Nonfundamental Asset Price Fluctuations and the Distributional Origins of Asset Premia*

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Abstract

This paper studies how nonfundamental asset price fluctuations affect macroeconomic aggregates, inequality, household portfolios, and asset premia. To address this question, I estimate a heterogeneous-agent business cycle model with incomplete markets, portfolio choice, and nonfundamental asset price shocks using a Bayesian approach in the sequence space. The estimated model generates equity and term premia in line with the data. Half of the equity premium is due to fundamental macroeconomic shocks, and the other half is compensation for the risk of nonfundamental asset price fluctuations. Despite this fact, nonfundamental asset price shocks have limited effects on aggregate variables and standard inequality measures. I use the model to examine which risk factors shaped asset premia across different time periods and the impact of monetary policy on asset premia.

***Keywords*—** Incomplete Markets, Household Savings, Asset Pricing, Equity Premium

***JEL codes*—** D31, D52, E21, G12

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1 Introduction

Asset prices display substantial volatility, reflecting not only fluctuations in economic fundamentals but also variation in expected returns.[1] A prominent strand of the finance literature attributes this excess volatility to nonfundamental asset price movements driven by shifts in investor beliefs. These shifts may arise because traders form expectations under bounded rationality, because of misperceptions,[2] or because they operate with incomplete or dispersed information.[3] While recent research has begun to explore the macroeconomic implications of such nonfundamental fluctuations[4], their role in shaping household portfolios and driving risk premia is insufficiently understood.

This paper contributes to filling this gap by developing a quantitative heterogeneous-agent New Keynesian model with portfolio choice and nonfundamental asset price shocks in a segmented equity market. The model features a standard New Keynesian supply side, where firms and unions set prices and wages under monopolistic competition and nominal rigidities. Households face idiosyncratic income risk and have access only to incomplete markets. To insure against aggregate shocks, they invest in bonds of varying maturities, physical capital, and an equity fund, and demand risk premia as compensation for holding this portfolio. Individual equities, by contrast, are traded in a segmented financial market, where noise traders induce asset price volatility through demand based on fluctuating expectations about future returns or price changes. I estimate the model using Bayesian methods on macroeconomic and financial time-series data, allowing me to quantify how nonfundamental shocks affect aggregate variables, the wealth and income distribution, and households along the distribution.

I find that nonfundamental asset price shocks are empirically important not only for explaining asset price volatility, but also for shaping the level of asset premia. Given incomplete markets and heterogeneous household exposures, even moderately risk-

[1] I follow Cochrane (2011) and use "expected returns", "discount rates", and "risk premia" as synonyms. See Cochrane (2011) and Shiller (2014) for literature reviews on the importance of expected returns for explaining asset price fluctuations.

[2] Seminal papers that feature non-rational noise-traders are Kyle (1985), De Long et al. (1990), and Campbell and Kyle (1993). More recent applications of noise traders in exchange rate markets are by Gabaix and Maggiori (2015), Itskhoki and Mukhin (2021), Fukui, Nakamura and Steinsson (2023), and Itskhoki and Mukhin (2025), among others.

[3] Seminal contributions are Futia (1981) and Singleton (1986), but the idea of goes back to the statement of Keynes (1936) that asset markets behave like beauty contests. More recent applications to financial markets and exchange rates include Allen, Morris and Shin (2006), Bacchetta and Wincoop (2006), Rondina and Walker (2021), Caines and Winkler (2021), Angeletos and Huo (2021), and Angeletos, Lorenzoni and Pavan (2023), among others. See Angeletos and Lian (2016) for a review.

[4] Martin and Ventura (2012) and Miao and Wang (2018) study the impact of nonfundamental asset price fluctuations on investment, Gali (2014), Caballero and Simsek (2020), and Gali (2021) on consumption.

averse households demand substantial compensation for bearing both fundamental and nonfundamental risks. By construction, nonfundamental shocks account for all excess volatility in empirical returns, to which the model is estimated. The model attributes roughly two thirds of the empirical return volatility to nonfundamental sources. Although equity holders are typically well-insured due to high savings, they demand compensation for being exposed to this asset price risk. The model produces an equity premium of 4.92 percent per year, which is slighly below, but broadly consistent with empirical estimates. Nonfundamental fluctuations in equity prices play an important role in generating this sizable equity premium. 45 percent of the equity premium arises from exposure to nonfundamental asset price risk. That is, given the correlation structure of asset returns and the consumption of the typically rich equity investor, fundamental business cycle risk still contributes also half to the observed equity premium.

I also show that the model generates an average one-year term premium of 0.36 percent per year and a ten-year term premium of 1.77 percent per year, which both match the data closely. Importantly, the model's ability to generate both equity and term premia disappears when the assumption of incomplete markets is removed. This highlights that a largely standard heterogeneous-agent business cycle framework is not only well suited to capturing aggregate dynamics and inequality, but also capable of reproducing key features of financial markets, such as risk premia.

At the same time, the effects of nonfunamental asset price fluctuations on macroeconomic aggregates and inequality are significant but modest. The shock contributes 7.8 percent of the variance of consumption growth at the business cycle frequency, while technology shocks still explain the bulk of the variance. In terms of distributional consequences, the shock raises the value of wealth for households at the top of the distribution in response to positive fluctuations, thereby increasing inequality. Quantitatively, however, this effect is small: nonfundamental asset price shocks account for only 6.2 percent of the variance in the Gini coefficient of wealth.

Finally, I use the model to examine how time-varying risk factors that drive the macroeconomy shape asset premia and to examine the role of monetary policy. When reestimated for the post-Volcker and post-2000 periods, the model matches the empirical variation in asset premia. In line with the increased macroeconomic volatility during the first period, the model produces higher asset premia in this same period. Consequently, the model also provides a microfoundation for time-varying asset premia. When studying the effect of monetary policy on asset premia, I show that more hawkish monetary policy, in the sense of higher inflation targeting, increases asset premia. The estimated model allocates the largest share of the time-series variation in aggregates over the estimation period to supply-side shocks, such that more hawkish monetary policy reduces inflation volatility at the cost of higher macroeconomic volatility. Households demand a higher premium for exposure to greater macroeconomic risk.

The model builds on the one-asset framework of Auclert, Rognlie and Straub (2025), which I extend to incorporate household portfolio choice following Auclert et al. (2024). I embed this household block into the quantitative macroeconomic environment of Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007), and introduce a segmented equity market featuring nonfundamental asset price shocks in the spirit of De Long et al. (1990), where noise traders drive deviations from fundamental values.[5]

Financial markets are segmented because households do not directly trade individual stocks. Instead, they invest only in a stock market index. Asset prices arise from the interaction of three agents: rational traders, noise traders, and an index fund. Rational traders price equities based on fundamentals, while noise traders generate unpredictable shifts in demand, leading to deviations from the present discounted value of expected future dividends. The index fund aggregates stocks into a diversified portfolio and sells shares of it to households, thereby exposing them indirectly to aggregate asset price fluctuations driven by noise. Households face uninsurable idiosyncratic income risk and self-insure by choosing from a portfolio of eight assets: equity, physical capital, and government bonds of six different maturities. For each structural shock, I compute the premia households require for holding each asset, allowing me to quantify average asset premia and decompose them by risk source. On the production side, the model features standard New Keynesian frictions. Retail firms differentiate wholesale goods and set prices subject to nominal rigidities and partial inflation indexation. Wholesale firms accumulate capital under adjustment costs, while unions set wages under Calvo-style stickiness, also with partial indexation. The government finances its expenditures through taxes and by issuing bonds of varying maturities. Monetary policy follows a standard Taylor rule aimed at stabilizing inflation and output.

To clarify the intuition behind the key findings, consider first the role of the nonfundamental asset price shock. By construction, this shock captures all fluctuations in equity prices that are not driven by economic fundamentals. It is therefore unsurprising that it accounts for a substantial share of equity price volatility in the model. Why, then, do such shocks generate only limited aggregate fluctuations? Two mechanisms are central. First, equity comprises only about one fifth of total household assets. As a result,

[5] In addition to microfounding nonfundamental asset price fluctuations through noise traders, I derive alternative formulations based on incomplete information, which yield an identical reduced-form pricing equation.

even large movements in equity prices induce relatively modest changes in aggregate household wealth. Second, the aggregate marginal propensity to consume (MPC) out of total wealth is low, as high-wealth low-MPC households hold most of the wealth. As a result, fluctuations in asset values translate only weakly into changes in aggregate consumption. Together, these factors imply that although nonfundamental shocks drive asset price volatility, they have muted effects on macroeconomic aggregates such as consumption.

A similar logic applies to their limited role in explaining wealth inequality. While nonfundamental asset price shocks primarily affect wealthier households—who hold disproportionate shares of risky assets—their overall impact on the wealth distribution remains small. This is because the primary sources of redistribution in the model stem from shocks with broader macroeconomic consequences, such as TFP, investment-specific technology, and government expenditure shocks. As a result, nonfundamental shocks have limited power in shaping inequality dynamics relative to other sources of economic risk.

While nonfundamental asset price shocks have limited effects on aggregate variables, they play a central role in shaping asset risk premia. The computation of these premia follows the approach of Auclert et al. (2024), which adapts standard consumption-based asset pricing theory to linearized heterogeneous-agent economies. In this framework, assets that comove positively with the intertemporal marginal rate of substitution must offer higher expected returns to compensate for the risk they impose. This mechanism is particularly relevant for equity holders exposed to nonfundamental asset price risk. Such shocks generate large and persistent fluctuations in asset returns that disproportionately affect wealthy households, who hold the majority of equity. Although these households have low marginal propensities to consume out of wealth, the magnitude of return fluctuations leads to elevated consumption volatility—substantially higher than that of the aggregate. As a result, equity holders demand a premium for bearing this risk.

This paper contributes to four strands of the literature. First, it relates to the work that decomposes asset premia through the lens of estimated macroeconomic models. The seminal contribution by Bansal and Yaron (2004) introduces long-run risk into asset pricing and shows that it helps replicate observed equity premia. Hansen, Heaton and Li (2008) extend this idea by estimating a structural model with long-run risk and evaluating its ability to match asset price behavior. Rudebusch and Swanson (2012) similarly use an estimated macro-finance model to highlight the role of long-run risk in explaining term premia. Closely related, Schorfheide, Song and Yaron (2018) estimate a DSGE model with Epstein-Zin preferences and decompose the equity premium into short- and long-run risk components, as well as a time-varying risk premium arising from changes in volatility. While these studies provide valuable decompositions, they primarily distinguish risk by its persistence—short-run versus long-run—rather than by its structural economic source. This paper goes one step further by decomposing the equity premium into contributions from specific macroeconomic shocks, such as productivity, fiscal policy, and nonfundamental asset price fluctuations. In doing so, it provides a more granular understanding of the economic drivers behind risk premia. Moreover, the model offers a microfoundation for time-varying risk premia, as households' exposure to macroeconomic shocks endogenously determines the compensation they require in equilibrium.

Second, it contributes to the large body of work studying how heterogeneity shapes our understanding of business cycle drivers. Numerous papers have examined the responses of heterogeneous-agent models to monetary[6] and fiscal[7] policy. By contrast, relatively few contributions study the role of asset price fluctuations in heterogeneous-agent settings. J. Fernández-Villaverde and Levintal (2024) examine the response of a heterogeneous-agent economy to the disaster shock introduced by Barro (2006), but they do not incorporate demand-side determinacy, so the response reflects only the partial-equilibrium reaction of households to changes in returns. Angeletos and Calvet (2006) analytically derive an equilibrium with heterogeneous agents and fluctuating future returns under CARA preferences, but they abstract from Keynesian frictions and do not study heterogeneity in household responses. The present paper differs from these approaches by examining how asset price fluctuations affect a heterogeneous-agent economy with Keynesian frictions, allowing general equilibrium forces, particularly shifts in wages and interest rates, to shape the household-level response. Closest to my approach are Gong (2025a) and Auclert et al. (2024). Gong (2025a) studies the transmission mechanism of changes in asset prices through wealth effects in a heterogeneous agent economy. Calibrating the wealth effects to a realistic degree, he is able to replicate business cycle fluctuations for several recessions. I differ in my contribution by studying nonfundamental asset price shocks, and focus on asset premia. Auclert et al. (2024) builds on Devereux and Sutherland (2011) and provides the methodology

[6] Among others, see McKay, Nakamura and Steinsson (2016), Kaplan, Moll and Violante (2018), Auclert (2019), Bayer et al. (2019), Acharya and Dogra (2020), Bilbiie (2020), McKay and Wieland (2021), Luetticke (2021), Kekre and Lenel (2022), Acharya, Challe and Dogra (2023), Bayer, Born and Luetticke (2024), Auclert, Rognlie and Straub (2024), and Gong (2025b). See McKay and Wolf (2023) for a summary.

[7] Among others, see Kaplan and Violante (2014), McKay and Reis (2016), Bayer, Born and Luetticke (2022), Auclert, Bardóczy and Rognlie (2023), and Angeletos, Lian and Wolf (2024).

I adopt in the paper. However, I extend their framework by allowing for nine distinct assets instead of two and embedding the household block into a fully-specified quantitative macroeconomic environment. My estimation results show that, when applied in this richer setting, their methodology can generate sizable equity premia, contrary to the findings in their tractable HANK model.

Third, this paper relates to the large literature on asset price bubbles. While early work focuses on the theoretical possibility of bubbles,[8] more recent research explores the implications of bubbles for investment dynamics[9] as well as fiscal and monetary policy.[10] The present paper differs by focusing on how asset price fluctuations affect consumption rather than investment. Moreover, while most of the existing literature emphasizes the supply-side effects of bubbles, particularly their role in relaxing binding financial frictions, this paper emphasizes demand-side transmission channels. Within the bubble literature, Gali (2014) and Gali (2021) are closest in terms of transmission mechanisms. In their overlapping-generations model, asset price bubbles affect household wealth and thus consumption, which in turn drives aggregate demand. However, Gali (2021) features only stylized heterogeneity via the perpetual youth structure of Yaari (1965) and Blanchard (1985). In contrast, the present paper allows for rich household heterogeneity and therefore provides a more granular assessment of distributional and aggregate effects. Loosely related is also the contribution of Caballero and Simsek (2020), who introduce volatility shocks to asset returns in a New Keynesian model with households holding heterogeneous beliefs. While their model includes New Keynesian frictions, it features only limited heterogeneity, distinguishing just two household types.

Finally, this paper relates to the empirical literature on how asset price fluctuations affect the macroeconomy. Typically, the impact of economic shocks is analyzed empirically. However, because asset prices and real activity are jointly determined, and only few empirical studies examine how asset price changes affect the distribution of households,[11] we adopt a model-based approach instead. Chodorow-Reich, Nenov and Simsek (2021) provides some of the most recent evidence on the aggregate effects of asset price fluctuations. In response to a 20% national increase in stock market valuations, they document a 1.7% increase in local labor supply after two years. Our model-based approach also allows us to study the distributional and welfare consequences of asset price

[8] See Samuelson (1958), Tirole (1985), Abel et al. (1989), and Santos and Woodford (1997).

[9] See Farhi and Tirole (2011), Martin and Ventura (2012), Miao, Wang and Xu (2015), Miao and Wang (2018), Larin (2020), and Guerron-Quintana, Hirano and Jinnai (2023).

[10] See Diamond (1965), Domeij and Ellingsen (2018), and Angeletos, Collard and Dellas (2023) for contributions studying fiscal policy, and Kiyotaki and Moore (2019), Asriyan et al. (2020), and Angeletos, Lorenzoni and Pavan (2023) on monetary policy.

[11] Chodorow-Reich, Nenov and Simsek (2021) reviews some of these contributions.

fluctuations. This links our work to studies such as Kuhn, Schularick and Steins (2020) and Cioffi (2021), which examine how asset prices affect the income and wealth distribution, as well as Fagereng et al. (2025), who investigates the welfare implications of asset price changes.

The remainder of the paper is organized as follows: Section 2 presents the model, Section 3 discusses the calibration and the Bayesian estimation of the model. Section 4 decomposes the equity premium and explains it through household heterogeneity. Section 5 studies the impact of the asset price shocks on macroeconomic aggregates and inequality. Section 6 uses the model to examine asset premia across different periods and the impact of monetary policy on them. Finally, section 7 concludes.

2 HANK Model with Nonfundamental Asset Price Shocks

This section presents a heterogeneous-agent New Keynesian (HANK) model that incorporates household portfolio choice, segmented financial markets, and nonfundamental asset price fluctuations. Households choose between equity, capital, and government bonds of varying maturities to self-insure against idiosyncratic income risk and to hedge exposure to aggregate shocks. Risk premia arise endogenously as households demand premia in compensation for utility fluctuations induced by macroeconomic risk. The financial sector features a segmented equity market for individual equities as households can only trade in an equity fund. Fundamental traders interact with noise traders such that equilibrium asset prices feature fluctuations unrelated to fundamentals. These nonfundamental fluctuations are transmitted to households indirectly through an index fund that intermediates between traders and household investors. The model embeds this financial structure into a quantitative general equilibrium framework with standard New Keynesian frictions in pricing, capital adjustment, and wage setting, following Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007). The government issues bonds of different maturities and conducts fiscal policy through taxes and spending, while monetary policy follows a standard Taylor rule.

2.1 Nonfundamental Asset Price Shocks in the Equity Market

The equity market model[12] builds on De Long et al. (1990) and Gabaix and Maggiori (2015). The market is segmented in the sense that households do not trade individual equities directly, but instead invest exclusively in an equity index fund. Three types of

[12] In Appendix I, I derive an alternative formulation based on incomplete information that yields the same reduced-form equilibrium asset price.

agents operate in the equity market: fundamental traders, noise traders, and an equity fund that intermediates between them and households. I assume a unit continuum of traders indexed by $l \in [0,1]$, of which a measure ν are fundamental traders ($l \in [0,\nu]$) and a measure $1-\nu$ are noise traders ($l \in (\nu,1]$). All traders live for two periods: they purchase a portfolio of assets in the first period and earn returns in the second. Since traders are owned by the equity fund, they finance their purchases with revenues collected from household investments and return profits to the fund, which are ultimately passed on to households. Both types of traders trade a continuum of individual equities indexed by $j \in [0,1]$, each issued by a retail firm. Individual equity prices are determined in equilibrium through market clearing. The index fund aggregates these equities into a diversified portfolio and sells shares of the fund to households.

Fundamental Traders: Each fundamental trader is risk-neutral[13], derives utility from the profits of their equity portfolio, discounts the future at the risk-free rate $1+r_{t+1}$, and incurs quadratic disutility from monitoring firm-specific fundamentals, which increases with the size of the trader's net position. Each fundamental trader $l \in [0,\nu]$ chooses a portfolio allocation $\{\theta_{ljt}\}_{j\in[0,1]}$ to maximize utility U_{lt}:

$$U_{lt} = \max_{\{\theta_{ljt}\}} \int_0^1 \left[-q^{eq}_{jt}\theta_{ljt} + \mathbb{E}_t \left(\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}} \right) \theta_{ljt} - \frac{1}{2}\theta^2_{ljt} \right] dj,$$

where d_{jt} and q^{eq}_{jt} denote the dividend and price of equity j, respectively. The functional form yields a linear demand schedule for each equity:

$$\theta_{ljt} = -q^{eq}_{jt} + \mathbb{E}_t \left[\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}} \right] \quad \forall\, l \in [0,\nu]. \tag{1}$$

Noise Traders: Noise traders represent the second group of market participants. Unlike fundamental traders, their investment behavior is unrelated to economic fundamentals. This may reflect behavioral motives or non-rational stock-picking strategies. Specifically, the demand of each noise trader for stock j is given by:

$$\theta_{ljt} = \tilde{\xi}_t + \epsilon^{\theta}_{ljt},$$

where $\tilde{\xi}_t$ is an aggregate noise-trader demand component and ϵ^{θ}_{ljt} is an idiosyncratic, iid shock to the noise trader–stock j demand.

[13] I can also integrate limits to arbitrage by assuming that fundamental traders are risk averse according to a CARA utility function as in De Long et al. (1990), or Bacchetta and Wincoop (2006).

Equity Fund: The equity fund intermediates between households and traders. It finances trader purchases using household contributions, collects dividend and capital gains from traders' equity holdings, and distributes the resulting returns back to households. The fund aggregates all equities into a single index, which households can invest in. The price of the index fund equals the average price of the underlying equities and pays the average of the underlying dividends:

$$q_t^{eq} = \int_0^1 q_{jt}^{eq} dj, \qquad d_t = \int_0^1 d_{jt} dj.$$

Equilibrium Asset Prices: In equilibrium, the aggregate demand for each equity must equal its supply (normalized to one), implying: $\int_0^1 \theta_{ljt} dl = 1$. In Appendix I I illustrate that this market-clearing condition implies that the price of equity j is:

$$q_{jt}^{eq} = \mathbb{E}_t \left[\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}} \right] + \xi_t, \tag{2}$$

where the effective asset price shock is defined as $\xi_t \equiv \frac{(1-\nu)\tilde{\xi}_t - 1}{\nu}$, and follows an AR(1) process $\xi_t = \rho_q \xi_{t-1} + \epsilon_t^q$ where $\epsilon_t^q \sim \mathcal{N}(0, \sigma_q^2)$. This formulation makes the role of non-fundamental fluctuations explicit and facilitates their estimation. In a symmetric equilibrium where all equities are identical,[14] the aggregate index fund price is:

$$q_t^{eq} = \mathbb{E}_t \left[\frac{d_{t+1} + q_{t+1}}{1 + r_{t+1}} \right] + \xi_t. \tag{3}$$

Hence, noise trader demand shifts the entire equity price level upward, increasing the valuation of the market even when fundamentals remain unchanged.

2.2 Household Sector with Portfolio Choice and Asset Pricing

The household side of the model combines a standard consumption–savings problem under idiosyncratic income risk with portfolio choice to hedge against aggregate fluctuations. Households earn net labor income, accumulate assets to self-insure against idiosyncratic shocks, and allocate their portfolios across available assets to mitigate exposure to aggregate risk.

Idiosyncratic Risk: There is a continuum of households indexed by $i \in [0, 1]$, which are ex-ante identical but differ ex-post due to uninsurable idiosyncratic risk in their

[14] I assume that all retail firms are symmetric. As a result, their equities have identical payoffs, which implies by equation (2) that equity prices are also identical. Thus, all equities are identical.

labor efficiency e_{it} and their patience, captured by their discount factor $\tilde{\beta}_{it}$. A Markov Chain describes the transitions between an individual state $(e_{it}, \tilde{\beta}_{it})$ and any other state $(e_{it+1}, \tilde{\beta}_{it+1})$. I assume that the labor productivity and discount factor processes are independent and the mass of agents in each state is always equal to the mass in the stationary distribution. I assume that there are two realizations of the discount factor: a high discount factor β^H for patient households and a low discount factor $\beta^L = \beta^H - \Delta^\beta$ for relatively impatient households. Each period, with probability ϖ a household obtains a new draw of the discount factor, where the probability for transmitting into either of the two patience states is equal to the stationary distribution of the respective states $(\omega, 1-\omega)$, where ω denotes the fraction of patient households in the stationary distribution economy. Finally, I normalize the cross-sectional mean of labor productivity to unity.

