Asset Market Participation, Redistribution, and Asset Pricing[*]

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March 13, 2026

Abstract

We study how redistribution between assetholders and non-assetholders links macroeconomic fluctuations to expected stock returns. Using U.S. household data, we show that aggregate and relative consumption growth forecast excess returns with opposite signs and at different horizons. We interpret these patterns through a production-based asset-pricing model with limited asset market participation and external habits. In the model, aggregate consumption captures variation in the price of risk, while relative consumption reflects changes in the quantity of risk borne by investors. Technology shocks drive most macroeconomic fluctuations, whereas redistributive shocks generate large short-run movements in inequality and represent the main source of risk priced in financial markets. This points to a macro–finance disconnect between the drivers of business cycles and those governing risk premia.

Keywords: Consumption, Heterogeneity, Limited participation, Asset pricing.
JEL Codes: E21, E25, E32, E44, G12.

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[*]We wish to thank Francesco Bianchi, Florin Bilbiie, Andreas Brunhart, Russell Cooper, Francesco Furlanetto, Ivan Jaccard, Kevin Lansing, Jun Li, Rory Mullen, Roberto Pancrazi, Dimitris Papanikolaou, Giorgio Primiceri, Søren Hove Ravn, Raffaele Rossi, Sergio Santoro, Yatheesan (Yad) Selvakumar, Paolo Surico, Oreste Tristani as well as presentation participants at the 2024 Annual Conference of the Money, Macro and Finance Society at the University of Manchester, 2024 CEPR Liverpool Workshop on Macroeconomics at the University of Liverpool, 2024 T2M Conference at the University of Amsterdam, 2023 SED Meeting in Cartagena, Université de Lausanne, the 2022 ICMAIF and ASSET Conferences in Rethymno, the 2022 ADRES Doctoral Conference at Paris School of Economics, the 2021 Macroeconomic Dynamics Workshop at Catholic University in Milan, the 2021 Workshop in Macroeconometrics at King's College London, the 2021 Ventotene Macroeconomics Workshop, University of Pavia, Aix-Marseille School of Economics and Warwick Business School for useful comments. Gaudio acknowledges support by the Fr5ench National Research Agency Grant ANR-17-EURE-0020 and by the Excellence Initiative of Aix-Marseille University - A*MIDEX.

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1 Introduction

Understanding how macroeconomic fundamentals shape asset prices remains a central challenge in macro–finance (Cochrane, 2017). Representative-agent, production-based asset-pricing models typically emphasize technological shocks as key drivers of both business cycles and risk premia (Jermann, 1998; Papanikolaou, 2011). Yet the empirical link between aggregate fluctuations and expected stock returns remains elusive. A large body of evidence instead highlights limited asset market participation as a key dimension of consumer heterogeneity shaping both the transmission of aggregate shocks and the determination of asset prices (see, e.g., Campbell and Mankiw, 1989; Mankiw and Zeldes, 1991; Malloy et al., 2009; Brunnermeier et al., 2021).

This paper argues that cyclical redistribution between asset market participants and non-participants constitutes a relevant source of fluctuations in expected stock returns. We focus on short-run, rather than secular, movements in inequality and show that fluctuations in assetholders' consumption relative to that of non-assetholders contain systematic information about expected returns that is neglected when focusing exclusively on aggregate data. Specifically, our key finding is that investors' consumption embeds two distinct components—an aggregate component reflecting overall macroeconomic conditions and a relative component capturing redistribution between participants and non-participants in financial markets—with sharply different asset-pricing implications. Although this perspective builds on the idea that heterogeneity in asset market participation is central to asset pricing (Mankiw and Zeldes, 1991; Vissing-Jørgensen, 2002), we highlight *cyclical* redistribution as an independent mechanism through which macroeconomic shocks affect expected returns. Our findings, therefore, point to a disconnect between the forces driving aggregate and expected return fluctuations, as the former mask the distributional consequences of shocks that matter for asset pricing in economies with limited participation.

Using U.S. household survey data combined with aggregate series, we document three main empirical facts. First, assetholders' consumption growth predicts future excess returns negatively, consistent with countercyclical risk premia (Fama and French, 1989), though this predictive power is weak and concentrated at long horizons. Second, once investors' consumption is decomposed into an aggregate and a relative component, both emerge as significant predictors with opposite signs: aggregate consumption predicts lower future returns, whereas relative consumption predicts higher returns at shorter horizons. Third, the predictive content of relative consumption is entirely driven by fluctuations associated with redistributive shocks that shift income between capital and labor, rather than by technology shocks.

To interpret these findings, we develop a production-based asset-pricing model with limited asset market participation and external habits. The model rationalizes the empirical evidence through two complementary mechanisms. Aggregate consumption captures variation in the *price* of risk, as expansions reduce investors' effective risk aversion (Campbell and Cochrane, 1999). This channel dominates, driving the overall countercyclicality of expected excess returns. On the other hand, controlling for aggregate conditions, relative consumption reflects variation in the *quantity* of risk borne by investors: when redistribution shifts income toward assetholders, a larger share of their consumption becomes tied to dividend income. This increases the covariance between their consumption growth and stock returns, raising the quantity of risk they bear and thus expected returns. Therefore, with limited participation, redistributive shocks alter the exposure of the marginal investor to aggregate risk. These shocks affect the distribution between financial and labor income only temporarily—albeit persistently—explaining why relative consumption predicts near-term but not long-run returns. When estimating the same predictive regressions on simulated data, the model-implied coefficients replicate both the signs and the horizon patterns observed in the data.

Through the model, we quantify the relevance of different aggregate drivers of macroeconomic and financial moments. Our decompositions underscore a fundamental macro–finance disconnect. Technology shocks account for most fluctuations in output, investment, and aggregate consumption, yet play a negligible role in explaining the dynamics of asset returns. By contrast, redistributive shocks contribute modestly to macroeconomic volatility but dominate asset-pricing moments, for they generate large procyclical short-run movements in relative consumption. Thus, the shocks that account for most business-cycle fluctuations are not those that drive asset-pricing dynamics, and *vice versa*. This distinction helps reconcile the apparent tension between the dominance of technology shocks in business-cycle accounting and the prominence of redistribution in asset-pricing dynamics.

We validate the model's conditional dynamics in the data. While all shocks generate similar expansionary effects on aggregate consumption, they have markedly different redistributive implications across households sorted by asset holdings. By inducing a pronounced decline in the labor share, redistributive shocks shift resources from non-assetholders—who primarily finance consumption out of labor income—to assetholders, whose consumption also depends on financial income. By contrast, neutral technology shocks compress consumption inequality, while investment-specific shocks have only limited distributional effects. Put differently, only redistributive shocks generate pronounced procyclicality in relative income and consumption, consistent with the mechanism highlighted by the model.

Related literature Our analysis relates to three strands of the literature. First, we contribute to the work linking macroeconomic conditions to expected-return fluctuations

(Fama and French, 1989; Lettau and Ludvigson, 2001; Cochrane, 2011, 2017; Atanasov et al., 2020). Rather than proposing a new aggregate predictor, we show that distributional information extracted from household data uncovers a state variable—cyclical redistribution—that captures variation in investors' risk exposure. In this sense, we reinterpret part of return predictability as reflecting shifts in the distribution of consumption across households, thereby placing limited asset market participation at center stage. In doing so, rather than emphasizing low-frequency movements in the labor share (Lettau and Ludvigson, 2013; Greenwald et al., 2019), we focus on its *cyclical* variation and trace its connection to expected-return dynamics. Thus, we relate to Menzly et al. (2004), who show that time variation in the dividend-to-consumption ratio predicts a procyclical component in expected excess returns, conditional on aggregate conditions. We show that a similar mechanism emerges naturally in a model with limited participation when redistributive shocks asymmetrically affect financial and labor income, thereby shaping relative consumption. More broadly, while shocks that shift resources from workers to capital owners during expansions have been proposed as a key source of priced risk (see, e.g., Lansing, 2015; Lettau et al., 2019), we provide direct evidence linking redistributive shocks, relative consumption, and stock-return predictability.

In this respect, we also contribute to the growing literature examining how movements in household inequality—along either the income or wealth dimension—predict stock returns (see, e.g., Toda and Walsh, 2019; Gomez, 2024, respectively). These studies typically consider redistribution *within* the group of investors, relating fluctuations in the income (or wealth) share of the wealthy to changes in the price of risk arising from heterogeneity in risk aversion. In that setting, redistribution generally implies countercyclical expected returns. By contrast, we focus on redistribution *between* asset market participants and non-participants and show that time variation in relative consumption relates to expected returns by capturing changes in the *quantity* of risk. This form of reallocation predicts *procyclical* risk premia, conditional on aggregate conditions, thereby highlighting a source of risk common to all investors.

Finally, the paper connects to work on limited asset market participation stressing how returns are more tightly linked to stockholders' consumption than to aggregate consumption (Mankiw and Zeldes, 1991; Vissing-Jørgensen, 2002; Malloy et al., 2009; Guvenen, 2009). We extend this literature by demonstrating that the asset-pricing implications of investor consumption depend critically on its decomposition into aggregate and relative components. This distinction clarifies how macroeconomic shocks map into risk premia and helps explain the term structure of return predictability in economies with heterogeneous participation.

Structure Section 2 introduces the data and presents the baseline predictive regressions, documenting the distinct roles of aggregate and relative consumption. Section 3 develops and calibrates the quantitative model. Section 4 evaluates the model's ability to replicate the empirical evidence and explain the mechanisms linking macroeconomic dynamics, redistribution and asset pricing. Section 5 provides empirical validation of the key model predictions. Section 6 concludes.

2 Asset market participation and expected returns

Time variation in expected stock returns reflects movements in the marginal investors' stochastic discount factor. In representative-agent settings, aggregate consumption growth serves as a sufficient statistic for these fluctuations: low growth signals bad times and elevated risk premia. Empirically, however, establishing a robust link between macroeconomic conditions and short- to medium-run movements in expected returns has proven challenging. When asset market participation is limited, aggregate consumption may mask economically relevant heterogeneity. If assetholders and non-assetholders experience different cyclical dynamics, shifts in consumption inequality between them may alter the risk borne by the investors who price assets, even when aggregate conditions remain unchanged. This suggests that redistribution between participants and non-participants could constitute an additional state variable for expected returns. To investigate this possibility, we relate fluctuations in assetholders' consumption—and its decomposition into aggregate and relative components—to subsequent excess stock returns over different horizons.

We estimate regressions of the form

$$r^{\mathrm{ex}}_{t,t+h} = \alpha + \boldsymbol{\beta}'\boldsymbol{x}_t + \varepsilon_{t+h}, \tag{1}$$

where $r^{\mathrm{ex}}_{t,t+h}$ denotes annualized excess returns from t to $t+h$, and $\boldsymbol{x}_t$ collects alternative predictors designed to capture time variation in expected excess returns. We begin by considering assetholders' cyclical consumption as a summary measure of fluctuations in the consumption of the investors who price assets. We then decompose this measure into an aggregate component—common to all households—and a relative component capturing fluctuations in consumption inequality between assetholders and non-assetholders. Estimating the regressions over different horizons allows us to distinguish persistent movements in expected returns from temporary shifts that tilt the term structure of risk premia.

2.1 Data

Our empirical analysis combines aggregate financial and macroeconomic data with household-level consumption information. Quarterly excess stock returns and the risk-free rate are obtained from Amit Goyal's data library (see Welch and Goyal, 2008). Aggregate macroeconomic series are drawn from the National Income and Product Accounts (NIPA), from which we construct real per-capita consumption by deflating nominal variables with the CPI and dividing by total U.S. population.

Household-level consumption data are constructed from the Consumer Expenditure Survey (CEX). We classify households into two representative groups—assetholders and non-assetholders—based on financial market participation (Mankiw and Zeldes, 1991; Malloy et al., 2009). Because the CEX may understate participation, particularly by omitting indirect asset holdings, we complement it with information from the Survey of Consumer Finances (SCF). Using SCF waves from 1989 to 2016, we estimate a probit model for the probability that a household holds liquid financial assets above a real $1,000 threshold as a function of socio-economic characteristics observed in both surveys. The estimated coefficients are then applied to the CEX to impute a participation probability for each household-quarter observation. This procedure mitigates measurement error in reported asset holdings and allows us to construct probability-adjusted consumption aggregates for assetholders and non-assetholders. In turn, group-level consumption is computed as the population-weighted average of real expenditures and expressed in per-capita terms. To ensure consistency with national accounts, we rescale the two series each quarter so that their weighted sum matches aggregate NIPA consumption. This reconciliation preserves cross-sectional variation while aligning levels and growth rates with the aggregate benchmark. Additional details on macroeconomic data are provided in Appendix A, and the construction of the household-level series is described in Appendix B.

To assess the robustness of the redistributive mechanism emphasized in this section, we also consider fluctuations in the labor share from the Bureau of Labor Statistics (BLS) as an alternative proxy for shifts in income between labor and capital. Although distinct from consumption inequality between participants and non-participants, labor-share movements capture changes in the income accruing to capital that may affect the risk borne by assetholders. The final sample spans 1982Q4–2017Q4, in line with the household-level consumption data.

2.2 Limited participation and return predictability

Table 1 reports multi-horizon predictive regressions of annualized excess stock returns on different measures of cyclical consumption. Cyclical movements are measured using two-year (eight-quarter) log growth rates, following Hamilton (2018).

Table 1: Predictive regressions

	Panel A	Panel B		Panel C	
	$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c^a,t} + \varepsilon_{t+h}$	$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c,t} + \beta_2 g_{rc,t} + \varepsilon_{t+h}$		$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c,t} + \beta_2 g_{ls,t} + \varepsilon_{t+h}$	
h	β_1	β_1	β_2	β_1	β_2
1	-0.95	-3.26	3.10	-0.57	-2.95
	(2.58)	(2.91)	(1.98)	(2.72)	(3.16)
	[0.71]	[0.26]	[0.12]	[0.83]	[0.35]
4	-2.34	**-4.02**	**2.57**	-1.42	**-3.46**
	(2.02)	(2.01)	(1.54)	(1.85)	(1.73)
	[0.25]	[0.05]	[0.10]	[0.44]	[0.05]
8	-3.21	**-5.10**	**2.27**	**-2.77**	**-3.14**
	(2.12)	(1.95)	(1.25)	(1.59)	(1.34)
	[0.13]	[0.01]	[0.07]	[0.09]	[0.02]
12	**-3.71**	**-5.14**	**1.45**	**-3.39**	**-2.69**
	(1.84)	(1.71)	(0.76)	(1.46)	(1.26)
	[0.05]	[0.00]	[0.06]	[0.02]	[0.03]
16	**-3.73**	**-4.69**	0.42	**-3.73**	-1.95
	(1.79)	(1.38)	(0.85)	(1.46)	(1.32)
	[0.04]	[0.00]	[0.62]	[0.01]	[0.14]
20	**-3.33**	**-4.07**	0.01	**-3.71**	-0.93
	(1.53)	(1.14)	(0.78)	(1.24)	(1.27)
	[0.03]	[0.00]	[0.99]	[0.00]	[0.47]

Notes: The table presents results of predictive regressions of the form $r^{\text{ex}}_{t,t+h} = \alpha + \boldsymbol{\beta x_t} + \varepsilon_{t+h}$, where h denotes the horizon in quarters and $r^{\text{ex}}_{t,t+h}$ denotes annualized excess returns between period t and $t+h$. $\boldsymbol{x_t}$ represents the matrix of (demeaned) predictors, which includes: in Panel A, assetholders' consumption growth; in Panel B, aggregate and relative consumption growth; in Panel C, aggregate consumption and labor share growth. Growth rates are computed as 8-quarters log-differences, expressed in annualized terms. For each regression, Newey-West corrected standard errors (h lags) appear in parentheses below the coefficient estimate, while p-values are reported in square brackets. Significant coefficients at the ten percent level are highlighted in bold. The sample covers the period 1982Q4-2017Q4.

