate reasonable dynamics in prices and quantities, the marginal utility of stockholders spikes when income risk increases. The equity premium in the model is substantial, driven by the price of risk for exposure to idiosyncratic income risk shocks that have a magnitude consistent with the data. Since high-elasticity firms are more affected by demand shocks, there is a cross-sectional premium for high-elasticity firms relative to low-elasticity firms.

Third, asset returns are predictable by the current level of idiosyncratic income risk. This predictability arises from endogenous countercyclical volatility in demand shocks. Since marginal utility is convex, the precautionary savings motive is nonlinear in the amount of idiosyncratic risk. When idiosyncratic risk is high, the precautionary motive spikes. Any additional shocks to income risk then lead to large changes in demand for consumption goods. While in the model uncertainty about future idiosyncratic risk is constant over time, the volatility of demand shocks from changes in idiosyncratic income shocks is countercyclical. Hence, the model generates predictability of asset returns by idiosyncratic risk without needing time variation in higher-order moments of income risk.[1]

Fourth, the predictability of stock returns by the level of idiosyncratic income risk is heterogeneous across firms. Firms with more elastic demand are more exposed to changes in income tail risk and therefore have a bigger increase in the risk premium when tail risk in labor income rises.

In empirical tests, I find support for these four model predictions. A benefit of the idiosyncratic risk channel is that income tail risk is relatively well measurable from cross-sectional data. I use two measures of idiosyncratic income risk. First, I directly estimate a process for time-varying skewness in permanent income growth rates, targeting the moments reported by Guvenen et al. (2014) using the approach of McKay (2017). Second, I use initial claims for unemployment benefits

[1] In contrast, endowment economy models where covariation between stock market returns and idiosyncratic consumption risk of the marginal investor is the source of the equity premium require time-varying uncertainty on future idiosyncratic risk (i.e., at least the fourth moment of individual income growth rates) to generate predictability in stock returns.

relative to the size of the labor force as a proxy for income tail risk, as proposed by Schmidt (2016), which has the benefits that it is available at a higher frequency and in real time.

To test the model prediction that heterogeneity in firm exposure to idiosyncratic income risk shocks is priced in equity markets, I follow a large asset pricing literature by sorting firms into portfolios. I consider a new cross section of firms that differ substantially in their business cycle exposures by sorting firms based on the beta of their stock returns to a tradable proxy for demand shocks: the return differential between firms that produce durable goods and firms that produce nondurables and services, which I label as the Durables Minus Nondurables and Services (DMNS) factor. I follow Gomes, Kogan, and Yogo (2009) in classifying industries by the durability of their output. It is well known that the demand for durable goods is more affected by macroeconomic shocks to aggregate demand than the demand for services (see e.g. Bils, Klenow, and Malin, 2012). Indeed, I find that the DMNS return factor is significantly negatively correlated with fluctuations in the amount of idiosyncratic income risk in the data.

Sorting firms in quintile portfolios based on their exposure to the DMNS factor, I find that firms with a high exposure to the DMNS factor have larger exposures to changes in income tail risk and earn a statistically significant average excess return of several percentage points per year over firms with a low exposure. The cross-sectional average return differential is not driven by differences between producers of durable good (a stock variable) and producers of non-durable goods (a flow), and holds in a within-industry sort. In firm-level panel regressions, I show that the return differential by DMNS factor exposure is also robust to including controls for industry–time fixed effects and other firm-level characteristics that are known to be associated with cross-sectional differences in average returns (in particular, book-to-market values and size).

Using these DMNS beta-sorted quintile portfolios, I estimate the risk premia that are associated with various potential risk factors. First, analyzing traded risk factors, I show that the risk premium on the DMNS factor is indeed positive and statistically significant. While market betas can also explain the differences in average returns, the DMNS factor dominates in a joint estimation. In addition, the risk premium on the DMNS factor remains significant when adding the returns on the standard Fama-French 25 portfolios to the sample and including the Fama-French factors as additional risk factors, while the market risk premium becomes insignificant or even negative. Second, I evaluate various macroeconomic (non-traded) factors. Consistent with the main model predictions, I estimate a significant risk premium for exposure to measured idiosyncratic income tail risk. The results are unique to the particular macroeconomic measure of labor market frictions and therefore do not merely pick up general heterogeneity in business cycle exposures.

In the model, heterogeneity in expected returns is due to heterogeneity in firm cash flow exposures to income risk fluctuations that generate aggregate demand shocks. Indeed, in a direct test of this cash flow channel, I find that firms with a high DMNS beta have cash flows that are highly exposed to changes in measured income tail risk, while firms with a low DMNS beta have no such exposure. Like the results on equity returns, these differences in exposures continue to hold in a within-industry portfolio sort. Consistent with a demand-based risk channel, I also find that firms with high DMNS betas have stronger stock price responses to monetary policy surprises than firms with low DMNS betas.

Finally, I examine time variation in risk and returns. Schmidt (2016) shows that the market risk premium varies over time depending on the level of idiosyncratic income risk. Importantly, I find that this predictability is strongly heterogeneous across firms. Firms with a high DMNS beta have returns that are highly predictable by the level of income tail risk, while firms with a low DMNS beta do not have predictable returns. The predictability increases monotonically with the DMNS beta of the portfolio. My model provides an explanation for these predictability patterns based on endogenous cash flow risk, without needing heteroskedasticity in income risk shocks. Consistent with this channel, the conditional volatility of stock returns and the conditional volatility of cash flow growth empirically vary with the current level of measured income risk for high-exposure firms but not for low-exposure firms.

Literature. This paper is most closely related to two broad strands of the macro-finance literature.

First, a recent literature in finance studies the asset pricing implications of price and wage rigidities in production economies, building on a large literature in macroeconomics on the price-setting behavior of firms over the business cycle. Using micro data on individual prices underlying the U.S. consumer price index, Bils and Klenow (2004), Nakamura and Steinsson (2008), and Klenow and Kryvtsov (2008) document a typical duration of regular prices of 4 to 11 months, with considerable heterogeneity across sectors. Gorodnichenko and Weber (2016) use data on stock market returns around monetary policy announcements to show that sticky prices are costly.

Uhlig (2007) and Favilukis and Lin (2016) introduce wage rigidities in production-based models to explain asset pricing facts. Li and Palomino (2014) develop a New Keynesian asset pricing model with sticky prices and sticky wages. Weber (2015) and Clara (2019) study heterogeneity in firm equity returns in multi-sector models with nominal rigidities, supported by empirical findings from micro data. Ozdagli and Velikov (2020) show that stocks with a higher monetary policy exposure earn a lower rather than a higher risk premium, consistent with a stabilizing role of monetary policy instead of being an independent source of risk. I contribute to this literature by proposing variation in idiosyncratic risk as a main source of demand risk over the business cycle and by testing the predictions of this New Keynesian model directly in data on equity returns.

Second, my paper contributes to a literature on the aggregate implications of uninsurable idiosyncratic risks. In the macroeconomic literature, studies of the impact of idiosyncratic risk on business cycle fluctuations typically focus on relatively short-lived unemployment risk (see e.g. Krusell and Smith, 1998; Krueger, Mitman, and Perri, 2016). Standard models predict that these are risks that many households, except those at the bottom of the wealth distribution, can relatively easily self-insure against. However, recent income data as described in Guvenen et al. (2014) shows that severe idiosyncratic income shocks in recessions are persistent. Persistent shocks have very different implications in a macroeconomic model because they affect the behavior of households across the whole distribution. McKay (2017) estimates a process for labor income where idiosyncratic risks are permanent and shows that aggregate consumption can respond strongly to increases in uncertainty about persistent labor market outcomes.[2] Berger, Dew-Becker, Schmidt, and Takahashi (2019) find substantial welfare benefits when monetary policy specifically targets income tail risk. I extend the analysis of a time-varying precautionary saving motive due to idiosyncratic risk by studying asset pricing implications in a model with nominal rigidities, heterogeneous firms, and limited stock market participation.

The potential asset pricing implications of undiversifiable idiosyncratic risks have been studied extensively in the finance literature, with seminal contributions from Mankiw (1986), Heaton and Lucas (1996), and Constantinides and Duffie (1996).[3] Constantinides and Ghosh (2017) and Schmidt (2016) use statistics from rich micro data on income and consumption to quantify this idiosyncratic risk channel. Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) consider the link with idiosyncratic stock price risk. These papers focus on asset pricing implications when investors face countercyclical idiosyncratic consumption risks in an endowment economy, in which case the comovement between stock prices and idiosyncratic consumption risks for the marginal investor makes stocks less appealing relative to safer assets. This relation directly leads to higher risk premia. In contrast, the model in this paper is focused on the precautionary saving motive induced by idiosyncratic income risk, affecting firm earnings through aggregate demand in a production economy with nominal rigidities. This different channel allows me to derive new predictions on the cross section of asset returns and time variation in expected returns.

My paper further builds on models of asset prices with limited stock market participation, motivated by the observation that a substantial fraction of the population does not own any stocks. Since equity holdings are concentrated in a subset of the population, the comovement between firm payoffs and the consumption of stockholders is greater than the comovement between firm payoffs and aggregate consumption, in particular since firm dividends are more volatile than wage income. This effect helps towards explaining the equity premium. Empirical evidence for a higher volatility and comovement of stockholder consumption goes back to Mankiw and Zeldes (1991).[4]

At a broader level, my analysis also relates to a literature started by Berk, Green, and Naik

[2] Challe and Ragot (2016), Ravn and Sterk (2017), Werning (2015), Den Haan, Rendahl, and Riegler (2018), and Bayer, Lütticke, Pham-Dao, and Tjaden (2019) also study aggregate consumption implications of idiosyncratic risk due to a precautionary saving motive.

[3] See also Cogley (2002); Constantinides (2002); Krebs (2003, 2007); De Santis (2007); Storesletten, Telmer, and Yaron (2007), among others.

[4] Further empirical evidence is provided by Attanasio, Banks, and Tanner (2002); Parker (2001); Vissing-Jørgensen (2002); Aït-Sahalia, Parker, and Yogo (2004). Basak and Cuoco (1998); Heaton and Lucas (1999); Guvenen (2009); Polkovnichenko (2004); Gomes and Michaelides (2008); Favilukis (2013) analyze theoretical models with limited participation.

(1999) and Gomes, Kogan, and Zhang (2003) that links heterogeneity in firm earnings and equity returns to fundamental sources of risk exposures in the production process. Van Binsbergen (2016) builds a model of good-specific habits that generates an endogenous relation between the demand for goods and expected returns.

2 Fluctuations in Idiosyncratic Labor Income Risk

Recent data on the annual labor income of workers show that households are subject to substantial idiosyncratic tail risk in labor earnings, and that the amount of idiosyncratic risk in labor income fluctuates over the business cycle. Guvenen et al. (2014) report statistics on the cross section of labor income growth rates of millions of US workers in administrative data. While the cross-sectional standard deviation of income growth rates – controlling for standard life-cycle effects – is nearly acyclical, the skewness of income growth rates is highly procyclical. In particular, negative tail risk in labor income spikes during recessions.

To capture macroeconomic variation in the amount of idiosyncratic labor income risk that workers face, I consider two macroeconomic indicators. The first measure, x_t, is directly estimated from statistics on the yearly distribution of individual income growth rates as reported by Guvenen et al. (2014). I specify a model of individual labor income, where x_t captures time-series variation in the skewness in the cross-sectional distribution of income growth rates. Following the approach of McKay (2017), I use a simulated method of moments (SMM) estimator to estimate the income process by matching the cross-sectional moments of 1-year, 3-year, and 5-year income growth rates in the model to the corresponding empirical moments. The targeted moments are the median, 10th percentile, and 90th percentile of the distribution of earnings growth rates in each year. To be able to use a quarterly macroeconomic time series for individual income risk in empirical tests and in an equilibrium model, while income is only observed at an annual frequency, I simulate the labor income process at a quarterly frequency and aggregate to annual observations when computing the moments.

The time series for x_t is constructed by assuming that x_t is a linear combination of four quarterly labor market indicators: the short-term unemployment rate, the long-term unemployment rate, average weekly hours, and initial claims to unemployment relative to the labor force. The factor loadings for x_t are then estimated together with the other parameters of the income process. Appendix A.1 describes the estimation procedure in further detail. The resulting path for x_t, for the estimated weights on the indicators, 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 labor market uncertainty, I use the ratio of initial claims for unemployment to the size of the labor force in isolation, as proposed by Schmidt (2016). Schmidt (2016) shows that initial claims for unemployment – the rate of involuntary job losses in the US – are closely related to tail risk in the distribution of labor earnings growth rates. I define the initial claims measure icl_t as the number of initial claims filed in that period relative to the total size of the US workforce, after removing a low-frequency trend component, and normalized to have the same mean and standard deviation as x_t.[5] In comparison to the measure x_t that is directly estimated based on individual income growth rates, the claims measure icl_t has the benefits that this proxy for labor income risk is available in real time and at a higher frequency.

The dashed line of Figure 1 plots the resulting series for icl_t at a quarterly frequency. The sample period for the two income risk measures is 1967–2019. Clearly, the two series x_t and icl_t have a strong overlap: the quarterly correlation is 0.71.

3 General Equilibrium Model

I develop a dynamic New Keynesian general equilibrium model with households that are subject to time-varying idiosyncratic income risk. The model features heterogeneous agents as well as heterogeneous firms, in a tractable way. With heterogeneous agents and incomplete markets, idiosyncratic risk generates variation in aggregate demand through a precautionary saving motive due to imperfect risk sharing and therefore drives fluctuations in firm output and asset prices. Heterogeneity in firm demand elasticity gives rise to cross-sectional variation in risk exposures and expected returns.

In this section, I discuss the main setup and outcomes of the model. Appendix A.2 contains further details and derivations.

3.1 Households

The economy is populated by a continuum of agents of two types $\nu \in \{s, n\}$: stockholders in the population subset $\mathcal{I}_s$, and non-stockholders in $\mathcal{I}_n$. The population shares are assumed to be constant and the total population size is normalized to unity. The measures of stockholders and non-stockholders are denoted by δ_s and δ_n, respectively. Both types of agents provide labor services and allocate their time between work and leisure. Households derive utility from differentiated consumption goods and have additively separable utility in consumption and labor.

Stockholders. Stockholders can trade any state-contingent claim among themselves and therefore are fully insured against any idiosyncratic shocks. The objective of the representative stockholder in $\mathcal{I}_s$ is

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

[5] Without detrending, the initial claims measure has a negative linear trend that is highly significant. To make sure that the empirical results are not driven by this linear trend, I remove trends at a very low frequency by using a one-sided HP filter with smoothing parameter 10^5. All empirical results hold when using the raw measure of initial claims relative to the size of the workforce, without detrending.

where C_t^s is consumption of a composite consumption good, $H_t^s = b_s C_{t-1}^s$ is an external habit level in consumption with strength b_s, L_{sjt} denotes the supplied amount of labor services of type j in efficiency units, β_s is the time discount factor (including a component that accounts for mortality risk), γ is the coefficient of relative risk aversion, $\chi_{0s} > 0$ is a weighting parameter for the disutility of labor relative to consumption, and χ_1 is the inverse of the Frisch elasticity of labor supply.

Non-stockholders. Non-stockholders have similar preferences to stockholders but face idiosyncratic labor income risk. Due to incomplete markets, workers cannot fully diversify this idiosyncratic risk. The preferences for household $i \in \mathcal{I}_n$ are given by

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

with habit level $H_t^i = b_n \Gamma_{it} C_{t-1}^n$, where C_{t-1}^n is aggregate consumption per capita by non-stockholders. Individual consumption, labor services, and the preference parameters are defined analogously to those of stockholders.

For non-stockholders, the disutility of providing labor services in efficiency units includes the additional idiosyncratic component $\Gamma_{it}^{-(\gamma+\chi_1)}$. The process Γ_{it} captures undiversifiable idiosyncratic risk in labor income. Note that labor income in the model is endogenous, since labor supply is elastic.[6] Modeling individual income risk through the disutility of labor in this form, combined with the assumption that the habit level fully adjusts in response to permanent idiosyncratic shocks, implies that the problem of non-stockholders is homothetic in the idiosyncratic component and individual labor income is proportional to Γ_{it} in equilibrium.[7]

Workers face permanent idiosyncratic income shocks ξ_{it}. Due to incomplete markets, non-stockholders can only partially insure against these permanent shocks. Let ψ be the residual exposure to idiosyncratic shocks that non-stockholders face, so that $\Gamma_{i,t+1} = \Gamma_{it} e^{\psi \xi_{i,t+1}}$. The distribution of permanent shocks is modeled such that workers are subject to tail risk in income, as in the data. Most people have a common change that is drawn from a distribution $N(\mu_{1t}, \sigma_{\xi,1}^2)$. A fraction p_2 of workers receive a large and persistent loss that is drawn from the distribution $N(\mu_{2t}, \sigma_{\xi,2}^2)$. Similarly, a fraction p_3 of workers receive a very positive shock with distribution

[6] The literature on portfolio choice and asset pricing with idiosyncratic income risk typically treats individual labor income as exogenous. However, for the model in this paper, it is important to have elastic labor supply to incorporate wage setting with sticky wages.

[7] In this specification, L_{ijt}/Γ_{it} can be interpreted as the number of actual hours worked by the agent on labor type j, and Γ_{it} as individual labor productivity. The disutility of labor is modeled to offset the wealth effect of changing labor productivity on effective labor supply such that the actual hours worked will be independent of the level of idiosyncratic human capital Γ_{it}.

$N(\mu_{3t}, \sigma^2_{\xi,3})$. Hence, the setup for residual idiosyncratic income risk is as follows:

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

The amount of tail risk depends on the aggregate state x_t, which follows an AR(1) process with persistence ρ_x and shocks $\epsilon_{xt} \sim N(0, \sigma^2_x)$. The conditional means of income growth for the three types of shocks are

$$\begin{aligned} \mu_{1t} &= \bar{\mu}_t \\ \mu_{2t} &= \bar{\mu}_t + \mu_2 - x_t \\ \mu_{3t} &= \bar{\mu}_t + \mu_3 - x_t, \\ \bar{\mu}_t &= -\frac{1}{\psi} \log\left((1 - p_2 - p_3) e^{\frac{1}{2}\psi^2 \sigma^2_{\xi,1}} + p_2 e^{\psi(\mu_2 - x_t + \frac{1}{2}\psi\sigma^2_{\xi,2})} + p_3 e^{\psi(\mu_3 - x_t + \frac{1}{2}\psi\sigma^2_{\xi,3})} \right). \end{aligned} \tag{4}$$

Note that $\bar{\mu}_t$ is defined such that the shocks to Γ_{it} are indeed idiosyncratic conditional on the state of the economy, i.e., $\mathbb{E}\left[\Gamma_{i,t+1}/\Gamma_{it} \mid x_t\right] = 1$.[8] For deriving the equilibrium conditions of the model, I define the key objects $g^n_0(x) \equiv \mathbb{E}\left[e^{-\gamma\psi\xi_{t+1}} \mid x_t = x\right]$ and $g^n_1(x) \equiv \mathbb{E}[e^{(1-\gamma)\psi\xi_{t+1}} \mid x_t = x]$ that capture the precautionary saving motive associated with idiosyncratic risk.[9]

Consumption. The composite good is a double Dixit-Stiglitz aggregate of the consumption goods that are produced within each sector and across sectors. Let C_{kt} be the consumption basket of goods in sector k. Consumption of the composite good is given by

$$C_t = \left(\sum_k \omega_k^{\frac{1}{\eta_c}} C_{kt}^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}}, \tag{5}$$

where ω_k is the weight of sector k. The consumption basket of each sector is aggregated from a continuum of individual consumption goods C_{kft} of firms $f \in [0,1]$ in sector k,

$$C_{kt} = \left(\int_0^1 C_{kft}^{\frac{\eta_{ck} - 1}{\eta_{ck}}} df \right)^{\frac{\eta_{ck}}{\eta_{ck} - 1}}. \tag{6}$$

Let P_t be the aggregate price index and P_{kt} be the price index for sector k that are determined competitively. The elasticity of demand that firms face in sector k is η_{ck} and may vary by k. The

[8] I assume that households are subject to mortality risk, accounted for in the time discount rate β. Upon death, individuals get replaced by a newborn of the same type with initial idiosyncratic component $\Gamma = 1$, such that the cross-sectional mean of Γ_{it} is well defined and equal to one.

[9] For completeness of notation, let $\Gamma_{it} \equiv 1$ for $i \in \mathcal{I}_s$, $g^s_0(x) \equiv 1$, and $g^s_1(x) \equiv 1$.

elasticity of demand across sectors is $\eta_c \leq \eta_{ck}$.

Asset markets. Asset markets are assumed to be fully segmented. Stockholders own shares in the firms that produce output for the economy, collecting firm dividends each period. Stockholders also have access to a complete market where they can trade all state-contingent claims among themselves. In contrast, non-stockholders can only invest in one-period risk-free nominal bonds, the price of which is set by the monetary authority.