Household problem: Households can save in $K+1$ assets, subject to a zero-borrowing constraint on their total portfolio wealth, and earn labor income, which is taxed at a rate τ_t. Households have Epstein-Zin preferences over their felicity from consumption c_{it} and labor n_{it}. $1/\rho$ denotes the intertemporal elasticity of substition and γ denote the risk-aversion parameter of households. Households have King, Plosser and Rebelo (1988) utility and obtain utility from consumption, but dislike supplying labor n_{it}, where $v(\cdot)$ quantifies their disutility. The problem of household i in period t, with idiosyncratic income productivity e_{it}, idiosyncratic discount factor β_{it}, and with portfolio holdings $\{a_{it}^k\}_{k=0}^K$, where a_{it}^k denotes their portfolio holding of asset $k \in [0, 1, ..., K]$ is given by:

$$V_{it} = \max_{\{c_{it}, n_{it}, \{a_{it}^k\}_{k=0}^K\}_{t=0}^\infty} \left((1-\beta_{it}) \left(c_{it} e^{-v(n_{it})} \right)^{1-\rho} + \beta_{it} \left(\mathbb{E}_t \left[V_{it+1}^{1-\gamma} \right] \right)^{\frac{1-\rho}{1-\gamma}} \right)^{\frac{1}{1-\rho}} \tag{4}$$

$$\text{s.t.} \quad c_{it} + \sum_{k=0}^K q_t^k a_{it}^k \leq \sum_{k=0}^K \left(q_t^k + x_t^k \right) a_{it-1}^k + e_{it}(1-\tau_t) w_t n_{it}, \tag{5}$$

$$\text{and} \quad \sum_{k=0}^K q_t^k a_{it}^k \geq 0. \tag{6}$$

The household's time-varying discount factor is defined as $\beta_{it} \equiv \tilde{\beta}_{it} \zeta_t$, where $\tilde{\beta}_{it}$ is the idiosyncratic component, and ζ_t is an aggregate discount factor shock. The aggregate component ζ_t evolves according to a log-linear AR(1) process with persistence ρ_ζ and innovation $\epsilon_\zeta \sim \mathcal{N}(0, \sigma_\zeta^2)$. In the household budget constraint (5), q_t^k and x_t^k denote the price and payoff of asset k, respectively. Households allocate wealth across a menu of nine assets: equity, capital, and government bonds with seven different maturities.

The pre-tax real wage per unit of efficient labor is denoted by w_t; however, individual households do not choose their own hours worked; instead, labor supply is determined collectively by unions in response to current labor demand.

Representative Agent Benchmark: I also solve a version with a representative household. The household faces the same maximization problem as in equations (4–6), but with homogeneous labor income $e_{it} = 1$ and a common, time-varying discount factor $\beta_{it} = \beta_t$.

Solving for Optimal Portfolios and Risk Premia: I solve the model using the sequence-space approach of Auclert et al. (2021), modeling aggregate shocks as first-order "MIT shocks": the economy is perturbed by unanticipated shocks at date $t = 0$, after which all future periods evolve under perfect foresight. In this deterministic environment all assets yield equal expected returns from period $t > 0$ onward, rendering households locally indifferent across assets and leaving portfolio choice indeterminate. However, at $t = 0$, realized shocks induce variation in ex-post returns, making the portfolio problem well-defined. Auclert et al. (2024) build on Tille and Wincoop (2010) and Devereux and Sutherland (2011) and develop a method to recover optimal portfolio allocations and associated risk premia in this setting. A full illustration of the method is provided in Appendix II. Below, I offer a brief overview of the intuition and key equations.

The core idea is that households, anticipating the economy's response to aggregate shocks, know their utility exposure to aggregate shocks and how asset returns change in period 0. Given this information, households take asset positions in period -1 to hedge against utility fluctuations. By imposing market clearing across all assets, the method jointly determines equilibrium portfolio positions, household exposure to aggregate risk, and the corresponding risk premia that compensate households for bearing this risk.

Portfolio Choice: This section describes how households choose asset holdings a_i^k across $K+1$ assets in a linearized environment. Let $\boldsymbol{\epsilon}$ be the vector of Z aggregate shocks, let $R^k(\boldsymbol{\epsilon})$ denote the state dependent gross return on asset k, and let $W_i \equiv \left(\mathbb{E}_t[V_{it}^{1-\gamma}]\right)^{\frac{1}{1-\gamma}}$ denote the value function after integrating out idiosyncratic income risk. Assuming that portfolio constraints do not bind, the optimal choice between asset k and a reference asset 0 is characterized by

$$\sum_{z=1}^{Z} \left(\frac{\partial \log R^k(\boldsymbol{\epsilon})}{\partial \epsilon_z} - \frac{\partial \log R^0(\boldsymbol{\epsilon})}{\partial \epsilon_z} \right) \frac{\partial \log W_i'}{\partial \epsilon_z} \;=\; b^k, \tag{7}$$

where the summation represents the expectation over aggregate shocks in the linearized environment, primes indicate derivatives, and b^k corresponds to the negative of the premium on asset k relative to asset 0. Equation (7) states that households choose portfolios so that, in expectation, the product of marginal utility and the return differential does not fluctuate after aggregate shocks.

Auclert et al. (2024) show that in a linearized economy, if there are at least as many linearly independent assets as aggregate shocks ($K \geq Z$), asset markets are complete with respect to aggregate risk. Market completeness means that, through trade in assets, all households share the same exposure of marginal utility to each shock:

$$\frac{d \log W_i'}{d\epsilon_z} = \lambda_z \quad \forall i. \tag{8}$$

In equilibrium, risk sharing is limited because market clearing and the limited willingness of other households to absorb risk prevent full insurance. As a result, households bear residual aggregate risk with exposures λ_z that are pinned down by the distribution across households of marginal utility responses to aggregate shocks.

For my quantitative application, I allow households to choose portfolios that deliver the risk sharing allocation characterized by equation (8), subject to market clearing. In equilibrium, the households that hold positive net positions in an asset are those that, before portfolio rebalancing in anticipation of shocks, are least affected in utility terms by the aggregate shocks that move the asset's return.[15] Examining how these net holders respond to a shock will later be useful to clarify the residual exposure to the aggregate risk that they bear. My assumption that portfolio constraints do not bind may overstate the degree of insurance households can obtain and understate the required compensation for risk. This implies that the model's implied risk premia represent a lower bound.[16]

Risk Premia: Because households cannot fully insure against aggregate risk, they demand a premium for bearing residual aggregate exposures. The methodology provides

[15] Note that these households still benefit from trading because the exchange of state contingent payoffs shifts income toward states where their marginal utility is high and away from states where it is low.

[16] Auclert et al. (2024) show how to compute constrained optimal portfolios in the case of two assets. Extending this to settings with more assets, such as the nine asset setup considered here, is more challenging. They note that imposing portfolio constraints tends to push results toward those implied by exogenous portfolio rules, for example constant shares, typically increasing the level of risk premia while reducing the extent of endogenous insurance. Importantly, they find limited effects on aggregate dynamics. Consequently, my estimates for risk premia are likely lower bounds, since portfolio restrictions would raise them.

a closed form approximation for the average risk premia that households demand.[17] For any asset k, its premium relative to the reference asset 0 is approximately

$$\frac{R^k(\sigma) - R^0(\sigma)}{R} \approx -\sum_{z=1}^{Z} X_{zk} \lambda_z \overline{\sigma}_z^2 \sigma^2 = -b^k, \tag{9}$$

where X_{zk} measures the sensitivity of asset k's return to shock z, and λ_z captures the average exposure of marginal utility from equation (8). Together, X_{zk} captures how payoffs load on shocks and λ_z captures the equilibrium exposure of marginal utility, so the premium reflects both the asset sensitivity and the degree of risk sharing. This reflects the standard consumption based asset pricing logic: risk premia arise when asset returns covary negatively with marginal utility. Assets that deliver low returns in states where marginal utility is high must offer a premium as compensation for poor consumption insurance. Since λ_z depends on the distribution of marginal utility responses across households, risk premia are also shaped by the heterogeneity of aggregate risk exposures.

Finally, since the risk premium is additively separable across shocks, I can compute the contribution of each shock z to an asset's total premium as

$$\Omega_{k,z} = \frac{X_{zk} \lambda_z \overline{\sigma}_z^2}{b^k}. \tag{10}$$

This decomposition makes it possible to identify which shocks drive asset premia.

In summary, the approach provides a tractable and powerful way to compute endogenous portfolio allocations and risk premia in heterogeneous agent models using only first order impulse responses and static model primitives, without solving the full second order model.

2.3 New Keynesian Firm Sector

We assume a three-tier production structure with a representative wholesale producer, a continuum of retailers, and a final goods producer. The wholesale producer creates a homogeneous wholesale good that is differentiated by retailers into a specific variety. The final goods producer bundles differentiated varieties into the final good. The wholesale firm accumulates capital subject to investment adjustment costs, while retailers set

[17] Asset premia depend on the stochastic structure of the economy, which is time invariant under a first order solution. Hence, I can only evaluate average premia over the estimation periods. In a counterfactual exercise, I reestimate the model for two different periods to study how changes in the volatility and persistence of shocks affect premia.

the prices of their product subject to a Calvo (1983) adjustment friction.

Final goods firm: The final goods firm bundles all j varieties using a Dixit-Stiglitz aggregator

$$Y_t = \left(\int_0^1 Y_{jt}^{\frac{1}{\mu_t^p}} \, dj \right)^{\mu_t^p} \tag{11}$$

with elasticity of substitution between varieties of $\mu_t^p/(\mu_t^p - 1) > 1$. We assume that μ_t^p follows a log-AR(1) process with persistence ρ_p and shocks $\epsilon_t^p \sim N(0, \sigma_p^2)$ around the mean of the steady state price markup μ_p. Cost minimization of the final goods producer yields demand Y_{jt} for the individual variety j as

$$Y_{jt} = \left(\frac{P_{jt}}{P_t} \right)^{-\mu_t^p/(\mu_t^p - 1)} Y_t, \tag{12}$$

where P_{jt} is the price of the individual variety j is offered at and $P_t = \int_0^1 \left(P_{jt}^{\frac{1}{1-\mu_t^p}} \, dj \right)^{1-\mu_t^p}$ denotes the aggregate price level.

Retail firms: There exists a unit interval of j monopolistically competitive retail firms. Each retail firm buys a homogeneous wholesale good from the wholesale firm at the price mc_t and costlessly differentiates the good into a variety j, for which the producer is a monopolist. As a result of monopolistic competition, each retailer generates a profit which it distributes to equity holders. Each retail firm sets the price for the variety P_{jt} subject to a Calvo (1983) adjustment friction with indexation of prices. Retailers that are unable to re-optimize during the period adjust their price according to the following indexation rule:

$$P_{jt} = P_{jt-1} \Pi_{t-1}^{\iota_p} \Pi^{1-\iota_p}, \tag{13}$$

where Π is the steady state inflation rate, and ι_p reflects the degree of indexation to lagged aggregate inflation Π_{t-1}. For retail firms able to re-optimize, the optimization is to choose a new reset price P_{jt}^* to maximize expected discounted profits until the next re-optimization, given by

$$\mathbb{E}_t \sum_{s=0}^{\infty} \lambda_p^s \bar{\beta}^s \left(\frac{P_{jt}^* \Gamma_{t,t+s}}{P_{t+s}} - mc_{t+s} \right) Y_{jt+s} \tag{14}$$

subject to demand by the final goods producer (12) and $\Gamma_{t,t+s} = \prod_{k=1}^{s} \Pi_{t+s-1}^{\iota_p} \Pi^{1-\iota_p}$. λ_p denotes the probability not to adjust the price in a given period and $\bar{\beta}$ denotes the average discount factor of households.[18] The corresponding first-order condition for price setting implies a Phillips curve,

$$\log(\Pi_t) = \frac{\bar{\beta}}{1+\bar{\beta}\iota_p}\mathbb{E}_t \log(\Pi_{t+1}) + \frac{\iota_p}{1+\bar{\beta}\iota_p}\log(\Pi_{t-1}) + \kappa_p\left(mc_t - \frac{1}{\mu^p}\right) + \mu_t^p, \tag{15}$$

where the slope of the Phillips curve is given by $\kappa_p = \frac{1-\lambda_p\bar{\beta}}{1+\iota_p\bar{\beta}}\frac{1-\lambda_p}{\lambda_p}$. I assume a symmetric equilibrium in which aggregate profits in the economy are $d_t = (1-\frac{1}{\mu_t})Y_t$. These profits are distributed to the owners of shares in the retail firms that are traded at the price q_t.

Wholesale firm: Wholesale goods are produced by a representative wholesale firm using labor and capital:

$$Y_t = Z_t K_{t-1}^{\alpha} N_t^{1-\alpha}, \tag{16}$$

where α is the capital share in production, Z_t is total factor productivity that follows a log AR(1) process with persistence ρ_Z and shocks $\epsilon_t^Z \sim N(0,\sigma_Z^2)$, N_t is the labor hired, and K_{t-1} is the capital stock owned by the wholesale firm. Capital accumulates within the firm subject to investment adjustment costs, so that for each unit invested, a firm has to pay the adjustment cost.

$$S\left(\frac{I_t}{I_{t-1}}\right) = \frac{1}{2\chi}\left(\frac{I_t}{I_{t-1}} - 1\right)^2, \tag{17}$$

where $1/\chi$ is the curvature of the function. Moreover, I allow for shocks to the marginal productivity of investment Ψ_t, such that the capital accumulation equation for the wholesale firm is

$$K_t = (1-\delta)K_{t-1} + \Psi_t\left[1 - S\left(\frac{I_t}{I_{t-1}}\right)\right] I_t, \tag{18}$$

where δ is the depreciation rate of capital. I assume that Ψ_t follows a log AR(1) process with persistence ρ_i and shocks $\epsilon_t^i \sim N(0,\sigma_i^2)$. The wholesale firm is perfectly competitive and takes the real wholesale price mc_t and real wage w_t as given, selling all output. In this setting, the wholesale firm entering period t with capital K_{t-1} and past investment I_{t-1} chooses the amount of labor N_t, capital K_t, and investment I_t to maximize its value:

$$J_t(K_{t-1}, I_{t-1}) = \max_{K_t, I_t, N_t} mc_t F(K_{t-1}, N_t) - w_t N_t - I_t + \mathbb{E}_t\left[\frac{1}{1+r_{t+1}} J_{t+1}(K_t, I_t)\right] \tag{19}$$

[18] I need to make an assumption about the discount rate with which firms discount future events. Here, I follow Auclert, Rognlie and Straub (2025) and choose the average discount factor in the economy. The average discount factor is the values of the discount factors of households multiplied by the stationary distribution of the Markov Chain that determines the idiosyncratic fluctuations in β_{it}.

subject to the capital accumulation equation (18). $1 + r_t$ is the gross real interest rate on assets. The optimization problem implies the standard first-order condition for labor demand $w_t = (1-\alpha) mc_t Z_t \left(\frac{K_{t-1}}{N_t}\right)^{\alpha}$, as well as the expression for Tobin's Q and the firm's investment decision:

$$Q_t = \mathbb{E}_t \left[\frac{1}{1+r_{t+1}} \left((1-\delta) Q_{t+1} + \alpha MC_{t+1} Z_{t+1} \left(\frac{K_t}{N_{t+1}} \right)^{\alpha-1} \right) \right] \tag{20}$$

$$1 = \Psi_t Q_t \left[1 - S\left(\frac{I_t}{I_{t-1}}\right) - S'\left(\frac{I_t}{I_{t-1}}\right) \frac{I_t}{I_{t-1}} \right] + \mathbb{E}_t \left[\frac{\Psi_{t+1} Q_{t+1}}{1+r_{t+1}} S'\left(\frac{I_{t+1}}{I_t}\right) \left(\frac{I_{t+1}}{I_t}\right)^2 \right] \tag{21}$$

Unions: Nominal wages are assumed to be sticky. As in Erceg, Henderson and Levin (2000), unions set nominal wages to maximize agent utility subject to adjustment costs. I adopt the microfoundations for nominal wage rigidities of staggered pricing as in Calvo (1983). I assume that the unions that are not able to adjust their price optimally adjust it following an indexation rule. Finally, I specify the disutility of labor as $v(n_{it}) = \gamma \frac{n_{it}^{1+\frac{1}{\phi}}}{1+\frac{1}{\phi}}$. I assume that unions allocate all labor hours uniformly across agents, so that $n_{it} = N_t$. This leads to the wage Phillips curve:

$$\begin{aligned} \log(\Pi_t^w) = & \frac{\bar{\beta}}{1+\bar{\beta}\iota_w} \mathbb{E}_t \log(\Pi_{t+1}^w) + \frac{\iota_w}{1+\bar{\beta}\iota_w} \log(\Pi_{t-1}^w) \\ & + \kappa_w \left(\gamma N_t^{\frac{1}{\phi}} - \frac{(1-\tau) w_t \int_0^1 e_{it} c_{it}^{-1/\sigma} di}{\mu^w} \right) + \mu_t^w, \end{aligned} \tag{22}$$

describing the dynamics of log-wage inflation Π_t^w as a function of aggregate hours N_t, aggregate posttax labor income $(1-\tau)w_t$, and the effective consumption aggregator $\int_0^1 e_{it} c_{it}^{-1/\sigma} di$ that measures how the consumption distribution affects the wealth effect on labor supply. μ_t^w follows a log-AR(1) process with coefficient ρ_w and shocks $\epsilon_t^w \sim N(0, \sigma_w^2)$.

2.4 Government Sector

The government sector consists out of a fiscal authority and a monetary authority.

Fiscal Authority: Fiscal policy sets the tax rate τ_t on dividends and labor, spends G_t on goods, and issues non-contingent debt B_t, with an average return R_{t-1}^F. Since the overall tax revenue is $\tau_t w_t N_t$, the government budget constraint is given by

$$B_t = R_{t-1}^F B_{t-1} + G_t - \tau_t w_t N_t \tag{23}$$

We assume that fiscal policy is specified in terms of plans for government spending G_t which follows a log-AR(1) process with persistence ρ_G and shocks $\epsilon_t^G \sim N(0, \sigma_G^2)$ and a tax rule:

$$\frac{\tau_t}{\tau^{ss}} = \left(\frac{\tau_{t-1}}{\tau^{ss}}\right)^{\rho_\tau} \left(\frac{B_{t-1}}{B_{t-2}}\right)^{(1-\rho_\tau)\gamma_\tau^B} \left(\frac{Y_t}{Y_{t-1}}\right)^{(1-\rho_\tau)\gamma_\tau^Y}, \tag{24}$$

where ρ_τ denotes the persistence of the tax rate, γ_τ^B denotes the elasticity of the tax rate to lagged debt growth, and γ_τ^Y denotes the elasticity of the tax rate to output growth. Given a real interest rate, the tax rule and the government budget constraint imply a process for bonds B_t.

Bond Maturity Structure: I model government debt instruments with a range of maturities. To incorporate different maturities in a tractable fashion, I follow Bayer, Born and Luetticke (2022) and assume that along all maturities the bonds are zero-coupon bonds with geometrical decay.[19] The bonds are priced recursively, and their ex-post returns contribute to the weighted average fiscal interest rate R_{t-1}^F the government has to pay to households.

Let q_t^n denote the price of a government bond at time t with maturity n and R_{t-1}^n denote the ex-post return of a bond. The price of each bond is set by a no-arbitrage condition and the ex-post return by definition:

$$q_t^n = \frac{(1-\delta^n)q_{t+1}^n + 1}{1 + r_{t+1}}, \quad \text{and} \quad R_{t-1}^n = \frac{(1-\delta^n)q_t^n + 1}{q_{t-1}^n} \quad \forall n \tag{25}$$

δ^n denotes the maturity-specific retirement rate of the bond and r_t is the risk-free real interest rate. The government pays the weighted average of the ex-post returns R_{t-1}^F across maturities:

$$R_{t-1}^F = \sum_n \omega_t^n \cdot R_t^n \quad \text{with} \quad \sum_n \omega_t^n = 1 \tag{26}$$

where ω_t^n denotes the share of government debt issued in maturity n at time t. This composite rate captures the average cost of servicing outstanding government debt, taking into account the maturity composition of the debt portfolio.

[19] This assumption makes the price and the ex-post return of long-term bonds more exposed to more persistent shocks. This feature helps to match the empirical fact that the price of long-run bonds fluctuate more in response to shocks as either their cash-flows or their discount rates are affected by the shock.

Monetary Policy: Monetary policy sets the nominal interest rate i_t, using the following Taylor rule:

$$1 + i_t = (1 + i_{t-1})^{\rho_r} \Pi_t^{(1-\rho_r)\phi_\pi} \left(\frac{Y_t}{Y_{t-1}} \right)^{(1-\rho_r)\phi_Y} \exp(\epsilon_t^r) \tag{27}$$

where ρ_r denotes the persistence of the monetary policy rule, ϕ_π and ϕ_Y denote the elasticities of the nominal interest rate to inflation and output growth, and $\epsilon_t^r \sim N(0, \sigma_r^2)$ is an iid monetary policy innovation. Finally, I define the ex-ante real interest rate as $1 + r_t = (1 + i_t)/\Pi_{t+1}$ according to a Fisher equation.

2.5 Market clearing

In equilibrium, the goods market, the labor market, as well as the asset market, have to clear:

$$Y_t = \int c_{it} di + I_t + G_t \qquad \int_0^1 n_{it} dj = N_t \qquad \int a_{it} di = B_t + q_t^{eq} + J_t. \tag{28}$$

We assume that all firms are symmetric such that $Y_{jt} = Y_t$, $d_{jt} = d_t$, $w_{jt} = w_t$, and $d_{jt} = d_t$.

3 Calibration and Estimation of the Model

This section illustrates the calibration of the steady state and the estimation of the model on U.S. time-series data. First, I calibrate the model to replicate key dimensions of household heterogeneity, and match time-series averages of aggregate variables. Thereafter, I illustrate the Bayesian estimation on U.S. time-series data, illustrate the estimation results and their validity.

3.1 Calibration of the Steady State

Table 1 portrays the parameters used in the calibration. The parameter choices of the household side largely follows Auclert, Rognlie and Straub (2025). To start with, the exogenous income process is the discretized permanent-transitory income process of Kaplan, Moll and Violante (2018), based on their estimates from the Social Security Administration data. I assume standard intertemporal elasticities of substitution and labor supply equal to one and calibrate the disutility from labor γ to normalize labor supply $N_t = 1$. Moreover, I set the risk-aversion parameter equal to 6 as in Guvenen (2009). This parameter value is between the commonly used value of 10 in the finance literature and the commonly used value of 1 when using CRRA preferences in macro models.

Next, I calibrate the heterogeneity in discount factors to match key moments from U.S. household microdata. I jointly choose the patient discount factor β^H, the gap Δ^β between patient and impatient types, and the stationary share of patient households ω to match aggregate assets, to target an aggregate marginal propensity to consume out of labor income of 0.10 per quarter, and to minimize the distance between the model implied wealth Lorenz curve and its U.S. counterpart.[20] The probability of a patience redraw ϖ follows Krusell and Smith (1997) by matching the arrival of a new generation every 25 years.