Panel A considers a specification in which the sole predictor is assetholders' consumption growth, $g_{c^a,t}$. The estimated coefficients are negative at all horizons, but become statistically significant only at longer ones: predictability emerges primarily for excess returns three to five years ahead. Thus, higher-than-average consumption growth among assetholders forecasts lower subsequent excess returns, echoing the evidence in Atanasov et al. (2020) but focusing on assetholders' consumption rather than aggregate consumption.

Assetholders' consumption growth reflects two distinct forces. On the one hand, it co-moves with aggregate consumption, capturing fluctuations in overall macroeconomic conditions. On the other hand, it varies with the distribution of consumption between assetholders and non-assetholders, reflecting changes in consumption inequality between market participants and non-participants. If these forces have different implications for expected returns, using assetholders' consumption as a single predictor may mask economically important variation.

Panel B separates these components by decomposing assetholders' consumption growth into an aggregate component, $g_{c,t}$, and a relative component capturing changes in consumption inequality, $g_{rc,t} \equiv g_{c^a,t} - g_{c^{na},t}$. To a first-order approximation,

$$g_{c^a,t} \approx g_{c,t} + \kappa g_{rc,t}, \tag{2}$$

where κ denotes the long-run share of non-assetholders' consumption. This specification allows aggregate conditions and redistribution to enter the predictive regression independently.

A key regularity is that the two components enter with opposite signs. Aggregate consumption growth predicts lower future excess returns—particularly from $h = 4$ quarters onward—consistent with countercyclical variation in risk premia. In contrast, higher relative consumption growth, that is, periods in which assetholders' consumption grows faster than that of non-assetholders, predicts higher subsequent excess returns. The predictive content of $g_{rc,t}$ is concentrated at short to medium horizons (up to roughly three years) and fades at longer maturities.

Thus, once assetholders' consumption is decomposed, predictability is present at most horizons, but reflects two distinct forces (in the spirit of Menzly et al., 2004). The aggregate component tracks persistent fluctuations in macroeconomic conditions and is associated with countercyclical expected returns. The relative component captures shifts in consumption inequality between participants and non-participants and is associated with procyclical expected returns, conditional on the aggregate state. The declining coefficient on $g_{rc,t}$ across horizons indicates that redistribution primarily shifts expected returns toward the near future, effectively tilting the term structure of risk premia rather than shifting it in parallel.[1]

If assetholders receive only capital income and non-assetholders only labor income, movements in the labor share would mechanically mirror shifts in relative consumption between participants and non-participants and thus provide an alternative proxy for the redistributive channel.[2] Under this interpretation, labor-share fluctuations naturally emerge as a candidate state variable for expected returns, as emphasized in Lettau et al. (2019). To assess whether the redistributive predictability we document is specific to the consumption-based measure, Panel C reports predictive regressions using aggregate consumption growth and changes in the labor share. The labor-share coefficients are economically and statistically meaningful, with a negative and declining profile across horizons. Increases in the labor share—consistent with temporary shifts in income away from capital—are therefore associated with lower near-term excess returns, mirroring the short- to medium-run role played by relative consumption in Panel B. This evidence supports the view that redistributive fluctuations—whether measured through consumption inequality or factor shares—constitute an independent state variable for expected returns beyond aggregate conditions.

2.3 Conditional predictive regressions

The previous results establish that redistributive fluctuations—captured by relative consumption and the labor share—forecast excess returns beyond aggregate consumption. We now ask which structural disturbances generate the redistributive variation that matters for expected returns. In macroeconomics and asset pricing, productivity shocks, such as neutral technology (TFP) and investment-specific technology (IST) innovations, are often viewed as fundamental drivers of macroeconomic and financial fluctuations (Jermann, 1998; Papanikolaou, 2011; Guvenen, 2009). If relative consumption merely reflects the propagation of such productivity disturbances, then its predictive content should be attributable to the components driven by technology shocks. If, instead, redistribution shocks represent an independent source of variation, then only the component associated with shifts in factor shares should forecast returns. To address this question, we construct *conditional* measures of relative consumption and the labor share by isolating the components of their fluctuations attributable to distinct structural shocks.

[1] At first glance, the positive association between relative consumption growth and expected returns may seem at odds with Toda and Walsh (2019) and Gomez (2024), who emphasize redistribution within the set of market participants. Our focus instead is on redistribution between participants and non-participants, conditional on aggregate conditions. Interpreted this way, the evidence points to time variation in the aggregate risk borne by investors, rather than to changes in how risk is allocated among them.

[2] In practice, however, this equivalence requires strong assumptions about income composition that are unlikely to hold in the data: the empirical correlation between relative consumption growth and labor-share growth is weak (-0.04), indicating that the two measures do not necessarily overlap.

Table 2: Conditional predictive regressions

	Panel A				Panel B			
	$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{rc,t} + \beta_3 g^{IST}_{rc,t} + \beta_4 g^{FS}_{rc,t} + \varepsilon_{t+h}$				$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{ls,t} + \beta_3 g^{IST}_{ls,t} + \beta_4 g^{FS}_{ls,t} + \varepsilon_{t+h}$			
h	β_1	β_2	β_3	β_4	β_1	β_2	β_3	β_4
1	−3.40	2.88	−2.16	6.40	−2.82	6.71	0.11	−5.59
	(3.16)	(6.80)	(10.46)	(4.43)	(2.83)	(10.36)	(6.13)	(3.98)
	[0.29]	[0.67]	[0.84]	[0.15]	[0.32]	[0.52]	[0.99]	[0.16]
4	**-4.41**	4.22	−0.30	**5.71**	**-2.96**	4.17	−3.75	**-4.52**
	(1.82)	(4.56)	(6.94)	(3.22)	(1.75)	(7.40)	(4.74)	(2.68)
	[0.02]	[0.36]	[0.97]	[0.08]	[0.09]	[0.57]	[0.43]	[0.09]
8	**-5.71**	1.18	2.75	**4.71**	**-3.55**	1.67	−5.27	**-3.06**
	(1.67)	(3.51)	(4.10)	(1.90)	(1.77)	(5.65)	(4.53)	(1.49)
	[0.00]	[0.74]	[0.50]	[0.02]	[0.05]	[0.77]	[0.25]	[0.04]
12	**-6.05**	−3.21	4.25	**3.69**	**-3.66**	−0.09	**-5.47**	**-2.01**
	(1.75)	(2.76)	(3.10)	(1.55)	(1.36)	(3.96)	(3.08)	(0.91)
	[0.00]	[0.25]	[0.17]	[0.02]	[0.01]	[0.98]	[0.08]	[0.03]
16	**-5.76**	−3.24	**5.29**	1.99	**-4.20**	2.61	**-6.65**	−0.84
	(1.45)	(2.55)	(2.61)	(1.55)	(1.21)	(2.69)	(1.75)	(0.87)
	[0.00]	[0.21]	[0.05]	[0.20]	[0.00]	[0.34]	[0.00]	[0.33]
20	**-4.92**	−2.86	4.82	0.67	**-4.24**	**4.40**	**-6.97**	0.56
	(1.12)	(1.76)	(3.17)	(1.44)	(0.99)	(2.22)	(1.19)	(0.91)
	[0.00]	[0.11]	[0.13]	[0.64]	[0.00]	[0.05]	[0.00]	[0.54]

Notes: The table presents results of predictive regressions of the form $r^{\text{ex}}_{t,t+h} = \alpha + \boldsymbol{\beta x_t} + \varepsilon_{t+h}$, where h denotes the horizon in quarters and $r^{\text{ex}}_{t,t+h}$ denotes annualized excess returns between period t and $t+h$. $\boldsymbol{x_t}$ represents the matrix of (demeaned) predictors, which includes: in Panel A, aggregate consumption and conditional relative consumption growth; in Panel B, aggregate consumption and conditional labor share growth. Growth rates are computed as 8-quarters log-differences, expressed in annualized terms. For each regression, Newey-West corrected standard errors (h lags) appear in parentheses below the coefficient estimate, while p-values are reported in square brackets. Significant coefficients at the ten percent level are highlighted in bold. The sample covers the period 1982Q4-2017Q4.

To separate productivity disturbances from redistributive innovations, we follow Santaeulalia-Llopis (2011) and estimate a trivariate VAR in TFP, the relative price of investment, and the (detrended) labor share. Identification relies on long-run restrictions: factor-share (FS) shocks do not affect TFP or the relative price of investment permanently; among technology innovations, only IST shocks have a permanent effect on the relative price of investment (see, among others, Gali, 1999; Fisher, 2006). Innovations to the labor share that are orthogonal to TFP and IST shocks can therefore be interpreted as redistribution shocks (e.g., Ríos-Rull and Santaeulalia-Llopis, 2010; Santaeulalia-Llopis, 2011; Choi and Ríos-Rull, 2021). Appendix C provides full details on the VAR specification and identification.[3] While these long-run restrictions ensure orthogonality to TFP and IST shocks, they do not guarantee a fully structural interpretation of the FS shock. In fact, the residual component may also capture other non-technology disturbances. To account for this, in the next subsection we test the robustness of our results to alternative shock specifications.

We construct the conditional component of relative consumption using an autoregressive distributed-lag specification with eight lags of the dependent variable and eight lags of each structural shock identified by the VAR.[4] The conditional counterpart of the labor share is retrieved directly from the VAR estimates. The fitted value associated with a given shock isolates the portion of fluctuations systematically attributable to that disturbance and its propagation dynamics.

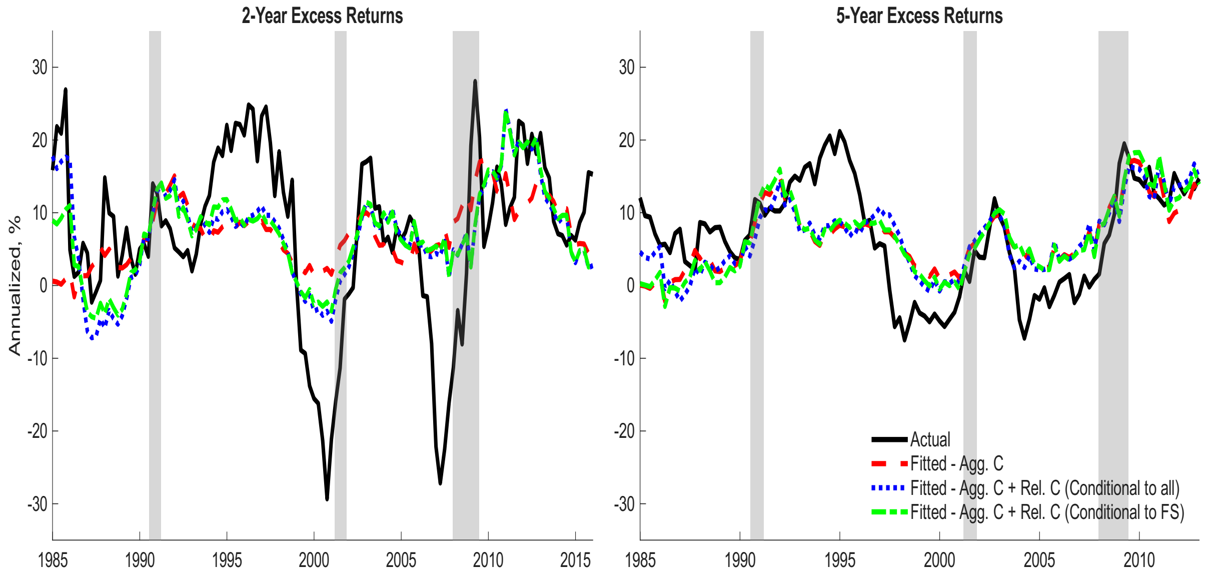
Table 2 shows that the predictive power of redistribution is concentrated entirely in the component associated with FS shocks. For both relative consumption and the labor share (Panels A and B), only the FS-driven components, $g_{j,t}^{FS}$ with $j = \{rc, ls\}$, are statistically significant at horizons from $h = 4$ to $h = 12$, precisely where the unconditional measures in Table 1 exhibit predictive content. In contrast, components attributable to neutral TFP and IST shocks display little systematic forecasting ability. Importantly, the coefficients on $g_{rc,t}^{FS}$ are larger in magnitude than those on the unconditional relative-consumption measure reported in Table 1, indicating that aggregating across shocks attenuates predictive power. Conditioning on FS shocks isolates the relevant redistributive variation and strengthens the estimated relationship with expected returns. The consistency of this pattern across relative consumption and labor-share specifications further reinforces the conclusion that the forecasting ability documented in Section 2.2 is driven by innovations in factor shares rather than by productivity disturbances.

To gauge the marginal contribution of redistributive fluctuations to expected re-

[3]Figure C.3 provides a historical decomposition of labor-share fluctuations. The labor share is mildly countercyclical, yet the observed countercyclicality is entirely attributed to factor-share shocks, while movements driven by TFP and IST shocks are mildly procyclical and generally account for the most persistent dynamics of the labor share.

[4]All specifications include a constant and a time trend.

Figure 1: Predictive regressions - Actual vs. fitted values



Notes: The black-solid line depicts realized 2-year (left panel) or 5-year (right panel) ahead excess returns (annualized and in percent). The corresponding fitted values are retrieved from: *i*) a univariate regression with aggregate consumption fluctuations only, i.e. $\hat{r}^{\text{ex}}_{t,t+h} = \hat{\alpha} + \hat{\beta} g_{c,t}$ (red-dashed line); *ii*) the regression in Panel A of Table 2 (blue dotted-line); *iii*) the regression in Panel A of Table 2, but considering relative consumption conditional to FS shocks only, i.e. $\hat{r}^{\text{ex}}_{t,t+h} = \hat{\alpha} + \hat{\beta}_1 g_{c,t} + \hat{\beta}_4 g^{FS}_{rc,t}$ (green dash-dotted line). All regressions are estimated over the sample 1982Q4-2017Q4.

turns, Figure 1 compares realized excess returns with fitted values from alternative specifications. Consistent with the horizon-specific evidence in Table 1, incorporating relative consumption primarily affects short-horizon forecasts: it introduces additional volatility and procyclicality in predicted two-year-ahead returns, while contributing little incremental variation at the five-year horizon. Strikingly, fitted values based on relative consumption conditional solely on FS shocks are nearly indistinguishable from those based on the full conditional specification. This pattern confirms that the forecasting power of relative consumption is almost entirely attributable to redistributive disturbances, rather than to productivity-led components.

2.4 Robustness

We now assess whether the predictive content of relative consumption conditional on factor-share (FS) shocks survives alternative identification schemes, measurement choices, and specification adjustments. To keep the discussion focused, Table 3 reports results for cumulative two-year-ahead excess returns ($h = 8$). Results for $h = 4$ and $h = 12$ are reported in Tables C.1 and C.2.