Limited stock market participation is empirically realistic: in the Survey of Consumer Finances (SCF), only about 50% of U.S. households are reported to own stocks. I impose full segmentation of asset markets to highlight the main idiosyncratic risk channel and to keep the model tractable. In this setup, non-stockholders that face idiosyncratic risk will be hand-to-mouth in equilibrium, so that the wealth distribution in the model is trivial. With trading between stockholders and non-stockholders, the model would be intractable since the whole wealth distribution would become a state variable. In addition, in reality, many stockholders also face time-varying idiosyncratic risks that cannot fully be shared on financial markets. In fact, Guvenen, Schulhofer-Wohl, Song, and Yogo (2017) show that cyclical income risk is highest at the bottom *and top* of the income distribution. It would therefore be unrealistic for resources to flow from non-stockholders to stockholders during a recession due to a precautionary saving motive of only the former group. Finally, for simplicity, I also assume that stockholders cannot save at the nominal risk-free rate set by the monetary authority so that non-stockholders are always the marginal investors in this asset.[10]

3.2 Wages

I follow Erceg, Henderson, and Levin (2000) in modeling the labor market. Firms use homogeneous labor as input in the production function, which they hire in a single labor market where they pay the aggregate wage rate W_t. This labor input is a bundle of differentiated labor services of various types that are aggregated in a competitive market. In particular, aggregate labor N_t is the CES aggregate of composite labor $N_{\nu t}$ that is provided by each agent type at the composite wage rate $W_{\nu t}$:

$$N_t = \left(\sum_{\nu} \delta_{\nu}^{\frac{1}{\eta_w}} N_{\nu t}^{\frac{\eta_w - 1}{\eta_w}} \right)^{\frac{\eta_w}{\eta_w - 1}}, \tag{7}$$

[10] The implications of the model would be similar if stockholders were also allowed to save at the nominal risk-free rate, since in bad times the effective discount rate of non-stockholders is much smaller than that of stockholders due to the precautionary saving motive and therefore non-stockholders would still be the marginal investors in the safe asset at the relevant times.

with elasticity of substitution η_w across composite labor by type. Composite labor for each type ν is itself aggregated from differentiated labor types j:[11]

$$N_{\nu t} = \left(\int_0^1 N_{\nu jt}^{\frac{\eta_w - 1}{\eta_w}} \, dj \right)^{\frac{\eta_w}{\eta_w - 1}}, \tag{8}$$

where labor market clearing implies that

$$N_{\nu jt} = \int_{i \in \mathcal{I}_\nu} L_{ijt} \equiv \delta_\nu L_{\nu jt}. \tag{9}$$

Thus, the labor that is used for production is the double composite of individual labor services of different labor types j provided by the agents of different types ν.

Nominal wages are sticky and the quantities of labor services are determined by labor demand. Each type of labor j provided by an agent type ν is represented by a labor union that sets the wage rate $W_{\nu jt}$ for that labor type optimally on behalf of the relevant households, subject to a friction a la Calvo (1983): in each period, the wage rate can be adjusted with probability $1 - \theta_w$. There are no costs of updating the wage when getting the opportunity to do so, and infinite costs otherwise.

The labor union allocates labor services to individual members, and divides the quantity of labor in such a way that actual labor hours are the same across agents. This means that effective labor services are proportional to Γ_{it}, i.e., $L_{ijt} = \Gamma_{it} L_{njt}$ for $i \in \mathcal{I}_n$. Appendix A.2.1 shows that this setup implies that the problem for non-stockholders is homogeneous in Γ, and therefore individual non-stockholders choose consumption and bond holdings proportionally: $C_{it} = \Gamma_{it} C_{nt}$ and $B_{it} = \Gamma_{it} B_{nt}$.

Because of this homogeneity, households of the same agent type have the same objectives for setting wages and therefore agree on the wage $W_{\nu jt}$ that is optimally chosen by the labor union when wages can be adjusted. The objective function in choosing the reset wage for the union that represents labor type j for all agents $i \in \mathcal{I}_\nu$ is given by

$$\max \quad \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}} \right)^{1-\gamma} \left[-\chi_{0\nu} \frac{L_{\nu,j,t+\tau}^{1+\chi_1}}{1+\chi_1} + \frac{\lambda_{\nu,t+\tau}}{\lambda_{\nu t}} \frac{W_{\nu jt}}{P_{t+\tau}} L_{\nu,j,t+\tau} \right], \tag{10}$$

where P_t is the aggregate price index and $\lambda_{\nu t} = (C_t^\nu - b_\nu C_{t-1}^\nu)^{-\gamma}$. Hence, labor unions set the reset wage to equalize the marginal benefit of receiving additional labor income in consumption utility to the marginal labor disutility cost of working additional hours, taking into account that the wage rate set today determines labor demand in future periods over paths where the wage rate is sticky.

Sticky wages are important for the quantitative implications of the model, since wage rigidities dampen the decrease in wages as demand falls and make dividends more volatile. With flexible wages, bad shocks lead to significant decreases in wages, as the rise in marginal utility

[11] For simplicity, I assume that the elasticity of substitution between individual types of labor services provided by agent type ν is the same as the elasticity of substitution η_w between composite labor provided by the agents. It is straightforward to allow for differences in these elasticities.

makes households more willing to supply labor. This channel serves as a hedge to firm profits. In contrast, when wages are sticky and firms face relatively high wage costs in bad states, the volatility of dividends is amplified relative to output, which boosts the equity premium.

3.3 Production

The economy consists of a continuum of monopolistically competitive firms in each sector of the economy. Firms face nominal rigidities; pricing is subject to a Calvo friction. In each period, firms get a chance to update their price with probability $1-\theta_{ck}$. Without updating, the price remains at its current level. In addition to variation in the elasticity of substitution across goods η_{ck}, sectors may also vary in the Calvo parameter θ_{ck} of price stickiness.

Firm production is determined by the demand for consumption goods. Firms hire a homogeneous bundle of labor services to produce output such that total demand at the posted price is met. The production technology is linear in labor, so that the production of firm f in sector k is given by

$$Y_{kft} = A_t N_t^{kf}, \tag{11}$$

where $A_t = e^{a_t}$ is aggregate productivity and N_t^{kf} is the amount of labor hired by the firm. The log of aggregate TFP follows an AR(1) process with persistence ρ_a and shocks $\epsilon_{at} \sim N(0, \sigma_a^2)$. I allow for a correlation ρ_{ax} between TFP shocks ϵ_{at} and income risk shocks ϵ_{xt}.

Firms pay out profits as dividends and set their prices P_{kft} to maximize the present value of future dividends. Thus, when getting a chance to update their price, firms choose the reset price to maximize the sum of discounted future dividends over all future paths where the price cannot be updated. Real dividends are given by

$$D_{kft} = \frac{P_{kft}}{P_t} Y_{kft} - \frac{W_t}{P_t} N_t^{kf}, \tag{12}$$

and the market value of the firm is

$$V_{kft} = \mathbb{E}_t \left[\sum_{\tau=0}^{\infty} \beta_s^{\tau} \frac{\lambda_{s,t+\tau}}{\lambda_{st}} D_{k,f,t+\tau} \right]. \tag{13}$$

Similarly, V_{kt} is defined as the value of a claim to total dividends D_{kt} in sector k, and V_t the value of a claim to aggregate dividends D_t.

3.4 Monetary Policy

The nominal interest rate in the economy is determined by a Taylor rule. The monetary authority sets the one-period gross nominal interest rate I_t according to the rule

$$\log I_t = \bar{i} + \phi_\pi \pi_t + \phi_y \Delta y_t + z_t, \tag{14}$$

where $\bar{i} \equiv -\log(\beta_n g_0^n(0))$, $\pi_t \equiv \log(P_t/P_{t-1})$ is inflation, $\Delta y_t \equiv \log(Y_t/Y_{t-1})$ is aggregate output growth, ϕ_π and ϕ_y are policy parameters, and z_t is an AR(1) process with persistence ρ_z and monetary policy shocks $\epsilon_{zt} \sim N(0, \sigma_z^2)$.

3.5 Equilibrium

The definition of general equilibrium in the economy is standard. Households choose their consumption optimally, given prices. Labor unions set wages optimally to maximize expected utility for the household labor type they represent. Firms choose their prices optimally to maximize firm value. The markets for consumption goods, labor, and financial assets clear. All agents in the economy have rational expectations.

3.6 Calibration

The model is calibrated at a quarterly frequency. I briefly describe the calibration of the parameters in each of the categories below. Appendix Table A.2 summarizes the baseline parameterization of the model.

Preferences and wage determination. According to the 2019 SCF, 52.6% of households are equity holders. I therefore assume equal shares of household types: $\delta_s = \delta_n = 0.5$. I set the rate of time preferences of stockholders to $\beta_s = 0.985$, so that the average annual real risk-free rate in the stochastic model is 1.5%. The time discount factor of non-stockholders is set to $\beta_n = \beta_s / g_0(0)$ to have the same discount rate for the two agent types in the deterministic steady state. I choose risk aversion to be $\gamma = 10$ for both types of agents, which is a commonly used value in the asset pricing literature (e.g. Mehra and Prescott, 1985; Bansal and Yaron, 2004). The consumption habit weight of non-stockholders is set to $b_n = 0.65$, in line with standard values in the literature (Christiano, Eichenbaum, and Evans, 2005; Galí, Smets, and Wouters, 2012). Following the empirical evidence on heterogeneity in the elasticity of substitution (see Guvenen (2006) for a review), I assume that stockholders have a higher tolerance for volatility in their consumption profiles and set the habit weight of stockholders to a lower value of $b_s = 0.45$.

Consistent with Rabanal and Rubio-Ramírez (2005) and Christiano et al. (2005), I pick $\chi_1 = 1$ as the inverse Frisch elasticity of labor supply and set the Calvo parameter of wage determination to $\theta_w = 0.64$.[12] Finally, the elasticities of substitution between labor types is set to $\eta_w = 12$, which implies a wage markup of 9% that is in the range of estimates from the literature.[13]

Income risk. As described in Section 2, I estimate the parameters of a labor income process that incorporates business cycle variation in idiosyncratic tail risk to match the empirical evidence of

[12]The weighting parameters on labor disutility, χ_{0s} and χ_{1s}, are chosen such that employment per capita is equalized for both agent types in the deterministic steady state and normalized to one.

[13]Altig, Christiano, Eichenbaum, and Linde (2011) have a wage markup of 5%, while the calibration of Erceg et al. (2000) generates a wage markup of 33%.

Guvenen et al. (2014). The estimated process for gross individual labor income is the product of aggregate labor income, an idiosyncratic permanent component, and an idiosyncratic transitory income shock. The distribution of permanent income shocks ξ_{it} is modeled as described above. The details of the estimation procedure are in Appendix A.1.

I use the estimated parameters of the idiosyncratic income process in the asset pricing model. Empirical studies have shown that transitory shocks are smoothed by most households (see e.g. Blundell et al., 2008). In the model, it is also much easier to self-insurance against transitory shocks. In contrast, permanent shocks are typically much harder to insure against. I therefore assume that transitory income shocks are fully insured, while non-stockholders are only partially insured against permanent income shocks and have residual exposure ψ. I set the degree of insurance such that $\psi = 0.265$, which is within the range of estimates by Blundell et al. (2008).[14]

Production. For simplicity, I focus on a two-sector version of the model. The two sectors differ in the elasticity of substitution between consumption goods that are produced in the sector. Sector 1 has a low elasticity of substitution between goods, while sector 2 has a high elasticity of substitution. I set $\eta_c = 2, \eta_{c1} = 3$, and $\eta_{c2} = 16$. These elasticities imply a steady state markup of 50% for firms in sector 1 and a markup of 7% for firms in sector 2. In the baseline version I set the Calvo parameter θ_{ck} of price stickiness to 0.75 for both sectors, which is in the range of values that are estimated from macro data as well as micro data (e.g. Rabanal and Rubio-Ramírez, 2005; Christiano et al., 2005; Nakamura and Steinsson, 2008; Galí et al., 2012).

The persistence of the TFP process is set to a standard value of $\rho_a = 0.95$. To parameterize the distribution of TFP shocks, I use the measure of TFP growth of Fernald (2014). Consistent with the empirical volatility of TFP growth and correlation between TFP growth and innovations to x_t, I select $\sigma_a = 0.0075$ and $\rho_{ax} = -0.5$. The negative correlation between ϵ_{at} and ϵ_{xt} is consistent with the countercyclicality of idiosyncratic income tail risk (Guvenen et al., 2014).

Monetary policy. The monetary policy parameters are chosen to match standard values in the literature. I set the parameters of the Taylor rule to $\phi_\pi = 1.24$ and $\phi_y = 0.33/4$, following Rudebusch (2002). The baseline model does not have residual monetary policy shocks: $\sigma_z = 0$.

3.7 Model Dynamics

The model is solved using a third-order approximation around the deterministic steady state. I simulate the economy for 2 500 periods – discarding the first 500 periods – and calculate the moments of macroeconomic quantities and financial variables on the sample paths. In each period I compute total sector dividends D_{kt} and cum-dividend sector values V_{kt}, so that the value-weighted portfolio return of firms in sector k follows as $R_{kt} = \frac{V_{kt}}{V_{k,t-1} - D_{k,t-1}}$.

[14] Blundell et al. (2008) estimate a degree of consumption insurance such that residual exposure is 0.31 with respect to permanent shocks to family earnings, and 0.22 when considering only male earnings.

The model has reasonable implications for the dynamics of macroeconomic variables. The annual volatility of output growth is 1.17% with an autocorrelation of 14%. Since dividends are more volatile than aggregate labor income, the consumption of stockholders is exposed to bigger fluctuations than aggregate consumption of non-stockholders. The volatility of the consumption growth of stockholders is 1.39%, while the volatility of total consumption growth of non-stockholders is 0.88%. The higher volatility of stockholders' consumption growth is consistent with empirical studies that calculate stockholders' volatility to be at least 1.5 to 2 times larger than non-stockholders' volatility (Mankiw and Zeldes, 1991; Attanasio et al., 2002; Aït-Sahalia et al., 2004).

The main source of risk in the model comes from fluctuations in aggregate demand by non-stockholders due to a time-varying precautionary saving motive. The Euler equation of non-stockholders that governs the intertemporal trade-off between consumption and saving is given by

$$1 = \beta_n \cdot g_0^n(x_t) \cdot I_t \cdot \mathbb{E}_t \left[\left(\frac{C_{t+1}^n - b_n C_t^n}{C_t^n - b_n C_{t-1}^n} \right)^{-\gamma} \frac{P_t}{P_{t+1}} \right]. \tag{15}$$

Faced with additional income risk when x_t is high (high value of $g_0^n(x_t)$), non-stockholders cut consumption to save for a potential future individual disaster. Due to nominal rigidities, output then falls in response to the reduction in aggregate demand.

Figure 2 highlights the main mechanisms in the model by plotting the impulse response functions to a one standard deviation increase in uninsured idiosyncratic labor income risk of non-stockholders. An increase in idiosyncratic income risk leads to a drop in output and wages. More notably, the negative demand shock initially leads to a slight increase (and not a decrease) in inflation. The reason for this effect is that increased income risk is accompanied by an increased volatility of future demand shocks, as discussed below. We further see that marginal utility rises sharply for both agents in response to increased income risk due to habit preferences, and more so for stockholders since they have concentrated stock ownership.

Price and wage dispersion generate inefficiencies in the model. Consumption goods as well as labor types are imperfect substitutes, so the efficient outcome is to have equal production and hours within each category. However, since not all prices and wages can be updated simultaneously, the stochastic model has dispersion in prices and wages. This dispersion increases the total number of hours worked for each level of output and the total output produced for each level of the composite consumption basket. Price dispersion is defined as

$$DS_{pkt} = \int_0^1 \left(\frac{P_{kft}}{P_{kt}} \right)^{-\eta_{ck}} df, \qquad DS_{pt} = \sum_k \omega_k \left(\frac{P_{kt}}{P_t} \right)^{-\eta_c} DS_{pkt}. \tag{16}$$

Figure 2 shows that price dispersion rises substantially when there is an increase in idiosyncratic income risk.

Thus, due to the nominal rigidities in the model, the time-varying precautionary saving motive of non-stockholders generates demand shocks that have real effects. While the stockholders that price financial claims are fully diversified, they are still exposed to fluctuations in idiosyncratic income risk due to these aggregate demand effects. Hence, what matters in the model is that the marginal consumer is affected by idiosyncratic tail risk, not (necessarily) the marginal investor. This mechanism addresses a common criticism of asset pricing models with idiosyncratic risk, namely that undiversifiable labor income risk may not directly affect the marginal utility of the agents that are relevant for pricing financial claims in a quantitatively meaningful way.

To illustrate the differences in the dynamics of asset prices across sectors, consider the pricing of claims to one-period ahead sector dividends. Let $\widetilde{R}_{k,t+1}$ be the return on the claim to the next-period dividends of sector k. Dividends are procyclical and mainly fluctuate with changes in income risk. As shown in Figure 2, dividends in the high-elasticity sector are much more affected by changes in tail risk. Due to the covariance of these cash flow shocks with marginal utility, this exposure is compensated by a risk premium. In Appendix A.2.7, I show that difference in expected returns across the two sectors can be approximated as:

$$\begin{aligned}\log \mathbb{E}_t \widetilde{R}_{2,t+1} - \log \mathbb{E}_t \widetilde{R}_{1,t+1} = &-(\eta_{c2} - \eta_c)\mathrm{Cov}_t(m_{t+1}, p_{2,t+1} - p_{1,t+1}) \\ &- (1 - \eta_{c2})\mathrm{Cov}_t(m_{t+1}, ds_{p,2,t+1} - ds_{p,1,t+1}) \\ &- (\eta_{c2} - \eta_{c1})\mathrm{Cov}_t(m_{t+1}, a_{t+1} - wp_{t+1} + p_{1,t+1} - ds_{p,1,t+1}),\end{aligned} \tag{17}$$

where m_{t+1} is the log real SDF, $p_{kt} \equiv \log(P_{kt}/P_t)$, $wp_t \equiv \log(W_t/P_t)$, and $ds_{pkt} \equiv \log(DS_{pkt})$.

The difference in expected returns consists of three components. The first component contributes negatively to the expected return differential, since the difference in relative prices has a slight positive correlation with marginal utility. However, the second and third components generate a positive overall return spread. The second component is the main contributor to the risk premium: the spread is largely driven by the positive covariance between marginal utility and price dispersion. When income risk rises, price dispersion in the high-elasticity sector rises much more than price dispersion in the low-elasticity sector. The third term corrects for differences in the scaling factor across sectors due to heterogeneity in demand elasticities, and also contributes positively to the return spread as a consequence of rising price dispersion in response to adverse shocks.

3.8 Asset Pricing Implications

Unconditional equity returns. Table 1 reports unconditional annualized moments of asset returns generated by the model. The first row shows the results for the baseline calibration. The equity premium is substantial: 7.5% per year. The volatility of market returns is 23%, so that the annual Sharpe ratio is 0.32. In the cross section, average equity returns are increasing in the elasticity of substitution that firms face. The return premium for high-elasticity firms is 2.6% per year. This premium is compensation for the higher exposure of these firms to changes in income tail risk: the last column shows that the return differential has a beta of -0.7 with respect to changes in x_t.

The other rows examine the sensitivity of these asset pricing results to variations in the key parameter values. Rows (2)–(5) show the results for different specifications of the exogenous processes. The asset pricing implications are similar for the case without technology shocks (row 2), with a slightly lower Sharpe ratio but bigger return spread due to increased stock market volatility. With uncorrelated technology shocks (row 3), volatility and risk premia are even higher. Idiosyncratic income risk is clearly the main source of fluctuations in asset prices: without idiosyncratic income risk (row 4), the equity premium and Sharpe ratio are much lower and there is hardly any return spread. Row (5) focuses on monetary policy shocks as an alternative driver of demand fluctuations and will be separately discussed below.

Row (6) highlights that with flexible prices, there is no variation in returns across sectors. The equity premium is still substantial due to wage rigidities, but sectors are not differently exposed to shocks and therefore the return spread is zero.

Row (7) shows the implications on asset prices when sectors vary in price stickiness instead of demand elasticity. I adopt a two-sector version of Weber (2015) with parameter values $\eta_c = 8, \eta_{ck} = 12, \theta_{c1} = 0.35$, and $\theta_{c2} = 0.85$. Similar to heterogeneity in demand elasticities, heterogeneity in price stickiness generates a return spread. This spread is consistent with the empirical findings of Weber (2015).[15] A difference between these models, as pointed out by Clara (2019), is the relation between markups and firm riskiness. With heterogeneity in price stickiness, the average markup is 9.2% in sector 1 versus 9.7% in sector 2 – firms in sector 2 choose slightly higher markups because the timing of the next price change is more uncertain. In contrast, with heterogeneity in demand elasticity, the average markup is 50.9% in sector 1 versus only 6.9% in sector 2.