The left panel of figure 1 compares the model-implied Lorenz curve with the empirical curve from the 2019 Survey of Consumer Finances. The overall fit is close, but the model understates wealth concentration at the very top, as is common in models without capital income heterogeneity. The right panel of figure 1 plots the model's aggregate intertemporal marginal propensities to consume. While I target an impact MPC out of labor income of 0.10 all other MPCs are untargeted. In line with estimates from microdata, the model's intertemporal MPCs are large on impact and then decline quickly. The untargeted MPC out of capital income is 0.01, which lies at the lower end of the empirical range 0 to 0.05 reported by Chodorow-Reich, Nenov and Simsek (2021).

I set the values of the firm and government sector to match time-series averages from U.S. national accounts. I provide a detailed description of the data used and the calculations in Appendix III. First, I set TFP Z_t so that output is normalized to one. I set α so as to target a quarterly capital-to-output ratio of 11.9 with a depreciation rate of $\delta = 1.775$ percent, consistent with time-series averages for the periods considered. The markup μ^p is chosen to generate a quarterly stock market-to-GDP ratio of $q_t/Y_t = 3.9$, consistent with historical averages. I assume that the wage markup equals $\mu^w = 1$, such that there are no union transfers in steady state. I set government expenditure equal to 21.1% of GDP and total government debt equal to 1.7 times quarterly GDP, corresponding to an annual debt-to-GDP ratio of 42.5%, both reflecting historical averages. The quarterly risk-free real interest rate is set at 1.0%, in line with the U.S. postwar average. The labor tax rate τ is set to 0.309 in order to balance the government's budget constraint.

To calibrate the maturity structure of government debt, I use historical averages from the database of De Graeve and Mazzolini (2023), which reports debt values at constant maturities for many OECD countries. First, I take the averages of the market value

[20] I target a lower quarterly MPC than Auclert, Rognlie and Straub (2024), since Orchard, Ramey and Wieland (2025) provide recent evidence that MPC estimates for nondurable consumption are below 0.2 per quarter.

Table 1 Calibration Details (Quarterly Frequency)

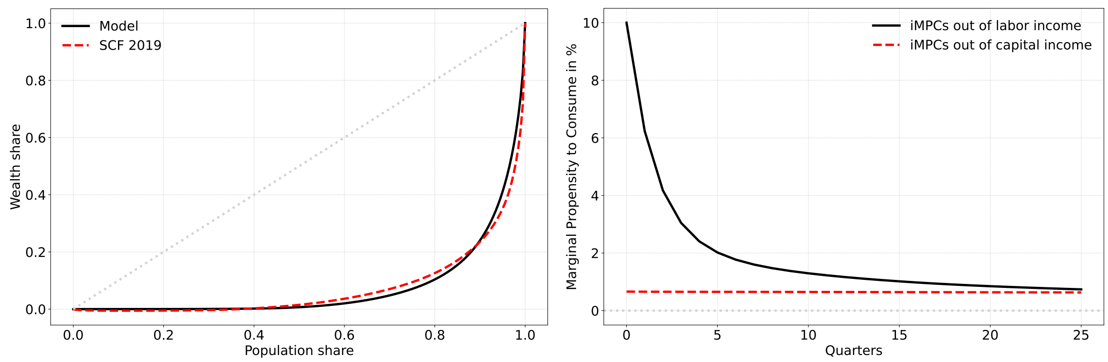
Parameter	Value	Description	Source / Target
Preferences			
σ	1.000	Elasticity of intertemporal sub.	Standard value
γ	6.000	Risk aversion	Guvenen (2009)
γ	0.787	Disutility from labor	Labor normalization
ϕ	1.000	Frisch elasticity of labor	Standard value
Idiosyncratic risk			
β^H	0.996	Discount factor patient HHs	Total Assets: 18.0
Δ^β	0.010	Difference discount factors	Aggregate MPC: 0.1
ω	0.635	Fraction of patient HHs	U.S. Lorenz Curve of wealth
ϖ	0.010	Prob. to change patience	Krusell and Smith (1997)
Firms			
Z	0.501	Steady state productivity	Output Normalization
α	0.286	Capital income share	Capital-to-Output: 11.9
δ	0.018	Capital depreciation	Historical Average from NIPA
μ^p	1.020	Price Markup	Equity-Price-to-Output: 3.8
μ^w	1.000	Wage Markup	No transfers in steady state
Government			
G	0.211	Government expenditure	Expenditure-to-Output: 0.21
B	1.700	Government debt	Debt-to-Output-Ratio: 1.7
r	1.000	Real interest rate in $(\%)$	Postwar quarterly average
τ	0.309	Tax rate	Finances debt and expenditure

Notes: All parameters in the table are calibrated to a quarterly frequency. Probabilities represent the probability within a single quarterly period. Interest rates are reported as quarterly rates.

of public debt at each maturity available in the dataset. I then combine neighboring maturities together in order to obtain seven groups that approximately represent the maturities of three months, six months, one year, two years, five years, ten years, and twenty years. I choose the tranches to obtain approximately equal weights and to cover key maturities along the yield curve. As data on duration by maturity is unavailable, I assume that all debt in the dataset consists of zero coupon bonds. For each group m, I set the duration parameter δ^m equal to the weighted average maturity of its empirical counterpart. I then label each of these groups according to a close full month or year.[21] Table 2 reports the resulting calibration parameters for the debt share and the

[21] I label the final tranche as 20 year bonds even though its average duration is closer to 25 years. The label reflects that most securities in this tranche have a 20 year maturity and that reliable yield data are available at the 20 year tenor. The longer average duration arises from a small share of bonds with

Figure 1 Fit of wealth inequality and aggregate marginal propensities to consume



Notes: The left panel illustrates the fit of the model-implied Lorenz for household wealth compared to the Lorenz curve estimated from the SCF in 2019 by Auclert, Rognlie and Straub (2025). The right panel illustrates the intertemporal marginal propensities to consume (iMPCs) of the model out of labor and capital income.

duration. 32.7% of government debt has a maturity equal to or below one year, 43.4% has a maturity between one year and five years, and 24% have a maturity longer than five years.

3.2 Bayesian Estimation of the Model

To I solve the model, using the sequence-space approach of Auclert et al. (2021). For the empirical implementation, I use a similar macroeconomic time series as in Bayer, Born and Luetticke (2024), covering the period from the third quarter of 1954 to the fourth quarter of 2019. I augment this dataset with updated series from Shiller (1989) on equity prices, dividends, and returns. The combined dataset includes growth rates of real GDP, consumption, investment, and wages. Hours worked, the (shadow) federal funds rate, the inflation rate, and real equity returns are expressed in logarithmic levels.[22] A detailed description of the data sources and the transformations applied is provided in Appendix III.

To estimate the model, I use the Differential Independence Mixture Ensemble (DIME) sampler of Boehl (2024). DIME merges differential evolution and independence sampling and runs an ensemble of chains that evolve jointly. It mixes a local and a global transition kernel. The local kernel explores the neighborhood of a chain. The global kernel reshuffles states across the current posterior support. This design shortens burn

maturities above 30 years.

[22] Following Bayer, Born and Luetticke (2024), I use the shadow federal funds rate constructed by Wu and Xia (2016) during periods when the federal funds rate is constrained by the zero lower bound.

Table 2 Calibration of the public debt structure

Bond Label	Maturity Tranche n	Share $\omega^{(n)}$ of Total Debt	Duration $1/\delta^{(n)}$ in Quarters
3M	$\leq 3M$	0.154	1.00
6M	$6M-9M$	0.129	2.31
1Y	$1Y$	0.043	4.00
2Y	$2Y$	0.138	8.00
5Y	$3Y-7Y$	0.296	18.32
10Y	$8Y-12Y$	0.095	37.36
20Y	$15Y \leq$	0.145	95.74

Notes: Maturities show the maturity of the zero coupon bonds in months (M) or years (Y). Share in total debt $\omega^{(n)}$ represents the fraction of total government debt with the respective maturity. The duration $\delta^{(n)}$ illustrates the average duration in quarters of the neighboring maturities I clustered together to create the seven subgroups.

in and yields efficient sampling. For my application DIME offers two advantages. First, combining many local chains with global moves allows it to traverse even multimodal posteriors. Second, it does not require mode finding before sampling. The sampler learns the shape of the posterior from the draws themselves, which increases robustness to misspecified priors. For the estimation, I use 128 parallel global chains, that run for 10,000 iterations. I discard the first 5,000 iterations as burn-in. Columns 1-4 of table 3 illustrate the parameters I estimate, their assumed prior distributions and their posteriors.

Priors Column 3 in table 3 illustrates the priors I use for the estimation. The priors on the stochastic processes are harmonized as much as possible.[23] Innovation standard deviations follow Inverse Gamma distributions with mean 0.1 and standard deviation 0.25. Autoregressive coefficients follow Beta distributions with mean 0.5 and standard deviation 0.2. This choice is weakly informative, keeps probability mass away from the boundaries, and treats the shocks symmetrically.

For policy parameters, the priors follow Bayer, Born and Luetticke (2024), which aligns the Taylor rule and interest rate inertia with common New Keynesian benchmarks. The inflation coefficient ϕ_π has a Gamma prior with mean 1.5 and standard deviation 0.3. The output coefficient ϕ_Y has a Normal prior with mean 0.1 and standard deviation 0.1. Interest rate smoothing and tax rate smoothing, ρ_r and ρ_τ, have Beta priors with mean 0.5 and standard deviation 0.2. The feedback of debt and output growth in the tax

[23] One might expect a higher prior for the standard deviation of the asset price shock, since equity returns are the most volatile observable. Robustness checks show that increasing the prior mean for this shock leaves the results unchanged.

rule, γ_τ^B and γ_τ^Y, follows standard Normal priors.

For price and wage stickiness, λ_p and λ_w, and for indexation, ι_p and ι_w, I adopt priors in the spirit of Smets and Wouters (2007). The stickiness parameters have Beta priors with mean 0.5 and standard deviation 0.1. The indexation parameters have Beta priors with mean 0.5 and standard deviation 0.2. Finally, following Justiniano, Primiceri and Tambalotti (2011), the investment adjustment cost parameter χ has a Gamma prior with mean 4.0 and standard deviation 2.0. Overall, the prior block is comparable to the main references and diffuse enough to let the data discipline the posterior.

Posterior estimates Column 4 in table 3 illustrates the mean, median, as well as the 5 and 95 percentiles of the posterior distribution. Checks on the convergence of the estimator are reported in Appendix IV.

The estimated shock processes are persistent, while the preference shock is the exception that only has little persistence with $\rho_\zeta \approx 0.047$. Moreover, innovation scales are heterogeneous. Investment and fiscal innovations have the largest standard deviations, followed by innovations in wages. In general, these magnitudes and persistence patterns are broadly in line with medium-scale New Keynesian estimates that feature persistent real and fiscal drivers together with comparatively lower price-setting volatility.

The estimates of the monetary policy rules are in line with former estimates. The posterior mean for interest rate smoothing is $\rho_r \approx 0.748$, which lies between 0.6 and 0.8 reported in benchmark studies. The inflation coefficient is $\phi_\pi \approx 1.691$ and well within typical post-1990 estimates. The output coefficient is $\phi_Y \approx 0.167$, which sits in the common range between 0.1 and 0.3. The fiscal block indicates modest persistence in the tax rule with $\rho_\tau \approx 0.255$, a positive feedback of debt with $\gamma_\tau^B \approx 1.022$, and a smaller feedback of activity with $\gamma_\tau^Y \approx 0.286$.

Nominal rigidities are moderate. The posterior implies price stickiness $\lambda_p \approx 0.499$ and wage stickiness $\lambda_w \approx 0.430$, which point to meaningful real rigidity with somewhat more frequent wage adjustment than price adjustment. Indexation is asymmetric. Price indexation is moderate with $\iota_p \approx 0.499$, whereas wage indexation is low with $\iota_w \approx 0.072$. Relative to standard medium-scale estimates, these values fall within familiar ranges and suggest that backward-looking behavior is more important in prices than in wages in this sample.

Table 3 Bayesian estimation results: shock and policy parameters

Shock Parameter	Distribution	Prior Mean	Prior SD	Posterior Mean	Posterior Median	Posterior 5%	Posterior 95%
$\sigma_q \cdot 100$	Inv. Gamma	10.0	25.0	0.420	0.420	0.325	0.543
ρ_q	Beta	0.5	0.2	0.985	0.984	0.978	0.990
$\sigma_\zeta \cdot 100$	Inv. Gamma	10.0	25.0	0.316	0.316	0.266	0.375
ρ_ζ	Beta	0.5	0.2	0.047	0.053	0.009	0.152
$\sigma_z \cdot 100$	Inv. Gamma	10.0	25.0	0.674	0.673	0.615	0.739
ρ_z	Beta	0.5	0.2	0.933	0.932	0.898	0.959
$\sigma_r \cdot 100$	Inv. Gamma	10.0	25.0	0.262	0.262	0.232	0.296
$\sigma_i \cdot 100$	Inv. Gamma	10.0	25.0	2.534	2.533	2.248	2.862
ρ_i	Beta	0.5	0.2	0.956	0.956	0.938	0.969
$\sigma_p \cdot 100$	Inv. Gamma	10.0	25.0	0.242	0.242	0.219	0.268
ρ_p	Beta	0.5	0.2	0.941	0.940	0.902	0.965
$\sigma_w \cdot 100$	Inv. Gamma	10.0	25.0	1.508	1.505	1.205	1.904
ρ_w	Beta	0.5	0.2	0.932	0.932	0.904	0.953
$\sigma_g \cdot 100$	Inv. Gamma	10.0	25.0	1.651	1.651	1.519	1.798
ρ_g	Beta	0.5	0.2	0.970	0.970	0.955	0.981

Policy Parameter	Distribution	Prior Mean	Prior SD	Posterior Mean	Posterior Median	Posterior 5%	Posterior 95%
ρ_r	Beta	0.5	0.2	0.748	0.748	0.707	0.787
ϕ_π	Gamma	1.5	0.3	1.691	1.689	1.595	1.802
ϕ_Y	Normal	0.1	0.1	0.167	0.167	0.101	0.233
ρ_τ	Beta	0.5	0.2	0.255	0.255	0.042	0.733
γ_τ^B	Normal	0.0	1.0	1.022	0.993	0.164	1.980
γ_τ^Y	Normal	0.0	1.0	0.286	0.261	-0.830	1.498
λ_p	Beta	0.5	0.1	0.499	0.499	0.325	0.672
λ_w	Beta	0.5	0.1	0.430	0.430	0.368	0.494
ι_p	Beta	0.5	0.2	0.499	0.499	0.229	0.771
ι_w	Beta	0.5	0.2	0.072	0.074	0.027	0.160
χ	Gamma	4.0	2.0	2.539	2.701	0.825	6.349

Notes: Posterior estimates are based on Bayesian inference using the DIME sampler by Boehl (2024). The sampler was run with 128 parallel chains for 10,000 iterations each. I discard the first 5,000 iterations as burn-in. Reported values are posterior means, medians, and 90 percent credible intervals. Shock standard deviations are scaled by 100 to enhance readability.

4 Decomposing Asset Premia

This section uses the estimated model to analyze U.S. asset premia. First, I show that the model replicates the untargeted level of premia observed over the estimation period. Thereafter, I decompose these premia into the contributions of individual structural shocks and explain their magnitude by tracing how aggregate risk is distributed across households.

4.1 Decomposing U.S. Asset Premia

While the model is estimated to match the dynamics of the equity return and the federal funds rate, it is not obvious that it can also reproduce the level of asset premia observed in the data. Table 4 shows that it does. It reports annualized premia in percentage points over the three month government bond for both the heterogeneous agent (HA) model and a representative agent (RA) version. The HA model generates sizable premia that are close to the time series averages over the estimation period. It produces an annualized equity premium of 4.92 percentage points, which is close to the average empirical equity premium of 5.01 percentage points. It also matches the slope of the yield curve and delivers term premia for five, ten, and twenty years of 1.26, 1.71, and 2.01 percentage points, respectively, compared with 1.29, 1.77, and 2.18 percentage points in the data.

Table 4 also enables a comparison between the asset premia predicted by the heterogeneous agent model (HA), and its representative agent counterpart (RA). While the HA model generates realistic asset premia, the RA model fails to do so. This comparison highlights that imperfect insurance against idiosyncratic income risk as in the HA model is important for generating realistic asset premia, even with recursive preferences and moderate risk aversion.

Overall, the model reproduces average asset premia well, which justifies using it as a laboratory to decompose premia in the next step. Table 5 reports a decomposition of the model implied equity premium, the one year term premium, and the ten year term premium into contributions from eight structural shocks. For each premium, the first column shows the absolute contribution of the component, while the second column reports its share in the total premium. A positive contribution indicates that households demand a premium for bearing the respective shock through the asset, whereas a negative contribution implies that the asset provides a hedge against that shock, leading households to price it at a discount.

For the equity premium, the asset-price shock constitutes the largest component, contributing 2.21 percentage points, or 44.9 percent of the total. Hence, a considerable share of the equity premium reflects risk unrelated to fundamental shocks. The remaining portion is explained by conventional business-cycle shocks. Supply-side shocks to aggregate productivity, investment-specific productivity, and the wage markup—jointly

Table 4 Annualized Asset Premia in Excess of the 3-month Government Bond Return

Asset	**Data** (%)	**HA** (%)	**RA** (%)
Equity	5.01	4.92	0.00074
Bond 6m	0.19	0.07	0.00007
Bond 1y	0.36	0.24	0.00009
Bond 2y	0.72	0.64	0.00014
Bond 5y	1.29	1.26	0.00022
Bond 10y	1.77	1.71	0.00026
Bond 20y	2.18	2.01	0.00028

Notes: Annualized asset premia for the estimated heterogeneous-agent model, a representative-agent variant, and their empirical counterparts. The empirical equity premium is calculated as the sample mean of annualized stock excess returns over a long term bond, proxied by the return on a ten year zero coupon bond. Empirical term premia are calculated as the excess returns on zero coupon bonds at constant maturities relative to the three month zero coupon bond. The empirical equity return series is identical to the series used in the estimation. Zero coupon yields are from the Board of Governors of the Federal Reserve System. Premia are computed following Auclert et al. (2024): $\frac{R_1 - R_0}{R} \approx -X\,\bar{\lambda}\,\sigma^2$, where X is the ex-post variation of an asset's excess return over the three month bond return and $\bar{\lambda}$ is the aggregate pricing kernel.

account for 42 percent of the total. For the one-year term premium, the monetary policy shock is the dominant source, contributing 0.16 percentage points (65 percent), followed by productivity and investment-specific productivity shocks with contributions of 0.04 and 0.05 percentage points (18 and 20 percent), respectively. At the ten-year horizon, this pattern reverses: the investment-specific technology shock explains 1.36 percentage points (80 percent) of the premium, while monetary policy accounts for only 0.21 percentage points (12 percent). Overall, the model associates short-maturity term premia primarily with monetary policy shocks and long-maturity premia with persistent investment-specific technology shocks.[24]

4.2 The Distributional Origins of Asset Premia

As highlighted before, the level of asset premia is determined by households' residual exposure to aggregate risk, which in turn depends on how the exposure to aggregate shocks is distributed across households. When trading in financial-market leaves households with substantial residual fluctuations in marginal utility after aggregate shocks, they demand premia for holding the exposed assets.

To illustrate how differential exposure to aggregate shocks translates into premia,

[24] Appendix V illustrates the impulse response of the economy to an investment specific technology shock.

Table 5 Decomposition of the Annualized Asset Premia into Risk Components

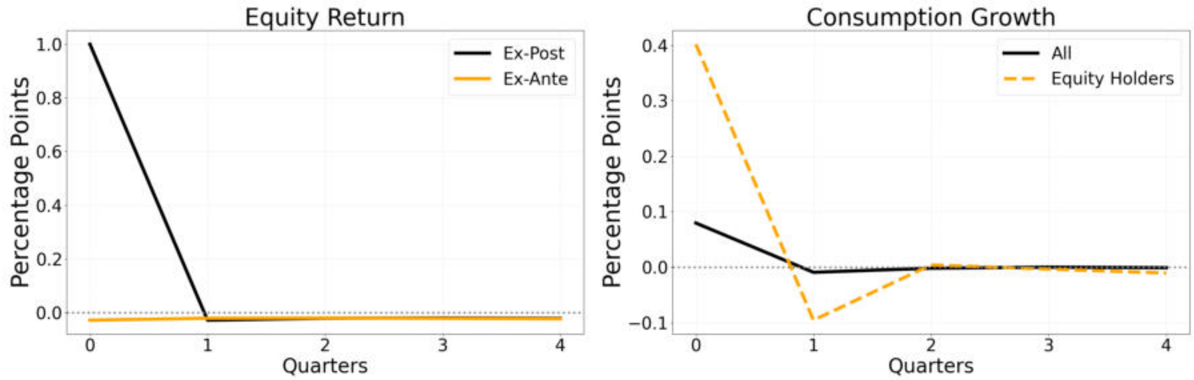
Risk Component	Equity Premium Abs.	Equity Premium Rel. (in %)	1Y Term Premium Abs.	1Y Term Premium Rel. (in %)	10Y Term Premium Abs.	10Y Term Premium Rel. (in %)
Asset-Price	2.21	44.86	-0.01	-5.56	-0.11	-6.46
Discount-Factor	-0.02	-0.44	-0.01	-5.61	-0.02	-1.15
Monetary Policy	0.25	5.13	0.16	65.37	0.21	12.09
Government Exp.	0.43	8.74	0.01	2.61	0.05	2.96
Productivity	0.62	12.65	0.04	17.86	0.13	7.60
Inv. spec. Prod.	0.82	16.63	0.05	20.22	1.36	79.93
Price Markup	-0.10	-1.97	0.00	1.92	-0.01	-0.39
Wage Markup	0.71	14.41	0.01	3.18	0.09	5.43
Total	4.92		0.24		1.71	

Notes: Contribution of aggregate shocks to the equity premium, 1 year term premium (1Y Term Premium), and the 10 year term premium (10Y Term Premium). The contribution is calculated according to equation (10), hence as the fraction of the total premium explained through one shock. For each premium, the first column illustrates the absolute contribution of the component, while the second column illustrates the relative contribution of the risk component to the overall premium. Positive values indicate premia, negative values indicate discounts households require for holding the respective assets.

Figure 2 reports impulse responses to a normalized asset-price shock that raises the equity price by one percent relative to the steady state. The left panel shows that the shock increases the ex-post equity return on impact, while higher prices today reduce expected future returns, lowering the ex ante return. The right panel illustrates the heterogeneous consumption responses across households. Consumption of equity holders rises by about 0.4 percentage points on impact, compared with less than 0.1 percentage points for aggregate consumption.

These consumption responses reflect how exposure to aggregate risk is distributed across households after financial market trading. In the stationary distribution, many households hold little or no wealth and remain highly exposed to idiosyncratic income fluctuations. Because a price decline that coincides with an idiosyncratic drop in labor income generates large utility losses, equity is costly to hold for low wealth households. Hence, the few households that ultimately hold equity are wealthy and well insured against idiosyncratic income fluctuations, with average wealth about 1.7 times the economy wide mean. Despite this wealth, the residual risk of the asset price shock is concentrated among this group of equity holders. As shown in Figure 2, this residual exposure to equity risk induces large fluctuations in their consumption growth, about four times the aggregate average. The amplification of equity holders' consumption response relative to the average illustrates the magnitude of their residual risk and helps

Figure 2 Impulse Responses to a normalized Asset Price Shock



Notes: Impulse responses for the ex-post and ex ante equity return, aggregate consumption growth, and consumption growth of equity holders. The left panel reports changes in equity returns in percentage points. The right panel reports changes in the growth rates of the two consumption measures in percentage points. Responses are to a normalized asset price shock that raises the equity price by one percent relative to its steady state. The shock corresponds to roughly one quarter of its estimated standard deviation.