Panels A through E examine whether the results depend on the baseline VAR identification. Panel A replaces the structural shocks with residuals from independent AR(1) processes for TFP, the relative price of investment, and the labor share, thus

Table 3: Conditional predictive regressions - Robustness

β_1	β_2	β_3	β_4
$r^{\text{ex}}_{t,t+8} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{rc,t} + \beta_3 g^{IST}_{rc,t} + \beta_4 g^{FS}_{rc,t} + \varepsilon_{t+8}$			
Panel A: AR shocks			
-5.10	3.06	-1.09	**5.79**
(1.86)	(3.31)	(2.97)	(3.42)
[0.01]	[0.36]	[0.71]	[0.09]
Panel B: Max-share identification			
-5.32	0.98	3.47	**4.83**
(1.77)	(3.79)	(3.38)	(2.66)
[0.00]	[0.80]	[0.31]	[0.07]
Panel C: VAR including profit share			
-4.96	1.57	2.61	**4.45**
(1.60)	(3.18)	(4.03)	(2.28)
[0.00]	[0.62]	[0.52]	[0.05]
Panel D: FS shocks orthogonal to oil shocks			
-5.95	1.20	2.57	**5.12**
(1.74)	(3.44)	(4.00)	(2.02)
[0.00]	[0.73]	[0.52]	[0.01]
Panel E: FS shocks orthogonal to MP and FP shocks			
-5.51	1.87	2.20	**4.64**
(1.60)	(3.64)	(4.23)	(2.01)
[0.00]	[0.61]	[0.60]	[0.02]
Panel F: Not-detrended labor share			
-5.50	2.67	2.82	**4.42**
(1.67)	(2.87)	(3.44)	(2.24)
[0.00]	[0.35]	[0.41]	[0.05]
Panel G: Naive labor share definition			
-5.81	2.27	0.77	**5.20**
(1.71)	(4.09)	(5.33)	(2.04)
[0.00]	[0.58]	[0.89]	[0.01]
Panel H: Stockholders vs. non-stockholders			
-5.65	2.34	-1.74	**5.83**
(1.79)	(5.30)	(6.22)	(2.19)
[0.00]	[0.66]	[0.78]	[0.01]
Panel I: Controlling for CAY			
-7.12	1.45	1.96	**4.77**
(1.90)	(3.52)	(3.94)	(1.60)
[0.00]	[0.68]	[0.62]	[0.00]
Panel J: First differences			
-0.73	1.54	-2.36	**3.22**
(0.45)	(1.52)	(2.16)	(1.49)
[0.10]	[0.31]	[0.28]	[0.03]

Notes: The table presents results of predictive regressions for different robustness exercises, with $h = 8$. For each regression, Newey-West corrected standard errors (8 lags) appear in parentheses below the coefficient estimate, while p-values are reported in square brackets. Significant coefficients at the ten percent level are highlighted in bold. The sample covers the period 1982Q4-2017Q4.

abstracting from cross-variable interactions embedded in the VAR. Panel B loosens the tight requirements of the long-run identification scheme and adopts a max-share approach (see, e.g., Francis et al., 2014), identifying shocks by their dominant contribution to forecast-error variance at a 40-quarter horizon. Panel C augments the VAR with the (detrended) log profit share, as constructed in Barkai and Benzell (2024), allowing us to separate redistributive shocks from variation in price markups, which mechanically depress the labor share as market power rises. Panels D and E orthogonalize the baseline FS shocks to oil shocks (Känzig, 2021) and to monetary and fiscal policy shocks (Ramey, 2016; Mertens and Ravn, 2013), respectively, mitigating the possibility that redistribution effects are driven by cost-push or demand disturbances. Across all these specifications, the coefficient on the FS-driven component of relative consumption remains positive, statistically significant, and broadly consistent with the baseline results.

Panels F-J consider additional robustness dimensions. Panel F clarifies that the results are not an artifact of the labor share detrending used in the baseline analysis. Panel G employs a narrower labor-share definition that excludes mixed income (by attributing only compensation for employees to labor income, following the ”naive” specification in Ríos-Rull and Santaeulalia-Llopis, 2010), showing that measurement choices for labor income do not alter the results. Panel H redefines household groups based solely on stockholdings rather than broader liquid-asset participation. Panel I controls for the aggregate consumption–wealth ratio (CAY), a prominent predictor of stock returns (Lettau and Ludvigson, 2001). Panel J uses quarter-on-quarter growth rates instead of eight-quarter differences. In all cases, the predictive power of relative consumption conditional on FS shocks persists, reinforcing the conclusion that redistributive disturbances constitute a robust driver of expected returns.

3 Framing the analysis

Our evidence suggests that time variation in expected returns reflects both aggregate fluctuations and redistributive shocks that shift income between market participants and non-participants. To shed light on the mechanisms underlying these findings, we develop a production-based asset-pricing model with limited participation in asset markets that incorporates redistributive shocks alongside neutral and investment-specific technology shocks.

3.1 Model

The economy features concentrated capital ownership. Non-assetholders, who constitute a fraction ω of the unit-mass population, are excluded from both bond and stock markets and therefore behave in a hand-to-mouth fashion, consuming their labor income each period. Assetholders, who make up the complementary fraction $1 - \omega$, own firms through equity shares and smooth consumption intertemporally by trading one-period bonds. Both types of agents supply labor to firms operating under perfect competition. Households are equally productive—there is no heterogeneity in labor efficiency—and therefore earn the same wage regardless of type. Similar to Lansing (2015), the labor supply of the assetholders is inelastic, consistent with the idea that asset prices are determined in securities markets by agents who remain fully-employed at all times. For simplicity, in the baseline analysis, we also assume that non-assetholders' labor supply is inelastic.[5] Firms are financed with both equity and corporate bonds. They combine labor and capital using a Cobb-Douglas technology with an exogenously time-varying labor share of income, facing capital-adjustment costs.

3.1.1 Households

The intertemporal utility of a type-j consumer, for $j = \{a, na\}$, is given by

$$\mathrm{E}_t \sum_{i=0}^{\infty} \beta^i \frac{\left(c_{t+i}^j - \chi_c^j h_{t+i}^j\right)^{1-\sigma}}{1-\sigma},$$

where $\beta \in (0,1)$ is the subjective discount factor, $\sigma > 0$ is the coefficient of relative risk aversion, c_t^j denotes consumption, χ_c^j is the habit-sensitivity parameter, and h_t^j is the habit stock, which evolves according to

$$h_t^j \;=\; m h_{t-1}^j + (1-m)\, c_{t-1}^j,$$

with $m \in [0,1)$ governing habit persistence. Therefore, $1-m$ captures the sensitivity of the reference level to changes in last period's consumption.

Assetholders' consumption and saving decisions are constrained by:

$$c_t^a + p_t^s q_{t+1}^s + p_t^f q_{t+1}^f = (p_t^s + d_t) q_t^s + q_t^f + w_t n^a, \tag{3}$$

where p_t^s and p_t^f denote, respectively, the prices of equity shares and one-period bonds, q_{t+1}^s and q_{t+1}^f are the quantities purchased at time t, d_t is the dividend paid by equity, w_t is the real wage, and n^a denotes labor supplied by assetholders. The constraint states that consumption and asset purchases must be financed through labor income and the payoff from previously held financial positions. Shares purchased in the previous period yield a dividend d_t, while one-period bonds pay one unit of consumption in the following period.

The two types differ only in their access to financial markets. Unable to smooth consumption intertemporally, non-assetholders consume their labor income each period, so that

$$c_t^{na} = w_t n^{na}. \tag{4}$$

[5] Section 4.4 shows that the core results hold even when allowing non-assetholders to flexibly supply labor.

Asset prices The first-order conditions for the assetholders' optimization problem with respect to c_t^a, q_{t+1}^s, and q_{t+1}^f are:

$$\lambda_t = (c_t^a - \chi_c^a h_t^a)^{-\sigma}, \tag{5}$$
$$p_t^s = \mathrm{E}_t[m_{t,t+1}(p_{t+1}^s + d_{t+1})], \tag{6}$$
$$p_t^f = \mathrm{E}_t m_{t,t+1}, \tag{7}$$

where λ_t denotes the Lagrangean multiplier on the budget constraint and $m_{t,t+1} \equiv \beta(\lambda_{t+1}/\lambda_t)$ is the assetholder's stochastic discount factor. The first-order conditions (6) and (7) govern asset-pricing dynamics. In particular, the risk-free rate is given by $r_t^f = 1/p_t^f = 1/\mathrm{E}_t m_{t,t+1}$, while the (unlevered) stock return is $r_{t+1}^s = \frac{p_{t+1}^s + d_{t+1}}{p_t^s}$.

3.1.2 Production

Firms operate under perfect competition and employ a technology featuring time-varying factor shares within an otherwise Cobb-Douglas structure (Young, 2004; Ríos-Rull and Santaeulalia-Llopis, 2010; Lansing, 2015; Gaudio, 2025):

$$y_t = A z_t k_t^{\alpha_t} n_t^{1-\alpha_t}, \tag{8}$$

where k_t denotes capital, z_t is TFP, and A is a scaling factor. Thus, movements in α_t capture redistribution shocks that shift the division of income between labor and capital, providing an additional exogenous source of variation in the income share of assetholders. An increase in α_t raises capital's share of income, thereby increasing dividend income relative to wages.

Following Blanchard (1997), such variation can be interpreted as reflecting technological or institutional changes that alter the relative importance of capital-intensive production methods and, consequently, the distribution of income across factors. A microfoundation for time variation in the Cobb–Douglas coefficient may arise from aggregation arguments. As shown by Houthakker (1955), a Cobb–Douglas production function can emerge from the aggregation of heterogeneous Leontief techniques with different capital intensities. Changes in the cross-sectional composition of production—toward more capital-intensive techniques—then translate into movements in the aggregate capital share. According to this interpretation, α_t reflects shifts in the prevalence of capital-intensive tasks or technologies.[6] Temporary fluctuations in technological adoption or business dynamism can therefore generate persistent but mean-

[6]This perspective is consistent with task-based models of production such as Autor et al. (2003) and Acemoglu and Restrepo (2018, 2020), where output is generated by a continuum of tasks and technological progress expands the set of tasks performed by capital rather than labor. Automation increases the fraction of capital-executed tasks, raising capital's income share without proportionally altering aggregate productivity.

reverting movements in the aggregate capital share.

Following Jermann (1998), capital accumulation obeys a law of motion with adjustment costs:

$$k_{t+1} = (1-\delta)k_t + \phi\left(\frac{i_t}{k_t}\right)k_t, \tag{9}$$

where δ is the depreciation rate and

$$\phi\left(\frac{i_t}{k_t}\right) = \left[\frac{a_1}{1-1/\chi_k}\left(\frac{i_t}{k_t}\right)^{1-1/\chi_k} + a_2\right] \tag{10}$$

is a concave adjustment-cost function. In particular, $\chi_k \to 0\ (\infty)$ corresponds to higher (lower) adjustment costs.

The firm's problem is to choose labor, capital, and investment to maximize

$$\max_{i_{t+i},n_{t+i},k_{t+i+1}} \mathrm{E}_t \sum_{i=0}^{\infty} m_{t,t+i}\left\{d_{t+i} - q_{t+i}[k_{t+1+i} - (1-\delta)k_{t+i} - \phi(i_{t+i}/k_{t+i})k_{t+i}]\right\}, \tag{11}$$

subject to (8), (9), and (10), q_t denotes the shadow price of capital, and dividends are defined as

$$d_t = y_t - w_t n_t - \frac{i_t}{\mu_t}. \tag{12}$$

Following Greenwood et al. (1988) and Liu et al. (2013), μ_t is the (inverse) relative price of investment and accounts for investment-specific technological (IST) change.

3.1.3 Financial leverage

As in Favilukis and Lin (2015), firms are financed through both debt and equity, with equity representing the riskier residual claim. To map the model's equity return and dividend to their empirical counterparts, we introduce financial leverage. The Modigliani-Miller propositions hold in our environment. Consequently, financial leverage does not affect equilibrium allocations, but only how returns and dividends are measured. By magnifying the volatility of equity dividends relative to firm cash flows, leverage amplifies the exposure of equity returns to underlying shocks and helps the model match the observed volatility of stock returns. Unlike Favilukis and Lin (2015), however, we abstract from default because the model features no idiosyncratic shocks at the firm level. As a consequence, debt is assumed to be risk-free (as in Guvenen, 2009). Firms adjust debt sluggishly according to

$$\begin{aligned} b_t &= \rho^b b_{t-1} + \left(1-\rho^b\right) b_t^*, \\ b_t^* &= \theta p_t^s, \end{aligned}$$

where b_t is the market value of corporate debt and b_t^* is the target debt level. The target level is assumed to be a constant fraction of the firm's ex-dividend value p_t^s. Combining this law of motion with the Modigliani-Miller second proposition implies that equity dividends and returns satisfy

$$d_t^E = d_t + b_t - b_{t-1} r_{t-1}^f. \tag{13}$$

Therefore, the levered return is

$$r_t^E = \frac{p_t^s + d_t - b_{t-1} r_{t-1}^f}{p_{t-1}^s - b_{t-1}}. \tag{14}$$

3.1.4 Exogenous state variables

The model features the same aggregate disturbances studied in the empirical conditional predictive regressions. To preserve consistency between the model and the empirical evidence, the baseline specification assumes that the joint dynamics of these state variables follow the trivariate VAR described in Appendix C.[7] This specification captures the dynamic interactions among TFP, the relative price of investment, and the labor share observed in the data, allowing the model to inherit the empirical propagation of the underlying shocks.

Following Ríos-Rull and Santaeulalia-Llopis (2010), the VAR can be interpreted as a reduced-form representation of equilibrium dynamics rather than as a structural description of primitive shocks. In this sense, our approach is related to Chari et al. (2007), in that TFP, the relative price of investment, and the labor share can be viewed as "wedges" that summarize the effects of deeper distortions or technological forces on production and income distribution. However, since many quantitative asset-pricing models assume independent AR(1) shock processes (e.g., Justiniano and Primiceri, 2008; Papanikolaou, 2011; Lansing, 2015), Section 4.4 shows that the core redistribution mechanism is robust to adopting such a specification.[8]

Finally, since TFP and IST shocks contain permanent components, the model exhibits nonstationary dynamics. We therefore express all variables in stationary form by detrending with respect to the balanced-growth path. Throughout, a tilde ($\sim$) denotes variables expressed as log deviations from trend.

[7] For tractability, we restrict the VAR to a single lag.

[8] Therefore, the VAR primarily serves as a disciplined benchmark that aligns the model's shock structure with the empirical identification.

Table 4: Baseline parameter values

Description	Parameter	Value
Calibrated		
Fraction of non-assetholders	ω	0.3300
Depreciation rate	δ	0.0271
Capital share of income	α	0.3500
Discount rate	β	0.9893
Local utility curvature	σ	3.0000
Estimated		
Capital adjustment cost	χ_k	0.3031
Habit weight	χ_c	0.8197
Habit stock persistence	m	0.6023
Target leverage	θ	0.0107
Leverage persistence	ρ^b	0.6633

Notes: The model is simulated at a quarterly frequency.

3.2 Calibration

A time period in the model is taken to be one quarter. We split the parameters into two groups. The first group of parameters is calibrated to match targeted long-run relationships. The second group is estimated both via impulse-response matching and by matching a subset of selected unconditional macroeconomic moments. The baseline parameter values are summarized in Table 4.

3.2.1 Calibrated parameters

The fraction of non-assetholder, ω, is set to 0.33, which represents a mid-value over the sample 1982Q4-2017Q4 (see Figure B.1). The calibration strategy for the depreciation rate (δ), the discount rate (β), and the unit parameter in the production function (A) follows Ríos-Rull and Santaeulalia-Llopis (2010). We target the capital-to-output ratio in yearly terms, $k/y = 2.31$, and the investment-output ratio, $i/y = 0.25$. Given these targets, from the relationship $i/y = \delta k/y$, we retrieve $\delta = 0.0271$. Evaluating the capital stock at the steady state and setting the capital share $\alpha = 0.35$—as in Choi and Ríos-Rull (2021)—we obtain $1 = \beta (1 - \delta + \alpha y/k)$, which yields $\beta = 0.9893$. Without loss of generality, we normalize steady-state output to one, thus solving equation (8) for $A = 1/n(k/n)^{-\alpha}$. Finally, the local utility curvature parameter, σ, is set to 3, which is in line with standard calibrations of production-based asset-pricing models, lying within the range of values adopted in Chen (2017) (2) and Lansing (2015) (3.3).