The next rows in Table 1 consider variation in preference and labor market parameters. Row (8) shows that a higher b_s of 0.65 raises the return spread across sectors but lowers the aggregate Sharpe ratio. In row (9), we see that a higher inverse Frisch elasticity of $\chi_1 = 2.5$ makes asset returns substantially more volatile. Row (10) considers less stickiness in wages, $\theta_w = 0.5$, which lowers the equity premium but increases the return spread. Row (11) reports lower risk premia for a lower elasticity of labor substitution, $\eta_w = 8$.

Row (12) shows that the return spread is slightly higher for a larger elasticity of substitution across sectors: $\eta_c = 3$. Rows (13) and (14) report the asset pricing moments for different values of η_{c2} – 11 and 21, respectively – and show that the return spread is highly dependent on (and increasing in) the dispersion in elasticities across sectors. Finally, row (15) shows that a more aggressive monetary policy to inflation dampens volatility and risk premia.

Source of demand shocks. Row (5) of Table 1 shows the asset pricing implications of an alternative version of the model where demand fluctuations are not generated by idiosyncratic income risk but by orthogonal monetary policy shocks. I set the persistence of z_t to $\rho_z = \rho_x = 0.88$;

[15] I focus on heterogeneity in demand elasticities as the main source of firm heterogeneity, for consistency with the empirical analysis that follows.

the volatility of shocks is set to $\sigma_z = 1.2\%$ to match the volatility of non-stockholders' aggregate consumption growth. It is common for models in the New Keynesian asset pricing literature to have a substantial volatility of monetary policy shocks.[16] The implications for unconditional asset prices are similar to the baseline model.[17] However, the empirical volatility of monetary policy surprises is much smaller. The volatility of monetary policy surprises on announcement days, aggregated to a quarterly frequency, is only 0.12%.[18] While clearly news about (future) monetary policy that affects asset prices is also announced outside of FOMC meetings (see e.g. Neuhierl and Weber, 2019), the central bank has a mandate to stabilize the economy and may therefore act to offset economic shocks. Consistent with a "stabilizer" channel of monetary policy, Ozdagli and Velikov (2020) show that stocks with a higher monetary policy exposure earn a lower (and not higher) risk premium. As an alternative *driver* of demand fluctuations over the business cycle, this paper proposes a time-varying precautionary saving motive due to empirically-measured idiosyncratic income risk, so that exposure to this factor is compensated with a risk premium.

An additional feature of the model in this paper is that it naturally generates time-varying expected returns and cross-sectional differences in this predictability, as opposed to models with linear demand shocks that are due, for instance, to monetary policy shocks. I will discuss these implications for return predictability next.

Predictability. Asset returns in the model are predictable by the level of idiosyncratic income risk. I run a predictability regression of one-year ahead asset returns on x_t, using overlapping quarterly observations:

$$R_{t:t+4} = b_0^r + b_1^r x_t + u_{t:t+4}^r. \tag{18}$$

The left plot in panel (a) of Figure 3 plots the predictive coefficients b^r in the baseline model for the two sector returns and the market return. The coefficients are standardized so that a one standard deviation increase in income risk x_t is associated with a 6 to 11 percentage points higher expected return. There is substantial heterogeneity in predictability across sectors: predictability is largest for the high-elasticity sector that is more exposed to shocks to idiosyncratic risk.

It is important to note that returns are predictable even though shocks to x (and TFP) are homoskedastic. Thus, 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 have predictability. Instead, return predictability is due to the particular way that time-varying idiosyncratic income risk generates demand shocks. For comparison, the second and third plots in panel (a) of Figure 3 report the predictability coefficients in alternative versions of the model where demand shocks are linear or absent.[19] Even though effective risk aversion varies by the

[16] For example, Weber (2015) uses a volatility σ_z of 0.85%.

[17] See De Paoli, Scott, and Weeken (2010) for a discussion of the importance of demand shocks for generating large risk premia in a New Keynesian asset pricing model.

[18] This volatility is calculated based on changes in Federal funds futures on days of monetary policy announcements, over the period 1994–2007. Further details are in Section 4.6.

[19] The version labeled "linear demand shocks" is characterized by $g_0(x) \equiv e^{g_{0,0}+g_{0,1}x}$ and $g_1(x) \equiv 1$.

state of the economy due to habit preferences, there is hardly any predictability in the model with linear demand shocks – which is analogous to the version with monetary policy shocks – and no predictability without demand shocks.[20] Predictability is thus a unique feature of the model with idiosyncratic tail risk.

The source of predictability in the model is the nonlinear relation between idiosyncratic risk and aggregate demand. Recall that aggregate demand shocks originate from variation in the strength of the precautionary motive over the business cycle. The precautionary saving channel endogenously generates stochastic volatility of demand shocks. To illustrate this effect, Figure 4 plots the mean and tails of the precautionary term $g_0(x_{t+1})$ conditional on x_t. As a result of non-stockholders' risk preferences combined with the process for idiosyncratic income risk, the precautionary saving term is convex in x_t. When income risk is at a high level, further changes in income risk lead to much stronger changes in the precautionary saving motive. This convexity leads to a stochastic and countercyclical volatility of demand shocks.

Thus, the expectation of future excess returns moves around over time due to business-cycle variation in the conditional volatility of stock returns, generated by fluctuations in the conditional volatility of endogenous demand shocks. To further illustrate this channel, I run the following regression in model-simulated data:

$$|R_{t:t+4}| = b_0^a + b_1^a x_t + u_{t:t+4}^a. \tag{19}$$

The plots in panel (b) of Figure 3 report the predictive coefficients for these regressions. Indeed, in the baseline model, the level of x_t predicts future volatility in stock returns. In contrast, there is no significant predictability in alternative versions of the model with linear or no demand shocks.

4 Empirical Analysis

In the model from Section 3, variation in the amount of non-diversifiable idiosyncratic income risk over time is a key source of risk in financial markets that is reflected in asset prices. In this section, I use the proxies for macroeconomic variation in idiosyncratic income risk that were introduced in Section 2 to examine 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. To test these predictions, I study a new cross section of firms that differ in exposure to the business cycle. These firms have significantly different unconditional and conditional average returns.

[20] Note that since x_t is significantly correlated with TFP, we would observe predictability by x_t even without demand shocks if TFP shocks would induce meaningful variation in expected returns.

4.1 Durable versus Nondurable Good Producers

In the model, firm heterogeneity in exposure to fluctuations in income tail risk is due to differences in demand elasticities. Since a direct measure of demand elasticity is not available in standard data sources, I use the return differential between producers of durable goods and producers of nondurable goods and services as a proxy for demand risk and the exposure of a firm's equity returns to this factor as a measure of exposure to demand shocks. By the logic of basic consumer theory, demand effects should be bigger for more durable goods, since expenditures on those products can be more easily shifted around over time (see e.g. Barsky, House, and Kimball, 2007). Durable good producers are therefore more exposed to demand fluctuations than producers of nondurables and services. Consistent with this effect, Figure A.1 illustrates the well-known stylized fact that expenditures on durable goods tend to be much more sensitive to business cycles than the consumption of nondurables and services.

To classify firms by the type of their output, I follow Gomes et al. (2009) that map industries, identified by 4-digit SIC codes, to National Income and Product Accounts (NIPA) product categories based on the 1987 benchmark input-output accounts from the Bureau of Economic Analysis (BEA). An industry is assigned to the sector where it has the highest value added: personal consumption expenditures (PCE) on durable goods, PCE on nondurable goods, PCE on services, investment, government expenditures, or net exports. Using this classification, I construct sector portfolios in the merged Compustat–CRSP database over a sample period from 1926 to 2019. I use the industry code from Compustat if available, and from CRSP otherwise. Since the goal is to uncover variation due to aggregate demand fluctuations, I exclude firms in the categories Financial (SIC codes 6000–6799), Utilities (4900–4949), Mining (1000–1499), and Petroleum Refining (2900–2999).

Sector returns. I compute weekly and monthly returns on value-weighted sector portfolios. Table 2 presents annualized statistics of monthly portfolio returns of the sector portfolios, as well as the exposure to changes in income risk.[21] As expected, the returns of durable good producers are much more correlated with income risk fluctuations than the returns of producers of nondurable goods and services. Consistent with (compensated) differences in risk exposures, Gomes et al. (2009) find that the difference in average returns between durable good producers and producers of services is significantly positive.

I use the difference in returns between producers of durable goods and producers of nondurable goods and services (DMNS) to construct a tradable factor that proxies for aggregate demand shocks:

$$R_{DMNS,t} = R_{durables,t} - \frac{1}{2}(R_{nondurables,t} + R_{services,t}). \tag{20}$$

In addition, following Papanikolaou (2011), I also compute the return spread between investment and consumption good producers (IMC) to construct a proxy for investment-specific technology

[21] In linking innovations in macroeconomic variables to asset returns, I use the "beginning-of-period" timing convention throughout, following Campbell (2003).

shocks.

Factor betas. Motivated by the above findings, I use the DMNS beta of firm equity returns as a proxy for exposure to demand fluctuations, which is the regression coefficient of the firm's stock return on the long–short DMNS portfolio return. I restrict attention to the sample of firms that produce consumption goods. For this sample, Papanikolaou (2011) shows that heterogeneity in exposure to investment-specific technology shocks (captured by the IMC beta) explains variation in realized returns and is associated with a return premium. In the empirical analysis, I therefore control for IMC exposures to account for any differences due to firm heterogeneity in future growth opportunities, which are outside of the scope of the model. Accordingly, the return betas for each firm are estimated in a two-factor specification:

$$R^e_{ft} = \beta_{f,0} + \beta_{f,DMNS} R_{DMNS,t} + \beta_{f,IMC} R_{IMC,t} + u_{ft}. \tag{21}$$

I estimate the betas for firm f at time t using weekly returns in excess of the risk-free rate in a backward-looking rolling window over a five-year horizon, requiring at least 52 weekly observations.

4.2 Sorting Stocks in Portfolios by DMNS Beta

The model predicts that the stochastic discount factor loads on innovations to idiosyncratic income risk and therefore that the exposure of firm equity and cash flows to fluctuations in income tail risk is compensated by a risk premium. Estimating the stochastic discount factor based on the full cross section of stocks to test this prediction is difficult due to measurement error in covariances. I therefore follow a standard approach in the finance literature by focusing on the price dynamics of portfolios of stocks that are sorted on economically relevant dimensions to reduce measurement error. Specifically, I sort stocks in portfolios by quintiles of the cross-sectional distribution of $\beta_{f,DMNS}$ and calculate monthly value-weighted returns on the quintile portfolios. The portfolios are rebalanced at a monthly frequency.

Portfolio returns. Table 3 reports the annualized mean and volatility of the returns on five DMNS beta-sorted portfolios. There is a clear cross-sectional pattern in portfolio returns: both the average and the volatility of returns are increasing by quintile of the DMNS beta. The difference between the average return on the highest quintile portfolio and the average return on the lowest quintile portfolio is 5.96%, which is statistically and economically significant. All portfolios load negatively on innovations to icl_t, with exposures that are monotonically increasing in absolute value by quintile. This pattern confirms that DMNS betas pick up variation in exposures to macroeconomic fluctuations in income tail risk.

These results do not simply represent another portfolio sort on product durability, as in Gomes et al. (2009), reflecting that firms selling goods that form a consumption *stock* have generally different risk characteristics from firms selling goods that provide a consumption *flow*. Instead, the return differences from a sort on DMNS betas hold within sectors and industries. Appendix Table A.3 shows that we get similar results on portfolio returns when restricting the sample to producers of nondurables and services only. The results are also robust to sorting firms in quintiles of the DMNS beta by industry, using the Fama-French 30 industry classification, as reported in Appendix Table A.4.[22]

Systematic risk. Are the differences in average portfolio returns due to a compensation for exposure to systematic risk? The bottom rows of Table 3 apply the CAPM and Fama–French–Carhart four-factor model to the returns on the DMNS beta-sorted portfolios and report annualized alphas and betas with respect to these factor models. Average excess returns on the portfolios are explained by the CAPM: the alphas are not significantly different from zero for all but one of the portfolios. The market betas of the portfolios are significant and monotonically increase from the first to the fifth DMNS beta-sorted portfolio. The high–low portfolio has a market beta of 0.6, and this market beta explains the return spread across portfolios. The four-factor model shows similar patterns. Thus, the DMNS beta of firm equity picks up exposure to systematic risk. Despite the empirical failures of the CAPM in describing the general relation between risk and expected returns (see Fama and French, 2004, for a review), the CAPM works well in explaining return differences across DMNS-sorted portfolios. In Section 4.4, I explore whether exposure to time-varying income risk can rationalize these findings.

4.3 Firm Panel Regressions

To further analyze differences in exposures, financial characteristics, and equity returns across firms, this section describes the results of firm-level panel regressions.

Firm returns. The portfolio-level findings on equity returns by DMNS beta also hold in a panel regression of individual firm returns. To rule out the possibility that the differences in average returns are explained by other well-known financial channels, I control for various alternative firm characteristics. I estimate the following regression specification:

$$R^e_{ft} = b_0 + b_1 Q^{DMNS}_{ft} + b_2 Q^{IMC}_{ft} + b' X_{ft} + \epsilon_{ft}, \tag{22}$$

where Q^{DMNS}_{ft} is the DMNS beta quintile and Q^{IMC}_{ft} is the IMC beta quintile of the firm. The controls X_{ft} include time or industry–time fixed effects, as well as controls for other firm

[22] The results on portfolio returns by DMNS beta also hold when doing a two-way sort of portfolios by DMNS beta and IMC beta (Table A.5), or when sorting firms purely by DMNS beta based on a single-factor specification (Table A.6). In addition, the results are also robust to the sample of firms that are included in the portfolios: Table A.7 describes the returns on portfolios that are based on all types of firms, not just consumption good producers, and Table A.8 reports the results for consumption good producers when firms in the Utilities, Mining, and Petroleum Refining categories are included in the sample.

characteristics that are known to be associated with differences in expected returns across firms. Appendix A.3 describes the construction of these variables.

Columns (1)–(4) of Table 4 report the estimates of these panel regressions for individual firm equity returns at a monthly frequency. Consistent with the earlier findings on portfolio returns, the beta on the DMNS return spread is associated with a significantly higher average return. The coefficient only slightly changes when including industry–year fixed effects, again highlighting that the results hold within industries. The relation between DMNS beta and average firm returns continues to be significantly positive when controlling for the size of the company and the book-to-market ratio in column (3), and thus cannot be explained by the size or value premium. The results are also robust to including additional controls for the beta on the aggregate stock market, idiosyncratic volatility, profitability, leverage, turnover, and the bid-ask spread, as shown in column (4).

Markups. Consistent with the model predictions, we have seen that firms that are more exposed to fluctuations in income tail risk have higher average returns. In the baseline model, firm heterogeneity in exposure to demand shocks is due to heterogeneity in the elasticity of demand. However, firms could differ in their exposures to aggregate demand fluctuations for other reasons. An alternative source of heterogeneity would be variation in the frequency of price adjustment, as in Weber (2015). While both demand elasticity and the frequency of price adjustment are not directly observable in standard data sources, the model predictions on firm markups provide a way to differentiate between these sources of heterogeneity as an explanation for the empirical differences in firm returns and exposures. As discussed in Section 3, the two types of cross-sectional firm differences have opposite implications for the sign of the relation between demand exposures and average markups in the model (see also Clara, 2019).

Columns (5)–(7) of Table 4 report the estimated coefficients of annual firm-level panel regressions of markups on firm characteristics. Controlling for industry–time fixed effects, average markups are declining in DMNS betas. Hence, high-exposure firms on average have relatively low markups. This finding is consistent with the baseline version of the model where firms are heterogeneous in demand elasticities, and inconsistent with a version of the model where firms differ in price stickiness.

4.4 Risk Premium Estimates

Next, I turn to cross-sectional asset pricing tests to formally examine whether exposure to fluctuations in income tail risk is compensated by a risk premium. Can the cross-sectional differences in average portfolio returns from Section 4.2 be explained by heterogeneous exposures to demand shocks that are generated by fluctuations in idiosyncratic income risk?

I estimate the compensation for exposures to possible risk factors in a linear factor model specification where expected returns are an affine function of factor betas. Risk premia are estimated in a two-stage procedure. In the first stage, I estimate betas from time-series regressions of the monthly excess returns of each portfolio p on risk factors F:

$$R^e_{pt} = \beta_{p,0} + \beta'_p F_t + \epsilon_{pt}. \tag{23}$$

In the second stage, I then run a cross-sectional regression of average excess returns on the estimated betas to estimate risk premia λ:

$$\mathbb{E}_T[R^e_{pt}] = \lambda_0 + \hat{\beta}'_p \lambda + \nu_p. \tag{24}$$

I compute standard errors of the estimated risk premia by putting the joint two-step procedure in the GMM framework, accounting for first-stage estimation errors in the betas and cross-sectional correlations in portfolio returns. To examine the model goodness of fit, I report the cross-sectional R^2 and the mean absolute pricing error (MAPE) of the second-stage regression.

In a first set of tests, I estimate risk premia that are associated with traded financial factors. The main factor of interest is R_{DMNS}, which serves as a traded proxy for demand shocks. I find that exposure to the DMNS return spread is compensated by a risk premium that is separate from standard risk factors. Panel A of Table 5 reports risk premium estimates based on monthly returns. In the first three columns, the assets included in the test are the five DMNS beta-sorted portfolios. I find a positive and significant risk premium on the DMNS return spread in column (1). As previously suggested by Table 3, column (2) shows that the CAPM also works well on the DMNS beta-sorted portfolios, although the average pricing error is slightly larger. However, in a joint estimation in column (3), the premium on the DMNS spread is significant but the premium on the market portfolio is no longer significant.

In columns (4)–(8) of Panel A of Table 5, I expand the set of assets for estimation by adding the standard 25 Fama-French portfolios sorted on size and book-to-market on top of the five DMNS beta-sorted portfolios. The estimated risk premium on the DMNS return spread is again significantly positive. This risk premium is still positive when adding the market, size, and book-to-market factors to the set of risk factors. The risk premium on the market portfolio is no longer positive. The four-factor specification that includes R_{DMNS} performs substantially better than the standard three-factor model on this set of portfolios: the R^2 rises from 0.57 to 0.75.

As a second step, I focus on risk premia estimates for non-traded (macroeconomic) factors, and in particular on the risk premium directly associated with measured idiosyncratic income tail risk. In the model, differences in expected returns arise from heterogeneity in exposure to fluctuations in income tail risk. I use the returns on the five DMNS beta-sorted portfolios to test the prediction that exposure to income tail risk is priced. The first two columns of Panel B of Table 5 report estimated risk premia on the two measures of income risk, *icl* and x, using quarterly portfolio returns. Consistent with the model prediction, the estimated risk premium on idiosyncratic income risk is positive and significant. The two measures give nearly identical results. Heterogeneity in exposure to idiosyncratic income risk explains 80% of the cross-sectional differences in average portfolio returns on the DMNS beta-sorted portfolios.

Since idiosyncratic income risk is countercyclical, it could just be the case that these risk premium estimates pick up general heterogeneity in portfolio exposures to the business cycle and are not specifically driven by the nature of time-varying income risk. However, I find that the results are unique to the particular macroeconomic measure of labor market frictions. The remaining columns of Panel B compare the risk premium estimates for income tail risk to risk premia on other macroeconomic factors: changes in measured TFP (column 3), utilization-adjusted TFP (column 4), aggregate consumption (column 5), industrial production (column 6), the variance of stock returns (column 7), and the term spread (column 8). In contrast to the results in columns (1) and (2) for measures of labor market risk, the other macroeconomic indicators are not significant at the 5% level. Income risk also performs better than other macroeconomic variables in terms of the cross-sectional R^2 and MAPE.

4.5 Cash Flow Exposures

The empirical results presented thus far have shown a significant dispersion in average returns in portfolios that are sorted by exposure to the DMNS return spread. Consistent with the model predictions, exposure to innovations to idiosyncratic risk in labor income explains return differences across these portfolios. In the model, heterogeneity in expected returns is due to differences in cash flow exposures to aggregate demand shocks generated by time-varying idiosyncratic income risk. In this section, I examine whether differences in the exposures of firm cash flows are consistent with the documented differences in the properties of stock returns across portfolios.

To analyze cash flows, I use two measures from Compustat data on financial statements: sales and operating income, where operating income is measured as sales minus the cost of goods sold. In addition, I use data on dividend payments from CRSP. I compute cash flow measures at the portfolio level by aggregating cash flows of the firms that are in the portfolio at an annual frequency. For computing cash flow growth in year t, I fix the composition of the portfolio at the beginning of $t-1$ and measure cash flows for the same portfolio in both $t-1$ and t. Panel A of Table 6 reports summary statistics on operating income growth, sales growth, and dividend growth for each portfolio. In line with a cash flow risk channel, the volatility of portfolio cash flow growth is heterogeneous and increases with the DMNS beta of the portfolio.