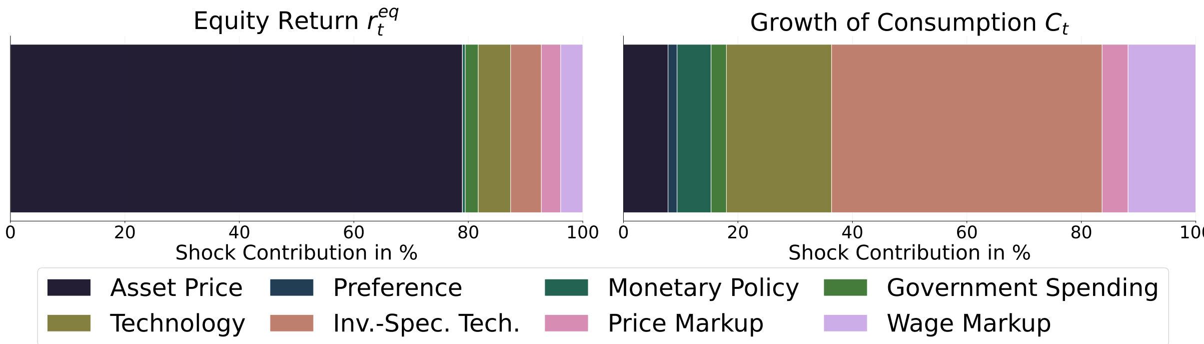
rationalize the size of the equity premium.

We can apply the same logic to rationalize the term premium. Unlike equity, a one year bond is not subject to large revaluation effects due to its low duration. Its returns vary little, so low wealth households tend to hold it because it provides consumption insurance with stable payoffs. Movements in one year bond returns mainly reflect monetary policy, which has limited direct impact on these households because their consumption is largely hand to mouth rather than set on the Euler margin. Together these features imply low residual exposure of one year bond holders to aggregate risk, which rationalizes the small one year term premium.

In contrast to the one year case, the ten year bond carries high duration, so its price is much more sensitive to shocks. By the same logic as above, this greater revaluation risk makes long maturity bonds a poor hedge for low wealth households, so they are concentrated in few high wealth portfolios. The owners therefore bear larger residual exposure to the shocks that move long bonds, most notably the investment specific productivity shock, whose persistence transmits through capital accumulation, production, and investment.[25] This pattern mirrors the equity logic and rationalizes an upward sloping and sizable term premium.

[25] See Appendix V for the impulse response to an investment specific productivity shock.

Figure 3 Conditional Variance Decomposition of Aggregate Variables



Notes: Conditional variance decompositions for the equity return and consumption growth computed at business cycle frequencies (forecast horizon of 6 to 32 quarters) based on the estimated model. The coloured areas show the share of each variable's variance attributable to a given structural shock.

5 Decomposing U.S. Business Cycles and Inequality

Having decomposed asset premia, I now return to study the drivers of U.S. business cycles and inequality. I focus on how the inclusion of the asset price shock changes these dynamics. To quantify its role, I compute conditional variance decompositions at business cycle frequencies using the frequency domain approach of Uhlig (2001).

5.1 Decomposing U.S. Business Cyclces

Figure 3 reports the conditional variance decomposition for equity returns and consumption growth. Appendix V illustrates the conditional variance decomposition for all aggregate variables.

The left panel shows that, 79 percent of the variation in equity returns is explained by the asset price shock. The remaining 21 percent is mainly driven by investment-specific technology, aggregate technology, and markup shocks. This confirms that most business cycle variation in equity returns originates not from fundamental shocks, but from sources captured by the asset price shock. While the asset price shock dominates the equity return, the right panel shows that it explains only 7.8 percent of the variance in aggregate consumption growth. Consumption dynamics are instead driven primarily by supply-side forces: investment-specific technology accounts for 47.3 percent of the variance, followed by aggregate technology, wage, and price markup shocks, which together contribute another 34.7 percent. In contrast, demand-side shocks jointly explain only 10.2 percent of the variation in consumption growth.

It might be surprising that the shock which explains the largest fraction of equity returns only explains a small fraction of the variation in consumption growth. Through the lens of the structural model, it is possible to investigate the transmission mechanisms in detail. Intuitively, equity accounts for less than one quarter of households' total assets, so even large swings in the value of equity generate only modest aggregate wealth effects. In addition, equity holders have low marginal propensities to consume out of total wealth, which means that changes in equity payoffs translate into only modest variation in consumption.

I can illustrate these channels formally through the decomposition of Auclert, Rognlie and Straub (2024).[26] Using their conceptual framework, up to first order, the change in aggregate consumption can be written as the sum of three household-side components:

$$d\mathbf{C} \;=\; \mathbf{M}\cdot d\mathbf{Z} \;+\; \mathbf{M}^r\cdot d\mathbf{r} \;+\; \mathbf{m}^{cap}\, d\mathrm{cap}_0, \tag{29}$$

The matrices $\mathbf{M}$ and $\mathbf{M}^r$ are Jacobians that capture, respectively, the marginal propensities to consume out of changes in the sequence of labor income $d\mathbf{Z}$ and the elasticities of aggregate consumption with respect to future real interest rates $d\mathbf{r}$. The vector $\mathbf{m}^{cap}$ is the marginal propensity to consume out of capital gains and measures how aggregate consumption changes when the value of assets changes by $d\mathrm{cap}_0$.[27]

The revaluation effect can be further decomposed into the contributions of individual assets.[28] When focusing on the direct effect of a change in the value of a single asset on consumption, this effect depends on the change in the valuation of the asset studied. The direct impact of an asset-price shock on consumption through the revaluation of equity can then be expressed as

$$d\mathbf{C}^{val} = \mathbf{m}^{cap}(1+r)q^{eq}\frac{\partial r^{eq}}{\partial \epsilon^q}d\epsilon^q, \tag{30}$$

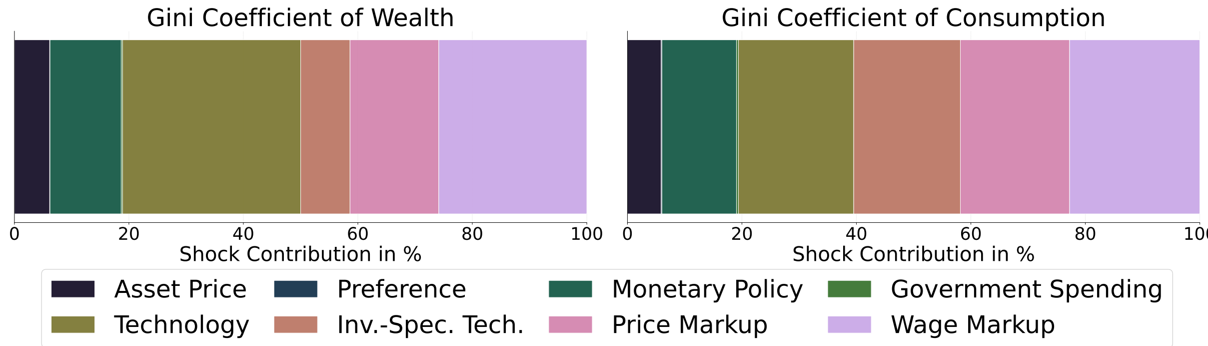
where $\mathbf{m}^{cap}$ denotes the MPC out of capital income, q^{eq} is the aggregate value of equity, and $\frac{\partial r^{eq}}{\partial \epsilon^q}d\epsilon^q$ denotes the impact impulse response (IRF) of the equity payoff to the asset price shock. The expression shows that aggregate consumption changes by the size of

[26] The following derivation builds on equations (34) and (35) in the main text, as well as the proof of Proposition 8 in the appendix of Auclert, Rognlie and Straub (2024). For a more detailed decomposition of wealth effects in heterogeneous-agent settings, see Gong (2025a), and for a general decomposition of transmission channels in HANK models, see Gong (2025b).

[27] Formally, the aggregate marginal propensity to consume (MPC) out of labor income is computed as $\mathbf{M} \equiv [\partial \mathcal{C}_t/\partial Z_s]_{ts}$, the elasticity of consumption with respect to the real interest rate is calculated as $\mathbf{M}^r \equiv [\partial \mathcal{C}_t/\partial \log(1+r_s)]_{ts}$, and, with slight abuse of notation, the MPC out of unexpected capital gains on asset k is calculated as $m_t^k \equiv \partial \mathcal{C}_t/\partial(p_0+d_0)$.

[28] With multiple assets, the revaluation term can be written as $d\mathrm{cap}_0 = (1+r)\boldsymbol{\omega}\; A\; d\boldsymbol{r}^{post}$, where $\boldsymbol{\omega} = [q^k/A]_k$ denotes portfolio shares across assets k, and $d\boldsymbol{r}^{post}$ represents the vector of ex-post changes in asset payoffs.

Figure 4 Conditional Variance Decomposition of Inequality Measures



Notes: Conditional variance decompositions of Consumption Gini and Wealth Gini at business cycle frequencies (6–32 quarter forecast horizon) based on the estimated model. The coloured areas indicate the share of the variance in the illustrated variable due to an individual shock.

the valuation adjustment, weighted by households' propensity to consume out of an additional unit of wealth.

Given the calibrated parameters, it is possible to compute the direct effect quantitatively. Assuming a one percent increase in asset prices (that is, $\frac{\partial r^{eq}}{\partial \epsilon^q} d\epsilon^q = 0.01$), an MPC out of capital income of one percent, and an equity value of $q^{eq} = 3.9$, the resulting consumption response is

$$dC^{val} = 0.01 \times (1 + r) \times 3.9 \times 0.01 \approx 0.04 \tag{31}$$

Hence, a one percent increase in equity prices raises aggregate consumption by only about 0.04 percent, indicating that the direct revaluation channel of the asset-price shock is quantitatively small. Even though such shocks can generate equity-return volatility on the order of ten percent per quarter, their effect on aggregate consumption volatility remains modest. Note that Chodorow-Reich, Nenov and Simsek (2021) estimate that a one dollar increase in stock market wealth raises consumption by 3.23 cents. The model based estimate obtained here is of a similar order of magnitude and complements their empirical findings from a structural perspective.

5.2 Decomposing U.S. Inequality

Figure 4 reports the conditional variance decomposition for the Gini coefficients of consumption and wealth as measures of inequality. Both decompositions indicate that inequality dynamics are shaped by a broad set of structural shocks rather than being dominated by a single source.

The decomposition of the wealth Gini shows that technology-related shocks account for the largest share of variation, explaining 31.1 percent of the total. Price and wage markup shocks follow, contributing 15.5 percent and 25.9 percent, respectively. The prominence of markup shocks is intuitive, as they affect households differently across the wealth distribution through changes in wages and profits. Monetary policy shocks represent the next major contributor, explaining 12.4 percent of the variation. Since monetary policy affects households directly through the Euler equation, it naturally generates heterogeneity in wealth outcomes by affecting asset holders and non-asset holders in distinct ways. Asset price shocks contribute more modestly, explaining 6.2 percent of the variation. This suggests that while asset price fluctuations influence short-run portfolio valuations, their aggregate contribution to long-run wealth inequality remains limited.

For the consumption Gini, technology shocks, investment-specific technology shocks, and price and wage markup shocks each explain roughly 20 percent of the total variance. The near uniform contributions across these supply side forces indicate that households are affected heterogeneously along the distribution. Monetary policy accounts for about 13 percent, consistent with differential exposure to changes in interest rates. The asset price shock explains only 5.9 percent, which mirrors the wealth results. Although the shock affects equity holders differently than the average household, equity holders form a relatively small group and their consumption responds with limited volatility.

Comparison to the literature Smets and Wouters (2007) showed that in representative-agent DSGE models, risk-premium and expenditure shocks account for the majority of short-run output fluctuations, while technology and markup shocks dominate at longer horizons. Justiniano, Primiceri and Tambalotti (2011) show that along business cycle frequencies 60 percent of output variation can be explained by shocks to the marginal efficiency of investment, and 25 percent by technology shocks. Consumption variation is explained by intertemporal preference shocks and technology shocks that account for 55 percent and 31 percent of the variation, respectively. Our heterogeneous-agent results indicate that supply-side shocks, particularly investment-specific and neutral technology shocks, drive most consumption variation. This result is closer to the results obtained by Auclert, Rognlie and Straub (2020) and Bayer, Born and Luetticke (2024), which attribute large importance to supply side shocks for output and consumption.

Regarding inequality, no single shock dominates its variance. Monetary and asset-price shocks have moderate effects, while technology and markup shocks matter more because they shift income and prices unevenly across households. Consistent with Auclert, Rognlie and Straub (2020) and Bayer, Born and Luetticke (2024), our results imply that supply-side disturbances are central to both aggregate and distributional dynamics, whereas demand or valuation shocks mainly drive short-run asset-market fluctuations.

6 Historical Analysis and the Impact of Monetary Policy

Since asset premia reflect households' exposure to aggregate risk, changes in the sources of aggregate risk over time imply corresponding variation in asset premia. This section examines the channels that drive this variation and isolates the role of monetary policy in shaping asset premia.

6.1 Historical analysis of asset premia

To begin, I investigate whether the model can account for historical variation in asset premia arising from shifts in the underlying sources of aggregate risk. Specifically, I re-estimate all model parameters for two distinct subperiods, 1979:Q3–1999:Q4 and 2000:Q1–2019:Q4. The first period corresponds to the Great Moderation following Volcker's appointment, while the second is characterized by greater international integration. The re-estimations use the same priors as in the main analysis. Appendix IV reports the Gelman and Rubin (1992) convergence statistics for both estimations, which indicate convergence to the posterior distribution.

Parameter estimates reported in Appendix VI show that the pre 2000 period is characterized by higher shock volatility and lower persistence than the model estimated on the full sample. An exception is the technology shock, which remains more persistent and continues to account for most of the business cycle variation in this period. The post 2000 period instead features lower shock volatility, more persistent but smaller shocks, a stronger and more stable monetary policy response to inflation, and reduced wage rigidities. In this later period, the government expenditure shock becomes highly persistent and explains most of the variation at business cycle frequencies. Consistent with these estimates, Table 11 in Appendix VI shows that macroeconomic aggregates were more volatile in the first subperiod than in the second.

Table 6 compares the model implied premia with their empirical counterparts after re-estimating the risk structure and policy parameters. Columns two and five report the empirical asset premia for the two subperiods, while columns three and six list the corresponding model implied premia. For the pre-2000 period, the model explains much of the observed equity premium (5.87 percent versus 8.21 percent) and closely matches

Table 6 Annualized Asset Premia in Excess of the 3-month Government Bond Return

	1979-Q3 to 1999-Q4			2000-Q1 to 2019-Q4	
Asset	**Data** (%)	**Model** (%)	**Alt. MP (%)**	**Data** (%)	**Model** (%)
Equity	8.21	5.87	6.02	3.27	4.56
Bond 6m	0.19	0.27	0.29	0.11	0.08
Bond 1y	0.36	0.57	0.60	0.21	0.19
Bond 2y	0.71	0.99	1.02	0.45	0.38
Bond 5y	1.29	1.40	1.43	1.11	0.63
Bond 10y	1.77	1.66	1.71	1.76	0.83
Bond 20y	2.18	2.14	2.20	2.31	1.14

Notes: Annualized premia for the estimated heterogeneous-agent model from re-estimated full models for the subperiods 1979-1999 and 2000-2019 compared to the data counterparts and with an alternative monetary policy rule (Alt. MP). Premia are computed following Auclert et al. (2024): $\frac{R_1-R_0}{R} \approx -X\,\bar{\lambda}\,\sigma^2$, where X is the ex-post variation of an asset's excess return over the three month bond return and $\bar{\lambda}$ is the aggregate pricing kernel. The equity premium is the sample mean of annualized stock excess returns over a long term bond, proxied by the return on a ten year zero coupon bond. Term premia are the excess returns on zero coupon bonds at constant maturities relative to the three month zero coupon bond. The equity return series match those used in the estimation. Zero coupon yields are from the Board of Governors of the Federal Reserve System.

the term premium across maturities. For the post-2000 period, it produces an equity premium of 4.56 percent—slightly above the empirical value of 3.27 percent, and fits the short end of the term structure but not the steepening at longer maturities. Overall, the model does not match the exact levels but captures the cross-period ordering, replicates the yield-curve slope in the first subperiod, and remains close for shorter maturities in the second. Qualitatively, it reproduces how changes in underlying risk factors shape the evolution of equity premia across periods, and quantitatively it tracks the behavior of term premia. In line with the higher macroeconomic risk before 2000, the model generates larger asset premia in the first subperiod than in the second.

6.2 The Impact of Monetary Policy on Asset Premia

The historical analysis raises the question of whether the observed variation in asset premia is driven by changes in the nature of aggregate risk itself or by shifts in policy parameters and macroeconomic frictions. To address this, I next analyze how monetary policy shapes asset premia by altering the transmission of aggregate risk. Using the mean posterior estimates reported in Table 3 from the model estimated over the full sample, I vary the policy stance by changing the responses to inflation (ϕ_π) and output (ϕ_y). This approach isolates the effects of a more hawkish or dovish monetary policy

Table 7 Annualized Asset Premia under varying Monetary Policy Stance

	Coefficient for Inflation (ϕ_π)			Coefficient for Output (ϕ_y)		
Premia	$\phi_\pi = 1.1$	$\phi_\pi = 1.69$	$\phi_\pi = 3.0$	$\phi_y = 0.0$	$\phi_y = 0.17$	$\phi_y = 0.5$
Equity	4.37	4.92	5.28	5.02	4.92	4.77
Bond 1y	0.17	0.24	0.34	0.27	0.24	0.21
Bond 10y	0.83	1.71	2.07	1.72	1.71	1.72
Std. Dev.	$\phi_\pi = 1.1$	$\phi_\pi = 1.69$	$\phi_\pi = 3.0$	$\phi_y = 0.0$	$\phi_y = 0.17$	$\phi_y = 0.5$
$100\sigma(c)$	0.53	0.55	0.61	0.56	0.55	0.53
$100\sigma(\pi)$	3.12	2.08	1.14	6.14	6.12	6.10
$100\sigma(r^{eq})$	6.10	6.12	6.20	2.16	2.08	1.94
$100\sigma(r^{10y})$	0.72	0.75	0.81	0.76	0.75	0.75

Notes: Annualized premia and volatility over the business cycle frequency computed with the posterior mean parameters of the estimated heterogeneous agent model for the full sample period. The table varies the monetary policy responses to inflation ϕ_π and output ϕ_y. Premia are computed following Auclert et al. (2024): $\frac{R_1 - R_0}{R} \approx -X\,\bar{\lambda}\,\sigma^2$, where X denotes the ex-post variation of an asset's excess return relative to the three month bond and $\bar{\lambda}$ denotes the aggregate pricing kernel. The variance over the business cycle frequency is computed based on Uhlig (2001).

while keeping the size of the underlying shocks constant.

Table 7 reports annualized asset premia and business-cycle volatilities of aggregate variables under alternative monetary policy stances. A stronger response to inflation ϕ_π raises asset premia across the board. In contrast, a stronger response to output ϕ_y lowers most premia. The intuition follows standard textbook logic. When business cycle risk is driven mainly by supply side shocks, a higher coefficient ϕ_π stabilizes inflation volatility at the cost of higher volatility in aggregate variables. Households that absorb the residual risk in asset markets then face more nondiversifiable risk and demand higher premia. On the contrary, raising the coefficient on output growth ϕ_y stabilizes output and reduces the risk that must be borne in asset markets, which lowers premia. Consequently, asset premia move with monetary policy because it alters the residual aggregate risk households must bear.

I can use this insight to examine how the change in the monetary policy stance between the two subperiods affects asset premia. The increase in the inflation response coefficient ϕ_π from 2.156 to 2.314 and the decrease in the output response coefficient ϕ_Y from 1.69 to 0.114 should, in principle, raise asset premia in the post 2000 period relative to the pre 2000 period. Column three of Table 6 shows how the model implied premia change when I use the mean posterior estimates from the pre 2000 period for all parameters except the monetary policy coefficients ϕ_π and ϕ_Y, which are replaced by their post 2000 values. For all assets, the model implied premia increase, confirming that a stronger reaction to inflation and a weaker response to output growth raise asset premia in an economy where supply shocks are dominant. This exercise also suggests that the observed difference between the two subperiods cannot be explained solely by changes in monetary policy but is likely driven by shifts in the underlying aggregate risk structure.

This insight contrasts with the macro-finance literature based on representative agent models. While Kung (2015), Campbell, Pflueger and Viceira (2020), and Bianchi, Kung and Tirskikh (2023) highlight the role of monetary policy in shaping asset prices through the correlation of the stochastic discount factor with inflation, growth, and asset returns, the present heterogeneous-household model shifts the focus to the distribution of risk and to how policy shapes the residual aggregate risk households are exposed to.

7 Conclusion

This paper develops and estimates a quantitative heterogeneous-agent New Keynesian model with portfolio choice and nonfundamental asset price shocks. By introducing noise traders in a segmented equity market, the model captures fluctuations in asset prices that are disconnected from economic fundamentals. While these nonfundamental shocks generate substantial volatility in equity prices, their aggregate macroeconomic effects are limited. This is due to the relatively small share of equity in total household wealth and low marginal propensities to consume out of wealth of equity holders. As a result, nonfundamental fluctuations play only a minor role in explaining movements in aggregate consumption, investment, and inequality.

Despite their limited impact on macroeconomic aggregates, nonfundamental shocks are crucial for understanding asset pricing. They account for 79 percent of the variance in equity returns and explain 44 percent of the model-implied equity premium. This result arises because equity holders, who are disproportionately wealthy, face substantial consumption volatility due to large return fluctuations, even though they are otherwise well-insured. The model thus bridges a gap in the literature by showing that nonfundamental asset price risk can generate sizable premia in a setting with realistic heterogeneity and limited aggregate effects. These findings suggest that the pricing of risk in financial markets is shaped not only by fundamentals but also by how nonfundamental shocks interact with portfolio heterogeneity and risk-sharing frictions.

The paper also provides insights into how different periods with varying aggregate risk affect asset premia and how monetary policy shapes them. Generally, periods with higher macroeconomic volatility are associated with higher risk premia. Monetary policy can influence the level of aggregate risk by shaping the transmission of aggregate shocks to shape the volatility of aggregate variables.

Future research can use my model framework to explore the effects of nonfundamental fluctuations in capital prices and the consequences of quantitative easing on the macroeconomy, households across the wealth and income distribution, and the formation of asset premia.

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Appendix

I Appendix: Derivations for Equity Price

This section illustrates the derivation of the equilibrium equity price in the main text, and illustrates an alternative derivation based on an incomplete information setting.