3.2.2 Estimated parameters

The remaining coefficients include the capital adjustment cost parameter (χ_k); assetholders' habit intensity (χ_c^a); the parameter capturing the persistence of the habit stock (m); the parameters governing the level and persistence of financial leverage (θ and ρ^b, respectively); and the parameters of the VAR governing the dynamics of the exogenous process for TFP, the relative price of investment, and the labor share.[9] These are estimated by matching both some empirical impulse-responses (e.g., Christiano et al., 2005; Iacoviello, 2005, among others), as well as a selected number of unconditional macroeconomic moments. Specifically, we match the responses of TFP, the relative price of investment, and the labor share to the TFP, IST, and FS shocks. Figure D.1 reports the estimated impulse-response functions from the model, alongside their empirical counterparts from the VAR model. We also target the unconditional volatility of the growth rates of output, consumption, investment, (levered) dividends, and relative consumption, as well as the unconditional correlation between output and relative-consumption growth.[10]

We estimate $\chi_k = 0.3031$, a value within the range reported by Jermann (1998), Guvenen (2009), and Chen (2017). The habit intensity parameter is $\chi_c = 0.8197$, close to Jermann (1998) (0.82). The persistence of the habit stock is estimated at $m = 0.6023$, implying a moderately persistent reference level. Finally, the leverage parameters are $\theta = 0.0107$ and $\rho^b = 0.6633$, corresponding to a relatively low target debt share and gradual adjustment toward it. As discussed below, the estimated value for the target debt parameter can be explained by the presence of FS shocks that make dividends particularly volatile, thus requiring only moderate financial leverage to match the unconditional volatility of dividend growth in the data.

3.3 Moment matching

The theoretical business-cycle and asset-pricing statistics, together with their empirical counterparts, are reported in Table 5.[11] The framework matches reasonably well several unconditional moments. In particular, it produces output and consumption growth volatilities that slightly exceed their empirical counterparts, while investment

[9]Both a_1 and a_2 in equation (10) are constructed so that capital adjustment costs do not affect the steady state of the economy. Thus, we set $a_1 = \delta^{1/\chi_k}$ and $a_2 = \delta - \frac{\delta}{1-1/\chi_k}$, which implies that $\phi\left(\frac{i}{k}\right) = \delta$, $\frac{i}{k} = \delta$ and $\phi'\left(\frac{i}{k}\right) = 1$ in the steady state.

[10]Altonji and Segal (1996) highlight that matching the unweighted distance between moments often performs better in small samples than using optimal weighting matrices. Accordingly, we use the identity matrix to weight moments in the objective function. In addition, we assign double weight to the correlation between output and relative-consumption growth and to the VAR impulse responses, as they are central to our analysis.

[11]In the remainder, all statistics are computed using third-order pruned perturbation methods.

Table 5: Unconditional moments - Empirical vs. theoretical

Moment	Empirical	Simulated
Macroeconomic variables		
$\text{std}(g_y)$	0.71 [0.59,0.80]	1.26
$\text{std}(g_c)$	0.52 [0.42,0.61]	0.69
$\text{std}(g_i)$	3.17 [2.47,3.81]	3.19
$\text{std}(g_{d^E})$	5.15 [3.43,7.10]	5.25
$\text{std}(g_{rc})$	0.68 [0.56,0.79]	0.31
$\text{corr}(g_{rc}, g_y)$	0.16 [0.00,0.26]	0.15
$\text{AC}(g_{rc})$	0.62 [0.48,0.69]	0.52
$\text{std}(g_z)$	0.63 [0.55,0.72]	0.52
$\text{std}(g_\mu)$	0.47 [0.39,0.54]	0.39
$\text{std}(g_{ls})$	0.98 [0.75,1.23]	0.71
$\text{AC}(g_z)$	0.09 [−0.08,0.21]	0.20
$\text{AC}(g_\mu)$	0.48 [0.28,0.56]	0.73
$\text{AC}(g_{ls})$	−0.34 [−0.46,−0.17]	−0.11
Asset pricing variables		
$E(r^f)$	1.07 [0.18,1.78]	2.02
$E(r^E - r^f)$	4.41 [2.48,7.08]	4.56
$\text{std}(r^f)$	1.51 [1.06,1.82]	6.97
$\text{std}(r^E)$	15.57 [14.30,17.86]	21.81

Notes: Bootstrapped 90% confidence intervals in brackets. g_x denotes the first-differenced logarithm of a generic variable x. Macroeconomic moments refer to quarterly variables. Asset pricing moments are reported in annualized terms. Model-implied moments are computed via third-order pruned perturbation methods.

and dividend growth volatility are closely aligned with the data.[12] Furthermore, while the model understates the unconditional volatility of relative consumption growth (0.31 vs. 0.68 in the data), it reproduces its correlation with output (0.15 vs. 0.16 in the data) and persistence (0.52 vs. 0.62 in the data). Reproducing this correlation is important for disciplining the cyclical redistribution mechanism highlighted in the empirical analysis, as it governs the extent to which relative consumption moves procyclically with aggregate activity. Finally, the model closely matches the empirical standard de-

[12]Guvenen (2009) and Chen (2017) discuss how the joint calibration of preference parameters and capital adjustment costs typically implies trade-offs when matching the volatility of investment, dividends, and consumption.

viations and autocorrelations of the exogenous processes—TFP, the relative price of investment, and labor-share growth.

Turning to asset-pricing moments, recall that when financial market participation is limited to a fraction of households, the equity premium they require increases, reflecting the tighter link between their consumption growth and volatile financial income. Consistent with this mechanism, the model generates plausible excess returns. The average (annualized) equity premium is 4.56 (vs. 4.41 in the data), while the (annualized) standard deviation of (levered) stock returns is 21.81 (vs. 15.57 in the data).[13] The model also produces a realistic mean (annualized) risk-free rate (2.02 vs. 1.07 in the data), though it implies substantially higher volatility for the risk-free rate than observed empirically. As in Jermann (1998) and Lansing (2015), the combination of habit formation and capital adjustment costs—while essential for generating sufficiently volatile equity returns—amplifies fluctuations in investors' marginal utility, which in turn translates into an excessively volatile risk-free rate.

4 Reconnecting asset prices and the macroeconomy

This section evaluates the model's ability to replicate the predictive patterns documented in Section 2 and clarifies the mechanisms that generate them. The analysis proceeds in three steps. First, using simulated data, we assess whether the model replicates the predictive regressions linking aggregate and relative consumption to future excess returns. Second, we examine the model's conditional dynamics to unveil the distinct roles of technology and redistributive shocks in shaping future excess returns. Third, we quantify the contribution of each shock through variance and return decompositions. Robustness exercises show that the results are not driven by the baseline specification of exogenous processes or the assumption of inelastic labor supply.

4.1 Predictive regressions with simulated data

We begin by asking whether the model reproduces the predictive patterns uncovered in the data. Using simulated samples, we re-run the multi-horizon predictive regressions in Section 2. Regressions are estimated on the last $10{,}000$ observations of a simulated sample of $50,000$ periods, so as to ensure convergence to the ergodic distribution.

Table 6 shows that the model closely mirrors the empirical evidence. In Panel A, assetholders' consumption growth negatively predicts future excess returns across horizons, capturing the countercyclical component of risk premia generated by habit for-

[13]The empirical equity premium is estimated following Fama and French (2002), rather than using the historical average excess return. As argued by the authors, the latter approach tends to overstate the true equity premium, particularly in postwar samples.

mation. When investors' consumption rises above habit, effective risk aversion falls and required returns decline.

Panel B decomposes this effect into aggregate and relative components. Aggregate consumption growth enters with a negative and statistically significant coefficient. Relative consumption growth enters positively at short horizons, indicating that redistributive fluctuations contain additional predictive information beyond aggregate conditions. As in the data, this predictive content is concentrated at short to medium horizons and declines as the forecast horizon increases.

Panel C further decomposes relative consumption growth into the contributions of TFP, IST, and FS shocks, revealing a sharp asymmetry: only the FS shock-driven component positively predicts future excess returns at short horizons. The technology-driven components are small and statistically insignificant, instead.

This pattern is salient, as it implies that the short-run predictive power of relative consumption does not arise from the propagation of productivity shocks, but from redistributive disturbances that alter the composition of investors' income. In this sense, the model provides a structural counterpart to the empirical conditional regressions in Table 2, where isolating the redistributive component sharpened the predictive relation.

To understand why FS shocks uniquely generate short-horizon predictability, we now examine the model's conditional dynamics.

4.2 Conditional dynamics

Figure 2 reports the impulse responses of aggregate consumption, relative consumption, and the dividend-to-labor income ratio to TFP, IST, and FS shocks. While all shocks generate broadly similar responses of aggregate consumption, their redistributive implications differ sharply.[14] Expansionary FS shocks raise both relative consumption and the dividend-to-labor income ratio, indicating a shift of income toward capital. By contrast, TFP shocks primarily increase labor income relative to dividends, generating a countercyclical response of relative consumption. IST shocks, instead, have comparatively more muted redistributive effects. Altogether, these impulse responses provide a lens through which to interpret the predictive regressions. Specifically, they help separate variation in expected returns driven by changes in investors' attitude towards risk—as captured by the *price of risk*—from variation driven by changes in the exposure of assetholders' consumption to equity payoffs—the *quantity of risk*.

We first consider the price-of-risk channel. Under habit preferences, effective risk aversion is countercyclical: when aggregate consumption rises above habit, investors

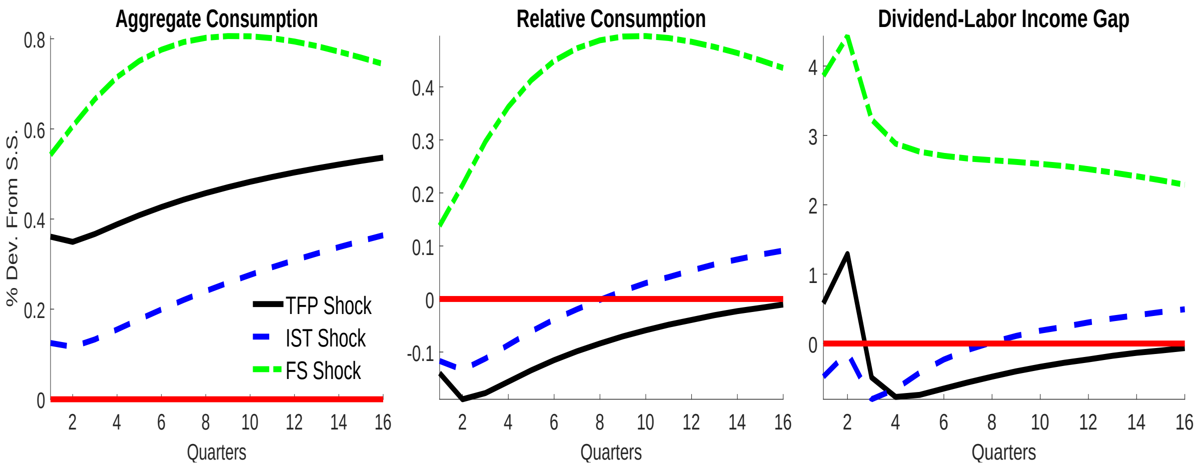
[14]Moreover, Figure D.2 demonstrates that all shocks imply a broad comovement of output, investment, and aggregate consumption.

Table 6: Predictive regressions - Simulated data

	Panel A	Panel B		Panel C			
	$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c^a,t} + \varepsilon_{t+h}$	$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c,t} + \beta_2 g_{rc,t} + \varepsilon_{t+h}$		$r^{\text{ex}}_{t,t+h} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{rc,t} + \beta_3 g^{IST}_{rc,t} + \beta_4 g^{FS}_{rc,t} + \varepsilon_{t+h}$			
h	β_1	β_1	β_2	β_1	β_2	β_3	β_4
1	**-1.25**	**-3.33**	**4.59**	**-3.66**	**3.98**	3.48	**5.33**
	(0.36)	(0.54)	(0.92)	(0.73)	(2.14)	(2.19)	(1.36)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.06]	[0.11]	[0.00]
4	**-0.43**	**-0.83**	0.83	**-1.37**	−0.27	−1.15	**2.07**
	(0.25)	(0.36)	(0.62)	(0.50)	(1.51)	(1.46)	(0.93)
	[0.09]	[0.02]	[0.18]	[0.01]	[0.86]	[0.43]	[0.03]
8	**-0.39**	**-0.58**	0.33	**-1.08**	−0.74	−1.34	**1.49**
	(0.22)	(0.31)	(0.54)	(0.45)	(1.32)	(1.30)	(0.86)
	[0.07]	[0.06]	[0.54]	[0.02]	[0.57]	[0.30]	[0.09]
12	**-0.46**	**-0.67**	0.39	**-1.15**	−0.67	−1.15	**1.47**
	(0.20)	(0.27)	(0.49)	(0.43)	(1.15)	(1.21)	(0.84)
	[0.02]	[0.01]	[0.43]	[0.01]	[0.56]	[0.34]	[0.08]
16	**-0.48**	**-0.64**	0.26	**-1.09**	−0.82	−1.13	1.28
	(0.18)	(0.24)	(0.45)	(0.40)	(1.04)	(1.12)	(0.80)
	[0.01]	[0.01]	[0.57]	[0.01]	[0.43]	[0.31]	[0.11]
20	**-0.51**	**-0.69**	0.29	**-1.06**	−0.49	−1.27	1.15
	(0.17)	(0.22)	(0.41)	(0.38)	(0.95)	(1.02)	(0.75)
	[0.00]	[0.00]	[0.48]	[0.01]	[0.60]	[0.21]	[0.13]

Notes: The table presents results of predictive regressions, estimated on simulated data, of the form $r^{\text{ex}}_{t,t+h} = \alpha + \boldsymbol{\beta x_t} + \varepsilon_{t+h}$, where h denotes the horizon in quarters and $r^{\text{ex}}_{t,t+h}$ denotes annualized excess returns between period t and $t+h$. $\boldsymbol{x_t}$ represents the matrix of (demeaned) predictors, which includes: in Panel A, assetholders' consumption growth; in Panel B, aggregate and relative consumption growth; in Panel C, aggregate consumption growth and relative consumption growth conditioned on each shock at a time. Growth rates are computed as 8-quarters log-differences, expressed in annualized terms. For each regression, Newey-West corrected standard errors (h lags) appear in parentheses below the coefficient estimate, while p-values are reported in square brackets. Significant coefficients at the ten percent level are highlighted in bold. The regressions are estimated over the last $10,000$ observations of a simulated sample of $50,000$ periods. Simulated time-series data are obtained by solving the model with third-order pruned perturbation methods.

Figure 2: Conditional dynamics - Mechanism



Notes: Responses of aggregate consumption, relative consumption, and dividend-to-labor income ratio to TFP, IST, and FS shocks.

become less risk-averse and required returns decline (Campbell and Cochrane, 1999). As shown in the bottom-right panel of Figure D.2, this countercyclical pattern holds conditional on all shocks, although it is stronger conditional on FS disturbances at short horizons. Because all shocks raise aggregate consumption on impact, aggregate consumption growth in the predictive regressions primarily captures variation in the price of risk. This explains the negative relationship between aggregate consumption growth and future excess returns (Fama and French, 1989) and accounts for the negative coefficient in both the multivariate and univariate specifications.

We next turn to the quantity-of-risk channel. Redistribution shocks alter not only aggregate conditions, but also the composition of assetholders' income. As shown in Figure 2, FS shocks raise relative consumption and increase the dividend-to-labor income ratio in tandem, shifting income toward capital. As a result, a larger fraction of investors' consumption is financed through dividend income, which is tightly linked to equity payoffs. Holding the aggregate state—and, thus, effective risk aversion—fixed, this shift increases the covariance between assetholders' consumption growth and stock returns. In asset-pricing terms, redistribution raises the quantity of risk borne by investors. This additional exposure predicts higher near-term excess returns, generating the positive coefficient on relative consumption growth in the predictive regressions. By contrast, technology shocks have muted effects on the dividend-to-wage ratio and relative consumption, and therefore contribute little to the covariance between relative consumption and returns.