Furthermore, the sensitivity of cash flows to changes in labor income risk is heterogeneous across portfolios in a way that is consistent with the main model mechanism. Panel B of Table 6 describes the exposure of operating income growth for the market portfolio and the five DMNS beta-sorted portfolios to changes in x, at an annual frequency. Changes in market-level cash flows are negatively related to income risk, and cash flow exposures are strongly heterogeneous: portfolios with high DMNS beta have a significant cash flow exposure to changes in x, while the cash flow growth of portfolios with a low DMNS beta is not significantly related to changes in x. Panel C reports similar results for sales growth.

Panel D of Table 6 shows that the findings on cash flows extend to the properties of firm dividends. Annual dividend growth for the market portfolio is significantly negatively related to changes in income tail risk. Exposures are again strongly heterogeneous across portfolios: for firms in the top quintile by DMNS beta, the relation between dividend growth and income risk is strongly negative, while no such relation exists for low-exposure firms.

Section 4.2 showed that the cross-sectional spread in equity returns also holds within industries. The same is true for cash flows. I repeat the analysis for the set of portfolios constructed by sorting firms in quintiles of the DMNS beta distribution by industry. Appendix Table A.9 reports the relation between cash flow growth measures for these portfolios and changes in income risk. The findings are very close to those in Table 6.

4.6 Monetary Policy Announcements

As a test of whether heterogeneity in the exposure of stock returns and firm cash flows to income tail risk is consistent with a demand channel interpretation, I next study the reaction of stock prices to unanticipated monetary policy actions. While changes in idiosyncratic income risk (and not monetary policy shocks) are the main driver of risk premia in the model presented in Section 3, we would still expect to see significant and heterogeneous stock price responses to monetary policy surprises if demand effects are important. It is well known that stock prices are highly responsive to policy announcements (Bernanke and Kuttner, 2005). I find that firms with high DMNS betas indeed have stronger stock price responses to monetary policy surprises than firms with low DMNS betas.

Following Bernanke and Kuttner (2005), I measure daily stock returns on days with monetary policy announcements. Monetary policy surprises are identified from the daily prices of Federal funds futures contracts before and after announcements by calculating the change in the target rate that is implied by the change in the price of current-month futures contracts. The expected component of the rate change is then given by the actual change in the Federal funds rate minus the surprise change. I use combined data on futures prices and realized Federal funds target rates from 1989 to 2007.[23] Before 1994, the timing of policy actions is ambiguous, since changes in the funds rate target were unannounced, and days of monetary actions often coincide with labor market reports. I follow Kuttner (2001) in defining the timing of the news and I exclude days with the release of an employment report from the sample. I additionally report the results for the period 1994–2007 where there is no ambiguity over the timing. Starting from 2008, the zero lower bound becomes binding and monetary policy is conducted with a target range instead of a specific point. For robustness, I also report the results for the period 1994–2019 using only the surprise component that is measured purely from futures rates.

Table 7 reports the results from regressing daily portfolio returns on monetary policy changes on announcement days. The first column lists the average equity responses to surprise and

[23] I exclude the September 17, 2001 and January 22, 2008 observations from the sample, since the monetary policy announcements on those days coincided with major news that triggered large stock market movements before the announcement itself.

expected changes in the target rate. Replicating the seminal finding from Bernanke and Kuttner (2005), an unexpected increase in the nominal interest rate leads to a significant reduction in asset prices. There are no significant effects for expected changes in the target rate. The findings are similar for the two alternative sample periods in columns (3) and (5) – a 25 basis points surprise increase in the target rate roughly leads to a one percent decline in stock prices on average.

The second column of Table 7 shows that the stock price response to monetary policy surprises is heterogeneous across firms. Controlling for industry–date fixed effects, the interaction terms between surprise target rate changes and both Q_{ft}^{DMNS} and Q_{ft}^{IMC} are significantly negative. Thus, the stock prices of firms with high DMNS betas react more strongly to monetary policy surprises, as would be predicted by the model. Notably, average stock returns on days with monetary policy announcements are significantly higher for firms with high DMNS betas, which means that the cross-sectional return spread is particularly large on days with important macroeconomic news. This finding is again consistent with a risk premium interpretation. The results from column (2) also hold for the alternative sample periods in columns (4) and (6).

4.7 Stock Return Predictability

In addition to cross-sectional differences in the unconditional distribution of firm equity returns, the model also generates time-series variation in expected returns: the current level of income risk predicts future equity returns. Importantly, this predictability is heterogeneous by firm exposure to demand shocks. I next evaluate these predictions by testing whether stock returns are predictable by measured income risk in the data.

Following the predictive regressions run on model-simulated data in Section 3, I regress future stock market returns over various horizons on the current level of income tail risk as measured by icl_t (monthly) or x_t (quarterly), using overlapping data from 1967–2019. For the predictive regressions, I standardize all predictors such that they have a unit standard deviation. First, column (1) of Table 8 reports the results of this regression for aggregate stock market returns. Consistent with the findings of Schmidt (2016), increased labor market uncertainty, as captured by initial claims to unemployment, predicts higher future returns on the market portfolio. A one standard deviation increase in icl_t is associated with an addition return of 2.9% over the next year. For the sample period in this paper, the coefficient of the one-year ahead return on icl_t is significant at a 10% confidence level but not at the 5% level. Using the alternative income risk measure x_t in quarterly data yields consistent results.[24]

Second, I find that return predictability is strongly heterogeneous across firms. Columns (2)–(7) of Table 8 show that the predictive coefficients for the DMNS beta-sorted portfolios monotonically increase with the portfolio exposures. While income risk does not predict returns on low-exposure stocks, the excess returns of high-exposure quintile portfolios are strongly predictable. In particular, income tail risk predicts the spread between high- and low-exposure

[24] Recall that x_t is directly measured from the distribution of income growth rates, but in contrast to icl_t, this measure is not available in real time.

stocks. A one standard deviation increase in icl_t is associated with an additional return of more than 10% on the top quintile portfolio in excess of the bottom quintile portfolio over the next year. This coefficient is highly statistically significant. The excess return on the high–low exposure portfolio is also predictable at horizons of three months and two years, and similarly holds when using the alternative measure x_t in quarterly data. Not surprisingly, the predictive coefficient of cumulative returns increases with the horizon.

The results on stock market predictability are not due to a correlation with other well-known financial market predictors. In Table 9, I control for alternative predictors in predictive regressions for the high–low exposure portfolio excess return. Panel A includes financial variables that have been proposed as predictors in the literature, in monthly forecasting regressions of one-year ahead returns with *icl* as the main predictor. In particular, I include controls for eleven standard monthly forecasting variables studied in Welch and Goyal (2008). For brevity, I report the results for a subset of seven of those – the remaining four variables that are not included are not significant.[25] We see that the financial predictors do not perform well in this sample period and including these variables does not alter the finding that income tail risk is a strong predictor of the high–low exposure portfolio excess return.

Like the risk premium estimates in Section 4.4, the predictability results are not driven by a generic relation between business cycle indicators and future stock returns. Panel B of Table 9 reports the estimated coefficients of predictive regressions for the high–low exposure portfolio excess return at a quarterly frequency, using x_t as the main predictor and controlling for other macroeconomic indicators. The results are specific to the particular macroeconomic measure of labor income tail risk. For instance, controlling for capacity utilization at the macroeconomic level in column (1) does not materially affect predictability by income risk. Column (2) shows that the predictability of the high–low exposure portfolio return is not explained by the durable goods expenditure–stock ratio from Gomes et al. (2009). Columns (3)–(6) illustrate that predictability by income tail risk is also robust to controlling for other business cycle indicators, such as the investment-to-capital ratio, inflation, consumer sentiment, and building permits.

4.8 Time-Varying Firm Risk

For expected returns to be varying over time, the volatility of stock returns or the price of risk need to vary over time. In the model, predictability of firm equity returns comes from time-series variation in the volatility of demand shocks: in bad times, the volatility of future cash flow shocks is amplified due to the nonlinearity of the precautionary saving motive. In this last part of the empirical analysis, I test the hypothesis that return predictability in the data is due to variation in the conditional volatility of equity returns and firm cash flow growth, by regressing the absolute value of future equity returns and cash flow growth on the current level of income risk.

First, panel A of Table 10 reports the results from regressing the absolute value of future

[25]These four other monthly predictors are the earnings–price ratio, default return spread, book-to-market ratio, and long-term yield.

portfolio returns on the current level of income risk. The first column shows that the level of income risk is positively related to the absolute value of future market returns, although this relation is not statistically significant. The remaining columns highlight that, consistent with the results on conditional average returns, predictability of the future volatility of excess returns is strongly heterogeneous and monotonically increases across the DMNS beta-sorted portfolios. The volatility of high-exposure firm returns is positively and significantly linked to the level of income tail risk, while the future volatility of low-exposure firm returns is not correlated with measured idiosyncratic income risk.

Second, as a direct test of whether stochastic volatility in stock returns is due to a time-varying volatility of firm cash flow shocks, I repeat the analysis for the volatility of future firm cash flow growth. Panel B reports predictive coefficients using the same specification as before, now applied to the absolute value of one-year ahead operating income growth. For firms in the top quintile of DMNS betas, a higher level of income risk predicts a significantly higher conditional volatility of future cash flow growth. There is no relation for low-exposure firms. Panel C of Table 10 applies the same strategy to the absolute value of five-year ahead dividend growth. While the coefficients for future dividend growth are not monotonic across portfolios, the (weakly) positive relation between the current level of income tail risk and the absolute value of future dividend growth of high-exposure firms is consistent with a countercyclical cash flow volatility for these firms.

5 Conclusion

Households face substantial tail risk in individual labor income, and the magnitude of this risk has been shown to fluctuate over the business cycle. This paper proposes a general equilibrium New Keynesian production-based asset pricing model where variation in idiosyncratic labor income risk drives the joint dynamics of macroeconomic outcomes and asset prices. Uninsured income risks affect the aggregate demand for consumption goods through a precautionary savings motive that is countercyclical. These demand effects strongly amplify cyclicality in firm cash flows. In the cross section, firms with more elastic demand are more exposed to fluctuations in the amount of idiosyncratic income risk. This additional riskiness of firms with high demand elasticity is compensated by a significant risk premium in equity returns. Due to nonlinearities in the precautionary saving motive, average returns are countercyclical and tail risk in labor income is a predictor of future returns.

The predictions of the model are supported by empirical patterns in equity returns. I proxy for demand-based risk by the Durables Minus Nondurables and Services (DMNS) return spread. In a new portfolio sort on the beta of equity returns on this DMNS factor, I show that firms with high DMNS betas earn an economically and statistically significant average return of several percentage points in excess of firms with low DMNS betas. Both the returns and the cash flows of firms with high DMNS betas are significantly more negatively associated with changes in income tail risk than firms with low DMNS betas, consistent with a risk-based explanation where idiosyncratic income risk is a priced source of risk in the cross section of stocks. In line with the model predictions, the current level of income risk predicts future excess returns and this predictability monotonically increases in firm exposure. Overall, these results imply that a time-varying precautionary saving motive due to idiosyncratic income risk can explain why firm earnings and asset prices strongly comove with the business cycle, and suggest that firms with bigger exposures to demand fluctuations earn a larger risk premium than firms with lower exposures to compensate for differences in cash flow risk, and that this risk premium is countercyclical due to time variation in future cash flow risk.

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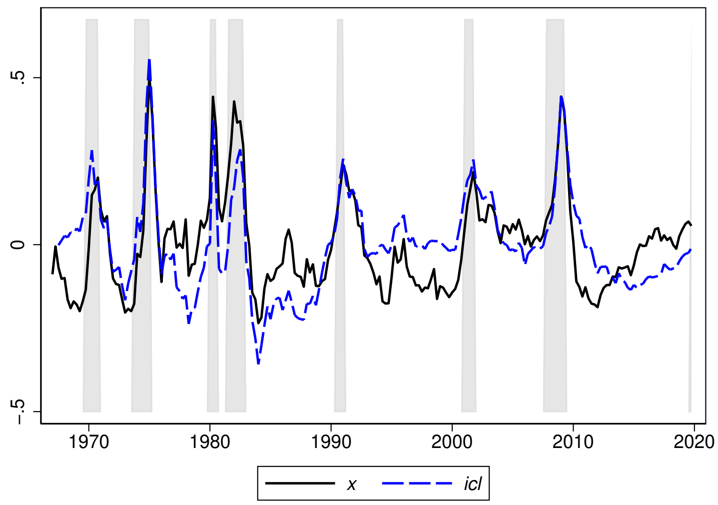
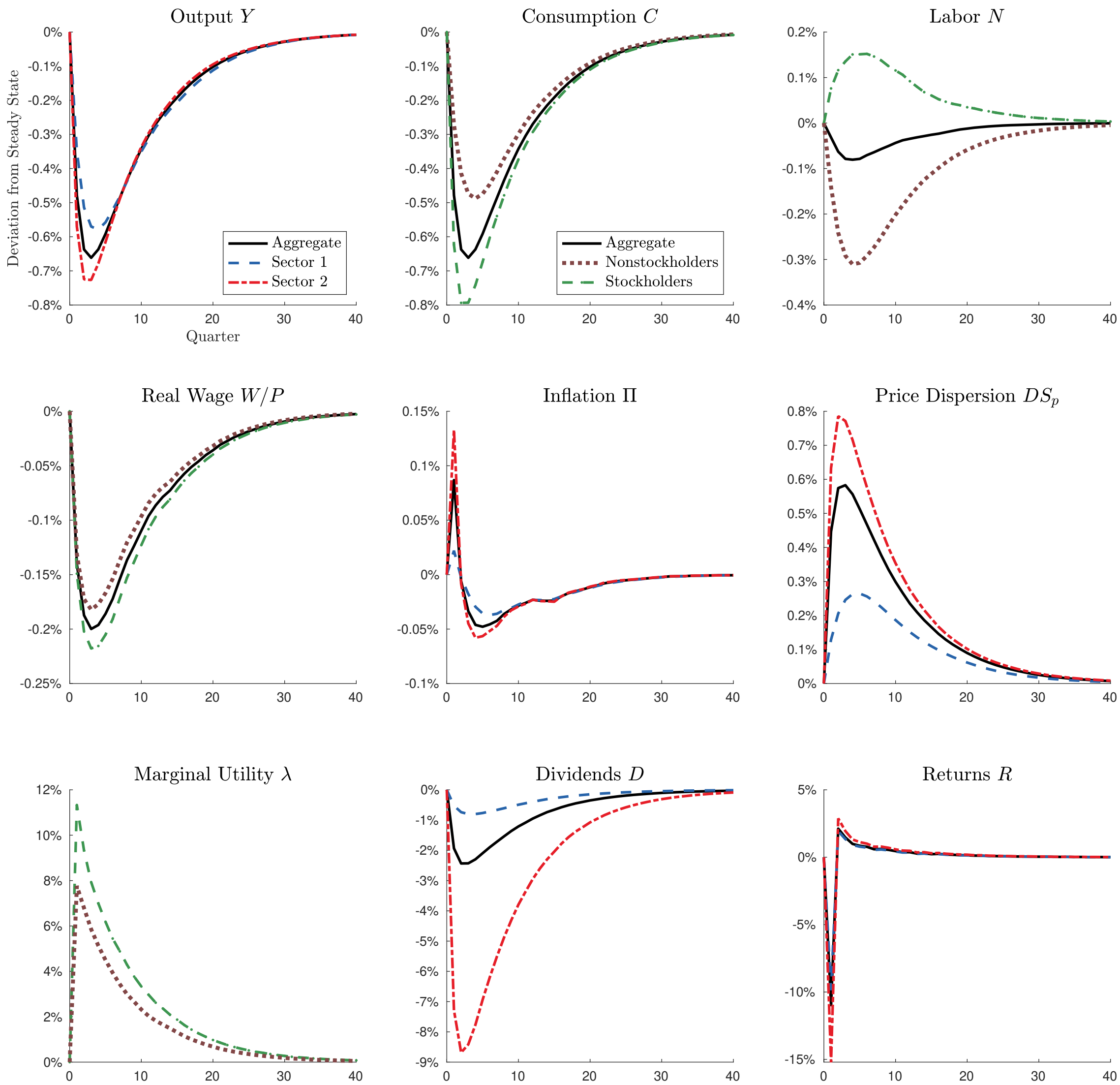
Figures and Tables

Figure 1: Time Series of Income Risk Measures x and icl_t



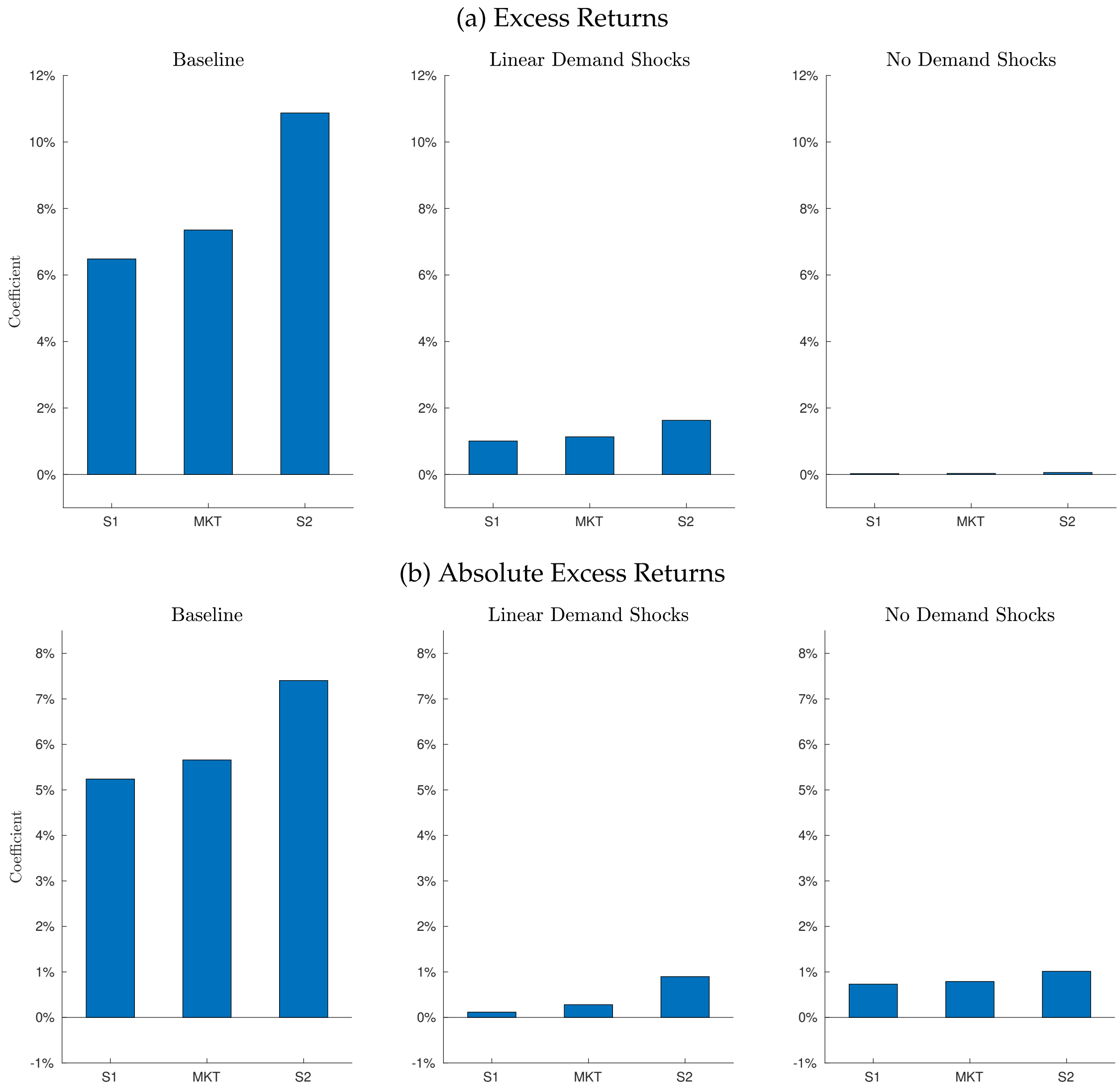
Notes: This figure plots the time series of two measures of idiosyncratic labor income risk: (1) the skewness process x_t (solid line) that is estimated from the cross-sectional moments of 1-year, 3-year, and 5-year income growth rates over time, and (2) the macroeconomic series icl_t (dashed line) that is defined as the number of initial claims to unemployment relative to the size of the labor force. NBER recession dates are shaded.

Figure 2: Model IRFs to Increase in Income Risk



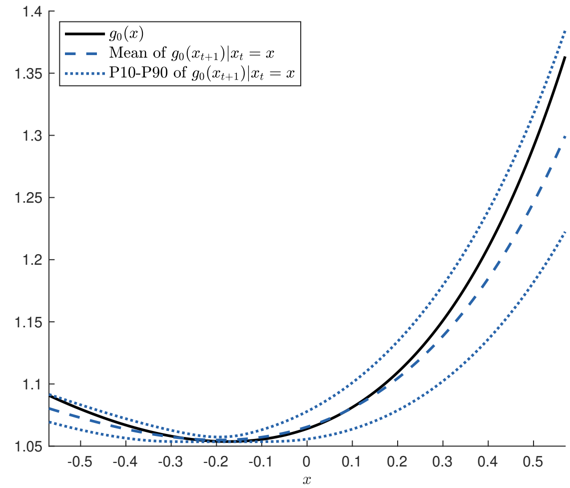
Notes: This figure plots impulse response functions (IRFs) with respect to a one standard deviation positive shock to idiosyncratic income risk x_t in the baseline model.