I.1 Derivation of Equilibrium Equity Price

For each equity j, market clearing requires that aggregate demand equals the (normalized) unit supply:

$$\int_0^1 \theta_{ljt}\, dl \;=\; 1. \tag{32}$$

From the fundamental trader problem, the optimal demand for equity j is

$$\theta^F_{ljt} \;=\; -\,q_{jt} \;+\; \mathbb{E}_t\left[\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}}\right] \quad \text{for all } l \in [0,\nu], \tag{33}$$

while noise traders follow the rule

$$\theta^N_{ljt} \;=\; \tilde{\xi}_t \;+\; \epsilon^\theta_{ljt} \quad \text{for all } l \in (\nu, 1], \tag{34}$$

where ϵ^θ_{ljt} is iid with zero mean across l (and j). Integrating (33) over the mass ν of fundamental traders and (34) over the mass $1-\nu$ of noise traders yields

$$\int_0^\nu \theta^F_{ljt}\,dl = \nu\biggl(-q_{jt} + \mathbb{E}_t\biggl[\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}}\biggr]\biggr)\,, \tag{35}$$

$$\int_\nu^1 \theta^N_{ljt}\,dl = (1-\nu)\tilde{\xi}_t \;+\; \underbrace{\int_\nu^1 \epsilon^\theta_{ljt}\,dl}_{=0}\,. \tag{36}$$

The trader-stock specific shock ϵ^θ_{ljt} washes out when averaged over traders due to its iid structure. Substituting (35) and (36) into (32) gives

$$\nu\biggl(-q_{jt} + \mathbb{E}_t\biggl[\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}}\biggr]\biggr) \;+\; (1-\nu)\tilde{\xi}_t \;=\; 1. \tag{37}$$

Solving (37) for q_{jt} yields

$$q_{jt} \;=\; \mathbb{E}_t\biggl[\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}}\biggr] \;+\; \frac{(1-\nu)\tilde{\xi}_t - 1}{\nu}. \tag{38}$$

Define the effective nonfundamental asset-price term as

$$\xi_t \;\equiv\; \frac{(1-\nu)\tilde{\xi}_t - 1}{\nu}, \tag{39}$$

then (38) becomes

$$q_{jt} \;=\; \mathbb{E}_t\biggl[\frac{d_{jt+1}+q_{jt+1}}{1+r_{t+1}}\biggr] \;+\; \xi_t, \tag{40}$$

which matches equation (2) in the main text. By assumption, ξ_t follows the AR(1) process $\xi_t = \rho_q \xi_{t-1} + \epsilon^q_t$ with $\epsilon^q_t \sim \mathcal{N}(0, \sigma^2_q)$. In a symmetric equilibrium with identical firms, $q_{jt} = q_t$ and $d_{jt} = d_t$ for all j. Aggregating (40) across j yields the index-fund pricing equation

$$q_t \;=\; \mathbb{E}_t\biggl[\frac{d_{t+1}+q_{t+1}}{1+r_{t+1}}\biggr] \;+\; \xi_t, \tag{41}$$

which coincides with equation (3).

I.2 Alternative Microfoundation of Asset Price Shock

This subsection provides an alternative microfoundation of asset price shocks based on incomplete information as in Futia (1981), Singleton (1986), Bacchetta and Wincoop (2006), Angeletos and Lian (2016), and Rondina and Walker (2021). This subsection provides an alternative microfoundation for nonfundamental asset price fluctuations based on incomplete information. Each trader $m \in [0,1]$ observes a noisy signal about the future payoff of each equity $j \in [0,1]$, given by:

$$x_{mjt} = d_{jt+1} + u_{mjt}, \quad \text{where } u_{mjt} \sim \mathcal{N}(\tilde{\xi}_t, \sigma_u^2).$$

The noise term u_{mjt} contains a cross-sectionally common distortion $\tilde{\xi}_t$, which biases the beliefs of all traders in the same direction.

Traders with Imperfect Information. Each trader lives for two periods,[29] is risk-neutral, discounts the future at the risk-free rate $1 + r_{t+1}$, and incurs quadratic disutility from monitoring firm-specific signals. Each trader chooses a portfolio allocation $\{\theta_{mjt}\}_{j\in[0,1]}$ to maximize:

$$U_{mt} = \max_{\{\theta_{mjt}\}} \int_0^1 \left[-q_{jt}\theta_{mjt} + \mathbb{E}_{mt}\left(\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}}\right)\theta_{mjt} - \frac{1}{2}\theta_{mjt}^2 \right] dj,$$

where $\mathbb{E}_{mt}[\cdot]$ denotes trader m's subjective expectation, based on the signal x_{mjt}. The optimal portfolio demand satisfies:

$$\theta_{mjt} = \mathbb{E}_{mt}\left[\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}}\right] - q_{jt}.$$

Equilibrium Asset Prices. Market clearing requires that the average demand equals the unit supply of each equity, that is:

$$\int_0^1 \theta_{mjt} dm = 1.$$

Substituting the demand expression yields the asset pricing equation:

$$q_{jt} = \bar{\mathbb{E}}_t\left[\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}}\right] - 1,$$

[29] By assuming that traders only live for two periods, higher-order believes beliefs of traders about next periods price become irrelevant. This assumption makes the solution more tractable, but as Bacchetta and Wincoop (2006) show in their paper, does not change the implications.

where $\bar{\mathbb{E}}_t[\cdot]$ denotes the cross-sectional average of individual expectations.

Belief Distortions and Nonfundamental Prices. Bayesian updating under normally distributed noise implies that all traders share a distorted belief about the average payoff:

$$\bar{\mathbb{E}}_t \left[\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}} \right] = \mathbb{E}_t^{\text{true}} \left[\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}} \right] + \frac{\tilde{\xi}_t}{1 + r_{t+1}}.$$

Substituting this into the pricing equation yields:

$$q_{jt} = \mathbb{E}_t^{\text{true}} \left[\frac{d_{jt+1} + q_{jt+1}}{1 + r_{t+1}} \right] + \xi_t,$$

where the effective asset price shock is defined as:

$$\xi_t \equiv \frac{\tilde{\xi}_t}{1 + r_{t+1}} - 1.$$

As in the main text, we assume ξ_t follows a stationary AR(1) process:

$$\xi_t = \rho_q \xi_{t-1} + \epsilon_t^q, \quad \epsilon_t^q \sim \mathcal{N}(0, \sigma_q^2).$$

Symmetric Equilibrium and Index Fund Pricing. Assuming that all equities are symmetric and deliver identical payoffs, the price of the equity index fund satisfies:

$$q_t = \mathbb{E}_t^{\text{true}} \left[\frac{d_{t+1} + q_{t+1}}{1 + r_{t+1}} \right] + \xi_t,$$

which corresponds exactly to equation (3) in the main text. Hence, distorted beliefs due to incomplete information can rationalize the same reduced-form expression for nonfundamental price movements as in the model with noise traders.

Implications for Returns. As before, asset price fluctuations translate into excess returns through:

$$r_t^e = \frac{q_t - q_{t-1} + d_t}{q_{t-1}},$$

such that nonfundamental shocks affect both prices and returns, even in the absence of changes to dividends or discount factors.

II Appendix: Derivations of the endogenous portfolios

This section derives the results of Auclert et al. (2024) in a unified manner.

Setting and perturbation

There exists a continuum of heterogeneous agents with index i who can allocate their wealth a_i to up to $K+1$ assets. An asset k has supply A^k and stochastic payoff $x^k(\epsilon)$, where $\epsilon \equiv (\epsilon_1, ..., \epsilon_Z)$ denotes the vector of Z exogenous shocks. We suppose that $\epsilon_Z = \sigma\bar{\epsilon}_Z$, with $\bar{\epsilon}_Z \sim N(0, \bar{\sigma}_Z^2)$, such that σ is the common volatility that exists in the economy. Denoting the value function of household i by W_i and given the price of asset k as p^k, the problem of household i is

$$\max_{a_i^k} \mathbb{E}_\epsilon \left[W_i \left(\sum_{k=0}^{K} x^k(\epsilon) a_i^k, \epsilon \right) \right] \tag{42}$$

$$\text{s.t.} \quad \sum_{k=0}^{K} p^k a_i^k = a_i \tag{43}$$

with $W_i(a', \epsilon) = \mathbb{E}_{s',s} \left[V(a', s', \epsilon)^{1-\gamma} \right]^{\frac{1}{1-\gamma}}$ denoting the weighted certainty equivalence operator, where s' denotes the idiosyncratic risk. Denoting the Lagrange multiplier on i's budget constraint by γ_i, the problem has the first-order conditions

$$\mathbb{E}_\epsilon \left[\frac{x^k(\epsilon)}{p^k} \frac{W_i'(\epsilon)}{\gamma_i} \right] = 1 \tag{44}$$

which must hold for every i and for every k. Writing di for distribution of agents i, market clearing in all asset markets imposes:

$$\int a_i^k di = A^k \quad \forall k. \tag{45}$$

Given primitives a_i and W_i, as well as the parameter σ, an equilibrium is a set of prices for each asset p^k and Lagrange multiplier for each agent γ_i, such that the optimality conditions (44) are satisfied for each (i, k) pair, and all asset markets clear, i.e. (45) holds for all k.

We now work out the implications of these equations for a perturbation in σ up to the second order. We write $p^k(\sigma)$ and $\gamma_i(\sigma)$ for the solution at a given σ and study their second-order Taylor expansion around $\sigma = 0$. We note that, given that the distribution of ϵ is symmetric, these must be even functions of σ: $p^k(-\sigma) = p^k(\sigma)$ and $\gamma_i(-\sigma) = \gamma_i(\sigma)$.

This implies, in particular, that $\frac{d\gamma_i}{d\sigma} = \frac{dp^k}{d\sigma} = 0$[30], a result that we will use several times below.

Zero-th and first-order perturbation: Applying (44) at $\sigma = 0$, we find $\gamma_i / W_i' = x^k / p^k$ for all i and k, where p^k is short-hand for $p^k(0)$, γ_i for $\gamma_i(0)$, x^k for $x^k(0)$, and W_i' for $W_i'(\sum_{k=0}^K x^k a_i^k, 0)$. Hence, the returns on all assets must equal a common constant R, and this is also the rate entering the Euler equation of all agents:

$$\gamma_i / W_i' = x^k / p^k = R \tag{46}$$

In particular, $\sum_{k=0}^K x^k a_i^k$ is also just $R \sum_{k=0}^K p^k a_i^k = Ra_i$. Equation (46) gives the usual result that, with no aggregate uncertainty, all assets must have equal returns.

Next, differentiating (44) with respect to σ (and around $\sigma = 0$) gives us

$$\mathbb{E}\left[\frac{dx^k}{d\sigma} W_i' + x^k \frac{dW_i'}{d\sigma}\right] = \frac{d\gamma_i}{d\sigma} p^k + \gamma_i \frac{dp^k}{d\sigma} \tag{47}$$

Given the definition $x^k(\epsilon) = x^k(\sigma\bar{\epsilon}_1, ..., \sigma\bar{\epsilon}_Z)$, and $W_i(\sum_{k=0}^K x^k(\sigma\bar{\epsilon}) a_i^k, \sigma\bar{\epsilon})$, we have that

$$\frac{dx^k}{d\sigma} = \sum_{z=1}^{Z} \frac{\partial x^k}{\partial \epsilon_z} \bar{\epsilon}_Z \quad \text{and} \quad \frac{dW_i'}{d\sigma} = \sum_{z=1}^{Z} \frac{dW_i'}{d\epsilon_z} \bar{\epsilon}_z \tag{48}$$

where we have defined the total deriviate of W_i' with respect to ϵ_z as

$$\frac{dW_i'}{d\epsilon_z} \equiv W_i'' \sum_{k=0}^{K} \frac{\partial x^k}{\partial \epsilon_z} a_i^k + \frac{\partial W_i'}{\partial \epsilon_z}$$

Since $\mathbb{E}[\bar{\epsilon}_z] = 0$, using equation (48) to substitute into (47), we see that the left-hand side is zero. The right-hand side of (47) is also zero, given our symmetry result above, so equation (47) holds regardless of portfolios.

Second-order perturbation: Now, differentiating (47) with respect to σ gives us:

$$\begin{aligned} \mathbb{E}\left[\frac{d^2 x^k}{d\sigma^2}\right] W_i' + 2\mathbb{E}\left[\frac{dx^k}{d\sigma}\frac{dW_i'}{d\sigma}\right] + x^k \mathbb{E}\left[\frac{d^2 W_i'}{d\sigma^2}\right] = \\ \frac{d^2\gamma_i}{d\sigma^2} p^k + 2\frac{d\gamma_i}{d\sigma}\frac{dp^k}{d\sigma} + \gamma_i \frac{d^2 p^k}{d\sigma^2} \end{aligned} \tag{49}$$

Using our symmetry results from above, and dividing all entries by $x^k W_i' = \gamma_i p^k$ from

[30] Up to first order, the portfolios are not determined such that the portfolio constraints do not bind. The only constraint that might bind is the constraint on total wealth.

(46), we can write this simply as:

$$\mathbb{E}\left[\frac{dx^k/x^k}{d\sigma}\frac{dW_i'/W_i'}{d\sigma}\right] = \alpha_i + \beta^k, \tag{50}$$

where α_i, which only depends on household i, β^k, which only depends on asset k, and δ_i^k, which depends on both are defined as

$$\alpha_i \equiv \frac{1}{2}\left(\frac{d^2\gamma_i/\gamma_i}{d\sigma^2} - \mathbb{E}\left[\frac{d^2W_i'/W_i'}{d\sigma^2}\right]\right)$$
$$\beta^k \equiv \frac{1}{2}\left(\frac{d^2p^k/p^k}{d\sigma^2} - \mathbb{E}\left[\frac{d^2x^k/x^k}{d\sigma^2}\right]\right)$$

Using (48), and the fact that $\mathbb{E}[\overline{\epsilon\epsilon}'] = \Sigma$, we can rewrite (50) as

$$\sum_{z=1}^{Z}\frac{\partial x^k/x^k}{\partial\epsilon_z}\frac{dW_i'/W_i'}{d\epsilon_z}\overline{\sigma}_z^2 = \alpha_i + \beta^k \quad \forall\, i,k \tag{51}$$

We note that this applies to the product of two first derivatives, and therefore, intuitively, places restrictions on the relationship between the impulse response of returns and marginal utilities. Finally, using (51) for asset k relative to asset 0 (where we note that 0 could correspond to any reference asset in the economy), we obtain:

$$\sum_{z=1}^{Z}\left(\frac{\partial x^k/x^k}{\partial\epsilon_z} - \frac{\partial x^0/x^0}{\partial\epsilon_z}\right)\frac{dW_i'/W_i'}{d\epsilon_z}\overline{\sigma}_z^2 = \underbrace{\beta^k - \beta^0}_{b^k} \quad \forall\, i,k \tag{52}$$

Equation (52) says that all households equalize their average sensitivity to shocks z, interacted with the relative returns on asset k, to a k-specific term b^k. We will soon see that this term has the interpretation of a relative risk premium on asset k. Stacking $\mathbf{b} \equiv (b^1, ..., b^K)'$ as a $K\times 1$ vector of relative risk premia, $\boldsymbol{\lambda}_i \equiv (\frac{dW_i'/W_i'}{d\epsilon_1}, ..., \frac{dW_i'/W_i'}{d\epsilon_Z})'$ as a $Z\times 1$ vector of sensitivities of marginal utility to each shock, defining the $Z\times K$ matrix $\mathbf{X}$ with elements equal to the relative returns of each asset to each shock $X_{zk} \equiv \frac{\partial x_k/x_k}{\partial\epsilon_Z} - \frac{\partial x_0/x_0}{\partial\epsilon_Z}$, and letting $\boldsymbol{\Sigma}$ denote the $Z\times Z$ matrix with $\overline{\sigma}_z^2$ on its diagonal, equation (52) becomes:

$$\mathbf{X}'\boldsymbol{\Sigma}\boldsymbol{\lambda}_i = \boldsymbol{b} \quad \forall\, i \tag{53}$$

Equation (53) is core for the portfolio choice, which I illustrate next.

Complete markets

Suppose that $K = Z$, such that the number of assets equals the number of shocks plus one. This effectively allows households to insure against all aggregate shocks by taking respective portfolio positions. We say that this corresponds to complete markets with respect to aggregate risk. Then $\mathbf{X}$ is a square matrix. Additionally, suppose the following assumptions are fulfilled:

Assumption 1 (Spanning)**.** *The rows of* $\mathbf{X}$ *are linearly independent.*

and

Assumption 2 (Constraints)**.** *There are no portfolio constraints, such that* $\eta_{it} = \delta_i^k = 0$ *and* $\mathbf{\Theta}'\boldsymbol{\eta}_i = \mathbf{0}_K$.

Assumption 1 says that the relative returns across assets vary sufficiently across shocks, while assumption 2 abstracts from portfolio constraints. Under the first assumption, the $Z \times Z$ matrix $\mathbf{X}'\mathbf{\Sigma}$ is invertible, while the second assumption abstracts from idiosyncratic binding constraints. Condition (53) can therefore be rewritten:

$$\boldsymbol{\lambda}_i = (\mathbf{X}')^{-1}\mathbf{\Sigma}^{-1}\mathbf{b} \equiv \boldsymbol{\lambda}, \tag{54}$$

which yields the first main result.

Proposition 1. *Suppose that* $K = Z$ *and assumptions 1 and 2 hold. Then for each shock* z*, there exists a* λ_z *such that*

$$\frac{dW_i'/W_i'}{d\epsilon_z} = \lambda_z \quad \forall\, i. \tag{55}$$

Proposition 1 provides us with a simple test of portfolio optimality in a setting where $K = Z$. To understand the test, note that standard first-order methods allow us relatively easily to solve for steady-state x^k, W_i, as well as $\frac{x^k}{\partial \epsilon_z}$ and $\frac{dW_i'}{d\epsilon_z}$ for given shocks z, conditional on given incoming portfolios $\{a_i^k\}$ for all agents. With these objects, one can form the matrix of relative returns $\mathbf{X}$ to test if the spanning assumption 1 is satisfied, and then test whether $\frac{dW_i'/W_i'}{d\epsilon_z}$ are equalized across agents i for all shocks z. If so, proposition 1 tells us that the portfolios are optimal.

Proposition 1 also implies a method for solving for optimal portfolios directly. Suppose that $\overline{a}_i^k$ is an exogenous portfolio and let t_i be the excess payoff from another portfolio a_i^k such that

$$t_i \equiv \sum_{k=0}^{K} x^k(\epsilon)(a_i^k - \overline{a}_i^k). \tag{56}$$

Moreover, let $\overline{W}_i\left(\sum_{k=0}^K x^k(\epsilon)\overline{a}_i^k, \boldsymbol{\epsilon}\right)$ denote the value function under the exogenous portfolio, whereas $W_i(t_i, \boldsymbol{\epsilon}) \equiv \overline{W}_i\left(\sum_{k=0}^K x^k(\epsilon)\overline{a}_i^k + t_i, \epsilon\right)$ denotes the value function under the portfolio a_i^k. With complete markets and assumptions 1 and 2 in place, households portfolios should satisfy the risk-sharing condition (55). We can find the corresponding excess payoff t_i, by imposing that it satisfies the risk-sharing condition. Given the exogenous portfolio $\overline{a}_i^k$, we can approximate the risk-sharing condition at the optimal portfolio around the utility change in the exogenous portfolio case as

$$\frac{d\overline{W}'_i/\overline{W}'_i}{d\epsilon_z} + \frac{\overline{W}''_i}{\overline{W}'_i}\frac{dt_i}{d\epsilon_z} = \lambda_z. \tag{57}$$

The first term on the right-hand side of (57) refers to the direct exposure to shocks under exogenous portfolios, whereas the second term denotes the ”transfer” exposure to shocks under a portfolio that achieves optimal aggregate risk-sharing. Intuitively, equation (57) provides a condition to solve for transfers contingent on shocks $dt_i/d\epsilon_z$:

$$\frac{dt_i}{d\epsilon_z} = \frac{\overline{W}'_i}{\overline{W}''_i}\left(\lambda_z - \frac{d\overline{W}'_i/\overline{W}'_i}{d\epsilon_z}\right) \tag{58}$$

and since transfers have to sum to zero, $\int \frac{dt_i}{d\epsilon_z} di = 0$, we obtain:

$$\lambda_z = \left(\int \frac{\overline{W}'_i}{\overline{W}''_i} di\right)^{-1} \int \frac{\overline{W}'_i}{\overline{W}''_i}\frac{d\overline{W}'_i/\overline{W}'_i}{d\epsilon_z} di. \tag{59}$$

We can use these two equations to derive λ_z via equation (59) and then obtain excess returns via equation (58). From the definition of the excess returns (56), we then obtain the relation between transfers and the endogenous portfolios that ensures optimal insurance against aggregate risk:

$$\frac{dt_i}{d\epsilon_z} = \sum_{k=0}^K \frac{dx^k}{d\epsilon_z}(\epsilon)(a_i^k - \overline{a}_i^k) \tag{60}$$

Using the definition of portfolio shares $\omega_i^k = \frac{a_i^k}{a_i}$ and $\overline{\omega}_i^k = \frac{\overline{a}_i^k}{a_i}$ we can rewrite equation

(60) to

$$
\begin{aligned}
\frac{\partial t_i}{\partial \epsilon_z} &= \sum_{k=0}^{K} \frac{\partial x^k}{\partial \epsilon_z}(\epsilon)(a_i^k - \overline{a}_i^k) \\
&= a_i \sum_{k=0}^{K} \frac{\partial x^k}{\partial \epsilon_z}(\epsilon)(\omega_i^k - \overline{\omega}_i^k) \\
&= a_i \sum_{k=1}^{K} \left(\frac{\partial x^k}{\partial \epsilon_z}(\epsilon) - \frac{\partial x^0}{\partial \epsilon_z}(\epsilon) \right) (\omega_i^k - \overline{\omega}_i^k).
\end{aligned}
$$

Using the definition of $\mathbf{X}$ from above, and defining vectors $\boldsymbol{\omega}_i = (\omega_i^1, ..., \omega_i^K)'$, $\overline{\boldsymbol{\omega}}_i = (\overline{\omega}_i^1, ..., \overline{\omega}_i^K)'$, and $\mathbf{t}_i = (\frac{\partial t_i}{\partial \epsilon_1}, ..., \frac{\partial t_i}{\partial \epsilon_Z})'$, we can write the optimal portfolio weights as

$$
\mathbf{t}_i = \mathbf{X}(\boldsymbol{\omega}_i - \overline{\boldsymbol{\omega}}_i)a_i \quad \Leftrightarrow \quad \boldsymbol{\omega}_i = \overline{\boldsymbol{\omega}}_i + \mathbf{X}^{-1}\frac{\mathbf{t}_i}{a_i} \tag{61}
$$

For $K = 1$ (two assets) the relation becomes

$$
\omega_i^1 = \overline{\omega}_i^1 + \frac{1}{a_i} \left(\frac{\partial x^1}{\partial \epsilon_z}(\epsilon) - \frac{\partial x^0}{\partial \epsilon_z}(\epsilon) \right)^{-1} \frac{dt_i}{d\epsilon_z}.
$$