Importantly, the redistribution induced by FS shocks is persistent but ultimately mean-reverting. The dividend-to-consumption ratio of investors rises on impact and declines gradually as the effects of the shock dissipate. Consequently, the increase in the relative consumption–return covariance is concentrated at shorter horizons. Risk premia are therefore shifted forward, rather than being permanently elevated: expected returns rise in the near term but revert over longer horizons, as income shares normalize. This mechanism explains why the coefficient on relative consumption growth declines with the forecast horizon and why redistribution shocks tilt the term structure of expected returns toward shorter maturities without altering long-run premia.

4.3 Macroeconomic and financial drivers

This subsection documents and quantifies a key macro–finance disconnect: shocks that drive macroeconomic aggregates are not the same as those that drive asset prices.

Shock contribution Table 7 confirms a sharp separation between macroeconomic and financial drivers. In the top panel, both short- and long-run variance decompositions show that IST shocks account for the majority of fluctuations in output, consumption, and investment, in line with Justiniano and Primiceri (2008). FS shocks play a secondary role for aggregate quantities, particularly at long horizons.[15]

The bottom panel tells a very different story. Redistribution shocks account for the vast majority of both the mean and the variance of excess returns, and for a substantial share of risk-free rate fluctuations. By contrast, technology shocks—especially IST shocks—contribute negligibly to equity-premium volatility. Thus, the shocks that dominate macroeconomic dynamics are not those that drive asset-pricing moments.

Notably, while both IST and FS shocks partly explain the unconditional volatility of relative consumption, its short-run volatility stems almost exclusively from the latter. This finding is key to understanding the emergence of a disconnect between the drivers of financial volatility and macroeconomic fundamentals.

[15] The short-run variance decomposition is performed as in den Haan (2000), while the shock contribution to long-run moments is obtained by following Jensen et al. (2018). Specifically, for the generic stationary variable x and the corresponding moment $\mathcal{M}(x)$, the relative contribution of shock ξ to the moment of interest is defined as $\mathcal{M}(x)_\xi = \frac{\mathcal{M}(x)-\mathcal{M}(x)_{-\xi}}{\sum_\xi[\mathcal{M}(x)-\mathcal{M}(x)_{-\xi}]}$ for $\xi = u^\mu, u^z, u^\alpha$, where $\mathcal{M}(x)_{-\xi}$ is the unconditional moment of x when shock ξ is turned off.

Table 7: Shock contribution

		TFP	IST	FS
Macro aggregates				
$\sigma^2_{\log(\tilde{y})}$	SR	10.85	63.16	25.99
	LR	11.63	73.80	14.57
$\sigma^2_{\log(\tilde{c})}$	SR	15.71	63.88	20.41
	LR	12.96	69.61	17.43
$\sigma^2_{\log(\tilde{inv})}$	SR	6.45	51.72	41.83
	LR	10.34	74.56	15.11
$\sigma^2_{\log(\tilde{rc})}$	SR	5.45	2.77	91.78
	LR	6.59	37.61	55.80
Financial moments				
$\mathrm{E}(r^f)$		20.19	1.43	78.38
$\mathrm{E}(r^E - r^f)$		18.16	0.57	81.27
$\sigma^2_{r^f}$		41.78	5.07	53.15
$\sigma^2_{(r^E - r^f)}$		23.63	0.90	75.47

Notes: Each entry indicates the (percentage) contribution of the corresponding shock to a specific macroeconomic or asset-pricing moment. Along each row, the sum of the three shock contributions amounts to 100. For the macroeconomic variables, the decomposition is presented over both the short run (SR) and the long run (LR). For the asset-pricing variables, the decomposition is only presented in terms of long-run moments.

Redistribution, equity premium and the risk-free rate. Under log-normality, power utility, and denoting logs with a hat, the expected excess return can be expressed as[16]

$$\begin{aligned} \mathrm{E}_t r^E_{t+1} - r^f_t &= \mathrm{RRA} \times \mathrm{Cov}_t(g_{c^a,t+1}, \hat{r}^E_{t+1}) \\ &= \mathrm{RRA} \times \Big[\mathrm{Cov}_t(g_{c,t+1}, \hat{r}^E_{t+1}) + \kappa \, \mathrm{Cov}_t(g_{rc,t+1}, \hat{r}^E_{t+1}) \Big]. \end{aligned} \tag{15}$$

Equation (15) shows that the equity premium depends not only on aggregate consumption risk, but also on redistribution-driven fluctuations in relative consumption. The second covariance term—absent in representative-agent environments—captures the additional exposure to financial risk generated by shifts in income between labor and capital. In the model, FS shocks uniquely generate strong positive comovement between relative consumption and stock returns. As shown in Figure 2, these shocks raise the dividend-to-wage ratio and increase assetholders' reliance on dividend income precisely when returns are high, thereby amplifying $\mathrm{Cov}_t(g_{rc,t+1}, \hat{r}^E_{t+1})$. In contrast, technology shocks imply limited redistribution and therefore contribute

[16] While these assumptions allow for closed-form expressions, they abstract from fluctuations in effective risk aversion implied by habit preferences. In our model, relative risk aversion is countercyclical conditional on all shocks, and its impulse responses are quantitatively similar across disturbances (see Figure D.2). Hence, allowing for time-varying risk aversion would not alter the qualitative implications of the decomposition below.

little to this covariance term. Consistently, we find that the unconditional covariance $\mathrm{Cov}(g_{rc}, \hat{r}^E) = 0.47$ (in percent terms) in the baseline model masks sharply different contributions from technology and redistributive shocks. Conditional on TFP and IST shocks only, this covariance becomes negative (-0.50), indicating that, in the absence of FS shocks, redistribution would lower the equity premium. By contrast, conditioning only on FS shocks more than doubles the covariance (0.98), confirming a stronger contribution of redistribution to average excess returns.

A similar decomposition applies to the risk-free rate.[17] Under the same assumptions,

$$\begin{aligned} r_t^f &= -\frac{1}{2}\mathrm{RRA}^2 \times \mathrm{Var}_t(g_{c^a,t+1}) \\ &= -\frac{1}{2}\mathrm{RRA}^2 \times \Big[\mathrm{Var}_t(g_{c,t+1}) + \kappa^2 \mathrm{Var}_t(g_{rc,t+1}) + 2\kappa\, \mathrm{Cov}_t(g_{c,t+1}, g_{rc,t+1})\Big]. \end{aligned} \tag{16}$$

While both technology and redistributive shocks increase $\mathrm{Var}_t(g_{rc,t+1})$ by generating fluctuations in relative consumption, only FS shocks induce a positive $\mathrm{Cov}_t(g_{c,t+1}, g_{rc,t+1})$. This further raises the volatility of assetholders' consumption growth and strengthens the precautionary saving motive, compressing the equilibrium risk-free rate.

Nonetheless, it should be noted that external habit models typically require a large effective risk aversion to match asset-pricing moments (Rudebusch and Swanson, 2008), and our model is no exception. In particular, the average risk aversion in our economy is $\mathrm{RRA} = 16.70$, implying that the bulk of the equity premium is generated by the presence of habits rather than high risk exposure.[18] However, our analysis highlights that redistribution between asset market participants and non-participants helps match asset-pricing moments only in the presence of redistributive, rather than technology, shocks.

Campbell–Shiller decomposition While the above decompositions clarify how redistribution affects average risk premia, they do not reveal whether shocks operate primarily through revisions in expected cash flows or in discount rates. To disentangle these channels, we follow Campbell (1991), who show that innovations in log (denoted by the hat) stock returns can be decomposed as

$$\begin{aligned} \hat{r}^E_{t+1} - E_t \hat{r}^E_{t+1} &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j g_{d^E,t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \hat{r}^E_{t+1+j} \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned} \tag{17}$$

[17] For simplicity, constants are omitted and average consumption growth is set to zero, consistent with the model.

[18] To contextualize this magnitude, note that the average effective risk aversion in Campbell and Cochrane (1999) is about 40, for example.

Table 8: Stock return innovations decomposition

	$\hat{r}^E_{t+1} - \mathrm{E}_t\hat{r}^E_{t+1}$	$N_{CF,t+1}$	$-N_{DR,t+1}$	$g_{d^E,t+1} - \mathrm{E}_t g_{d^E,t+1}$
TFP Shock	3.83	0.80	3.03	1.04
IST Shock	0.43	1.20	-0.77	-0.27
FS Shock	9.34	1.25	8.09	4.30

Notes: Decomposition of innovations in stock returns based on Campbell (1991). Innovations in stock returns and dividend growth (first and last column, respectively) are computed as the value of the variable's IRF at impact. Cash flow news ($N_{CF,t+1}$) is computed as the sum over $j = \{0, ..., J\}$ (the period after the shock) of the products between the value of the IRF of dividend growth at period j and ρ^j, with $\rho = 0.99$. The sum is truncated at $J = 50$. Given equation (17), discount rate news ($-N_{DR,t+1}$) is computed residually.

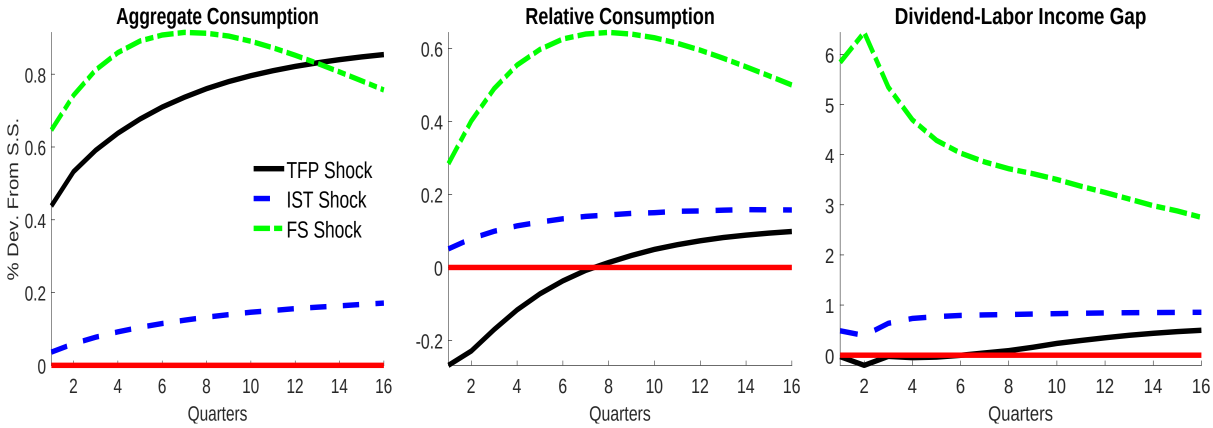
where $N_{CF,t+1}$ denotes cash-flow news and $N_{DR,t+1}$ discount-rate news.

Table 8 reports this decomposition conditional on each structural shock. The first three columns report return innovations and their decomposition into cash-flow and discount-rate news, while the last column reports the contemporaneous innovation in dividend growth, which helps interpret the dynamics of cash flows following each shock. Three patterns emerge. First, FS shocks generate return innovations that are substantially larger than those associated with technology shocks. Second, for redistribution shocks, most of the return innovation reflects revisions in discount rates, whereas cash-flow news plays a comparatively minor role. TFP and IST shocks, by contrast, produce much smaller return innovations, with a more balanced contribution of cash-flow and discount-rate news.

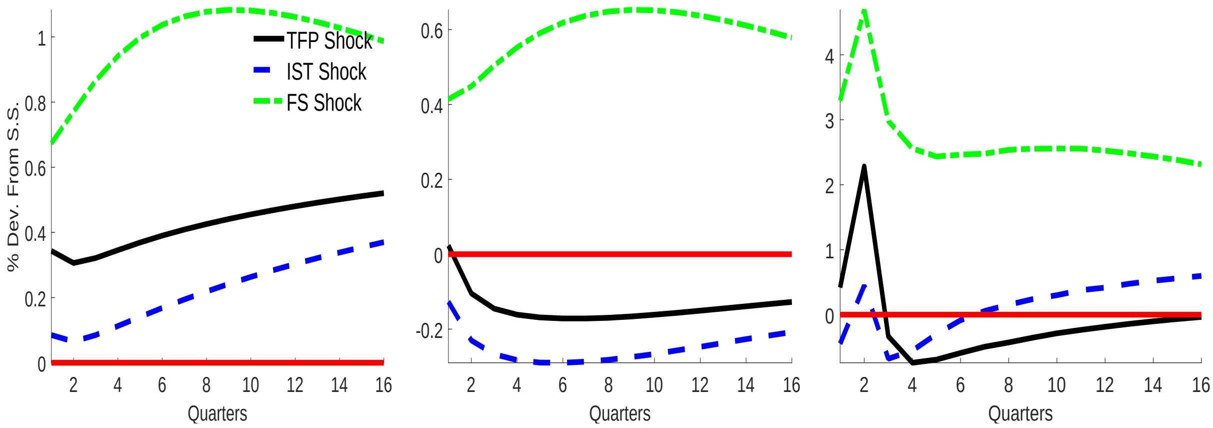
These findings help refine our interpretation of the model's mechanism. On the one hand, redistribution shocks primarily affect stock prices through changes in required returns rather than through large revisions in the expected path of dividends. In other words, FS shocks operate mainly through the discount-rate channel—amplified by habit preferences—consistent with their dominant contribution to equity-premium volatility and the overall countercyclicality of expected excess returns. On the other hand, FS shocks also generate some persistence in dividend growth. This is consistent with the predictability of dividend growth and its contribution to expected returns documented in Antolín-Díaz et al. (2026), pointing to a complementary channel of (short-run) return predictability operating through dividends.

Together, these dynamics reinforce the short-run link between assetholders' consumption and financial income. By raising dividend income during expansions, FS shocks strengthen the covariance between investor consumption and stock returns and help explain the positive association between relative consumption growth and future excess returns documented in the predictive regressions.

Figure 3: Conditional dynamics – Mechanism – Robustness



(a) AR shocks



(b) Flexible labor

Notes: Responses of aggregate consumption, relative consumption, and dividend-to-labor income ratio to TFP, IST, and FS shocks in the model robustness exercises.

4.4 Model robustness

We assess whether the redistribution mechanism identified in the baseline model hinges on specific assumptions about the shocks or labor supply. To this end, we consider two alternative model specifications. First, we replace the baseline trivariate VAR with independent univariate AR processes for TFP growth, relative investment-price growth, and the (log) labor share, thereby removing endogenous interactions among shocks. Second, we allow non-assetholders to supply labor elastically. Appendix D provides details on the model setups and recalibration.