Figure 3: Predictability in Model



Notes: This figure plots the coefficients of predictive regressions in model-simulated data. In panel (a), the dependent variable is the four-quarters ahead value-weighted return on the firms in sector 1 (S1), the market (MKT), and sector 2 (S2), respectively. In panel (b), the dependent variable is the absolute value of the four-quarters ahead value-weighted return. The left column shows the results for the baseline model with shocks to income risk. The middle and right columns consider alternative versions of the model with linear demand shocks and no demand shocks, respectively.

Figure 4: Idiosyncratic Income Risk and the Precautionary Saving Motive



Notes: This figure plots the relation between income tail risk x and the precautionary saving term $g_0(x)$. The solid line plots $g_0(x_t)$ when current income tail risk x_t is x. The dashed and dotted lines describe the distribution of $g_0(x_{t+1})$ conditional on $x_t = x$.

Table 1: Equity Returns in General Equilibrium Model

	Mean				Volatility				SR	$\beta_{\Delta x}$
	MKT	S1	S2	S2-S1	MKT	S1	S2	S2-S1	MKT	S2-S1
(1): Baseline	7.53	7.10	9.68	2.58	23.43	21.07	32.73	11.89	0.32	-0.70
(2): No technology shocks	7.28	6.75	9.92	3.18	25.73	23.16	35.85	12.88	0.28	-0.91
(3): Uncorrelated shocks	9.69	9.01	13.04	4.03	29.07	26.22	40.38	14.50	0.33	-0.89
(4): No idiosyncratic risk	2.08	2.03	2.28	0.26	13.47	13.11	14.83	1.81	0.15	-0.06
(5): No idiosyncratic risk, monetary policy shocks	6.68	6.58	7.80	1.22	19.12	18.35	25.42	12.47	0.35	-0.04
(6): No price stickiness	6.48	6.48	6.48	-0.00	20.59	20.59	20.59	0.00	0.31	0.00
(7): Heterogeneity in price stickiness, homogeneous demand elasticities	7.73	5.62	10.72	5.10	28.84	19.17	38.97	20.23	0.27	-1.18
(8): $b_s = 0.65$	4.87	4.39	7.20	2.81	24.59	22.22	33.96	12.03	0.20	-0.70
(9): $\chi_1 = 2.5$	14.19	13.64	16.79	3.15	35.53	33.35	44.22	11.68	0.40	-0.39
(10): $\theta_w = 0.5$	5.20	4.59	8.43	3.84	22.51	19.38	35.02	16.09	0.23	-1.06
(11): $\eta_w = 8$	5.23	4.86	7.24	2.38	20.17	17.75	29.85	12.57	0.26	-0.79
(12): $\eta_c = 3$	7.66	7.08	9.69	2.61	24.31	21.25	32.87	11.84	0.32	-0.69
(13): $\eta_{c2} = 11$	7.05	6.84	7.70	0.87	21.70	20.38	25.36	5.18	0.32	-0.30
(14): $\eta_{c2} = 21$	8.19	7.50	13.29	5.79	25.49	22.07	43.34	21.57	0.32	-1.25
(15): $\phi_\pi = 1.3$	5.98	5.74	7.18	1.44	19.99	18.38	26.36	8.37	0.30	-0.50

Notes: This table describes the annualized moments of equity returns for the baseline model of Section 3, and for various alternative parameter values. The first four columns report mean returns, columns (5)–(8) report the volatility, column (9) reports the Sharpe ratio, and column (10) reports the return beta with respect to Δx. The described portfolios are the market portfolio (MKT), the value-weighted return of the firms in sectors 1 (S1) and 2 (S2), and the return spread between sector 1 and sector 2 (S2-S1).

Table 2: Excess Returns on Sector Portfolios

	Services	Nondurables	Durables	Investment	Other	DMNS
Mean	6.63***	8.63***	9.63***	8.97***	8.63***	1.99
	(1.82)	(1.69)	(2.53)	(2.58)	(2.09)	(1.37)
Volatility	17.60	16.36	24.47	24.95	20.24	13.33
Exposures						
Δicl	-0.15***	-0.13**	-0.30***	-0.26***	-0.27***	-0.16***
	(0.05)	(0.06)	(0.07)	(0.07)	(0.06)	(0.04)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for sector portfolios, using the mapping of 4-digit SIC codes to output types from Gomes et al. (2009). The DMNS portfolio return is defined as $R_{DMNS,t} = R_{durables,t} - \frac{1}{2}(R_{nondurables,t} + R_{services,t})$. Portfolio exposures are measured by the univariate beta with respect to Δicl. The sample period is 1926M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Excess Returns on DMNS Beta-Sorted Portfolios

	DMNS Beta					
	Low	2	3	4	High	High–Low
Mean	5.22***	8.15***	9.01***	8.56***	11.18***	5.96***
	(1.59)	(1.69)	(2.10)	(2.32)	(2.68)	(2.00)
Volatility	15.34	16.25	20.19	22.32	25.75	19.21
Exposures						
R_{DMNS}	-0.06	0.10	0.39***	0.60***	1.20***	1.26***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)
Δicl	-0.10**	-0.12**	-0.16***	-0.25***	-0.31***	-0.21***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.05)
CAPM						
α_{CAPM}	-0.10	1.89***	0.92	-0.45	1.20	1.30
	(0.91)	(0.73)	(0.74)	(0.77)	(1.07)	(1.57)
R_{MKT}	0.67***	0.79***	1.02***	1.14***	1.26***	0.59***
	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.05)
4-Factor Model						
α_{4F}	0.77	1.99***	0.76	-1.22	1.72	0.95
	(1.00)	(0.74)	(0.76)	(0.79)	(1.33)	(1.90)
R_{MKT}	0.70***	0.82***	0.98***	1.09***	1.20***	0.50***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
R_{HML}	-0.13***	-0.03	0.11***	0.18***	0.14***	0.27***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.05)	(0.07)
R_{SMB}	-0.11**	-0.11***	0.11***	0.12***	0.05	0.16**
	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.07)
R_{MOM}	-0.04	0.01	-0.03	0.01	-0.10*	-0.06
	(0.04)	(0.02)	(0.02)	(0.03)	(0.06)	(0.08)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for five portfolios of firms that produce consumption goods, sorted by their DMNS beta. Preranking return betas are calculated in a two-factor specification using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. Risk exposures are measured by univariate betas with respect to R_{DMNS} and Δicl. I also report the alphas and betas with respect to the CAPM and the Fama-French-Carhart four-factor model. The sample period is 1927M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Firm-Level Regressions of Equity Returns and Markups

	Equity Return				Markup		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DMNS beta quintile	0.806^{**} (0.366)	0.719^{***} (0.265)	0.672^{**} (0.284)	1.064^{**} (0.437)	1.003 (1.230)	-3.341^{***} (1.058)	-3.800^{***} (1.040)
IMC beta quintile	-0.949 (0.612)	-0.664 (0.418)	-0.603 (0.408)	-0.077 (0.413)	-7.955^{***} (1.760)	-5.799^{***} (1.300)	-4.425^{***} (1.130)
Log ME			0.072 (0.397)	-1.448^{***} (0.450)			9.342^{***} (1.160)
Log B/M			2.737^{***} (0.526)	1.873^{***} (0.621)			6.561^{***} (1.544)
Market beta				-1.031 (1.560)			
Idiosyncratic volatility				-1.231^{***} (0.320)			
Profitability				5.113^{***} (1.745)			
Leverage				0.665^{**} (0.299)			
Turnover				-49.054 (65.215)			
Bid-ask spread				-1.273^{***} (0.253)			
Time FE	Yes	No	No	No	Yes	No	No
Industry x time FE	No	Yes	Yes	Yes	No	Yes	Yes
Observations	589666	550088	508419	297631	43133	39812	38323
R^2	0.161	0.334	0.335	0.300	0.029	0.269	0.281

Notes: This table reports estimated coefficients from firm-level regressions of monthly equity returns (columns 1–4) and annual markups (columns 5–7) on the DMNS beta quintile of the firm, controlling for the IMC beta quintile and various other controls. Industry fixed effects are by 4-digit SIC code. The sample includes firms with a lagged CRSP closing price of at least \$5. The sample period is 1963–2019. The results are expressed in percentage terms. Standard errors are reported in parentheses and are two-way clustered by firm and date.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Estimated Risk Premia

A. Monthly	5 DMNS Portfolios			5 DMNS, 25 FF Portfolios				
Traded Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_{DMNS}	3.80**		3.48**	6.26***		6.66***		4.45***
	(1.49)		(1.47)	(2.14)		(1.59)		(1.48)
R_{MKT}		7.87***	5.23		6.36**	3.92	-2.45	-8.60**
		(2.99)	(4.43)		(3.20)	(3.88)	(2.99)	(3.87)
R_{HML}							4.34***	4.41***
							(1.28)	(1.28)
R_{SMB}							1.35	1.90
							(1.17)	(1.17)
Intercept	5.63***	0.74	3.26	4.51***	2.74	5.19	10.73***	16.72***
	(1.58)	(2.34)	(3.82)	(1.59)	(2.64)	(3.31)	(2.32)	(3.29)
MAPE	0.75	0.78	0.73	1.49	1.61	1.49	1.19	0.96
R^2	0.80	0.80	0.82	0.37	0.25	0.38	0.57	0.75

B. Quarterly	5 DMNS Portfolios							
Non-Traded Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δicl	-11.35**							
	(5.49)							
Δx		-11.59**						
		(5.61)						
Δ TFP			2.30*					
			(1.26)					
Δ TFP (util-adj)				-3.84				
				(2.90)				
Δ log consumption					2.34			
					(1.91)			
Δ log industrial production						2.92*		
						(1.63)		
Δ stock variance							-2.67	
							(1.67)	
Δ term spread								5.37
								(4.71)
Intercept	3.42	4.59*	2.37	10.20**	-2.90	5.16*	1.54	4.83
	(2.57)	(2.41)	(2.86)	(4.73)	(7.46)	(2.68)	(3.35)	(3.75)
MAPE	0.91	0.93	1.05	1.16	1.06	1.16	0.93	1.14
R^2	0.80	0.78	0.74	0.53	0.69	0.63	0.73	0.67

Notes: This table reports risk premium estimates for various monthly traded factors (panel A) and quarterly non-traded factors (panel B), estimated on the five DMNS beta-sorted portfolios. In columns (5)–(8) of panel A, the set of portfolios is expanded with the 25 Fama-French portfolios sorted on size and book-to-market. The risk premium is the slope of a cross-sectional regression of average portfolio returns on portfolio betas. Betas are estimated from a time series regression for each portfolio. The Mean Absolute Pricing Error (MAPE) and R^2 of the cross-sectional regressions are reported as measures of goodness-of-fit. Average returns and betas of monthly predictors are measured over the full sample period 1927M7 – 2019M12. Quarterly betas are estimated over the period 1967Q3 – 2019Q3. The results are expressed in percentage terms. GMM standard errors are reported in parentheses, accounting for correlation in the residuals across assets and estimation error in calculating the first-stage betas.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Portfolio Cash Flow Exposures

	Market	DMNS Beta					
		Low	2	3	4	High	High–Low
A. Summary Statistics							
Operating income growth							
Mean (%)	7.31	7.34	7.36	8.33	7.26	6.11	-1.23
Volatility (%)	4.44	5.77	3.94	4.29	5.16	11.83	12.57
Sales growth							
Mean (%)	6.84	7.28	6.94	7.84	7.17	5.54	-1.74
Volatility (%)	4.02	5.13	4.39	4.05	4.61	7.13	7.69
Dividend growth							
Mean (%)	6.54	6.27	7.86	7.04	5.22	6.19	-0.07
Volatility (%)	6.15	14.06	5.24	12.20	12.75	21.48	26.76
B. Operating Income Growth Exposures							
Δx	-0.16***	-0.00	-0.05	-0.06	-0.17***	-0.56***	-0.56***
	(0.04)	(0.05)	(0.03)	(0.03)	(0.05)	(0.10)	(0.10)
R^2	0.270	0.000	0.027	0.033	0.208	0.444	0.393
C. Sales Growth Exposures							
Δx	-0.11***	-0.00	-0.02	-0.02	-0.08*	-0.30***	-0.29***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.06)	(0.07)
R^2	0.146	0.000	0.003	0.006	0.065	0.345	0.292
D. Dividend Growth Exposures							
Δx	-0.17***	0.01	-0.05	-0.28*	0.04	-0.72***	-0.72***
	(0.06)	(0.12)	(0.05)	(0.14)	(0.23)	(0.16)	(0.22)
R^2	0.151	0.000	0.015	0.106	0.002	0.218	0.143

Notes: This table reports summary statistics and exposures for annual operating income growth, sales growth, and dividend growth, as well as their univariate betas with respect to changes in income tail risk Δx, for the market portfolio and quintile portfolios by DMNS beta. Operating income is sales minus the cost of goods sold. Sales and cost of goods sold are from Compustat. Dividends are from CRSP. Portfolio cash flow growth from $t-1$ to t is measured by fixing the portfolio weights at the beginning of $t-1$. The sample period is 1967–2019. The results are expressed in percentage terms. Standard errors are reported in parentheses.

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 7: Stock Price Responses to Monetary Policy Surprises

	1989–2007		1994–2007		1994–2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Surprise change	-3.88***		-5.63***		-4.68***	
	(1.17)		(1.14)		(1.41)	
Expected change	0.24		0.25			
	(0.34)		(0.35)			
Surprise change × DMNS beta quintile		-0.30**		-0.49***		-0.42**
		(0.15)		(0.15)		(0.20)
DMNS beta quintile		2.32**		2.87***		3.92***
		(0.92)		(1.06)		(1.24)
Surprise change × IMC beta quintile		-1.08**		-1.67***		-1.45**
		(0.49)		(0.58)		(0.57)
IMC beta quintile		-1.28		-1.49		-0.03
		(1.32)		(1.69)		(1.23)
Industry × year FE	No	Yes	No	Yes	No	Yes
Observations	167070	163452	125270	122479	198062	192081
R^2	0.008	0.194	0.015	0.195	0.008	0.238

Notes: This table reports estimated coefficients from regressions of daily firm stock price changes on surprise and expected changes in the Federal Funds rate, and their interactions with the DMNS beta quintile and IMC beta quintile of the firm, on days with monetary policy announcements. Industry fixed effects are by 4-digit SIC code. The sample includes firms with a lagged CRSP closing price of at least $5. The three different sample periods are 1989–2007, 1994–2007, and 1994–2019, excluding September 17, 2001 and January 22, 2008. The results are expressed in percentage terms. Standard errors are reported in parentheses and are two-way clustered by firm and date.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Return Predictability Across Portfolios and by Horizon

		Market	DMNS Beta					
			Low	2	3	4	High	High–Low
A. Monthly Frequency								
3 months ahead	*icl*	0.71	-0.13	0.12	0.84	1.38*	2.50***	2.63***
		(0.59)	(0.51)	(0.51)	(0.63)	(0.75)	(0.91)	(0.65)
	R^2	0.008	0.000	0.000	0.010	0.021	0.052	0.086
12 months ahead	*icl*	2.87*	-0.16	0.63	3.32	5.21**	10.23***	10.39***
		(1.68)	(1.66)	(1.85)	(2.06)	(2.22)	(3.12)	(2.22)
	R^2	0.028	0.000	0.002	0.034	0.066	0.177	0.278
24 months ahead	*icl*	2.38	-1.40	-1.63	1.41	4.35	13.98**	15.38***
		(3.01)	(2.85)	(3.88)	(4.31)	(4.48)	(5.75)	(3.91)
	R^2	0.009	0.003	0.004	0.003	0.022	0.153	0.254
B. Quarterly Frequency								
1 quarter ahead	x	1.14*	0.06	0.66	1.49**	2.09**	2.60**	2.54***
		(0.67)	(0.57)	(0.56)	(0.70)	(0.82)	(1.07)	(0.81)
	R^2	0.018	0.000	0.007	0.026	0.043	0.052	0.082
4 quarters ahead	x	3.92*	0.24	2.26	5.08**	7.37***	10.08***	9.84***
		(2.04)	(1.97)	(1.90)	(2.10)	(2.19)	(3.38)	(2.58)
	R^2	0.048	0.000	0.019	0.074	0.124	0.161	0.239
8 quarters ahead	x	3.14	-1.21	0.39	3.33	6.65	11.27*	12.48***
		(3.56)	(3.86)	(3.54)	(4.15)	(4.15)	(5.96)	(4.80)
	R^2	0.015	0.002	0.000	0.014	0.048	0.095	0.165

Notes: This table reports estimated coefficients from predictive regressions of cumulative future excess returns on measures of current idiosyncratic income risk, for the market portfolio and quintile portfolios by DMNS beta. The income risk measures icl_t and x_t are standardized to have a unit standard deviation. The sample period consists of overlapping data from 1967–2019. Standard errors are corrected for heteroskedasticity and autocorrelation using Newey-West estimation with maximum lag length equal to the horizon minus 1, and are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Comparison of Predictors for the High–Low DMNS Beta Return Spread

A. Monthly Predictors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
icl	10.40***	10.37***	10.45***	8.84***	10.33***	9.82***	10.63***
	(2.23)	(2.19)	(2.13)	(1.49)	(2.23)	(1.89)	(2.06)
Dividend yield	0.21						
	(1.70)						
T-bill rate		-0.49					
		(1.75)					
Term spread			1.87				
			(1.51)				
Default spread				4.67**			
				(2.25)			
Long term return					1.03		
					(0.65)		
Stock variance						3.11***	
						(1.20)	
Net issuing							-3.06
							(2.36)
R^2	0.278	0.279	0.287	0.328	0.281	0.302	0.302

B. Quarterly Predictors	(1)	(2)	(3)	(4)	(5)	(6)
x	8.09***	10.36***	10.27***	10.19***	10.17***	8.97***
	(2.43)	(2.44)	(2.60)	(2.40)	(2.39)	(2.31)
Capacity utilization	-3.67*					
	(1.95)					
Durables expenditure-stock ratio		1.05				
		(2.23)				
Investment-capital ratio			1.38			
			(2.37)			
Inflation				-3.47**		
				(1.48)		
Consumer sentiment					0.60	
					(2.26)	
Building permits						-3.44*
						(1.82)
R^2	0.263	0.241	0.243	0.268	0.240	0.266

Notes: This table reports estimated coefficients from predictive regressions of the cumulative one-year ahead return of the high-minus-low DMNS beta long-short portfolio on measures of current idiosyncratic income risk and alternative return predictors. All return predictors are standardized to have a unit standard deviation. The sample period consists of overlapping data from 1967–2019. Standard errors are corrected for heteroskedasticity and autocorrelation using Newey-West estimation with maximum lag length equal to the horizon minus 1, and are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Predictability of the Volatility of Returns and Cash Flows

	Market	DMNS Beta					
		Low	2	3	4	High	High–Low
A. 1-Year Returns							
x	1.54	-1.32	0.58	2.10	2.62	6.84**	8.17***
	(1.14)	(1.08)	(1.20)	(1.44)	(1.65)	(2.91)	(2.64)
R^2	0.020	0.014	0.003	0.028	0.036	0.136	0.212
B. Operating Income Growth							
x	0.61	0.47	0.02	-0.58	-0.21	2.38**	1.91
	(0.54)	(0.68)	(0.41)	(0.51)	(0.60)	(1.01)	(1.16)
R^2	0.023	0.009	0.000	0.020	0.002	0.092	0.049
C. 5-Year Dividend Growth							
x	0.10	5.17***	-1.86	7.31**	3.45	8.66*	3.49
	(1.94)	(1.60)	(1.97)	(3.24)	(3.37)	(4.82)	(5.62)
R^2	0.000	0.161	0.017	0.104	0.033	0.059	0.009

Notes: This table reports estimated coefficients from predictive regressions of the absolute value of cumulative 12-month ahead excess returns (panel A, at a monthly frequency), one-year ahead operating income growth (panel B, annual frequency), and five-year ahead dividend growth (panel C, annual frequency) on measured idiosyncratic income risk, for the market portfolio and quintile portfolios by DMNS beta. The income risk measure x_t is standardized to have a unit standard deviation. The sample period consists of overlapping data from 1967–2019. Standard errors are corrected for heteroskedasticity and autocorrelation using Newey-West estimation with maximum lag length equal to the horizon minus 1, and are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A.1 Tail Risk in Labor Income over the Business Cycle

To quantify time-varying idiosyncratic income risk, I estimate the parameters of a model for individual labor income. The income process is a simplified version of McKay (2017), where individual income growth is subject to tail risk and the tails of the distribution depend on macroeconomic conditions. The model is estimated by targeting the moments of the cross-sectional distribution of income growth rates reported by Guvenen et al. (2014).