Finally, we can calculate the risk premia associated with the individual assets. We want to approximate risk-premia up to second order around $\sigma = 0$. First, let $R^k(\sigma) = \mathbb{E}\left[x^k(\sigma)\right]/p^k(\sigma)$ define the expected return on asset k. From equation (46), we have $R^k(0) = R$. The derivative of the expected return with respect to σ is

$$
\frac{dR^k(\sigma)}{d\sigma} = \mathbb{E}\left[\frac{dx^k(\sigma)}{d\sigma}\right]\frac{1}{p^k(\sigma)} - \mathbb{E}\left[\frac{x^k(\sigma)}{p^k(\sigma)}\right]\frac{dp^k(\sigma)/p^k(\sigma)}{d\sigma} = 0, \tag{62}
$$

which uses equation (48), $\mathbb{E}\left[\frac{dx^k}{d\sigma}\right] = 0$ and $\frac{dp^k}{d\sigma} = 0$ from our symmetry result. Finally, the second-order derivative of the expected return of asset k with respect to σ is

$$
\begin{aligned}
\frac{d^2R^k(\sigma)}{d\sigma^2} =& \mathbb{E}\left[\frac{d^2x^k(\sigma)}{d\sigma^2}\right]\frac{1}{p^k(\sigma)} - 2\mathbb{E}\left[\frac{dx^k(\sigma)}{d\sigma}\right]\frac{dp^k(\sigma)/p^k(\sigma)}{d\sigma}\frac{1}{p^k(\sigma)} \\
&- \mathbb{E}\left[x^k(\sigma)\right]\left[\frac{\frac{d^2p^k(\sigma)}{d\sigma^2}p^k(\sigma)^2 - 2\frac{dp^k(\sigma)}{d\sigma}p^k(\sigma)}{(p^k(\sigma))^4}\right] \\
=& \mathbb{E}\left[\frac{d^2x^k(\sigma)}{d\sigma^2}\right]\frac{1}{p^k(\sigma)} - \mathbb{E}\left[\frac{x^k(\sigma)}{p^k(\sigma)}\right]\left[\frac{d^2p^k(\sigma)/p^k(\sigma)}{d\sigma^2}\right],
\end{aligned} \tag{63}
$$

where we have used again that the derivatives of the first order of payoffs $x^k(\sigma)$ and prices $p^k(\sigma)$ are zero. Note that $\frac{d^2R^k(\sigma)}{d\sigma^2} = -2R^k(\sigma)\beta^k$. A second-order Taylor expansion of the expected return $R^k(\sigma)$ around $\sigma = 0$ yields

$$R^k(\sigma) \approx R^k(0) + \frac{dR^k(0)}{d\sigma}\sigma + \frac{1}{2}\frac{d^2R^k(0)}{d\sigma^2}\sigma^2 = R - R\beta^k\sigma^2,$$

such that the relative risk premium of asset k against asset 0 has the second order expansion

$$\frac{R^k(\sigma) - R^0(\sigma)}{R} \approx -(\beta^k - \beta^0)\sigma^2 = -b^k\sigma^2. \tag{64}$$

We can use equation (52) and from proposition 1 equation (55) to obtain:

$$b^k = \sum_{z=1}^{Z} \underbrace{\left(\frac{\partial x^k/x^k}{\partial \epsilon_z} - \frac{\partial x^0/x^k}{\partial \epsilon_z}\right)}_{X_{zk}} \underbrace{\frac{dW_i'/W_i'}{d\epsilon_z}}_{\lambda_z} \overline{\sigma}_z^2 = \sum_{z=1}^{Z} X_{zk}\lambda_z\overline{\sigma}_z^2 \tag{65}$$

such that

Proposition 2. *Suppose markets are complete and assumptions (1) and (2) hold. Then, the risk premia of asset k relative to asset 0 satisfies, to second order*

$$\frac{R^k(\sigma) - R^0(\sigma)}{R} \approx -\sum_{z=1}^{Z} X_{zk}\lambda_z\overline{\sigma}_z^2\sigma^2. \tag{66}$$

Proposition 2 allows us to approximate the risk premia on an assets k using only the information from a first-order perturbation.

III Appendix: Data sources and transformations

This section describes the data used for the calibration and in the Bayesian estimation of the model in the main text.

III.1 Calculation of Time-Series Averages for Calibration

To pin down steady-state targets, I compute time series for four aggregate ratios and for the depreciation rate using U.S. national accounts and market data, then take sample averages over 1954:Q1 to 2020:Q1. The data are obtained from FRED unless noted otherwise.

Capital-to-Output Ratio K_t/Y_t**:** Fixed assets (K1TTOTL1ES000) divided by GDP (FYGDP). Since capital is reported at an annual frequency, the series is multiplied by four to obtain a quarterly equivalent, computed as Capital-to-GDP $=$ Capital $\times$ $4/$GDP.

Debt-to-Output Ratio B_t/Y_t**:** Federal debt held by the public as percent of Gross Domestic Product (FYPUGDA188S). The series is multiplied by four to ensure consistency with the quarterly GDP concept.

Government Expenditure-to-Output Ratio G_t/Y_t**:** Government consumption and investment expenditures (GCEA) divided by GDP (FYGDP), both expressed in billions of dollars. The ratio is scaled to percentages as Expenditure-to-GDP $=$ GCEA/GDP $\times$ 100.

Stock Market Value-to-Output Ratio $Q_t^{\mathbf{eq}}/Y_t$**:** Market value of listed domestic companies relative to GDP (DDDM01USA156NWDB). The series, is converted from a percent of GDP to a quarterly ratio using Stock-Market-to-GDP $=$ DDDM01USA156NWDB$/100 \times 4$.

Depreciation Rate δ_t**:** Computed from the ratio of total current-cost depreciation of fixed assets (M1TTOTL1ES000) to the corresponding capital stocks (K1TTOTL1ES000). The annual depreciation rate is defined as $\delta_{\text{annual}} =$ Depreciation/Capital $\times$ 100, and the quarterly depreciation rate used in the model equals $\delta = \delta_{\text{annual}}/4$.

The sample means of these variables serve as calibration targets for the steady state.

III.2 Calculation of Time-Series Averages for Government Debt

Maturity Structure of Government Debt $\omega^{(n)}, 1/\delta^{(n)}$**:** The calibration of the public debt structure is based on the historical database of De Graeve and Mazzolini (2023). I importing the quarterly, nominal market value of US government debt, which is broken down into 19 distinct maturity buckets ranging from 3 months to over 30 years. To convert these nominal values into real terms, each series is deflated using the GDP deflator (GDPDEF), which is sourced from the FRED database. Subsequently, for each quarter in the sample, the real value in each maturity bucket is divided by the total real value of all outstanding debt. This step normalizes the data, transforming the absolute monetary values into a time series of portfolio shares for each maturity, which sum to 100% in each period. The time-series average of these shares is then computed for each of the 19 maturities to establish a single, representative weight for the entire historical period. To create a more tractable structure for the model, these 19 buckets are then aggregated into seven broader tranches. For each of these seven final groups, the total share ($\omega^{(n)}$)

is calculated by summing the average weights of the constituent maturities. The average duration ($1/\delta^{(n)}$) for each tranche is then determined by calculating the weighted average of the numerical maturities (e.g., ”6M” is converted to 0.5 years) within that group, using their historical average shares as the weights. This procedure yields the final calibration parameters presented in Table 2.

III.3 Estimation on Time-Series Data

The observables used for the estimation can be summarized as

$$obs_t = \begin{bmatrix} \Delta\log(Y_t) \\ \Delta\log(C_t) \\ \Delta\log(I_t) \\ \Delta\log(w_t) \\ \Delta\log(q_t) \\ \Delta\log(d_t) \\ \log(N_t) \\ \log(1+r_t^{eq}) \\ \log(\frac{1}{q_t^{3m}}) \\ \log(1+\pi_t^p) \end{bmatrix} - \begin{bmatrix} \overline{\Delta\log(Y_t)} \\ \overline{\Delta\log(C_t)} \\ \overline{\Delta\log(I_t)} \\ \overline{\Delta\log(w_t)} \\ \overline{\Delta\log(q_t)} \\ \overline{\Delta\log(d_t)} \\ \overline{\log(N_t)} \\ \overline{\log(1+r_t^{eq})} \\ \overline{\log(\frac{1}{q_t^{3m}})} \\ \overline{\log(1+\pi_t^p)} \end{bmatrix}. \tag{67}$$

The Δ denotes the first difference between variables, and bars over variables denote the time-series averages. Except for the stock price and dividend series, all series are obtained from the St. Louise FED - FRED database. All data series from FRED are available at a quarterly frequency. The time series of stock prices, and dividends are obtained from the online database of Robert Shiller. The data was first generated for Shiller (1989), but was updated until today. The up-to-date time series can be accessed here. I extract monthly data on nominal stock prices Q_t^{eq} and dividends D_t from the online dataset and convert them to real series. I illustrate the transformation from monthly to quarterly frequency below and from nominal to real below.

Output Y_t: Sum of gross private domestic investment (GPDI), personal consumption expenditures for nondurable goods (PCND), durable goods (PCDG), and services (PCESV), and government consumption expenditures and gross investment (GCE) divided by the GDP deflator (GDPDEF) and the civilian noninstitutional population (CNP16OV).

Consumption C_t**:** Sum of personal consumption expenditures for nondurable goods (PCND), durable goods (PCDG), and services (PCESV) divided by the GDP deflator (GDPDEF) and the civilian noninstitutional population (CNP16OV).

Investment I_t**:** Gross private domestic investment (GPDI) divided by the GDP deflator (GDPDEF) and the civilian noninstitutional population (CNP16OV).

Real wage w_t**:** Hourly compensation in the nonfarm business sector (COMPNFB) divided by the GDP deflator (GDPDEF).

Hours worked N_t**:** Nonfarm business hours worked (HOANBS) divided by the civilian noninstitutional population (CNP16OV).

Inflation π_t**:** Computed as the log-difference of the GDP deflator (GDPDEF).

Nominal interest rate $\frac{1}{q_t^{3m}}$**:** Quarterly average of the effective federal funds rate (FEDFUNDS). From 2009-Q1 to 2015-Q4, I use the shadow federal funds rate of Wu and Xia (2016) instead of the federal funds rate, which was at the zero-lower bound.

Real stock prices q_t**:** The nominal stock price Q_t^{eq} (S&P Comp. P) is available at a monthly frequency in Robert Shiller's database. I convert the series to a quarterly frequency by taking the average over the realizations of the monthly stock price. Thereafter, the quarterly series is divided by the GDP deflator (GDPDEF) to obtain real stock prices.

Real dividends d_t**:** The nominal dividend D_t (Dividend) is available at a monthly frequency in Robert Shiller's database. I convert the series to a quarterly frequency by taking the average over the realizations of the monthly stock price. Thereafter, the quarterly series is divided by the GDP deflator (GDPDEF) to obtain the real dividend.

Real dividends d_t**:** The nominal dividend (Dividend) is available at a monthly frequency in Robert Shiller's database. I convert the series to a quarterly frequency by taking the average over the realizations of the monthly dividend. Thereafter, the quarterly series is divided by the GDP deflator (GDPDEF) to obtain the real dividend.

Real return r_t^{eq}**:** I use the quarterly nominal equity price Q_t^{eq} and the quarterly nominal dividend D_t to calculate the nominal equity return as $r_t^{eq,nom} = (Q_t^{eq} - Q_{t-1}^{eq})/Q_{t-1}^{eq} + D_t/D_{t-1}^{eq}$ based on the calculation of Jordà et al. (2019). I then convert the return from nominal to real by dividing it by the inflation rate obtained above: $1 + r_t^{eq} \equiv \frac{q_t + d_t}{q_{t-1}} = \frac{1 + r_t^{eq,nom}}{1 + \pi_t^p}$.

III.4 Calculation of Average Asset Premia

This subsection describes how I construct the data averages reported in Table 4. The calculation of the equity premium uses the monthly version of the real equity return r_t^{eq} defined above. Term premia are based on Treasury yields at different maturities, described next.

Treasury yields $y_t^{(n)}$: I use monthly Treasury Constant Maturity rates from FRED for maturities 3M, 6M, 1Y, 2Y, 5Y, 10Y, and 20Y (series GS3M, GS6M, GS1, GS2, GS5, GS10, GS20).

Equity premium: Using the monthly real equity return r_t^{eq} based on Shiller (1989), I compute the monthly equity excess return as the difference between r_t^{eq} and the 10Y Treasury Constant Maturity yield. The equity premium is the sample average of this monthly excess return over the estimation window. I obtain an equity premium of 5.01 percentage points, which is in line with the averages reported by Jordà et al. (2019), among others.

Term premia: For each maturity $n \neq$ 3M, the term premium is calculated as the average yield difference $tp_t^{(n)} = y_t^{(n)} - y_t^{(3M)}$. All statistics are in annualized percentage points. The slope of the yield curve is strongly dependent on the country studied, as well as the period considered.[31] The estimates I obtain for the post-war U.S. term-premia are in line with the estimates used by other authors, see Campbell, Pflueger and Viceira (2020) for example.

IV Appendix: Estimation Diagnostics

To check convergence of the estimation, we use the Gelman and Rubin (1992) statistic and inspect the trace plots of the individual chains.

Table 8 reports the Gelman–Rubin potential scale reduction factor (Gelman and Rubin, 1992) for the estimation over the entire sample period, as well as for the subperiod from 1979 to 1999 and from 2000 to 2019. The statistic compares dispersion within

[31] See Kung (2015) for a discussion.

each Markov chain to dispersion across chain means. When chains started from deliberately dispersed initial values have reached the common stationary distribution, these two sources of variation align and the statistic approaches one. Values meaningfully above one indicate that between chain dispersion remains elevated, which signals incomplete mixing. Following Vats and Knudson (2021), I use the conservative threshold of 1.01 to determine convergence. All parameters for all estimations fall well below this threshold, supporting the conclusion that in all estimation exercises the chains have converged to the stationary posterior distribution.

Figures 5 and 6 illustrate the trace plots of the 128 chains over 5000 draws from the posterior after a 5000 draw burn-in. Visual inspection of the trace plots indicates satisfactory mixing. For all parameters the chains feature stationary fluctuations around a stable level, no visible drift or regime shifts, as well as overlap of different chains overlap which suggests convergence. Shock standard deviations appear especially well behaved with tight stationary bands. Autoregressive coefficients mix somewhat more slowly as expected when persistence is high. In sum the traces support reliable posterior inference.

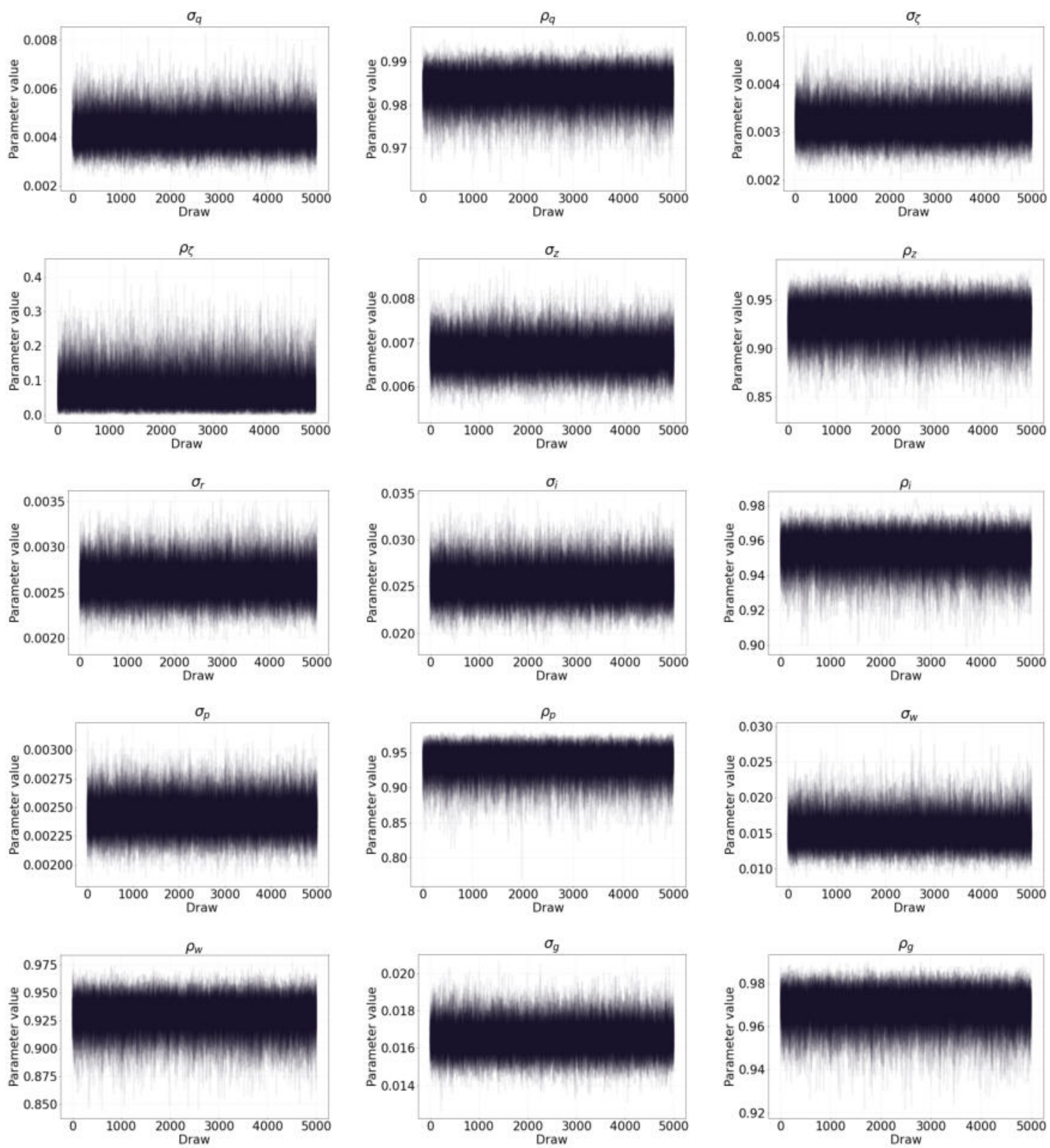
The traces for the policy parameters and frictions indicate generally satisfactory mixing after the burn-in period. The chains for ρ_r, ϕ_π, and ϕ_y fluctuate around stable centers with frequent crossovers and no visible drift, which points to convergence. The frictions λ_p, λ_w, and ι_p also show tight stationary bands and good overlap. The fiscal block is somewhat more variable: ρ_τ explores a wider interval and moves more slowly. The level parameter χ mixes the most slowly and spans the widest range, implying higher autocorrelation and a lower effective sample size relative to the others. Overall the figure supports reliable inference for most parameters, with mild caution warranted for χ and to a lesser extent for ρ_τ.

Table 8 Gelman Rubin $\hat{R}$ statistics

Parameter	Full Sample	1979 to 1999	2000 to 2019
Structural Shocks			
σ_q	1.00119	1.0025	1.0021
ρ_q	1.00107	1.0035	1.0026
σ_ζ	1.00061	1.0020	1.0010
ρ_ζ	1.00063	1.0034	1.0029
σ_z	1.00071	1.0013	1.0016
ρ_z	1.00145	1.0022	1.0033
σ_r	1.00160	1.0018	1.0017
σ_i	1.00130	1.0021	1.0031
ρ_i	1.00270	1.0050	1.0052
σ_p	1.00075	1.0011	1.0017
ρ_p	1.00160	1.0087	1.0047
σ_w	1.00178	1.0032	1.0045
ρ_w	1.00125	1.0021	1.0020
σ_g	1.00128	1.0025	1.0015
ρ_g	1.00132	1.0033	1.0017
Policy and Frictions			
ρ_r	1.00142	1.0044	1.0032
ϕ_π	1.00279	1.0074	1.0045
ϕ_y	1.00238	1.0061	1.0049
ρ_τ	1.00319	1.0064	1.0058
γ_τ^b	1.00251	1.0047	1.0069
γ_τ^y	1.00238	1.0057	1.0063
λ_p	1.00315	1.0056	1.0048
λ_w	1.00229	1.0045	1.0032
ι_p	1.00244	1.0084	1.0051
ι_w	1.00214	1.0060	1.0056
χ	1.00283	1.0052	1.0053

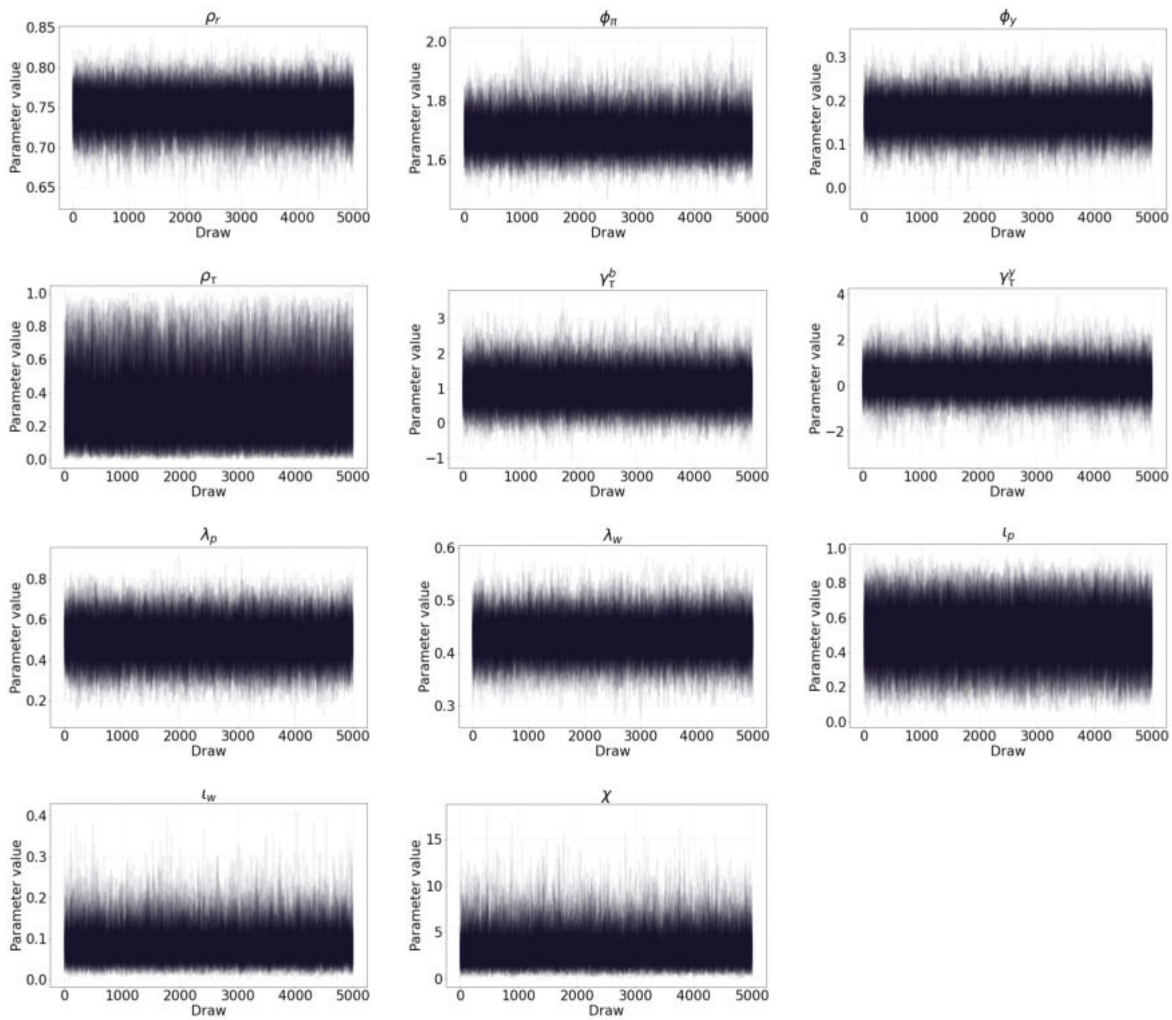
Notes: Values report the potential scale reduction factor $\hat{R}$ of Gelman and Rubin (1992) for each parameter. Values below 1.01 indicate convergence. The first column shows the statistic for the estimation over the full sample, while the last two columns show the parameter for the full estimation over the subperiods 1979 to 1999 and 2000 to 2019.