Figure 3 reports the resulting impulse responses. In both cases, FS shocks continue to generate procyclical relative consumption and a pronounced increase in dividend income relative to labor income, whereas technology shocks produce substantially weaker redistributive effects. The central mechanism—namely, shocks affecting income shares drive cyclical redistribution and alter investors' exposure to risk—

Table 9: Conditional predictive regressions on simulated data - Robustness

$r^{ex}_{t,t+8} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{rc,t} + \beta_3 g^{IST}_{rc,t} + \beta_4 g^{FS}_{rc,t}$			
β_1	β_2	β_3	β_4
Panel A: AR shocks			
-0.94	**-1.81**	1.38	1.02
(0.42)	(1.06)	(2.36)	(0.72)
[0.03]	[0.09]	[0.56]	[0.16]
Panel B: Flexible labor			
-2.43	-3.05	**-2.02**	**3.48**
(0.73)	(1.87)	(1.06)	(1.26)
[0.00]	[0.10]	[0.06]	[0.01]

Notes: The table presents results of predictive regressions, estimated on simulated data, for different model robustness exercises. For each regression, Newey-West corrected standard errors (8 lags) appear in parentheses below the coefficient estimate, while p-values are reported in square brackets. Significant coefficients at the ten percent level are highlighted in bold. The regressions are estimated over the last 10,000 observations of a simulated sample of 50,000 periods. Simulated time-series data are obtained by solving the model with third-order pruned perturbation methods.

remains intact.[19]

Table 9 confirms that the model-implied predictability patterns are similarly robust. When shocks follow independent AR processes, the magnitude of coefficients is somewhat attenuated, but aggregate consumption retains a negative predictive coefficient and the FS-driven component of relative consumption remains positively associated with future returns. Allowing for endogenous labor supply strengthens the baseline findings, with redistribution shocks continuing to account for the bulk of short-horizon predictability.

We also consider an extension with monopolistically competitive firms and markup shocks, allowing labor-share fluctuations to arise from variations in price markups rather than factor shares. As shown in Figure D.5, markup shocks increase relative consumption while reducing aggregate consumption. They therefore fail to reproduce the procyclicality of redistribution that lies at the core of our mechanism and characterizes the empirical evidence. This further supports our interpretation of FS shocks as the main driver of cyclical redistribution and asset-pricing dynamics.

5 Validating the mechanism

The model delivers a sharp prediction: although all structural shocks generate expansions in aggregate activity, only redistributive shocks raise dividend income relative to labor income and make relative consumption strongly procyclical. By con-

[19]Moreover, in this setting FS shocks reduce hours worked while still generating an economic expansion, a feature that we also document in the data (see Appendix D.3). Therefore, the failure to produce a positive (conditional) comovement between GDP and hours rules out FS shocks as a key driver of business-cycle fluctuations (Gali, 1999; Francis and Ramey, 2005), consistent with the baseline results reported in Table 7.

trast, neutral technology shocks compress consumption inequality during expansions. These distinct transmission mechanisms underpin our interpretation of short-run return predictability. In this section, we test whether the conditional dynamics implied by the model are borne out in the data.

To this end, we estimate the following autoregressive distributed-lag model (similar to Romer and Romer, 2004; Cloyne et al., 2019):

$$x_t = \alpha_0 + \alpha_1 t + \sum_{r=0}^{R} \beta_r u_{j,t-r} + \sum_{p=1}^{P} \delta_p x_{t-p} + e_t, \tag{18}$$

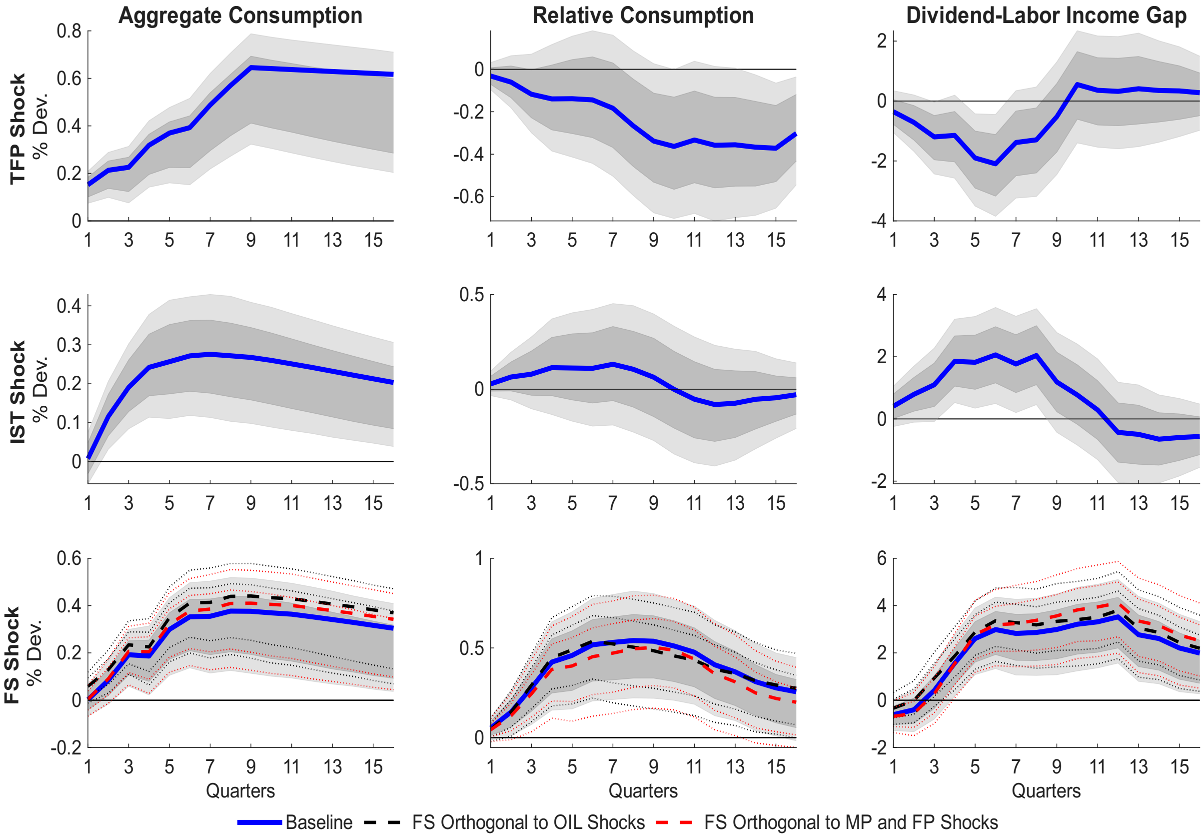
where t denotes the time trend, while x_t denotes the (log) variable for which we compute the impulse-response function to either of the three shocks, as captured by $u_{j,t}$ where $j \in \{TFP, IST, FS\}$. The number of lags for both the shock and the endogenous variable is selected using a corrected Akaike information criterion. Inference is based on wild bootstrap standard errors (Gonçalves and Kilian, 2004). Figure 4 depicts the estimated impulse response functions for aggregate (non-durable and services) consumption, relative consumption, and the dividend-to-labor income ratio. Shocks are generated so that a positive TFP shock increases TFP, whereas positive IST and FS shocks decrease the relative price of investment and the labor share of income, respectively (in line with Figure C.1).

Three main results emerge. First, all three shocks generate broadly similar expansions in aggregate consumption. Moreover, Figure E.1 shows that the same pattern holds for output, investment, and total consumption (including durables). From the perspective of aggregate quantities alone, the three disturbances are therefore hard to distinguish, as they all induce pronounced macroeconomic comovement.

Second, despite a similar transmission to aggregate consumption, stark differences emerge regarding distributional effects, which are crucial for understanding risk premia. The figure highlights how each shock affects inequality between assetholders and non-assetholders in markedly different ways. Facing a TFP shock, non-assetholders' consumption rises relatively more than that of the assetholders, thus implying a contraction in relative consumption. Relative consumption, instead, expands following an expansionary IST shock, although the response is not statistically significant. Conversely, a positive FS shock significantly widens the gap between the consumption of the two agents.[20] Therefore, FS shocks induce strong procyclicality in consumption

[20] While classifying households into assetholders and non-assetholders, we implicitly assume that the transition between groups is a reason for no particular concern and that shocks do not trigger significant endogenous changes in assetholding status. This condition is required to interpret the consumption responses as actual changes in expenditures, rather than as mere compositional effects. Figure E.2 supports this view. Despite the conditional behavior of the share of assetholders being in line with that of relative consumption—as expected on theoretical grounds—little variation emerges, regardless of the specific shock we consider.

Figure 4: Empirical conditional dynamics - Mechanism



Notes: The figure displays the IRFs of aggregate consumption (first column), relative consumption between assetholders and non-assetholders (second column), and after-tax dividend-to-labor income ratio (third column), to the identified neutral technology (TFP, top row), investment-specific technology (IST, middle row), and factor-share (FS, bottom row) shocks, estimated over the sample 1982Q4-2017Q4. Dark and light-grey shaded areas represent the 68% and 90% confidence intervals, respectively. Consumption is measured as non-durables and services expenditure.

inequality, while this is conditionally countercyclical in connection with TFP shocks. This pattern is precisely the one required by the model's mechanism: only shocks that expand inequality in good times can generate positive comovement between relative consumption and stock returns, and hence short-run return predictability. The unconditional correlation between relative consumption growth and GDP (0.16) thus reflects the net effect of these opposing forces, masking the sharply different conditional dynamics across shocks.

Finally, the dynamics of relative consumption are closely linked to movements in the dividend-to-labor-income ratio. FS shocks raise dividend income disproportionately relative to wages, generating a transitory shift in the composition of assetholders' income toward financial claims. By contrast, TFP shocks primarily raise labor income, compressing inequality and weakening this covariance channel.[21] These findings hold

[21]Consistently, Figure E.3 clarifies that similar conclusions hold when considering the dynamics of

when orthogonalizing FS shocks to oil or monetary and fiscal policy shocks (black- and red-dashed lines, respectively, in Figure 4) or when identifying the exogenous disturbances in the VAR with the not-detrended labor share, the naive labor-share definition, the profit share, or the max-share identification scheme (Figure E.4).

Overall, the empirical impulse responses validate the central mechanism of the model. While technology shocks account for broad macroeconomic comovement, only redistributive shocks systematically tilt income toward dividends during expansions, generating procyclical consumption inequality and short-run return predictability. These findings reinforce the interpretation that time variation in expected returns reflects not only fluctuations in aggregate activity, but also shifts in the distribution of income—and thus risk exposure—across households.

6 Concluding remarks

This paper examines the link between macroeconomic and financial fluctuations through the lens of limited asset market participation. We decompose assetholders' consumption growth into two components that have distinct implications for expected stock returns. Aggregate consumption growth primarily captures variation in investors' effective risk aversion, whereas changes in relative consumption—arising from redistribution between participants and non-participants—reflect variation in the exposure of investors' income to equity payoffs. Together, these channels provide an economic interpretation of why aggregate and relative consumption exhibit opposite predictive patterns for future excess returns.

We devise a quantitative model that embodies these channels, helping to clarify their functioning in connection with different structural shocks. Technology shocks account for the bulk of macroeconomic fluctuations but generate limited redistribution. In contrast, FS shocks primarily drive asset-pricing moments by reallocating income toward investors during expansions, increasing the covariance between their consumption and stock returns. This asymmetry implies a sharp distinction between the shocks that dominate aggregate activity and those that shape risk premia. Consistent with the model's predictions, the data show that redistributive shocks raise dividends relative to labor income and make relative consumption strongly procyclical, whereas expansionary TFP shocks compress inequality.

Taken together, our findings highlight the importance of limited participation and consumption distribution dynamics for understanding the joint behavior of macroeconomic aggregates and expected asset returns.

aggregate and relative after-tax income.

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Internet Appendix to
Asset Market Participation, Redistribution, and Asset Pricing

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March 13, 2026

A Data sources

Below is the list of sources for the macroeconomic and financial data employed in the empirical analysis. Real per-capita measures are obtained by dividing nominal values by the U.S. population and the end-of-the-quarter monthly Consumer Price Index for all items computed by the Bureau of Labor Statistics.

- GDP: Gross domestic product, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rates, NIPA, Table 1.1.5, Line 1.
- Investment: Gross Private Domestic Investment, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rates, NIPA, Table 1.1.5, Line 7.
- Non-durables: Nondurable goods, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rate, NIPA, Table 1.1.5, Line 5.
- Services: Services, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rate, NIPA, Table 1.1.5, Line 6.
- Durables: Durable goods, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rates, NIPA, Table 1.1.5, Line 4.
- Total Consumption: Non-durables + Services + Durables.

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- CPI: Consumer Price Index for All Urban Consumers: All Items in U.S. City Average, Index 1982-1984=100, Quarterly (End-of-Quarter Monthly Value), Seasonally Adjusted. FRED Code: CPIAUCSL.
- Gross Income: Personal Income, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rates. NIPA, Table 2.1, Line 1.
- Net Income: Disposable Personal Income, Billions of Dollars, Quarterly, Seasonally Adjusted at Annual Rates. NIPA, Table 2.1, Line 27.
- Population: Population (midperiod, thousands), Quarterly, NIPA, Table 2.1, line 40.
- Relative Price of Investment: Relative price of "consumption" to price of "equipment", percent, change at an annual rate (=400 $\times$ change in natural log), from Fernald (2014).
- TFP: Business sector TFP, percent change at an annual rate (=400 $\times$ change in natural log), from Fernald (2014).
- Labor Share of Income: Nonfarm Business Sector: Labor Share for All Workers, Index 2017=100, Quarterly, Seasonally Adjusted. FRED Code: PRS85006173.
- Aggregate Hours: Index/Level and Office of Productivity And Technology and Work Hours: Hours Worked, Nonfarm Business. BLS. Code: PRS85006033.
- Population 16+: Civilian noninstitutional population, Level (in thousands), 16 years and over (End-of-Quarter Monthly Value). BLS. FRED Code: LNU00000000.
- GNP: Gross National Product, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate. FRED Code: GNP.
- Profits: Nonfinancial corporate business: Profits before tax (without IVA and CCAdj), Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate. FRED Code: A464RC1Q027SBEA.
- Gross Value Added: Gross value added of nonfinancial corporate business, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate. FRED Code: A455RC1Q027SBEA.
- Quarterly risk-free rate, stock return, dividend-price ratio, dividend yield, dividends, and stock price are sourced from Amit Goyal's website (as discussed in Welch and Goyal, 2008). The equity premium is computed from the average dividend yield and dividend growth following Fama and French (2002).

After-tax dividend and labor income. The definition of after-tax aggregate dividend and labor income series follows Lettau and Ludvigson (2013) and relies on data from the NIPA, Table 2.1. Specifically, after-tax labor income is defined as compensation of employees (Line 2) + transfer payments (Line 16) − employee contributions for social insurance (Line 25) − taxes. Taxes are defined as [wages and salaries (Line 3) / (wages and salaries + proprietors' income with IVA and Ccadj (Line 9) + rental income (Line 12) + personal income receipt on assets (Line 13))] times personal current taxes (Line 26). After-tax dividend income is defined similarly as personal dividend income (Line 15) − taxes, where the latter are defined as above, but replacing dividend income in the numerator.

B Construction of household-level series from the CEX

In this appendix, we describe the dataset and preliminaries used to construct quarterly time series of consumption and income at the household level over the period 1982-2017 from the U.S. CEX.

B.1 Description of the dataset

The CEX is a national survey collecting household-level data on detailed consumption expenditures together with income, financial, and demographic information on a sample that is designed to represent the non-institutionalized civilian population of the US. The survey is divided into two parts: the Interview Survey and the Diary Survey. The analysis developed in this paper focuses on the first one. Data from the CEX are from the 1980Q1 to 2018Q1. The survey is a rotating panel containing interviews of about 4,500 households per quarter before 1999, increasing to about 7,500 thereafter. About 20% of the sample is replaced each quarter. In each interview, households report detailed expenditures made in the previous three months. Households are interviewed every 3 months for a maximum of 5 interviews. The first interview is just for practice, and as such is not made publicly available, while financial information is collected only in the last interview.

B.2 Sample choice

Our analysis employs data for the sample 1980Q1-2018Q1. Standard restrictions are applied to the sample. Only households that completed the survey, i.e., for which five interviews are available in the FMLY/FMLI files, are included. Matching households across quarters is not possible around changes in sample design, which happened at the beginning of 1986, 1996, 2005, and 2015.[1] Such changes imply new household ID numbers. Therefore, all the households that did not finish their interviews before their ID changed are dropped.