Labor income process. Consider the following process for realized quarterly household labor earnings $\widetilde{Y}_{it}$, that are subject to idiosyncratic risk:

$$\widetilde{Y}_{it} = W_t L_t \Theta_{it} U_{it} \tag{A.1.1}$$

$$\log \Theta_{it} = \log \Theta_{i,t-1} + \xi_{it}, \tag{A.1.2}$$

where $U_{it} = e^{u_{it}}$ is a transitory income shock that has a lognormal distribution, $u_{it} \sim N(-\frac{1}{2}\sigma_u^2, \sigma_u^2)$, and ξ_{it} is a permanent idiosyncratic shock. The aggregate component of individual labor income is given by $W_t L_t$. For the purpose of estimating the idiosyncratic labor income process, aggregate labor income is treated as given. In the general equilibrium model, wages W_t and aggregate labor supply L_t are determined endogenously by clearing the labor market.

Permanent idiosyncratic income shocks are drawn from one of three normal distributions:

$$\xi_{i,t+1} \sim \begin{cases} N(\mu_{1t}, \sigma^2_{\xi,1}) & \text{with probability } 1 - p_2 - p_3 \\ N(\mu_{2t}, \sigma^2_{\xi,2}) & \text{with probability } p_2 \\ N(\mu_{3t}, \sigma^2_{\xi,3}) & \text{with probability } p_3, \end{cases} \tag{A.1.3}$$

where the amount of risk that households face depends on the aggregate state of the economy as given by x_t:

$$\mu_{1t} = \bar{\mu}_t \tag{A.1.4}$$

$$\mu_{2t} = \bar{\mu}_t + \mu_2 - x_t \tag{A.1.5}$$

$$\mu_{3t} = \bar{\mu}_t + \mu_3 - x_t \tag{A.1.6}$$

$$\bar{\mu}_t = -\log\left((1 - p_2 - p_3)e^{\frac{1}{2}\sigma^2_{\xi,1}} + p_2 e^{\mu_2 - x_t + \frac{1}{2}\sigma^2_{\xi,2}} + p_3 e^{\mu_3 - x_t + \frac{1}{2}\sigma^2_{\xi,3}}\right). \tag{A.1.7}$$

With a relatively large probability of $1 - p_2 - p_3$, household receive the first shock type, which is the "typical" outcome. The second shock type is a negative tail event, with an average loss conditional on the state of the economy of μ_{2t} and location parameter $\mu_2 < 0$. The third shock is a positive tail event, with conditional average gain μ_{3t} and location parameter $\mu_3 > 0$. The process

x_t captures variation in the skewness of income growth rates over the business cycle. When x_t is high (low), both tails of the distribution are shifted to the left (right). The normalization factor $\bar{\mu}_t$ is determined such that $\mathbb{E}_t[e^{\xi_{i,t+1}}] = 1$ conditional on the aggregate state, ensuring that the shock is idiosyncratic.[26]

Macroeconomic indicators. Following McKay (2017), I assume that the processes for aggregate income growth ($\Delta \log W_t L_t$) and time-varying income risk (x_t) are linear combinations of quarterly macroeconomic indicators. I construct the following macroeconomic variables based on the FRED database of the Federal Reserve Bank of St. Louis: the short-term unemployment rate ($\tilde{u}^s = (\texttt{UNEMPLOY} - \texttt{UNEMP15OV})/\texttt{CLF16OV}$), medium-term unemployment rate ($\tilde{u}^m = (\texttt{UNEMPLOY15} - \texttt{UNEMP27OV})/\texttt{CLF16OV}$), long-term unemployment rate ($\tilde{u}^l = \texttt{UNEMP27OV}/\texttt{CLF16OV}$), average weekly hours (PRS85006023), and initial claims to unemployment relative to the size of the labor force (ICSA/CLF16OV). All series are HP filtered with smoothing parameter 10^5 to remove very low-frequency trends.

First, I assume that income tail risk is given by $x_t = X'_{xt}\phi_x$. In the set of macroeconomic variables X_{xt}, I include (1) the short-term unemployment rate, (2) the long-term unemployment rate, (3) average weekly hours, and (4) initial claims to unemployment relative to the labor force. For computational convenience, the matrix of macroeconomic indicators X_x across periods is transformed into its principal components.

Second, let X_{wt} be the set of macroeconomic indicators for aggregate income growth. I assume that aggregate income growth is given by $\Delta \log W_t L_t = X'_{wt}\phi_w - x_t\phi_{wx}$. In X_{wt}, I include (1) average year-on-year income growth from Guvenen et al. (2014), transformed from annual to quarterly observations by dividing growth rates equally over quarters, (2) the ratio of medium-term unemployment to previous-period short-term unemployment, and (3) a constant. Again, X_w is transformed into its principal components for numerical convenience.

Simulation. For given parameter values of the income process, I calculate the moments of the distribution of labor income growth by simulating a panel of individual labor income realizations. I simulate the trajectories of aggregate wages and tail risk, idiosyncratic income shocks, and mortality over the sample period 1967–2019 for a panel of 100 000 individuals.

The simulations are initialized with a permanent income level $\Gamma = 1$ for all individuals.[27] Guvenen et al. (2014) exclude observations where income is below a minimum threshold (1 300 in 2005). I similarly exclude observations below $1\,300/50\,000 = 2.6\%$ of average income. For comparison with the data, the quarterly simulations of individual income from the model are aggregated to annual observations. Based on the aggregate income observations I then calculate the moments of the distribution of individual income growth.

[26] Households have a survival probability of $1 - \omega$ in each period. I set $\omega = 1/160$ so that mortality risk is 2.5% per year. Due to mortality risk, the cross-sectional variance of the permanent component Θ_{it} is finite.

[27] The parameter estimates do not depend on the initial income distribution since the targeted statistics are moments of income growth rates.

Estimation. I estimate the parameters of the income process by targeting the annual moments of the income growth distribution reported by Guvenen et al. (2014) for incomes observed between 1978 and 2011. The sample moments are the 10th percentile ($p10$), the median ($p50$), and the 90th percentile ($p90$) of income growth over 1-year, 3-year, and 5-year horizons. The objective of the procedure is to minimize the sum of squared residuals for each year and each horizon, where the residuals are defined as

- $(p50_{\text{model}} - p50_{\text{data}})/p90_{\text{data}}$;
- $(p50_{\text{model}} - p10_{\text{model}})/(p50_{\text{data}} - p10_{\text{data}}) - 1$;
- $(p90_{\text{model}} - p50_{\text{model}})/(p90_{\text{data}} - p50_{\text{data}}) - 1$.

In addition to these annual observations, I also add to the objective the distance between the average location of $p10$ and $p90$ in the model and in the data for each horizon.

Starting with an initial guess for the parameters of the income process, I simulate the model, compute the value of the objective function, and update the parameter values. These steps are repeated until the loadings of aggregate income growth and x_t on the macroeconomic indicators and the parameters σ_u, $\sigma_{\xi,1}$, $\sigma_{\xi,2}$, $\sigma_{\xi,3}$, p_2, p_3, μ_2, and μ_3 that minimize the objective function have been determined. To limit the degrees of freedom, I impose the restrictions $p_2 = p_3$ and $\sigma_{\xi,2} = \sigma_{\xi,3}$.

Results. Table A.1 reports the estimated parameters of the labor income process. Figure A.2 plots the annual average and percentiles of the income growth distribution in the model compared to the data. The income process fits the moments of labor income growth in the data well, in particular over longer horizons.

Variation in the distribution of income risk over time is captured by the tail risk process x_t. Section 2 discusses the time series for x_t that results from the estimation. Figure A.3 illustrates how the distribution of permanent income growth depends on the macroeconomic state by plotting the log density of the permanent shock ξ for $x = -\bar{\sigma}$ (expansion) and $x = \bar{\sigma}$ (recession), where $\bar{\sigma} = 0.143$ is the unconditional standard deviation of x. The figure shows that when x is high (i.e., when idiosyncratic risk is high), the density significantly shifts to the left. In particular, while the center of the distribution is relatively stable, the right tail becomes much smaller and the mass at the left tail increases considerably.

A.2 Model Derivations

This section contains the derivations for the New Keynesian asset pricing model discussed in Section 3.

A.2.1 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

$$\begin{aligned} \max \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_s^{\tau} \left[\frac{(C^s_{t+\tau} - H^s_{t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0s} \int_0^1 \frac{L^{1+\chi_1}_{s,j,t+\tau}}{1+\chi_1} dj \right] \\ \text{s.t.} \quad & P_t C^s_t = \int_0^1 W_{sjt} L_{sjt} dj + P_t \frac{D_t}{\delta_s}. \end{aligned} \tag{A.2.1}$$

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, where we have imposed market clearing for the state-contingent claims that are in zero net supply.

Let Λ_{st} be the Lagrange multiplier on the budget constraint. The first-order condition with respect to consumption is

$$(C^s_t - b_s C^s_{t-1})^{-\gamma} = \Lambda_{st} P_t \equiv \lambda_{st}. \tag{A.2.2}$$

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

$$1 = \mathbb{E}_t \left[M_{t+1} R_{t+1} \right], \tag{A.2.3}$$

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

$$M_{t+1} = \beta_s \frac{\lambda_{s,t+1}}{\lambda_{st}} = \beta_s \left(\frac{C^s_{t+1} - b_s C^s_t}{C^s_t - b_s C^s_{t-1}} \right)^{-\gamma}. \tag{A.2.4}$$

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

$$\begin{aligned} \max \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_n^{\tau} \left[\frac{(C^i_{t+\tau} - H^i_{t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0n} \Gamma_{i,t+\tau}^{-(\gamma+\chi_1)} \int_0^1 \frac{L^{1+\chi_1}_{i,j,t+\tau}}{1+\chi_1} dj \right] \\ \text{s.t.} \quad & P_t C^i_t = \int_0^1 W_{njt} L_{ijt} dj + B_{i,t-1} I_{t-1} - B_{it}. \end{aligned} \tag{A.2.5}$$

The individual habit level is given by $H^i_t = \Gamma_{it} H^n_t$, where $H^n_t \equiv b_n C^n_{t-1}$.

Next, decompose consumption and bond holdings as $C^i_t = \Gamma_{it} \tilde{C}^i_t$ and $B_{it} = \Gamma_{it} \tilde{B}_{it}$. Per the setup of the labor market in Section 3.2, the labor union for labor type j allocates employment $L_{ijt} = \Gamma_{it} L_{njt}$ to individual agent i. The non-stockholders' utility maximization problem can be rewritten as

$$\begin{aligned} \max \quad & \mathbb{E}_t \sum_{\tau=0}^{\infty} \beta_n^{\tau} \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}} \right)^{1-\gamma} \left[\frac{(\tilde{C}^i_{t+\tau} - H^n_{t+\tau})^{1-\gamma}}{1-\gamma} - \chi_{0n} \int_0^1 \frac{L^{1+\chi_1}_{n,j,t+\tau}}{1+\chi_1} dj \right] \\ \text{s.t.} \quad & P_t \tilde{C}^i_t = \int_0^1 W_{njt} L_{njt} dj + \tilde{B}_{i,t-1} I_{t-1} \frac{\Gamma_{i,t-1}}{\Gamma_{it}} - \tilde{B}_{it}. \end{aligned} \tag{A.2.6}$$

Because of the permanent nature of shocks to Γ_{it}, it follows (starting with zero initial bond holdings) that $\tilde{C}^i_t$ and $\tilde{B}_{it}$ do not depend on i so that optimal individual consumption and bond holdings are proportional to the individual component of labor income: $C^i_t = \Gamma_{it} C^n_t$ and $B_{it} = \Gamma_{it} B_{nt}$, where B_{nt} are aggregate bond holdings of non-stockholders.[28]

Now, take the first-order conditions with respect to consumption:

$$(C^n_t - b_n C^n_{t-1})^{-\gamma} = \Lambda_{nt} P_t \equiv \lambda_{nt}. \tag{A.2.7}$$

From the first-order condition w.r.t. B_{nt}, we get the Euler equation for the nominal risk-free asset:

$$1 = \beta_n I_t \mathbb{E}_t \left[\left(\frac{\Gamma_{i,t+1}}{\Gamma_{it}} \right)^{-\gamma} \frac{\Lambda_{n,t+1}}{\Lambda_{nt}} \right] = \beta_n g^n_0(x_t) I_t \mathbb{E}_t \left[\frac{\Lambda_{n,t+1}}{\Lambda_{nt}} \right]. \tag{A.2.8}$$

A.2.2 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_{kt} be the consumption basket from goods in sector k. Consumption of the composite good is given by

$$C_t = \left(\sum_k \omega_k^{\frac{1}{\eta_c}} C_{kt}^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}}, \tag{A.2.9}$$

with weights ω_k over the sectors. The consumption basket from sector k is aggregated from individual consumption goods C_{kft} of firms f:

$$C_{kt} = \left(\int_0^1 C_{kft}^{\frac{\eta_{ck} - 1}{\eta_{ck}}} df \right)^{\frac{\eta_{ck}}{\eta_{ck} - 1}}. \tag{A.2.10}$$

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

$$\begin{aligned} \min \quad & \sum_k P_{kt} C_{kt} \equiv P_t C_t \\ \text{s.t.} \quad & \left(\sum_k \omega_k^{\frac{1}{\eta_c}} C_{kt}^{\frac{\eta_c - 1}{\eta_c}} \right)^{\frac{\eta_c}{\eta_c - 1}} = C_t. \end{aligned} \tag{A.2.11}$$

[28] Since nominal risk-free bonds are in zero net supply, $B_{nt} = 0$ in equilibrium.

The first-order condition is

$$P_{kt} = \Omega_c C_t^{\frac{1}{\eta_c}} \omega_k^{\frac{1}{\eta_c}} C_{kt}^{-\frac{1}{\eta_c}}, \tag{A.2.12}$$

with Lagrange multiplier Ω_c. The solution is

$$C_{kt} = \omega_k \left(\frac{P_{kt}}{P_t}\right)^{-\eta_c} C_t, \tag{A.2.13}$$

with price index

$$P_t = \left(\sum_k \omega_k P_{kt}^{1-\eta_c}\right)^{\frac{1}{1-\eta_c}}. \tag{A.2.14}$$

Analogously, at the sector level,

$$C_{kft} = \left(\frac{P_{kft}}{P_{kt}}\right)^{-\eta_{ck}} C_{kt} \tag{A.2.15}$$

$$P_{kt} = \left(\int_0^1 P_{kft}^{1-\eta_{ck}} df\right)^{\frac{1}{1-\eta_{ck}}}. \tag{A.2.16}$$

A.2.3 Labor Demand

A competitive labor aggregator combines labor services from individual agent and labor types, hired at the posted wages $W_{\nu jt}$, 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

$$\begin{aligned} \min \quad & \sum_\nu W_{\nu t} N_{\nu t} \equiv W_t N_t \\ \text{s.t.} \quad & \left(\sum_\nu \delta_\nu^{\frac{1}{\eta_w}} N_{\nu t}^{\frac{\eta_w - 1}{\eta_w}}\right)^{\frac{\eta_w}{\eta_w - 1}} = N_t. \end{aligned} \tag{A.2.17}$$

The first-order condition of this problem is

$$W_{\nu t} = \Omega_w N_t^{\frac{1}{\eta_w}} \delta_\nu^{\frac{1}{\eta_w}} N_{\nu t}^{-\frac{1}{\eta_w}}, \tag{A.2.18}$$

with Lagrange multiplier Ω_w. The solution is

$$N_{\nu t} = \delta_\nu \left(\frac{W_{\nu t}}{W_t}\right)^{-\eta_w} N_t, \tag{A.2.19}$$

with wage index

$$W_t = \left(\sum_\nu \delta_\nu W_{\nu t}^{1-\eta_w}\right)^{\frac{1}{1-\eta_w}}. \tag{A.2.20}$$

Similarly, within agent type, we get

$$\begin{aligned} N_{\nu jt} &= \left(\frac{W_{\nu jt}}{W_{\nu t}}\right)^{-\eta_w} N_{\nu t} \\ W_{\nu t} &= \left(\int_0^1 W_{\nu jt}^{1-\eta_w} dj\right)^{\frac{1}{1-\eta_w}}. \end{aligned} \tag{A.2.21}$$

A.2.4 Wage Setting

Labor is demand driven: hours for labor type j by agent type ν are fulfilled at the posted wage rate $W_{\nu jt}$ to meet total labor demand. As a consequence, individual labor hours for individual $i \in \mathcal{I}_\nu$ are given by

$$L_{ijt} = \Gamma_{it} L_{\nu jt} = \frac{1}{\delta_\nu} \Gamma_{it} N_{\nu jt} = \Gamma_{it} \left(\frac{W_{\nu jt}}{W_{\nu t}}\right)^{-\eta_w} \left(\frac{W_{\nu t}}{W_t}\right)^{-\eta_w} N_t, \tag{A.2.22}$$

so that the total supply of hours for labor type j of agent type ν, $\delta_\nu L_{\nu jt}$, meets the demand $N_{\nu jt}$.

The maximization problem for the labor union in setting the reset wage $W_{\nu jt}$ is given by

$$\max \quad \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}}\right)^{1-\gamma} \left[-\chi_{0\nu} \frac{L_{\nu,j,t+\tau}^{1+\chi_1}}{1+\chi_1} + \lambda_{\nu,t+\tau} \frac{W_{\nu jt}}{P_{t+\tau}} L_{\nu,j,t+\tau} \right] \tag{A.2.23}$$

$$\text{s.t.} \quad L_{\nu,j,t+\tau} = \left(\frac{W_{\nu jt}}{W_{\nu,t+\tau}}\right)^{-\eta_w} \left(\frac{W_{\nu,t+\tau}}{W_{t+\tau}}\right)^{-\eta_w} N_{t+\tau}. \tag{A.2.24}$$

The first-order condition is

$$\begin{aligned} 0 &= \eta_w \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}}\right)^{1-\gamma} \chi_{0\nu} \left(\frac{W_{\nu t}^*}{W_{\nu,t+\tau}}\right)^{-\eta_w(1+\chi_1)} \left(\frac{W_{\nu,t+\tau}}{W_{t+\tau}}\right)^{-\eta_w(1+\chi_1)} \frac{N_{t+\tau}^{1+\chi_1}}{W_{\nu t}^*} \\ &\quad + (1-\eta_w) \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}}\right)^{1-\gamma} \lambda_{\nu,t+\tau} \left(\frac{W_{\nu t}^*}{W_{\nu,t+\tau}}\right)^{-\eta_w} \left(\frac{W_{\nu,t+\tau}}{W_{t+\tau}}\right)^{-\eta_w} \frac{N_{t+\tau}}{P_{t+\tau}} \\ &\Leftrightarrow \\ &\frac{\eta_w}{\eta_w - 1} \frac{\chi_{0\nu}}{\lambda_{\nu t}} \left(\frac{W_t}{P_t}\right)^{\eta_w \chi_1} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}}\right)^{1-\gamma} \left(\frac{W_{t+\tau}}{W_t}\right)^{\eta_w(1+\chi_1)} N_{t+\tau}^{1+\chi_1} \\ &= \left(\frac{W_{\nu t}^*}{P_t}\right)^{1+\eta_w \chi_1} \mathbb{E}_t \sum_{\tau=0}^{\infty} (\beta_\nu \theta_w)^\tau \left(\frac{\Gamma_{i,t+\tau}}{\Gamma_{it}}\right)^{1-\gamma} \frac{\lambda_{\nu,t+\tau}}{\lambda_{\nu t}} \left(\frac{W_{t+\tau}}{W_t}\right)^{\eta_w} \frac{P_t}{P_{t+\tau}} N_{t+\tau}. \end{aligned} \tag{A.2.25}$$

Hence, the optimal reset wage is

$$\left(\frac{W_{\nu t}^{*}}{P_t}\right)^{1+\eta_w\chi_1} = \frac{\eta_w}{\eta_w - 1}\chi_{0\nu}\lambda_{\nu t}^{-1}\left(\frac{W_t}{P_t}\right)^{\eta_w\chi_1}\frac{F_{w\nu t}}{K_{w\nu t}} \tag{A.2.26}$$

$$F_{w\nu t} = N_t^{1+\chi_1} + \beta_\nu\theta_w g_1^\nu(x_t)\mathbb{E}_t\left[\left(\frac{W_{t+1}}{W_t}\right)^{\eta_w(1+\chi_1)} F_{w,\nu,t+1}\right] \tag{A.2.27}$$

$$K_{w\nu t} = N_t + \beta_\nu\theta_w g_1^\nu(x_t)\mathbb{E}_t\left[\frac{\lambda_{\nu,t+1}}{\lambda_{\nu t}}\left(\frac{W_{t+1}}{W_t}\right)^{\eta_w}\frac{P_t}{P_{t+1}}K_{w,\nu,t+1}\right]. \tag{A.2.28}$$