Figure 5 Traceplots for shock parameters after 5000 burn-in draws



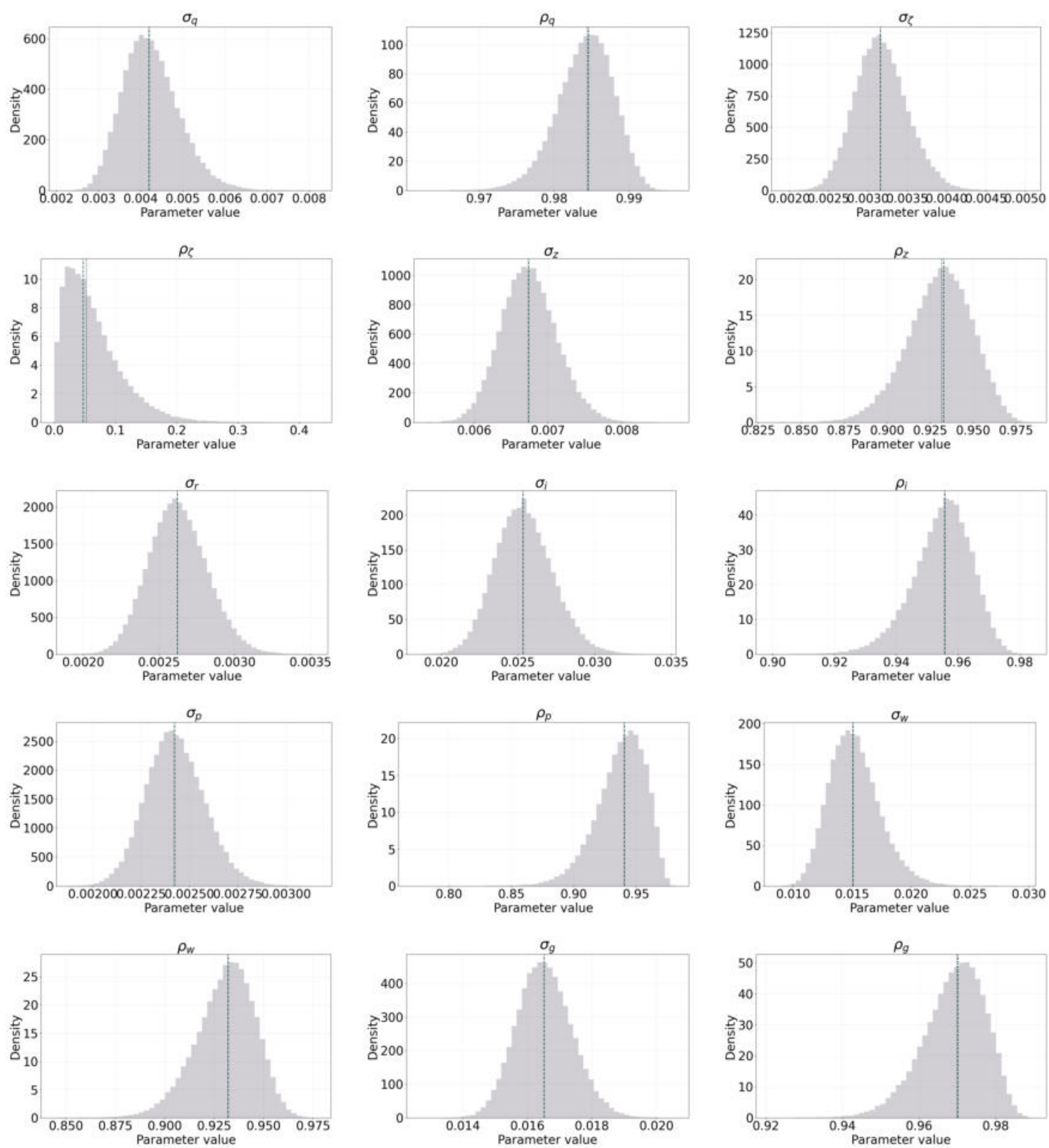
Notes: Traceplots of the 128 chains used in estimation. The traceplots only illustrates the last 5000 draws from all 128 chains. I discarded the first 5000 draws per chain as burn-in.

Figure 6 Traceplots for policy parameters and frictions after 5000 burn-in draws



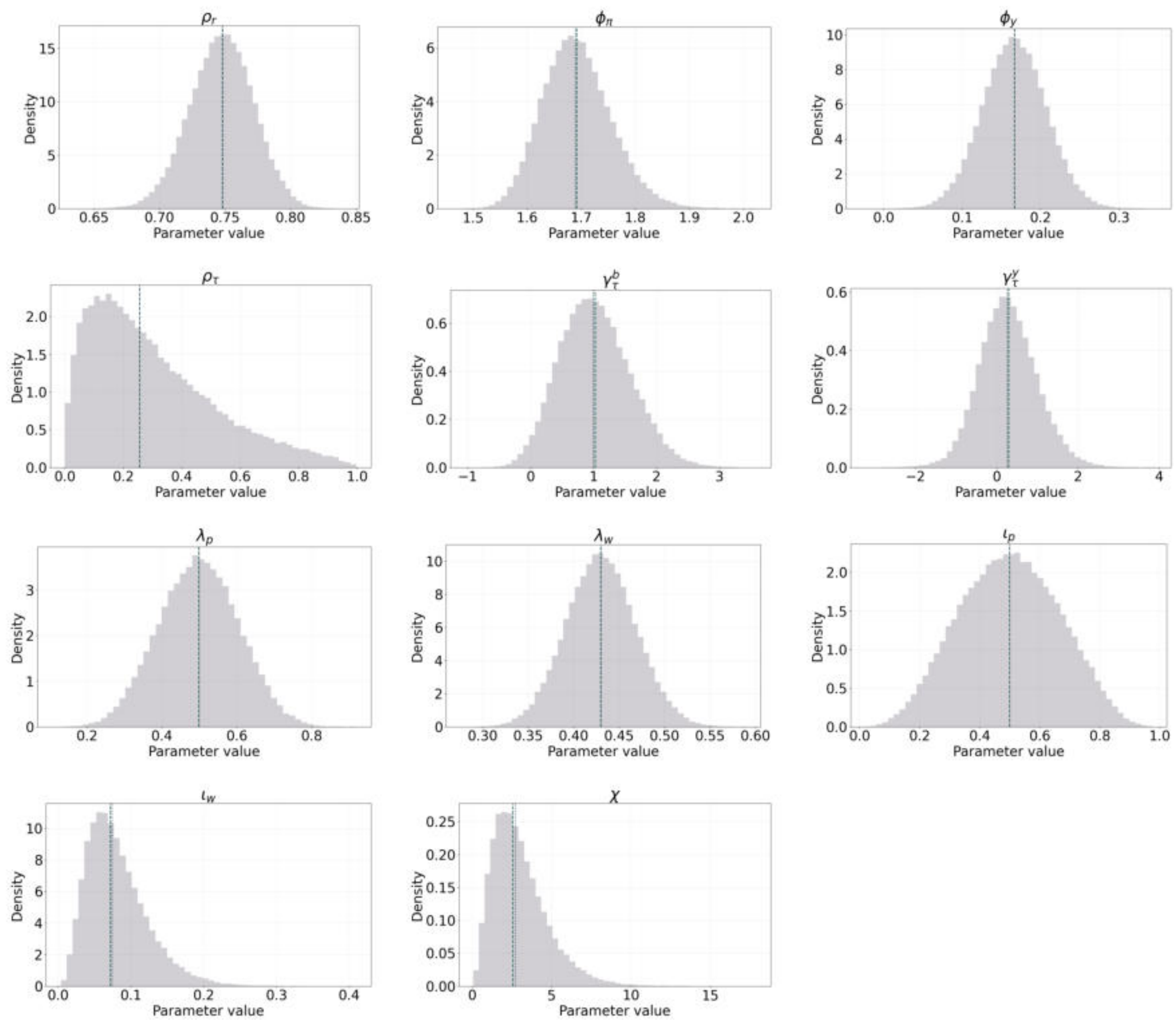
Notes: Traceplots of the 128 chains used in estimation. The traceplots only illustrates the last 5000 draws from all 128 chains. I discarded the first 5000 draws per chain as burn-in.

Figure 7 Posterior histogram of shock parameters



Notes: Posterior histogram from Bayesian estimation. The histogram only illustrates the last 5000 draws from all 128 chains. I discarded the first 5000 draws per chain as burn-in.

Figure 8 Posterior histogram of policy parameters and frictions

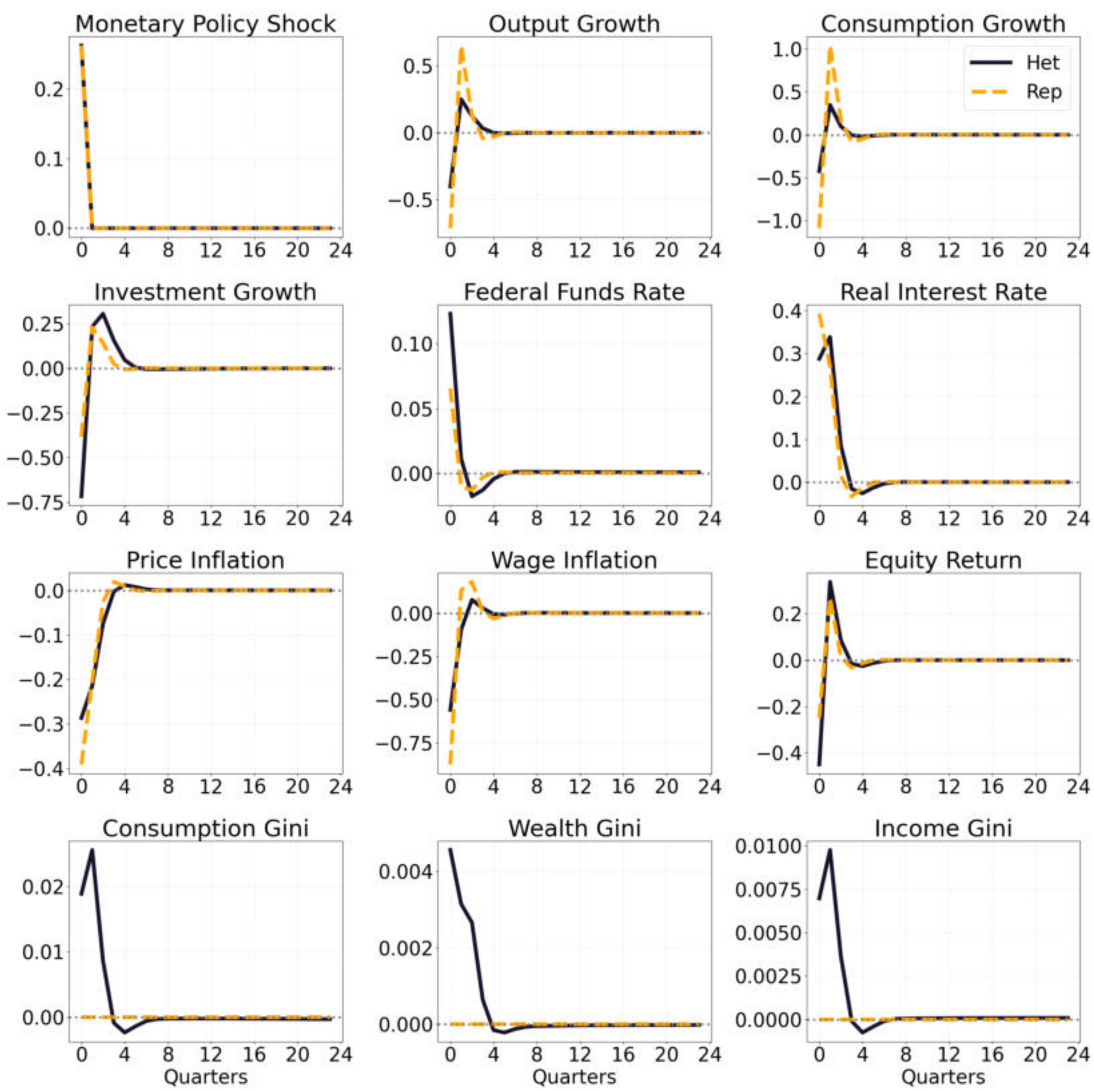


Notes: Posterior histogram from Bayesian estimation. The histogram only illustrates the last 5000 draws from all 128 chains. I discarded the first 5000 draws per chain as burn-in.

V Appendix: Structural Analysis

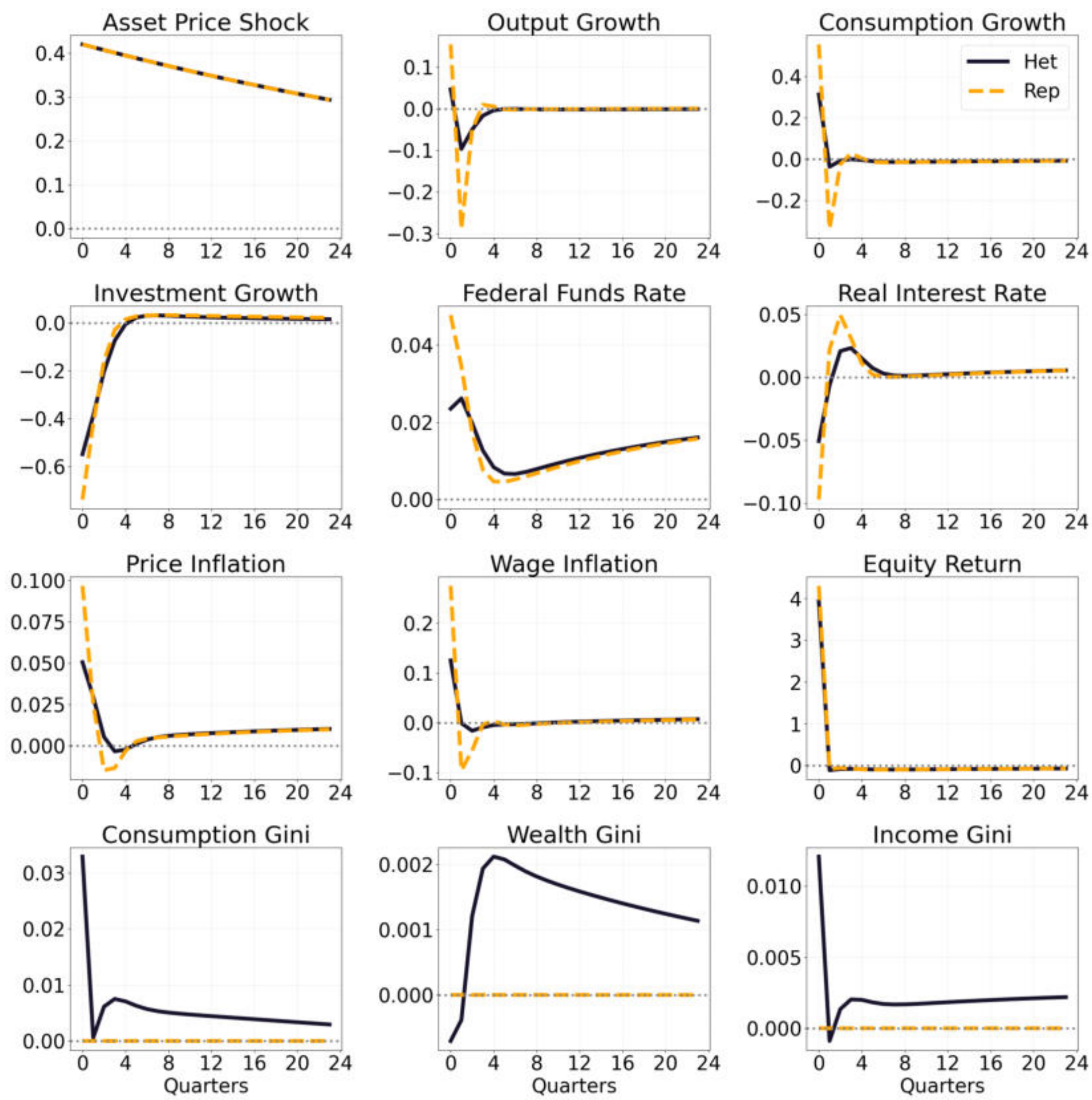
This section presents the structural results after estimation. Figures 9 to 12 show impulse responses of the estimated heterogeneous agent and representative agent models to monetary policy, asset price, investment-specific technology, and government expenditure shocks. Figure 13 reports conditional variance decompositions for all aggregate variables and Figure 14 illustrates the historical decomposition for the aggregate series.

Figure 9 Impulse response functions to a Monetary Policy Shock



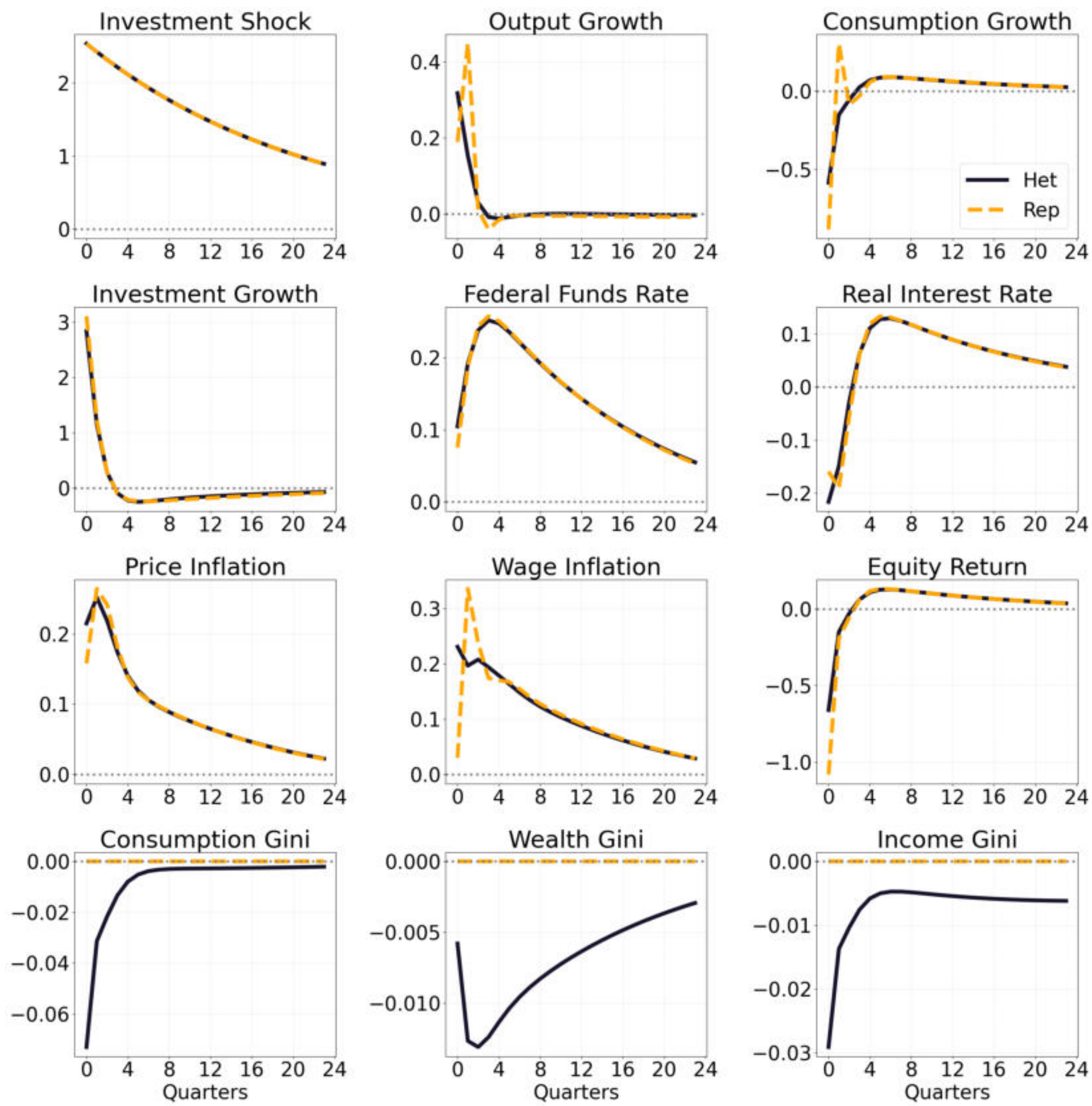
Notes: Impulse response functions (IRFs) of aggregates to monetary policy shock in the heterogeneous agent (Het) model and the representative agent (Rep) model version. The impulse responses shock absolute deviations from the steady state variable in response to the shock. The plots illustrates all responses as percentage points differences from their steady state values.