Households with negative net income or incomplete income responses are excluded from the sample. Regarding the latter restriction, for the period 1980-2013, the variable RESPSTAT is used, which indicates whether the household is a complete or an incomplete income reporter. Since 2014, this variable has no longer been available. Hence, we use the variable ERANKH, which measures the weighted cumulative percent expenditure outlay ranking of the household to total population is left blank for incomplete income reporters. Moreover, all consumption observations for households interviewed in the years 1980 and 1981 are dropped as the 'food' question was changed in 1982, leading to a drop in reported food expenditures.[2] Finally, we exclude all households that denote a change in the household head's age between any two consecutive interviews that is different from either 0 or 1.

B.3 Assetholding status definition

The FMLY/FMLI files report household-level financial information on holdings of "stocks, bonds, mutual funds, and other such securities" and of liquid accounts such as savings and checking accounts.

For the period 1980-2012, we use the following variables: SECESTX, which reports the amount of the household holdings in the aforementioned asset categories (on the last day of the month preceding the interview); CKBKACTX, which reports the amounts (at the last day of the month preceding the interview) "in checking accounts, brokerage accounts, and other similar accounts"; SAVACCTX, which asks "On the last day of (last month), what was the total amount your CU had in savings accounts in banks, savings and loans, credit unions, and similar accounts?". Since 2013, these three variables have been removed from the survey. However, at the same time, a new variable STOCKX was added, which asks "As of today, what is the total value of all directly-held stocks, bonds, and mutual funds?". Similarly, the new variable LIQUIDX was introduced, which measures the amounts invested in "checking, savings, money market accounts, and certificates of deposit or CDs".

Given these variables, we define a household as an assetholder if the sum of SECESTX, CKBKACTX, and SAVACCTX or STOCKX and LIQUIDX exceeds the thresh-

[1] The year-specific documentation files report this type of information. These files can be found at: http://www.nber.org/ces

[2] As noted by Malloy et al. (2009), the 'food' question was changed back to the initial one in 1988, but there is no sensible way to solve this issue without losing a substantial number of observations.

old of 1000$. To keep comparability with the SCF variables, dollar amounts in year t are multiplied by the absolute variation between year $t-1$ and year t in the (yearly average of the monthly) current-methods version of the CPI for all urban consumers (CPI-U-RS).[3]

Crucially, indirect holdings cannot be retrieved from the CEX, as also noted by Malloy et al. (2009). In fact, the stock-market participation rate that we retrieve from this survey trends up until the early 2000s, to then stabilize around 10%, which is way below the actual share of US households that are typically classified as stockholders. Moreover, in 2013, the 'financial assets' question was changed to consider only direct holdings. In fact, Lettau et al. (2019) argue that the CEX provides inferior measures for financial holdings, as compared with other surveys such as the SCF, which can potentially explain the lower estimated rates.

B.4 Imputation procedure

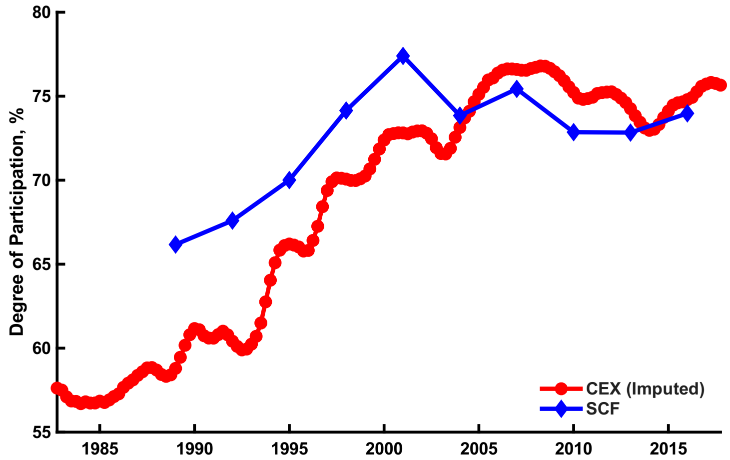
To refine the assetholding status definition to account for indirect holdings, we follow the imputation procedure proposed by Attanasio et al. (2002) and Malloy et al. (2009). Specifically, we perform a probit analysis based on the SCF. This dataset contains wealth information on both direct and indirect stock or assetholdings that can be used to predict the probability that a household holds assets, directly or indirectly, in the CEX. We use the SCF from 1989 through 2016. For the asset definition, we generate a dummy variable equal to 1 if the sum of (direct and indirect) holdings in equity, bonds, savings accounts, and checking accounts exceeds the threshold of 1000$ (in real terms).

Following Malloy et al. (2009), we then estimate a probit model where the dependent variable is the assetholding dummy and the regressors are the observable characteristics that are also available in the CEX: age, age squared, an indicator for the household head with education of > 12 but < 16 years (highschool), one for education > 16 years (college), an indicator for race not being white/caucasian, year dummies, (log) real total household income before taxes, an indicator for positive interest+dividend income, and a constant. We also include interaction terms between age and high school (agehs) and between age and college (ageco).[4] Here are the estimated coefficients (with t-statistics in parentheses) from the probit regression for assetholdings:

[3] Available at: https://www.bls.gov/cpi/research-series/home.htm

[4] Importantly, SCF weights are employed to map household-level estimates into population estimates.

Figure B.1: Asset-ownership rates



Notes: The figure compares the rates of direct and indirect asset-ownership, as measured from the SCF (blue line) and the CEX (red line).

$$
\begin{aligned}
x'_{SCF}b_{asst} = {} & \underset{(-56.72)}{-5.07} + \underset{(13.72)}{0.022}age \underset{(-5.96)}{-0.00008}age^2 + \underset{(14.75)}{0.51}\,highschool + \underset{(35.86)}{1.22}\,college \\
& \underset{(-2.92)}{-0.002}agehs \underset{(-13.07)}{-0.008}ageco \underset{(-45.76)}{-0.38}nonwhite + \underset{(1.57)}{0.03}Y_{1992} + \underset{(9.27)}{0.20}Y_{1995} \\
& + \underset{(15.93)}{.35}\ Y_{1998} + \underset{(20.19)}{0.43}\,Y_{2001} + \underset{(14.65)}{0.31}\,Y_{2004} + \underset{(17.50)}{0.37}\,Y_{2007} + \underset{(16.67)}{0.33}\,Y_{2010} + \underset{(16.30)}{0.32}\,Y_{2013} \\
& + \underset{(18.42)}{0.37}\,Y_{2016} + \underset{(44.36)}{0.37}\,log(income) + \underset{(73.13)}{0.95}\,(int + div > 0).
\end{aligned}
$$

We then use these coefficients to predict the probability that a household in the CEX holds assets as $\Phi(x'_{CEX}b_{asst})$, where Φ is the CDF of the standard normal distribution and x_{CEX} is the vector of the same regressors as in the SCF. When predicting the assetholding probability for a household in the CEX, we use the dummy *1992* coefficient for the years 1990-1993, the dummy *1995* coefficient for the years 1994-1996, the dummy *1998* coefficient for the years 1997-1999, and so on.

We employ a 'continuous' measure of participation, whereby every household contributes to the population weight, consumption, and income of the representative assetholder, according to the predicted probability. Specifically, we use the probability predicted for the last month each household is observed, since financial information is reported only in the last interview. Notice that this imputation procedure is applied only to those households that have non-missing responses to all the questions involved in the imputation procedure. Otherwise, the household receives a probability 0 of being an assetholder.

Figure B.1 compares the resulting participation rate with the one from the SCF. As for the resulting consumption series, the participation rates in the CEX are smoothed through a backward-looking 4-quarter moving average filter. We can see that the imputed series closely tracks the original (SCF) one, with differences of the order of a few percentage points. The level discrepancy between the two participation rates likely reflects the different survey designs. As stressed by Lettau et al. (2019), the SCF contemplates relatively wealthy households. On the other hand, the CEX has some well-known limitations when trying to measure the top-end of the wealth distribution, mostly due to under-reporting.

B.5 Household-level consumption and income series

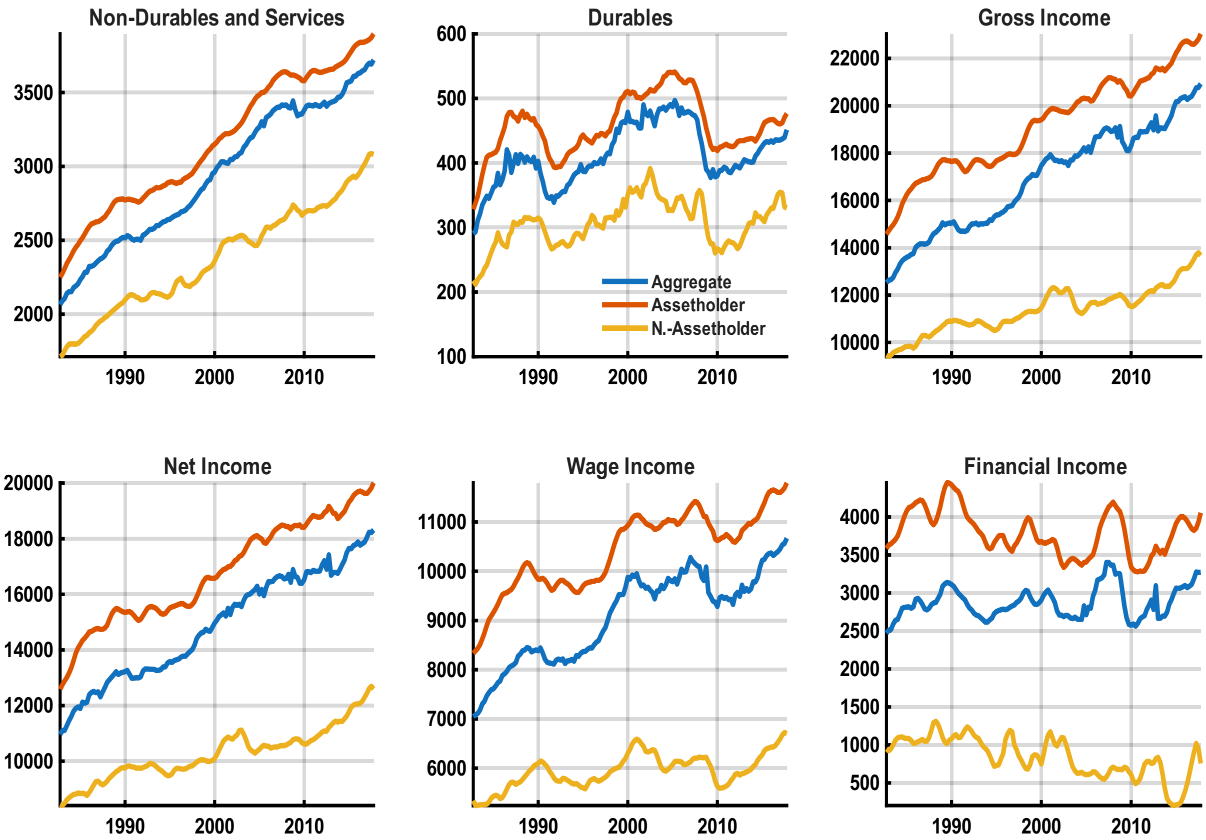
We compute consumption of non-durable goods and services and durable goods aggregated from the disaggregated expenditure categories reported in the monthly expenditure files (MTAB and MTBI files) of the CEX. Non-durables and services consist of food, alcoholic beverages, apparel and services, gasoline and motor oil, household operations, utilities, tobacco, public transportation, fees and admissions, personal care products, reading, other vehicle expenses, and other entertainment supplies, equipment, and services. Durable goods include purchases of vehicles, house furnishings, and tv and audio equipment. Finally, gross and net income are defined as before and after-tax income, respectively, while financial income is computed as the sum of dividend and interest income. Wage income is given by the sum of wages and salaries.

The ultimate aim of the analysis is to obtain time series of both consumption and income—for a representative assetholder and a non-assetholder—by employing the assetholding status definition obtained from the imputation procedure described above. To do so, we compute population-weighted quarterly mean expenditure and income by aggregating from monthly data, and following the formulae provided in the CEX documentation.[5] Nominal expenditure values are deflated by the end-of-the-quarter CPI for all items and divided by family size to obtain per-capita expenditures.

In line with Cloyne et al. (2019), the group-specific consumption expenditure and income series are adjusted every quarter by the ratio between the corresponding aggregate NIPA series and the estimated CEX aggregate. Finally, to limit some of the noise inherent to survey data and to seasonally adjust the consumption and income series, these are smoothed through a backward-looking moving average encompassing the current and the previous three quarters. Figure B.2 displays the results based on the chosen sorting criterion. Mean estimates are also calculated for the representa-

[5]In particular, we employ the example codes provided at the link: `https://www.bls.gov/cex/pumd-getting-started-guide.htm#section5`. These codes allow one to compute calendar period estimates.

Figure B.2: Household-level consumption and income



Notes: Selected consumption and income variables for the representative household (blue line) from the NIPA, together with the representative assetholder (orange line) and the representative non-assetholder (yellow line), as estimated from the CEX, based on the probability-weighted assetholding status imputed from the SCF.

tive household, i.e., over the whole sample and for all households, so as to obtain an aggregate consumption estimate from the CEX. The final quarterly consumption and income series cover the sample 1982Q4-2017Q4.

C Shock identification and additional results

In this appendix, we extensively discuss shock identification and report additional evidence on stock-return predictability.