Since wage updating is time-dependent and not state-dependent, the law of motion for the real wage is given by

$$\left(\frac{W_{\nu t}}{P_t}\right)^{1-\eta_w} = (1-\theta_w)\left(\frac{W_{\nu t}^{*}}{P_t}\right)^{1-\eta_w} + \theta_w\left(\frac{W_{\nu,t-1}}{P_{t-1}}\right)^{1-\eta_w}\left(\frac{P_t}{P_{t-1}}\right)^{\eta_w-1}. \tag{A.2.29}$$

A.2.5 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

$$\begin{aligned} D_{kft} &= \frac{P_{kft}}{P_t}Y_{kft} - \frac{W_t}{P_t}N_t^{kf} \\ &= \omega_k C_t\left[\left(\frac{P_{kft}}{P_{kt}}\right)^{1-\eta_{ck}}\left(\frac{P_{kt}}{P_t}\right)^{1-\eta_c} - \frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{kft}}{P_{kt}}\right)^{-\eta_{ck}}\left(\frac{P_{kt}}{P_t}\right)^{-\eta_c}\right] \\ &= \omega_k C_t\left[\left(\frac{P_{kft}}{P_t}\right)^{1-\eta_{ck}}\left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}-\eta_c} - \frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{kft}}{P_t}\right)^{-\eta_{ck}}\left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}-\eta_c}\right]. \end{aligned} \tag{A.2.30}$$

When getting the chance to update their price P_{kft}, firms choose the reset price to maximize the present value of future dividends, so that the objective is to maximize

$$\mathbb{E}_t\sum_{\tau=0}^{\infty}(\beta_s\theta_{ck})^\tau\frac{\lambda_{s,t+\tau}}{\lambda_{st}}C_{t+\tau}\left[\left(\frac{P_{kft}}{P_{t+\tau}}\right)^{1-\eta_{ck}}\left(\frac{P_{k,t+\tau}}{P_{t+\tau}}\right)^{\eta_{ck}-\eta_c} - \frac{W_{t+\tau}}{P_{t+\tau}}\frac{1}{A_{t+\tau}}\left(\frac{P_{kft}}{P_{t+\tau}}\right)^{-\eta_{ck}}\left(\frac{P_{k,t+\tau}}{P_{t+\tau}}\right)^{\eta_{ck}-\eta_c}\right]. \tag{A.2.31}$$

The first-order condition is

$$\begin{aligned} &\frac{P_{kt}^{*}}{P_t}\mathbb{E}_t\sum_{\tau=0}^{\infty}(\beta_s\theta_{ck})^\tau\frac{\lambda_{s,t+\tau}}{\lambda_{st}}\left(\frac{P_t}{P_{t+\tau}}\right)^{1-\eta_{ck}}\left(\frac{P_{k,t+\tau}}{P_{t+\tau}}\right)^{\eta_{ck}-\eta_c}C_{t+\tau} \\ &= \frac{\eta_{ck}}{\eta_{ck}-1}\mathbb{E}_t\sum_{\tau=0}^{\infty}(\beta_s\theta_{ck})^\tau\frac{\lambda_{s,t+\tau}}{\lambda_{st}}\left(\frac{P_t}{P_{t+\tau}}\right)^{-\eta_{ck}}\frac{W_{t+\tau}}{P_{t+\tau}}\frac{1}{A_{t+\tau}}\left(\frac{P_{k,t+\tau}}{P_{t+\tau}}\right)^{\eta_{ck}-\eta_c}C_{t+\tau}. \end{aligned} \tag{A.2.32}$$

It follows that the optimal reset price P_{kt}^* is given by

$$\frac{P_{kt}^*}{P_t} = \frac{\eta_{ck}}{\eta_{ck}-1}\frac{F_{pkt}}{K_{pkt}} \tag{A.2.33}$$

$$F_{pkt} = \frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}-\eta_c} C_t + \beta_s\theta_{ck}\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}}\left(\frac{P_t}{P_{t+1}}\right)^{-\eta_{ck}} F_{p,k,t+1}\right] \tag{A.2.34}$$

$$K_{pkt} = \left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}-\eta_c} C_t + \beta_s\theta_{ck}\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}}\left(\frac{P_t}{P_{t+1}}\right)^{1-\eta_{ck}} K_{p,k,t+1}\right]. \tag{A.2.35}$$

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

$$\left(\frac{P_{kt}}{P_t}\right)^{1-\eta_{ck}} = (1-\theta_{ck})\left(\frac{P_{kt}^*}{P_t}\right)^{1-\eta_{ck}} + \theta_{ck}\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{1-\eta_{ck}}\left(\frac{P_t}{P_{t-1}}\right)^{\eta_{ck}-1}. \tag{A.2.36}$$

A.2.6 Aggregates

We can now compute quantities and market values at the sector and aggregate level.

First, total labor demand in sector k is

$$N_t^k = \int_0^1 N_t^{kf} df = \frac{1}{A_t}\int_0^1 Y_{kft} df = \frac{C_{kt}}{A_t}\underbrace{\int_0^1\left(\frac{P_{kft}}{P_{kt}}\right)^{-\eta_{ck}} df}_{DS_{pkt}}, \tag{A.2.37}$$

where price dispersion is

$$DS_{pkt} = (1-\theta_{ck})\left(\frac{P_{kt}^*}{P_{kt}}\right)^{-\eta_{ck}} + \theta_{ck} DS_{p,k,t-1}\left(\frac{P_{kt}}{P_{k,t-1}}\right)^{\eta_{ck}}. \tag{A.2.38}$$

The total dividend in sector k is

$$D_{kt} = \int_0^1 D_{kft} df = \omega_k\left(\frac{P_{kt}}{P_t}\right)^{1-\eta_c} C_t\left[1 - \underbrace{\frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{kt}}{P_t}\right)^{-1} DS_{pkt}}_{\hat{\mu}_{kt}^{-1}}\right]. \tag{A.2.39}$$

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

$$V_{kt} = \mathbb{E}_t\left[\sum_{\tau=0}^{\infty}\beta_s^\tau\frac{\lambda_{s,t+\tau}}{\lambda_{st}} D_{k,t+\tau}\right] = D_{kt} + \beta_s\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}} V_{k,t+1}\right]. \tag{A.2.40}$$

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

$$N_t = \sum_k N_t^k = \frac{C_t}{A_t}\underbrace{\sum_k \omega_k\left(\frac{P_{kt}}{P_t}\right)^{-\eta_c} DS_{pkt}}_{DS_{pt}}. \tag{A.2.41}$$

Aggregate dividends are

$$D_t = \sum_k D_{kt} = C_t \left[1 - \underbrace{\frac{W_t}{P_t} \frac{1}{A_t} DS_{pt}}_{\hat{\mu}_t^{-1}} \right], \tag{A.2.42}$$

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

$$V_t = D_t + \beta_s \mathbb{E}_t \left[\frac{\lambda_{s,t+1}}{\lambda_{st}} V_{t+1} \right]. \tag{A.2.43}$$

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

$$C_t = \delta_s C_t^s + \delta_n C_t^n = Y_t \tag{A.2.44}$$

$$C_t^s = \int_0^1 W_{sjt} L_{sjt} dj + \frac{D_t}{\delta_s} = \left(\frac{W_{st}}{P_t} \right)^{1-\eta_w} \left(\frac{W_t}{P_t} \right)^{\eta_w} N_t + \frac{D_t}{\delta_s} \tag{A.2.45}$$

$$C_t^n = \int_0^1 W_{njt} L_{njt} dj = \left(\frac{W_{nt}}{P_t} \right)^{1-\eta_w} \left(\frac{W_t}{P_t} \right)^{\eta_w} N_t. \tag{A.2.46}$$

A.2.7 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 as in Li and Palomino (2014). Let $\widetilde{R}_{k,t+1}$ be the return on the claim to the next-period dividends of sector k. Any real return R that is spanned by traded assets satisfies the fundamental asset pricing relation

$$1 = \mathbb{E}_t[M_{t+1} R_{t+1}]. \tag{A.2.47}$$

Assume for expositional purposes that the SDF and asset returns are jointly lognormally distributed and the continuously compounded real risk-free rate r_f is constant:

$$\mathbb{E}_t[r_{t+1}] + \frac{1}{2} \mathrm{Var}_t[r_{t+1}] - r_f = -\mathrm{Cov}_t(m_{t+1}, r_{t+1}), \tag{A.2.48}$$

where $m_{t+1} \equiv \log M_{t+1}$ and $r_{t+1} \equiv \log R_{t+1}$. Taking the difference in expected returns on the claims to next-period dividends between the two sectors, we get

$$\begin{aligned} \log \mathbb{E}_t[\widetilde{R}_{2,t+1}] - \log \mathbb{E}_t[\widetilde{R}_{1,t+1}] &= -\mathrm{Cov}_t(m_{t+1}, \widetilde{r}_{2,t+1} - \widetilde{r}_{1,t+1}) \\ &= -\mathrm{Cov}_t(m_{t+1}, d_{2,t+1} - d_{1,t+1}). \end{aligned} \tag{A.2.49}$$

Define $p_{kt} \equiv \log(P_{kt}/P_t)$. Using (A.2.39), the difference in log dividends is given by

$$d_{2t} - d_{1t} = \log \omega_2 - \log \omega_1 + (1 - \eta_c)(p_{2t} - p_{1t}) + \log(1 - \hat{\mu}_{2t}^{-1}) - \log(1 - \hat{\mu}_{1t}^{-1}). \tag{A.2.50}$$

Next, use a log-linear approximation of sector markups:

$$\log(1-\hat{\mu}_{kt}^{-1}) \approx \log(1-\hat{\mu}_{k}^{-1}) + \frac{1}{\hat{\mu}_k - 1}(\log \hat{\mu}_{kt} - \log \hat{\mu}_k), \tag{A.2.51}$$

where $\hat{\mu}_k = \frac{\eta_{ck}}{\eta_{ck}-1}$ is the steady-state markup in sector k.

Finally, let $wp_t \equiv \log(W_t/P_t)$ and $ds_{pkt} \equiv \log(DS_{pkt})$. Plugging in the definition of markups from (A.2.39), we obtain

$$\begin{aligned}\log \mathbb{E}_t \widetilde{R}_{2,t+1} - \log \mathbb{E}_t \widetilde{R}_{1,t+1} &= -(1-\eta_c)\mathrm{Cov}_t(m_{t+1}, p_{2,t+1} - p_{1,t+1}) - (\eta_{c2} - 1)\mathrm{Cov}_t(m_{t+1}, \log \hat{\mu}_{2,t+1}) \\ &\quad + (\eta_{c1} - 1)\mathrm{Cov}_t(m_{t+1}, \log \hat{\mu}_{1,t+1}) \\ &= -(\eta_{c2} - \eta_c)\mathrm{Cov}_t(m_{t+1}, p_{2,t+1} - p_{1,t+1}) \\ &\quad - (1-\eta_{c2})\mathrm{Cov}_t(m_{t+1}, ds_{p,2,t+1} - ds_{p,1,t+1}) \\ &\quad - (\eta_{c2} - \eta_{c1})\mathrm{Cov}_t(m_{t+1}, a_{t+1} - wp_{t+1} + p_{1,t+1} - ds_{p,1,t+1}).\end{aligned} \tag{A.2.52}$$

A.2.8 Equilibrium Conditions

This section summarizes all equilibrium conditions.

Household consumption and saving:

$$\lambda_{\nu t} = (C_t^\nu - b_\nu C_{t-1}^\nu)^{-\gamma} \qquad \nu \in \{s, n\} \tag{A.2.53}$$

$$1 = \beta_n g_0^n I_t \mathbb{E}_t \left[\frac{\lambda_{n,t+1}}{\lambda_{nt}} e^{-\pi_{t+1}} \right] \tag{A.2.54}$$

$$C_t^s = \frac{W_{st}}{P_t} \frac{N_{st}}{\delta_s} + \frac{D_t}{\delta_s} \tag{A.2.55}$$

$$C_t^n = \frac{W_{nt}}{P_t} \frac{N_{nt}}{\delta_n} \tag{A.2.56}$$

Demand and price indices for consumption goods and labor services:

$$C_{kt} = \omega_k \left(\frac{P_{kt}}{P_t} \right)^{-\eta_c} C_t \qquad \forall\, k \tag{A.2.57}$$

$$1 = \left(\sum_k \omega_k \left(\frac{P_{kt}}{P_t} \right)^{1-\eta_c} \right)^{\frac{1}{1-\eta_c}} \tag{A.2.58}$$

$$N_{\nu t} = \delta_\nu \left(\frac{W_{\nu t}}{P_t} \right)^{-\eta_w} \left(\frac{W_t}{P_t} \right)^{\eta_w} N_t \qquad \nu \in \{s, n\} \tag{A.2.59}$$

$$\frac{W_t}{P_t} = \left(\sum_\nu \delta_\nu \left(\frac{W_{\nu t}}{P_t} \right)^{1-\eta_w} \right)^{\frac{1}{1-\eta_w}} \tag{A.2.60}$$

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

$$\left(\frac{W_{\nu t}^*}{P_t} \right)^{1+\eta_w \chi_1} = \frac{\eta_w}{\eta_w - 1} \chi_{0\nu} \lambda_{\nu t}^{-1} \left(\frac{W_t}{P_t} \right)^{\eta_w \chi_1} \frac{F_{w\nu t}}{K_{w\nu t}} \tag{A.2.61}$$

$$F_{w\nu t} = N_t^{1+\chi_1} + \beta_\nu \theta_w g_1^\nu(x_t) \mathbb{E}_t \left[\left(\frac{P_t}{W_t} \frac{W_{t+1}}{P_{t+1}} e^{\pi_{t+1}} \right)^{\eta_w (1+\chi_1)} F_{w,\nu,t+1} \right] \tag{A.2.62}$$

$$K_{w\nu t} = N_t + \beta_\nu \theta_w g_1^\nu(x_t) \mathbb{E}_t \left[\frac{\lambda_{\nu,t+1}}{\lambda_{\nu t}} \left(\frac{P_t}{W_t} \frac{W_{t+1}}{P_{t+1}} \right)^{\eta_w} e^{\pi_{t+1}(\eta_w - 1)} K_{w,\nu,t+1} \right] \tag{A.2.63}$$

$$\left(\frac{W_{\nu t}}{P_t} \right)^{1-\eta_w} = (1 - \theta_w) \left(\frac{W_{\nu t}^*}{P_t} \right)^{1-\eta_w} + \theta_w \left(\frac{W_{\nu,t-1}}{P_{t-1}} \right)^{1-\eta_w} e^{\pi_{t+1}(\eta_w - 1)} \tag{A.2.64}$$

Price setting for sector k:

$$\frac{P^*_{kt}}{P_t} = \frac{\eta_{ck}}{\eta_{ck}-1}\frac{F_{pkt}}{K_{pkt}} \tag{A.2.65}$$

$$F_{pkt} = \frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}-\eta_c} C_t + \beta_s\theta_{ck}\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}}e^{\pi_{t+1}\eta_{ck}}F_{p,k,t+1}\right] \tag{A.2.66}$$

$$K_{pkt} = \left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}-\eta_c} C_t + \beta_s\theta_{ck}\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}}e^{\pi_{t+1}(\eta_{ck}-1)}K_{p,k,t+1}\right] \tag{A.2.67}$$

$$\left(\frac{P_{kt}}{P_t}\right)^{1-\eta_{ck}} = (1-\theta_{ck})\left(\frac{P^*_{kt}}{P_t}\right)^{1-\eta_{ck}} + \theta_{ck}\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{1-\eta_{ck}} e^{\pi_t(\eta_{ck}-1)} \tag{A.2.68}$$

$$DS_{pkt} = (1-\theta_{ck})\left(\frac{P^*_{kt}}{P_{kt}}\right)^{-\eta_{ck}} + \theta_{ck}DS_{p,k,t-1}e^{\pi_t\eta_{ck}}\left(\frac{P_{kt}}{P_t}\right)^{\eta_{ck}}\left(\frac{P_{k,t-1}}{P_{t-1}}\right)^{-\eta_{ck}} \tag{A.2.69}$$

Market clearing for consumption goods:

$$DS_{pt} = \sum_k \omega_k\left(\frac{P_{kt}}{P_t}\right)^{-\eta_c} DS_{pkt} \tag{A.2.70}$$

$$Y_t = A_t N_t DS_{pt}^{-1} \tag{A.2.71}$$

$$C_t = \delta_s C_t^s + \delta_n C_t^n = Y_t \tag{A.2.72}$$

Dividends and total equity values:

$$D_{kt} = \omega_k\left(\frac{P_{kt}}{P_t}\right)^{1-\eta_c} C_t\left[1-\frac{W_t}{P_t}\frac{1}{A_t}\left(\frac{P_{kt}}{P_t}\right)^{-1} DS_{pkt}\right] \qquad \forall\, k \tag{A.2.73}$$

$$V_{kt} = D_{kt} + \beta_s\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}}V_{k,t+1}\right] \qquad \forall\, k \tag{A.2.74}$$

$$D_t = C_t\left[1-\frac{W_t}{P_t}\frac{1}{A_t}DS_{pt}\right] \tag{A.2.75}$$

$$V_t = D_t + \beta_s\mathbb{E}_t\left[\frac{\lambda_{s,t+1}}{\lambda_{st}}V_{t+1}\right] \tag{A.2.76}$$

Exogenous processes and monetary policy rule:

$$\log A_t = \rho_a \log A_{t-1} + \epsilon_{at} \tag{A.2.77}$$

$$x_t = \rho_x x_{t-1} + \epsilon_{xt} \tag{A.2.78}$$

$$\log I_t = -\log(\beta_n g_0^n(0)) + \phi_\pi \pi_t + \phi_y \log(Y_t/Y_{t-1}) + z_t \tag{A.2.79}$$

$$z_t = \rho_z z_{t-1} + \epsilon_{zt}. \tag{A.2.80}$$

A.2.9 Deterministic Steady State

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

$$\frac{P_k}{P} = \frac{P_k^*}{P} = \frac{\eta_{ck}}{\eta_{ck}-1}\frac{W}{P} \qquad \forall\, k \tag{A.2.81}$$

$$DS_p = \sum_k \omega_k \left(\frac{P_k}{P}\right)^{-\eta_c} \tag{A.2.82}$$

$$N_\nu = \delta_\nu \left(\frac{W_\nu}{P}\right)^{-\eta_w} \left(\frac{W}{P}\right)^{\eta_w} N \qquad \nu \in \{s,n\} \tag{A.2.83}$$

$$C^n = \frac{W_n}{P}\frac{N_n}{\delta_n}, \qquad C^s = \frac{1}{\delta_s}\left(\frac{N}{DS_p} - \delta_n C^n\right), \tag{A.2.84}$$

$$\lambda_\nu = (C^\nu(1-b_\nu))^{-\gamma} \qquad \nu \in \{s,n\} \tag{A.2.85}$$

$$\left(\frac{W_\nu}{P}\right)^{1+\eta_w\chi_1} = \frac{\eta_w}{\eta_w-1}\chi_{0\nu}\lambda_\nu^{-1}\left(\frac{W}{P}\right)^{\eta_w\chi_1} N^\chi \qquad \nu \in \{s,n\} \tag{A.2.86}$$

$$\frac{W}{P} = \left(\delta_s\left(\frac{W_s}{P}\right)^{1-\eta_w} + \delta_n\left(\frac{W_n}{P}\right)^{1-\eta_w}\right)^{\frac{1}{1-\eta_w}} \tag{A.2.87}$$

$$1 = \sum_k \omega_k \left(\frac{P_k}{P}\right)^{1-\eta_c} \tag{A.2.88}$$

For given values of $W/P, W_s/P, W_n/P$, and N, (A.2.81)–(A.2.85) 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.2.86)–(A.2.88). Given those steady state values, the other steady-state values are straightforward:

$$F_{w\nu} = \frac{N^{1+\chi_1}}{1-\beta_\nu\theta_w g_1^\nu(0)}, \qquad K_{w\nu} = \frac{N}{1-\beta_\nu\theta_w g_1^\nu(0)}, \qquad \nu \in \{s,n\} \tag{A.2.89}$$

$$F_{pk} = \frac{\frac{W}{P}\left(\frac{P_k}{P}\right)^{\eta_{ck}-\eta_c}}{1-\beta_s\theta_{ck}}, \qquad K_{pk} = \frac{\left(\frac{P_k}{P}\right)^{\eta_{ck}-\eta_c} C}{1-\beta_s\theta_{ck}}, \qquad \forall\, k \tag{A.2.90}$$

$$\frac{W_\nu^*}{P} = \frac{W_\nu}{P} \quad \nu \in \{s,n\}, \qquad DS_{pk} = 1 \quad \forall\, k, \qquad \pi = 0, \tag{A.2.91}$$

$$C = Y = N \cdot DS_p^{-1}, \qquad C_k = \omega_k \left(\frac{P_k}{P}\right)^{-\eta_c} C \quad \forall\, k, \tag{A.2.92}$$

$$D_k = \omega_k \left(\frac{P_k}{P}\right)^{1-\eta_c} C \left[1 - \frac{W}{P}\left(\frac{P_k}{P}\right)^{-1}\right], \qquad V_k = \frac{D_k}{1-\beta_s}, \qquad \forall\, k \tag{A.2.93}$$

$$D = C\left[1 - \frac{W}{P}DS_p\right], \qquad V = \frac{D}{1-\beta_s}. \tag{A.2.94}$$

A.3 Data Construction

This section presents additional details regarding the construction of data used for the empirical analysis.