Figure 10 Impulse response functions to an Asset Price Shock



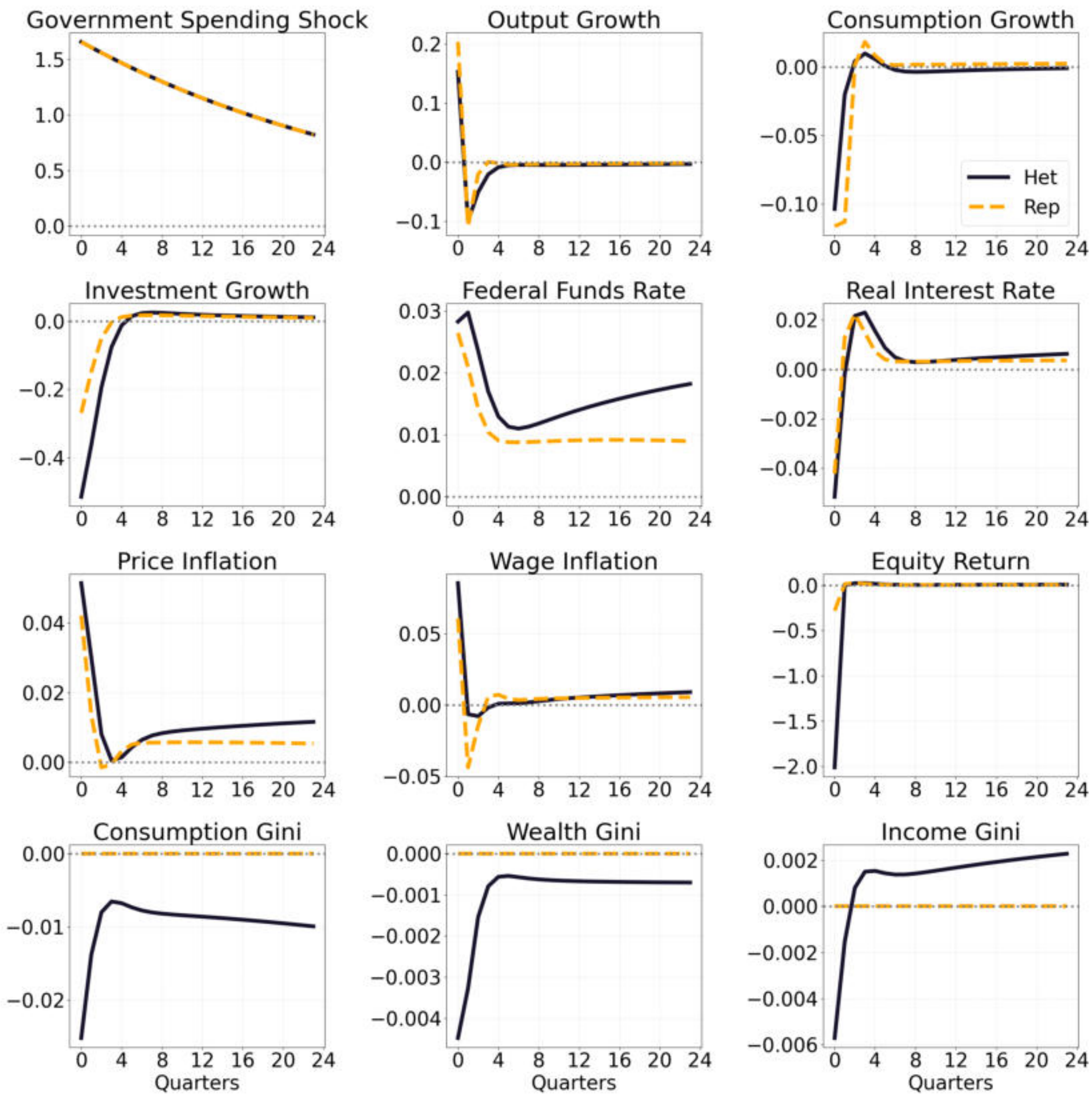
Notes: Impulse response functions (IRFs) of aggregates to monetary policy shock in the heterogeneous agent (Het) model and the representative agent (Rep) model version. The impulse responses shock absolute deviations from the steady state variable in response to the shock. The plots illustrates all responses as percentage points differences from their steady state values.

Figure 11 Impulse response functions to an Investment Specific Productivity Shock



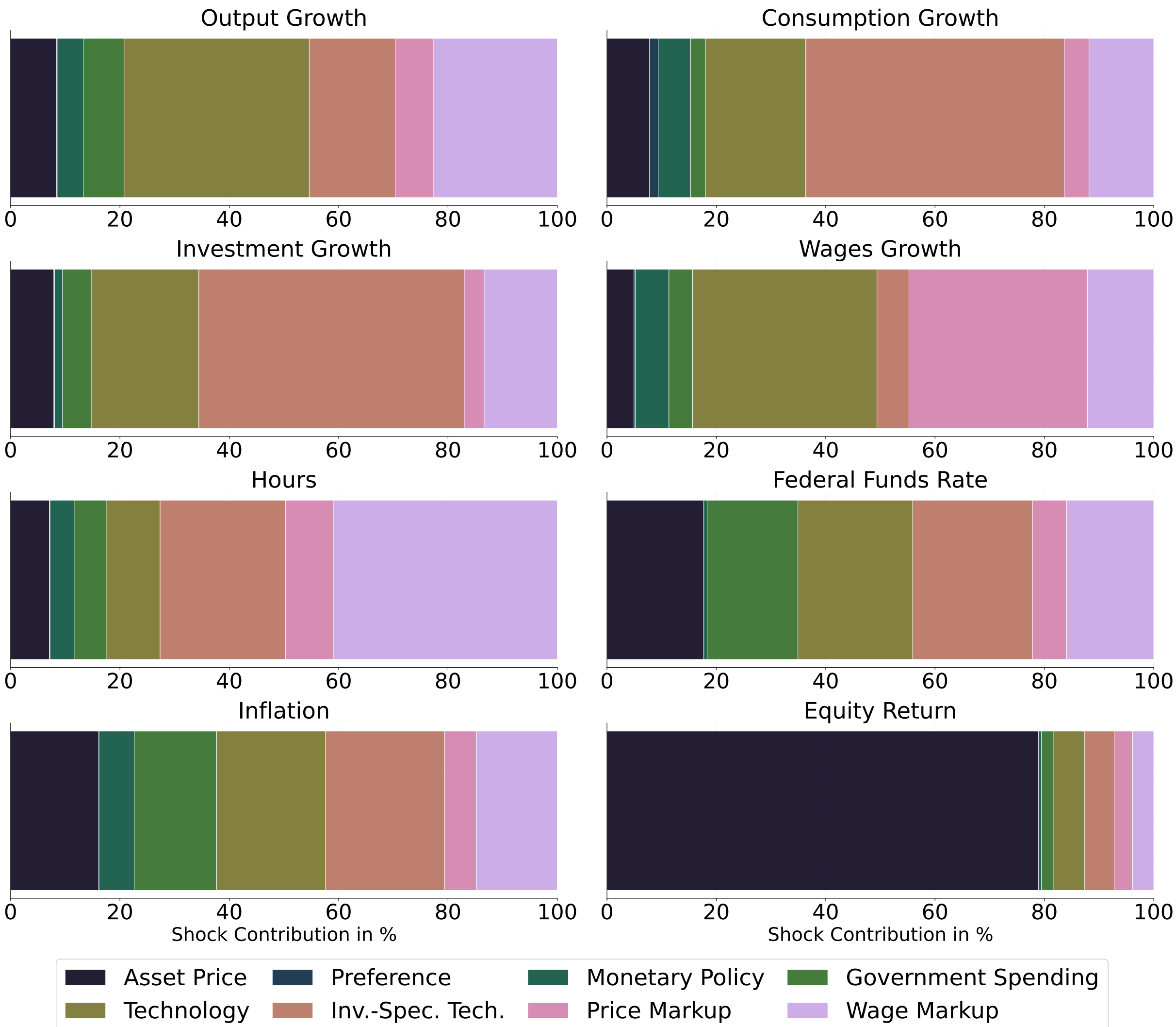
Notes: Impulse response functions (IRFs) of aggregates to an investment specific productivity shock in the heterogeneous agent (Het) model and the representative agent (Rep) model version. The impulse responses shock absolute deviations from the steady state variable in response to the shock. The plots illustrates all responses as percentage points differences from their steady state values.

Figure 12 Impulse response functions to a Government Expenditure Shock



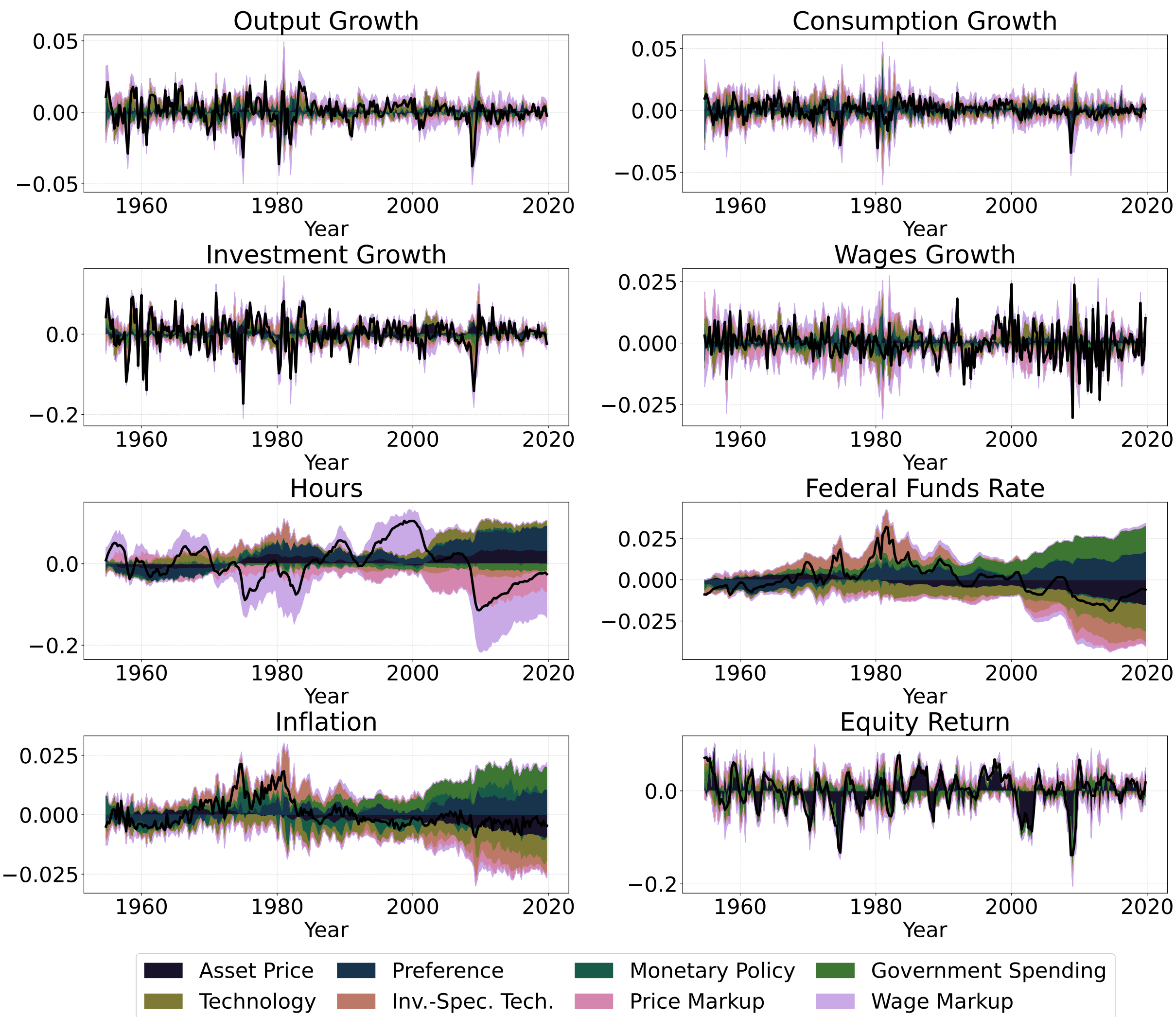
Notes: Impulse response functions (IRFs) of aggregates to a government expenditure shock in the heterogeneous agent (Het) model and the representative agent (Rep) model version. The impulse responses shock absolute deviations from the steady state variable in response to the shock. The plots illustrates all responses as percentage points differences from their steady state values.

Figure 13 Forecast Error Variance Decomposition of all Aggregate Variables



Notes: Conditional variance decompositions for the growth rates of output, consumption, investment, and wages, the log of hours, the federal funds rate, inflation, and the equity return, computed at business cycle frequencies (forecast horizon of 6 to 32 quarters) based on the estimated model. The coloured areas show the share of each variable's variance attributable to a given structural shock.

Figure 14 Historical Decomposition of Observed Variables



Notes: Historical decomposition of time-series data into the contribution of individual structural shocks.

VI Appendix: Estimates from Estimation on Subperiods

The following tables illustrate the estimated parameters from the reestimation of the model over the subperiods 1979-Q2 to 1999-Q4 and for 2000-Q1 to 2019-Q4.

Comparing parameter estimates across the full sample (1954–2019) and the two subperiods (1979–1999 and 2000–2019) reveals several systematic differences. First, the estimated shock volatilities are considerably smaller in both subperiods relative to the full sample, consistent with a calmer macroeconomic environment after the 1980s. During 1979–1999, volatilities such as σ_i, σ_z, and σ_r already decline compared to the full sample, but remain larger than in 2000–2019, where most volatilities fall further, especially for price and wage shocks, indicating a more stable nominal environment. Second, the persistence of shocks remains high across all samples but exhibits heterogeneity across types. Technology and fiscal shocks (ρ_z, ρ_g) become increasingly persistent, approaching one in the post-2000 period, while investment specific technology and policy shocks (ρ_i, ρ_r) display lower persistence in both subperiods, with the most pronounced reduction during 1979–1999.

Third monetary policy parameters evolve notably over time. The response to inflation ϕ_π rises from about 1.7 in the full sample to above 2.1 in 1979–1999 and around 2.3 in 2000–2019, suggesting a progressively stronger anti-inflation stance. The output response ϕ_y remains moderate but declines from roughly 0.17 to 0.11 after 2000, indicating a slightly weaker focus on output stabilization. The interest-rate smoothing parameter ρ_r decreases from 0.75 in the full sample to 0.60 in 1979–1999 and returns to 0.73 in 2000–2019, implying more volatile rate adjustments in the earlier period and more gradual adjustments thereafter.

Fourth, fiscal and nominal rigidities also shift across subperiods. The fiscal feedback to debt γ_τ^b strengthens markedly from about 1.0 in the full sample to 1.6 in 1979–1999 and almost 2.0 in 2000–2019, pointing to tighter fiscal discipline in both subperiods, while the output response γ_τ^y turns mildly positive only after 2000. Nominal rigidities remain broadly similar, although wage rigidity and indexation (λ_w, ι_w) decline sharply in the later period, consistent with more flexible labor markets. The adjustment cost parameter χ remains close to 2.5 across all samples, showing little sensitivity to the estimation window.

Overall, the post-2000 period is characterized by lower macroeconomic volatility, more persistent but smaller shocks, a stronger and steadier monetary response to inflation, and reduced wage rigidities. The pre-2000 period retains somewhat higher volatility and less persistent shocks, while the full-sample estimates largely average across

Table 9 Bayesian estimation results for 1979 to 1999: shock and policy parameters

		Prior		Posterior			
Shock Parameter	**Distribution**	**Mean**	**SD**	**Mean**	**Median**	**5%**	**95%**
$\sigma_q \cdot 100$	Inv. Gamma	10.0	25.0	1.368	1.371	0.922	2.022
ρ_q	Beta	0.5	0.2	0.882	0.881	0.821	0.927
$\sigma_\zeta \cdot 100$	Inv. Gamma	10.0	25.0	0.476	0.475	0.380	0.599
ρ_ζ	Beta	0.5	0.2	0.062	0.069	0.012	0.210
$\sigma_z \cdot 100$	Inv. Gamma	10.0	25.0	0.510	0.510	0.436	0.598
ρ_z	Beta	0.5	0.2	0.999	0.999	0.997	1.000
$\sigma_r \cdot 100$	Inv. Gamma	10.0	25.0	0.471	0.470	0.394	0.564
$\sigma_i \cdot 100$	Inv. Gamma	10.0	25.0	2.214	2.211	1.918	2.567
ρ_i	Beta	0.5	0.2	0.808	0.808	0.734	0.866
$\sigma_p \cdot 100$	Inv. Gamma	10.0	25.0	0.287	0.287	0.239	0.348
ρ_p	Beta	0.5	0.2	0.610	0.611	0.341	0.831
$\sigma_w \cdot 100$	Inv. Gamma	10.0	25.0	1.100	1.094	0.830	1.482
ρ_w	Beta	0.5	0.2	0.939	0.939	0.910	0.960
$\sigma_g \cdot 100$	Inv. Gamma	10.0	25.0	1.278	1.277	1.085	1.508
ρ_g	Beta	0.5	0.2	0.907	0.908	0.817	0.953

		Prior		Posterior			
Policy Parameter	**Distribution**	**Mean**	**SD**	**Mean**	**Median**	**5%**	**95%**
ρ_r	Beta	0.5	0.2	0.599	0.601	0.522	0.668
ϕ_π	Gamma	1.5	0.3	2.156	2.154	1.925	2.421
ϕ_Y	Normal	0.1	0.1	0.169	0.169	0.092	0.245
ρ_τ	Beta	0.5	0.2	0.436	0.445	0.100	0.825
γ_τ^B	Normal	0.0	1.0	1.622	1.622	0.752	2.494
γ_τ^Y	Normal	0.0	1.0	-0.005	-0.010	-1.494	1.489
λ_p	Beta	0.5	0.1	0.500	0.500	0.329	0.672
λ_w	Beta	0.5	0.1	0.456	0.457	0.378	0.533
ι_p	Beta	0.5	0.2	0.501	0.501	0.228	0.773
ι_w	Beta	0.5	0.2	0.340	0.340	0.137	0.626
χ	Gamma	4.0	2.0	2.524	2.669	0.837	6.298

Notes: Posterior estimates use the same priors as in the full sample. Reported values are posterior means, medians and 90 percent credible intervals. Shock standard deviations are scaled by 100 to enhance readability.

these two regimes, reflecting the transition from a high-volatility to a low-volatility macroeconomic environment.

Finally, I examine the volatility of aggregate variables at business cycle frequencies across the two subperiods. Table 11 reports the variances of key aggregates, computed using the posterior mean estimates for each period. For all variables considered, the

Table 10 Bayesian estimation results for 2000 to 2019: shock and policy parameters

		Prior		Posterior			
Shock Parameter	**Distribution**	**Mean**	**SD**	**Mean**	**Median**	**5%**	**95%**
$\sigma_q \cdot 100$	Inv. Gamma	10.0	25.0	1.036	1.033	0.719	1.504
ρ_q	Beta	0.5	0.2	0.941	0.940	0.908	0.962
$\sigma_\zeta \cdot 100$	Inv. Gamma	10.0	25.0	0.443	0.443	0.351	0.558
ρ_ζ	Beta	0.5	0.2	0.065	0.073	0.013	0.206
$\sigma_z \cdot 100$	Inv. Gamma	10.0	25.0	0.556	0.556	0.462	0.668
ρ_z	Beta	0.5	0.2	0.955	0.954	0.900	0.982
$\sigma_r \cdot 100$	Inv. Gamma	10.0	25.0	0.292	0.292	0.244	0.353
$\sigma_i \cdot 100$	Inv. Gamma	10.0	25.0	1.548	1.543	1.245	1.948
ρ_i	Beta	0.5	0.2	0.902	0.902	0.807	0.955
$\sigma_p \cdot 100$	Inv. Gamma	10.0	25.0	0.363	0.362	0.308	0.430
ρ_p	Beta	0.5	0.2	0.877	0.875	0.799	0.931
$\sigma_w \cdot 100$	Inv. Gamma	10.0	25.0	3.803	3.764	2.709	5.530
ρ_w	Beta	0.5	0.2	0.951	0.950	0.920	0.971
$\sigma_g \cdot 100$	Inv. Gamma	10.0	25.0	1.331	1.330	1.153	1.543
ρ_g	Beta	0.5	0.2	0.993	0.992	0.987	0.996

		Prior		Posterior			
Policy Parameter	**Distribution**	**Mean**	**SD**	**Mean**	**Median**	**5%**	**95%**
ρ_r	Beta	0.5	0.2	0.730	0.731	0.664	0.786
ϕ_π	Gamma	1.5	0.3	2.314	2.310	2.033	2.647
ϕ_Y	Normal	0.1	0.1	0.114	0.114	0.036	0.191
ρ_τ	Beta	0.5	0.2	0.231	0.238	0.043	0.633
γ_τ^B	Normal	0.0	1.0	1.955	1.928	0.879	3.119
γ_τ^Y	Normal	0.0	1.0	0.629	0.620	-0.735	2.021
λ_p	Beta	0.5	0.1	0.500	0.500	0.328	0.671
λ_w	Beta	0.5	0.1	0.231	0.233	0.165	0.308
ι_p	Beta	0.5	0.2	0.499	0.500	0.227	0.771
ι_w	Beta	0.5	0.2	0.222	0.223	0.082	0.473
χ	Gamma	4.0	2.0	2.541	2.692	0.846	6.303

Notes: Posterior estimates are based on Bayesian inference using the same priors as in the full sample. Reported values are posterior means, medians, and 90 percent credible intervals. Shock standard deviations are scaled by 100 to enhance readability.

standard deviations decline from the first to the second subperiod.

Table 11 Variation of variables at business cycle frequencies for the two subperiods

Variable	1979-1999	2000-2019
$100\sigma(y)$	4.15	1.36
$100\sigma(c)$	1.39	0.58
$100\sigma(\pi)$	6.10	4.33
$100\sigma(r^{eq})$	7.57	6.07
$100\sigma(r^{1y})$	1.03	0.32
$100\sigma(r^{10y})$	1.43	0.56

Notes: Volatility of aggregate variables over the business cycle frequency computed (6 - 32 quarters) with the posterior mean parameters of the estimated heterogeneous agent model for the respective sample periods. The variance over the business cycle frequency is computed based on Uhlig (2001) and scaled by 100 for better readability.

VII Appendix: The Impact of Monetary Policy on Asset Premia

Table 12 illustrates the impact that monetary policy stance has on asset premia for more assets, as well as lists the variance of more aggregate variables. For all assets considered, the picture remains identical. More aggressive inflation stabilization (higher ϕ_π) leads to higher variance in all variables, with exception of inflation, and increases all asset premia. Stronger output stabilization (higher ϕ_y) reduces the volatility of all aggregate variables, and reduces all asset premia, with the only exception being the 10-year term premium, which increases again from 1.71 to 1.72 percent in the last two columns.

Table 12 Annualized Asset Premia under varying Monetary Policy Stance

	Coefficient for Inflation (ϕ_π)			**Coefficient for Output** (ϕ_y)		
Premia	$\phi_\pi = 1.1$	$\phi_\pi = 1.69$	$\phi_\pi = 3.0$	$\phi_y = 0.0$	$\phi_y = 0.17$	$\phi_y = 0.5$
Equity	4.37	4.92	5.28	5.02	4.92	4.77
Bond 6m	0.07	0.07	0.12	0.09	0.07	0.04
Bond 1y	0.17	0.24	0.34	0.27	0.24	0.21
Bond 2y	0.36	0.64	0.82	0.66	0.64	0.62
Bond 5y	0.64	1.26	1.54	1.27	1.26	1.26
Bond 10y	0.83	1.71	2.07	1.72	1.71	1.72
Bond 20y	0.92	2.01	2.45	2.04	2.01	1.99
Std. Dev.	$\phi_\pi = 1.1$	$\phi_\pi = 1.69$	$\phi_\pi = 3.0$	$\phi_y = 0.0$	$\phi_y = 0.17$	$\phi_y = 0.5$
$100\sigma(y)$	1.06	1.07	1.17	1.09	1.07	1.03
$100\sigma(c)$	0.53	0.55	0.61	0.56	0.55	0.53
$100\sigma(\pi)$	3.12	2.08	1.14	6.14	6.12	6.10
$100\sigma(r^{eq})$	6.10	6.12	6.20	2.16	2.08	1.94
$100\sigma(r^{1y})$	0.24	0.20	0.24	0.21	0.20	0.19
$100\sigma(r^{10y})$	0.72	0.75	0.81	0.76	0.75	0.75

Notes: Annualized premia and volatility over the business cycle frequency computed with the posterior mean parameters of the estimated heterogeneous agent model for the full sample period. The table varies the monetary policy responses to inflation ϕ_π and output ϕ_y. Premia are computed following Auclert et al. (2024): $\frac{R_1 - R_0}{R} \approx -X\,\bar{\lambda}\,\sigma^2$, where X denotes the ex post variation of an asset's excess return relative to the three month bond and $\bar{\lambda}$ denotes the aggregate pricing kernel. The variance over the business cycle frequency is computed based on Uhlig (2001).