A.3.1 Macroeconomic Data

In addition to the macroeconomic variables used for the estimation of the income risk process, (see Section A.1), I also obtain the following macroeconomic time series from the FRED database:

- Real personal consumption expenditures per capita on durable goods;
- Real personal consumption expenditures per capita on nondurable goods;
- Real personal consumption expenditures per capita on services;
- Current-cost net stock of durable goods;
- PCE price deflator of durable goods;
- Industrial production index;
- Total industry capacity utilization;
- University of Michigan consumer sentiment index;
- New private housing units authorized by building permits.

As a measure of aggregate consumption, I use the sum of real consumption expenditures per capita on nondurable consumption and services. Using the above series, I also compute the durable expenditure-stock ratio, following the approach of Gomes et al. (2009).

Finally, I obtain updated time series for changes in TFP and utilization-adjusted TFP from Fernald (2014).

A.3.2 Financial Data

Data on monthly and daily stock returns are from CRSP. I calculate dividends from the difference of holding period returns with and without dividends. Turnover is monthly volume as a fraction of the number of shares outstanding. The bid-ask spread is $2 \times (\text{ask} - \text{bid})/(\text{ask} + \text{bid})$. Market beta is the regression coefficient of a firm's equity return on the market return and idiosyncratic volatility is the volatility of the residual of this regression.

Balance sheet data is obtained from Compustat. The book-to-market ratio is the ratio of the book value of equity to price times the number of shares outstanding. Markups are measured as revenues minus costs of goods sold as a fraction of firm revenues. Profitability is revenue minus cost of goods sold minus general expenses minus interest divided by the book value of equity, and leverage is measured as the ratio of long-term debt plus debt in current liabilities to the book value of equity.

Data on the Fama-French factors, momentum return, Treasury-bill rate, and returns on 25 portfolios sorted by size and book-to-market come from the data library of Kenneth French.

Finally, I use data from Welch and Goyal (2008) on return predictor variables that have been studied in the literature, updated through 2020. For details on the variables construction, I refer the reader to Welch and Goyal (2008).

A.3.3 Monetary Policy Announcements

I follow Kuttner (2001) and Bernanke and Kuttner (2005) in measuring monetary policy shocks. Surprises in monetary policy rates can be derived from futures contracts on the Federal funds rate. Since monthly futures contracts are traded with a settlement price that is based on the average Federal funds rate, the implied surprise change Δi_t^U in the target rate on day t can be derived as

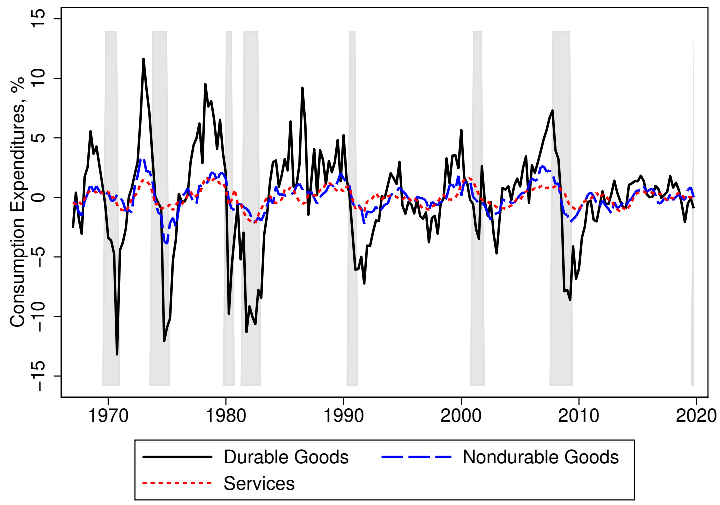
$$\Delta i_t^U = \frac{D(t)}{D(t) - d(t)}(f_t^1 - f_{t-1}^1),$$

where f_t^1 is the price of a futures contract that expires at the end of the current month, $d(t)$ is the current day of the month, and $D(t)$ is the total number of days in the month. The expected change is then computed as the realized change in the policy rate minus the surprise change.

Data on futures prices are available on Bloomberg. As described in the main text, I follow Kuttner (2001) in defining the timing of the news before 1994. I also follow Kuttner (2001) in using the non-scaled change in the one-month futures price when the announcement falls in the last three days of the month, and in using the lagged two-month futures price as the base when the announcement is on the first day of the month.

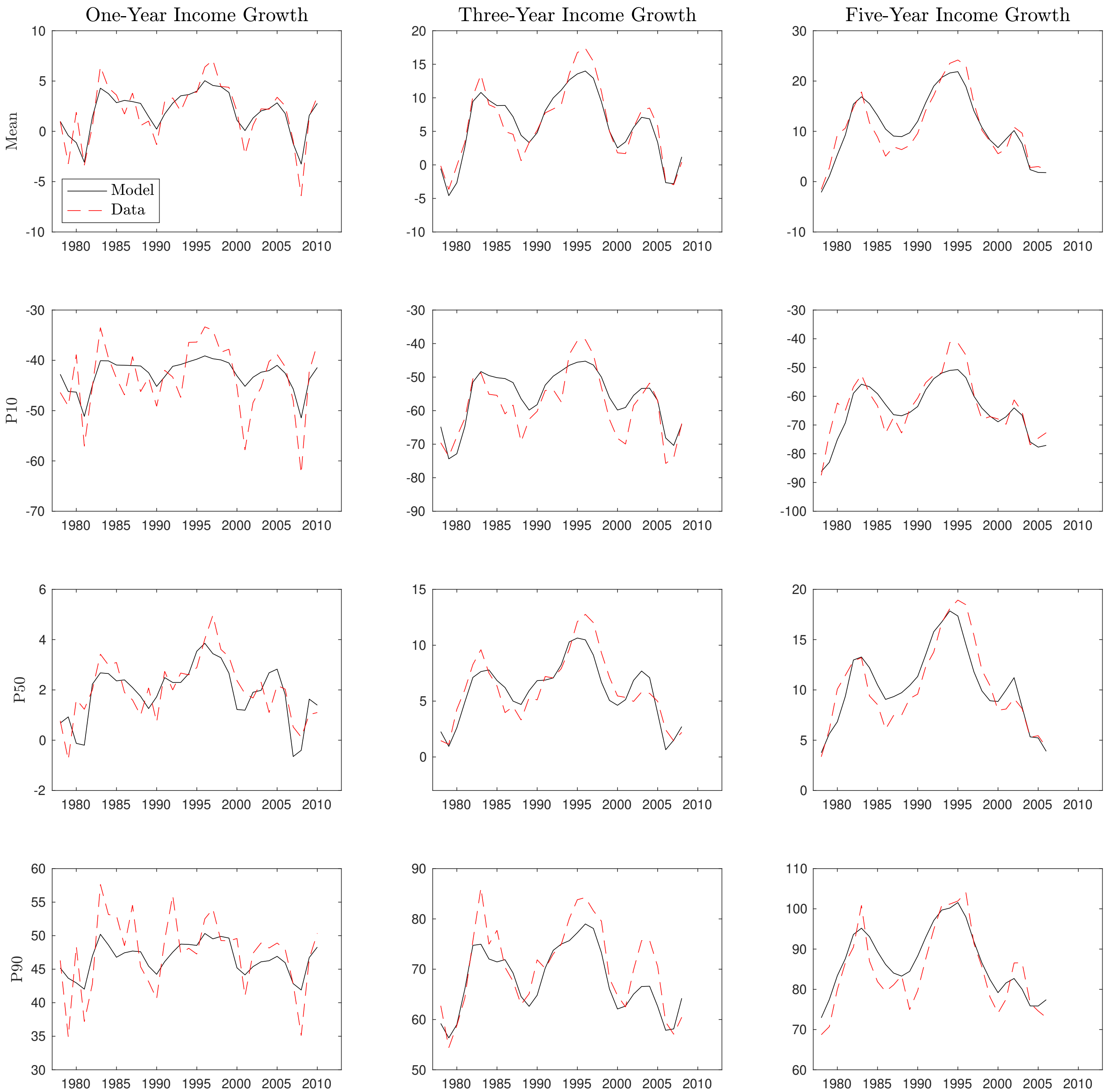
A.4 Additional Figures and Tables

Figure A.1: Consumption Expenditures over the Business Cycle



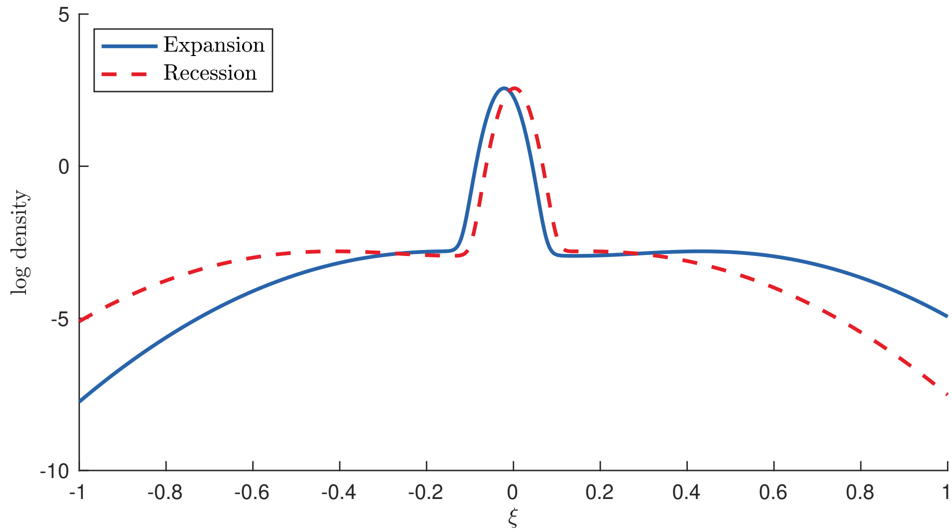
Notes: This figure plots the time series of real personal consumption expenditures per capita, relative to a long-term trend, on durable goods (solid line), nondurable goods (dashed line), and services (dotted line). The quarterly series are HP filtered with a standard bandwith parameter of 1 600. NBER recession dates are shaded.

Figure A.2: Distribution of Labor Income Growth Rates in Model and Data



Notes: This figure compares moments of income growth rates in the estimated model for labor income to the empirical counterparts over time.

Figure A.3: Density of the Permanent Idiosyncratic Income Shock



Notes: This figure plots the log density of the permanent shock ξ for $x = -\bar{\sigma}$ (expansion) and $x = \bar{\sigma}$ (recession), where $\bar{\sigma} = 0.143$ is the unconditional standard deviation of x.

Table A.1: Estimated Parameter Values of the Income Process

Symbol	Interpretation	Value
σ_u	Volatility of transitory component	0.404
$\sigma_{\xi,1}$	Typical volatility of permanent component	0.029
$\sigma_{\xi,2} = \sigma_{\xi,3}$	Tail volatility of permanent component	0.260
$p_2 = p_3$	Probability of tail event	0.038
μ_2	Location of left tail	-0.308
μ_3	Location of right tail	0.347

Notes: This table reports the estimated parameters of the labor income process. The details of the estimation procedure are in Appendix A.1.

Table A.2: Baseline Model Parameter Values

Symbol	Interpretation	Value
δ_s	Measure of stockholders	0.5
β_s	Time discounting of non-stockholders	0.985
β_n	Time discounting of non-stockholders	$\beta_s/g_0(0)$
γ	Coefficient of relative risk aversion	10
b_s	Habit weight stockholders	0.45
b_n	Habit weight non-stockholders	0.65
χ_1	Inverse Frisch elasticity	1
η_w	Elasticity of substitution across labor types	12
θ_w	Wage stickiness	0.64
ω_1	Consumption weight sector 1	0.5
η_c	Elasticity of substitution across sectors	2
η_{c1}	Elasticity of substitution in sector 1	3
η_{c2}	Elasticity of substitution in sector2	16
θ_{ck}	Price stickiness	0.75
ρ_a	Persistence of TFP	0.95
σ_a	Volatility of TFP shocks	0.0075
ρ_x	Persistence of income tail risk	0.88
σ_x	Volatility of shocks to income tail risk	0.0670
ρ_{ax}	Correlation between TFP and tail risk shocks	-0.5
ψ	Transmission of idiosyncratic shocks	0.26
ϕ_π	Taylor rule inflation	1.24
ϕ_y	Taylor rule output	0.33/4

Notes: This table summarizes the parameter values in the baseline version of the general equilibrium asset pricing model, as described in Section 3.

Table A.3: Excess Returns on DMNS Beta-Sorted Portfolios – Nondurables and Services Only

	DMNS Beta					
	Low	2	3	4	High	High–Low
Mean	5.77***	7.18***	8.82***	9.84***	10.67***	4.90**
	(1.61)	(1.69)	(1.89)	(2.29)	(2.86)	(2.15)
Volatility	15.48	16.28	18.19	22.01	27.46	20.72
Exposures						
R_{DMNS}	-0.04	0.06	0.32***	0.51***	0.82***	0.86***
	(0.07)	(0.07)	(0.08)	(0.07)	(0.11)	(0.09)
Δicl	-0.11**	-0.12**	-0.13**	-0.22***	-0.29***	-0.19***
	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)	(0.05)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for five portfolios of firms that produce nondurable goods or services, sorted by their DMNS beta. Preranking return betas are calculated in a two-factor specification using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. Risk exposures are measured by univariate betas with respect to R_{DMNS} and Δicl. The sample period is 1927M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Excess Returns on DMNS Beta-Sorted Portfolios – Sort Within Industry

	DMNS Beta					
	Low	2	3	4	High	High–Low
Mean	6.00^{***}	6.90^{***}	8.35^{***}	9.90^{***}	10.51^{***}	4.52^{**}
	(1.65)	(1.75)	(1.99)	(2.29)	(2.68)	(1.92)
Volatility	15.85	16.81	19.17	22.03	25.78	18.44
Exposures						
R_{DMNS}	0.11	0.11	0.32^{***}	0.55^{***}	1.10^{***}	0.99^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)
Δicl	-0.14^{**}	-0.13^{**}	-0.15^{**}	-0.21^{***}	-0.31^{***}	-0.17^{***}
	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.05)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for five portfolios of firms that produce consumption goods, sorted by their DMNS beta. The quintiles are computed within industry (30 Fama-French industries). Preranking return betas are calculated in a two-factor specification using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. Risk exposures are measured by univariate betas with respect to R_{DMNS} and Δicl. The sample period is 1927M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Excess Returns on Beta-Sorted Portfolios – Two-Way Sort

	DMNS Beta					
	Low	2	3	4	High	High–Low
IMC Beta:						
Low	5.76***	8.17***	7.67***	9.50***	11.56***	5.80**
	(1.62)	(1.67)	(2.06)	(2.35)	(2.84)	(2.48)
(2)	8.24***	8.49***	9.33***	10.32***	9.75***	1.51
	(1.90)	(1.81)	(2.06)	(2.39)	(2.92)	(2.51)
(3)	8.89***	9.46***	9.84***	9.09***	12.14***	3.25
	(2.26)	(2.20)	(2.23)	(2.37)	(3.03)	(2.33)
(4)	4.78*	7.10***	8.88***	9.80***	7.73**	2.94
	(2.71)	(2.52)	(2.76)	(2.72)	(3.15)	(2.34)
High	5.14	5.04	8.01**	8.93**	14.39***	9.25***
	(3.58)	(3.38)	(3.39)	(3.61)	(3.89)	(2.87)
Average	6.56***	7.65***	8.75***	9.64***	11.11***	4.55**
	(1.99)	(2.03)	(2.25)	(2.42)	(2.91)	(1.78)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for 25 portfolios of firms that produce consumption goods, two-way sorted by their DMNS beta and IMC beta. Preranking return betas are calculated in a two-factor specification using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. The sample period is 1927M7–2019M12. Standard errors are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Excess Returns on DMNS Beta-Sorted Portfolios – One-Factor Specification

	DMNS Beta					
	Low	2	3	4	High	High–Low
Mean	5.83***	7.77***	8.84***	8.88***	11.19***	5.36***
	(1.54)	(1.75)	(2.10)	(2.44)	(2.72)	(2.02)
Volatility	14.80	16.84	20.22	23.47	26.15	19.47
Exposures						
R_{DMNS}	-0.07	0.22***	0.44***	0.66***	1.19***	1.25***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.04)
Δicl	-0.09*	-0.14**	-0.17***	-0.24***	-0.31***	-0.22***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.05)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for five portfolios of firms that produce consumption goods, sorted by their DMNS beta. Preranking return betas are calculated in a one-factor specification (without IMC) using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. Risk exposures are measured by univariate betas with respect to R_{DMNS} and Δicl. The sample period is 1927M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Excess Returns on DMNS Beta-Sorted Portfolios – All Firms

	DMNS Beta					
	Low	2	3	4	High	High–Low
Mean	5.70***	7.85***	8.70***	9.25***	10.51***	4.81***
	(1.73)	(1.78)	(2.14)	(2.42)	(2.68)	(1.71)
Volatility	16.67	17.16	20.62	23.31	25.78	16.44
Exposures						
R_{DMNS}	0.13*	0.28***	0.49***	0.72***	1.05***	0.92***
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.04)
Δicl	-0.17***	-0.17***	-0.22***	-0.27***	-0.31***	-0.14***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for five portfolios of firms that produce any type of goods, sorted by their DMNS beta. Preranking return betas are calculated in a two-factor specification using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. Risk exposures are measured by univariate betas with respect to R_{DMNS} and Δicl. The sample period is 1927M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.8: Excess Returns on DMNS Beta-Sorted Portfolios – All Non-Financial Industries

	DMNS Beta					
	Low	2	3	4	High	High–Low
Mean	5.58***	7.20***	9.34***	9.25***	10.85***	5.27***
	(1.53)	(1.63)	(1.92)	(2.21)	(2.63)	(1.92)
Volatility	14.69	15.63	18.45	21.27	25.30	18.50
Exposures						
R_{DMNS}	-0.05	0.10*	0.32***	0.52***	1.14***	1.19***
	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)
Δicl	-0.07	-0.10*	-0.13**	-0.19***	-0.30***	-0.23***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.05)

Notes: This table reports annualized moments of monthly returns in excess of the 30-day Treasury-bill rate for five portfolios of firms that produce consumption goods (including firms in the categories Utilities, Mining, and Petroleum Refining), sorted by their DMNS beta. Preranking return betas are calculated in a two-factor specification using weekly data and a window of five years. Portfolios are value weighted and are rebalanced monthly. Risk exposures are measured by univariate betas with respect to R_{DMNS} and Δicl. The sample period is 1927M7–2019M12; exposures are measured from 1967–2019. Standard errors are reported in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: Portfolio Cash Flow Exposures – Sort Within Industry

	Market	DMNS Beta					
		Low	2	3	4	High	High–Low
A. Summary Statistics							
Operating income growth							
Mean (%)	7.31	6.94	7.75	7.87	6.97	6.32	-0.62
Volatility (%)	4.44	5.16	4.49	4.08	5.32	12.41	12.86
Sales growth							
Mean (%)	6.84	7.07	7.20	7.77	6.47	5.76	-1.30
Volatility (%)	4.02	5.08	4.45	4.45	4.66	6.95	7.39
Dividend growth							
Mean (%)	6.54	5.87	8.04	6.07	9.63	1.80	-4.07
Volatility (%)	6.15	15.99	7.67	8.11	15.44	31.52	36.55
B. Operating Income Growth Exposures							
Δx	-0.16***	0.02	-0.05	-0.09**	-0.14**	-0.55***	-0.57***
	(0.04)	(0.05)	(0.03)	(0.04)	(0.06)	(0.10)	(0.10)
R^2	0.270	0.003	0.023	0.105	0.144	0.390	0.394
C. Sales Growth Exposures							
Δx	-0.11***	0.01	-0.03	-0.06	-0.08	-0.27***	-0.28***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
R^2	0.146	0.001	0.011	0.041	0.052	0.298	0.289
D. Dividend Growth Exposures							
Δx	-0.17***	0.06	-0.07	-0.03	-0.43	-0.82***	-0.88***
	(0.06)	(0.14)	(0.06)	(0.12)	(0.27)	(0.21)	(0.27)
R^2	0.151	0.003	0.017	0.002	0.150	0.132	0.113

Notes: This table reports summary statistics and exposures for annual operating income growth, sales growth, and dividend growth, as well as their univariate betas with respect to changes in income tail risk Δx, for the market portfolio and quintile portfolios by DMNS beta. The quintiles are computed within industry (30 Fama-French industries). Operating income is sales minus the cost of goods sold. Sales and cost of goods sold are from Compustat. Dividends are from CRSP. Portfolio cash flow growth from $t-1$ to t is measured by fixing the portfolio weights at the beginning of $t-1$. The sample period is 1967–2019. The results are expressed in percentage terms. Standard errors are reported in parentheses.

$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$