C.1 Shock identification

Our identification strategy follows the procedure outlined by Santaeulalia-Llopis (2011). We specify a trivariate Vector Autoregression (VAR) model with four lags, where the growth rate of the (inverse) relative price of investment to that of consumption goods ($\Delta \log(\mu_t)$), the growth rate of total factor productivity ($\Delta \log(z_t)$) and the linearly detrended (log) labor share of income ($\log(ls_t)$) are the endogenous variables. The choice of detrending the labor share follows Choi and Ríos-Rull (2021), and is intended to deal with the secular decline observed over the last few decades. We define the system

$$\boldsymbol{y}_t = \boldsymbol{\alpha} + \sum_{j=1}^{4} \boldsymbol{\Gamma}_j \boldsymbol{y}_{t-j} + \boldsymbol{\epsilon}_t, \tag{C.1}$$

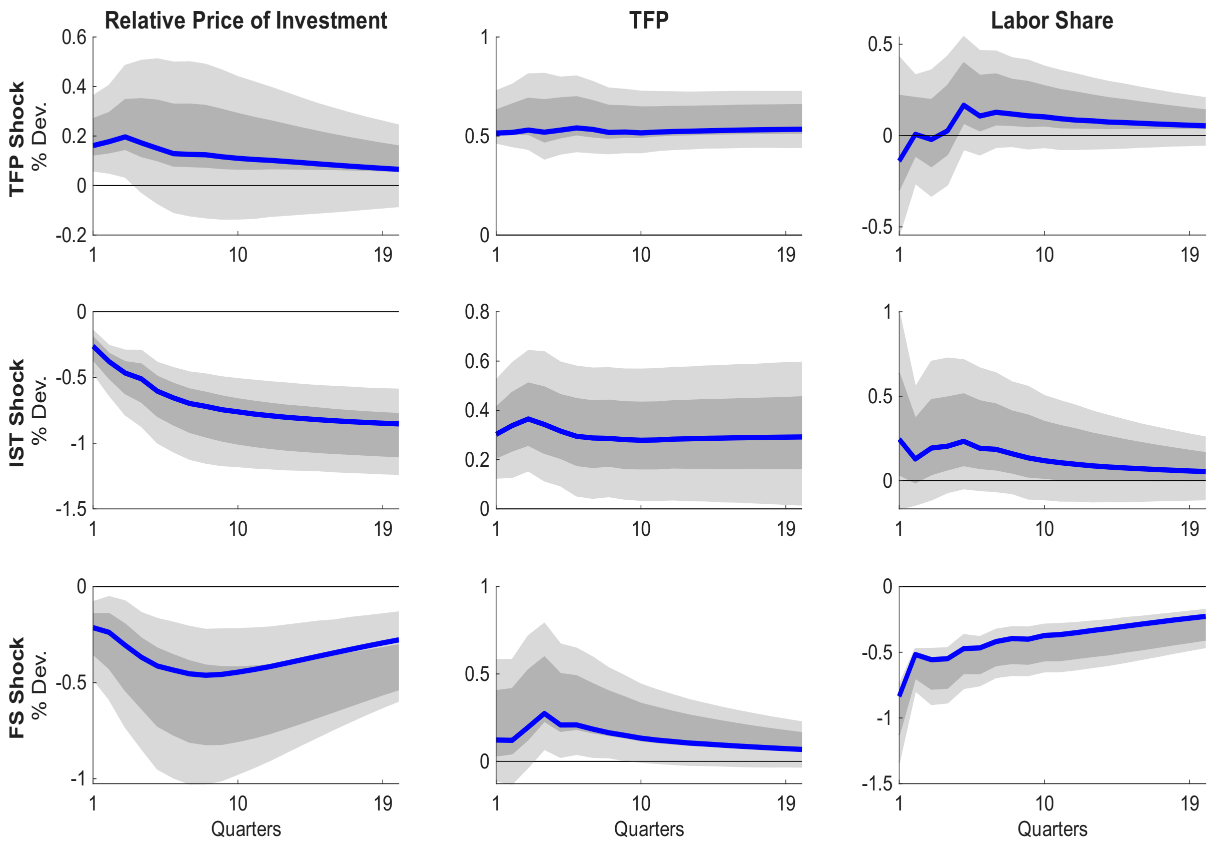
where $\boldsymbol{y}_t = [\Delta \log(\mu_t), \Delta \log(z_t), \log(ls_t)]'$, $\boldsymbol{\alpha}$ is a vector of constant terms, $\boldsymbol{\Gamma}_j$ (with $j = 1, ..., 4$) are the matrices of dynamic coefficients and $\boldsymbol{\epsilon}_t \sim N(0, \Sigma)$ is a vector of normally-distributed innovations with mean zero and variance-covariance matrix Σ.

We estimate the reduced-form system (C.1) over the 1981Q4-2017Q4 sample.[6] The innovations $\boldsymbol{\epsilon}_t$ are linearly related to the structural shocks, $\boldsymbol{\epsilon}_t = \boldsymbol{H}\boldsymbol{u}_t$, and the matrix $\boldsymbol{H}$ is identified based on (standard) long-run restrictions. The identification strategy imposes that shocks to the factor share of income do not affect the long-run levels of TFP and the relative price of investment, and are therefore purely redistributive in the long run. As for the remaining shocks, we follow Fisher (2006) in assuming that neutral technology shocks do not affect the relative price of investment in the long run. Thus, investment-specific technology shocks are the only ones capable to permanently affect the relative price of investment.

The interpretation of the FS shocks warrants further discussion. From an identification standpoint, these shocks capture innovations to the labor share that are orthogonal to both neutral and investment-specific technology shocks. In this sense, FS shocks can be interpreted as redistribution shocks, representing a residual component that may also reflect other non-technological disturbances. Nevertheless, following Blanchard (1997), such variation can be viewed as arising from technological or institutional changes that modify the relative importance of capital-intensive production methods and, consequently, the distribution of income across factors. Similarly, in task-based models of production such as Autor et al. (2003) and Acemoglu and Restrepo (2018, 2020), automation increases the fraction of tasks performed by capital, raising capital's income share without proportionally affecting aggregate productivity. Temporary fluctuations in technological adoption or business dynamism can there-

[6] This sample is chosen for three main reasons. First, given that the household-level data are available over 1982Q4-2017Q4, and we use a VAR(4) model, we considered that the first 4 time-series observations are discarded. Second, Fisher (2006) documents the presence of a structural break in the trend of the relative price of investment in 1982. Finally, the sample is consistent with a large literature focusing on the Great Moderation period (e.g., Stock and Watson, 2002). Note that labor-share detrending is performed from 1947Q1 to avoid overfitting low-frequency variation in the last part of the sample.

Figure C.1: IRFs from VAR

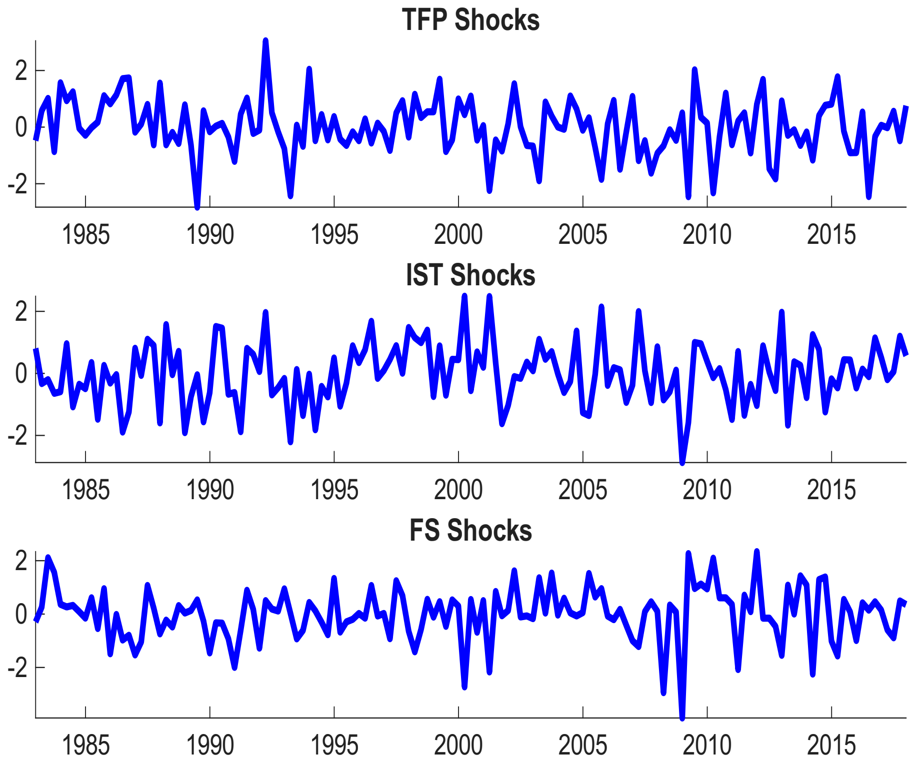


Notes: The figure displays the impulse-response functions, estimated from the VAR in equation (C.1), to the identified neutral technology (TFP, top panels), investment-specific technology (IST, middle panels), and factor-share (FS, bottom panels) shocks over the sample 1982Q4-2017Q4. Light-grey (dark-grey) shaded areas represent the 90% (68%) confidence intervals. The latter are computed using the moving block bootstrap (Bruggemann et al., 2016), with small-sample bias correction (Kilian, 1998).

fore generate persistent, though mean-reverting, movements in the aggregate capital share. Our empirical evidence on the transmission of these shocks to both aggregate and household-level variables is consistent with this interpretation.

Related mechanisms are labeled "distribution shocks" in Lansing (2015), or "factor-share shocks" in Ríos-Rull and Santaeulalia-Llopis (2010), Lettau and Ludvigson (2013), and Greenwald et al. (2019). However, the factor-share shock identified here differs from that in Lettau and Ludvigson (2013). In our framework, factor-share shocks have a transitory—although potentially persistent—effect on the labor share and are restricted to be purely redistributive in the *long run*, meaning that they may affect macroeconomic variables only in the short run. By contrast, in Lettau and Ludvigson (2013) factor-share shocks have permanent effects on labor earnings while leaving aggregate consumption unchanged, implying that they are purely redistributive at all

Figure C.2: Structurally-identified shocks



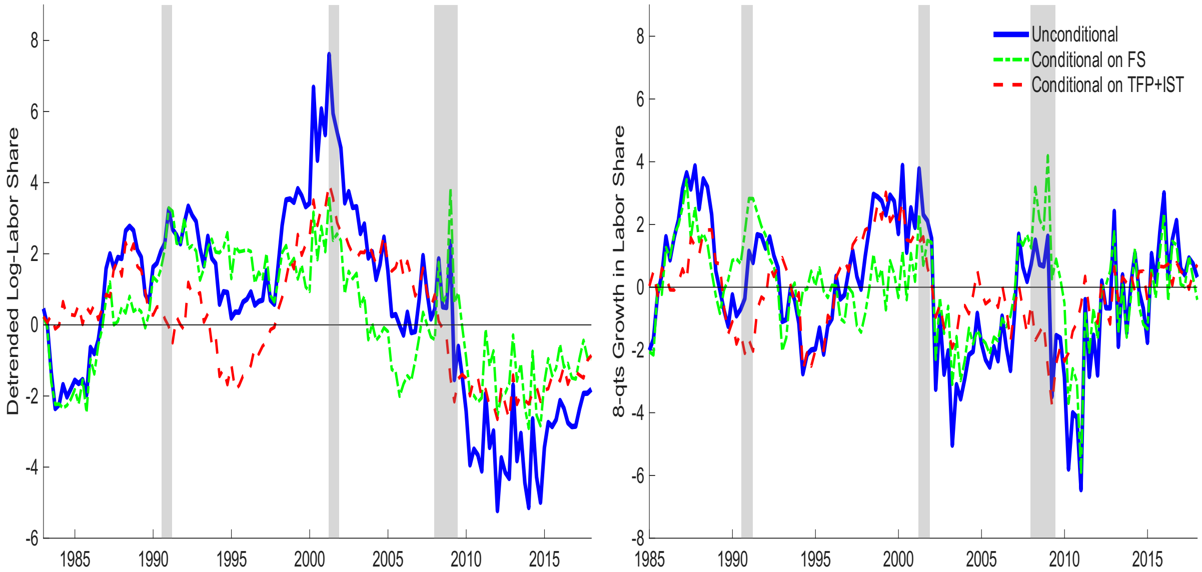
Notes: The figure displays the time series of the identified neutral technology (TFP, top panel), investment-specific technology (IST, middle panel), and factor-share (FS, bottom panel) shocks over the sample 1982Q4-2017Q4.

horizons.

Finally, our baseline identification scheme implicitly assumes that the identified shocks fully account for the dynamics of all three variables in the system. In Section 2.4, we present several robustness exercises concerning the identification scheme in the context of the predictive regressions.

Results The impulse-response functions are reported in Figure C.1, while the resulting time-series of the orthogonal shocks is depicted in Figure C.2. A neutral technology (TFP) shock persistently increases the relative price of investment, while the labor share falls on impact, to then display a temporary increase above the trend (i.e., the overshooting property discussed in Ríos-Rull and Santaeulalia-Llopis, 2010; Choi and Ríos-Rull, 2021). An investment-specific (IST) shock is associated with a permanent fall in the relative price of investment and a permanent increase in TFP, while the labor share displays a mild and short-lived expansion. Finally, a FS shock is associated with a significant, transitory yet prolonged decline in the labor share, while contracting the relative price of investment and expanding TFP. Notably, the last column of

Figure C.3: Labor share decomposition



Notes: The figure displays the conditional decomposition of the labor share both in (detrended) log-levels (left panel) and in 8-quarter growth rates (right panel), as computed from the historical decomposition from the trivariate VAR in equation (C.1) over the sample 1982Q4-2017Q4.

Figure C.1 highlights that positive FS shocks significantly contract labor income in favor of capital income. In contrast, the labor share expands in response to both TFP and IST shocks.

All in all, the impulse responses underscore significant dynamic interdependence among the endogenous variables, which suggests caution against assuming that endogenous variables can be taken as proxies for the underlying shocks.

Historical decomposition of the labor share To provide further intuition on the distinct role played by technology and redistributive shocks, Figure C.3 reports a historical breakdown of the observed variation in the labor share over the sample under scrutiny. The left panel reports the decomposition for the detrended log-labor share, while the right panel reports the decomposition of the two-year growth rates. The main takeaway is that TFP and IST shocks account for the more persistent component of fluctuations in the data, whereas FS shocks govern the cyclical behavior of the labor share. In the left panel, the red-dashed line (i.e., the component stemming from technology shocks only) appears smoother and closely tracks the blue one (i.e., the unconditional series). Conversely, the right panel shows that the mild counter-cyclicality of the unconditional measure reflects the differential impact of technology and redistributive shocks: the component attributable to redistributive shocks (green dash-dotted line) rises sharply during recessions (indicated by the shaded bands) and drives most of the cyclical variation in the unconditional series, while the component associated with technology shocks is procyclical and tends to reduce the labor share during downturns. Furthermore, FS shocks alone contribute to more than 60% of the variation in the two-year changes in the labor share. This underlines that cyclical shifts in income distribution between labor and capital appear as a critical state variable for expected returns, precisely because they mainly reflect the impact of redistributive shocks. This is consistent with our finding that movements in relative consumption predict expected returns primarily in the short run, while becoming largely irrelevant at longer horizons.

C.2 Additional results

This section reports additional robustness results for the predictive regression (for $h = 4$ and $h = 12$).

Table C.1: Conditional predictive regressions - Robustness - $h = 4$

$r^{\text{ex}}_{t,t+4} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{rc,t} + \beta_3 g^{IST}_{rc,t} + \beta_4 g^{FS}_{rc,t}$			
β_1	β_2	β_3	β_4
Panel A: AR shocks			
-4.58	3.95	0.40	5.76
(1.98)	(4.77)	(3.89)	(3.68)
[0.02]	[0.41]	[0.92]	[0.12]
Panel B: Max-share identification			
-4.32	3.78	3.52	**4.68**
(1.81)	(4.38)	(3.37)	(2.75)
[0.02]	[0.39]	[0.30]	[0.09]
Panel C: VAR including profit share			
-3.81	1.41	1.96	**5.85**
(1.71)	(3.22)	(5.44)	(3.27)
[0.03]	[0.66]	[0.72]	[0.08]
Panel D: FS shocks orthogonal to oil shocks			
-4.75	4.21	-0.66	**6.37**
(1.89)	(4.46)	(6.78)	(3.33)
[0.01]	[0.35]	[0.92]	[0.06]
Panel E: FS shocks orthogonal to MP and FP shocks			
-4.22	5.03	-1.20	**5.87**
(1.78)	(4.75)	(7.29)	(3.16)
[0.02]	[0.29]	[0.87]	[0.07]
Panel F: Not-detrended labor share			
-4.86	2.37	3.48	6.23
(1.88)	(3.31)	(3.29)	(4.36)
[0.01]	[0.48]	[0.29]	[0.16]
Panel G: Naive labor share definition			
-4.60	4.84	-1.06	**5.83**
(1.83)	(4.89)	(7.54)	(3.38)
[0.01]	[0.32]	[0.89]	[0.09]
Panel H: Stockholders vs. non-stockholders			
-4.48	6.96	-5.82	**6.71**
(1.84)	(6.27)	(8.60)	(3.68)
[0.02]	[0.27]	[0.50]	[0.07]
Panel I: Controlling for CAY			
-5.24	4.60	-0.98	**5.58**
(1.97)	(4.53)	(6.65)	(3.11)
[0.01]	[0.31]	[0.88]	[0.08]
Panel J: First differences			
-0.15	1.41	-2.42	2.94
(0.75)	(2.02)	(2.65)	(1.89)
[0.84]	[0.49]	[0.36]	[0.12]

Notes: Results of predictive regressions for different robustness exercises, with $h = 4$.

Table C.2: Conditional predictive regressions - Robustness - $h = 12$

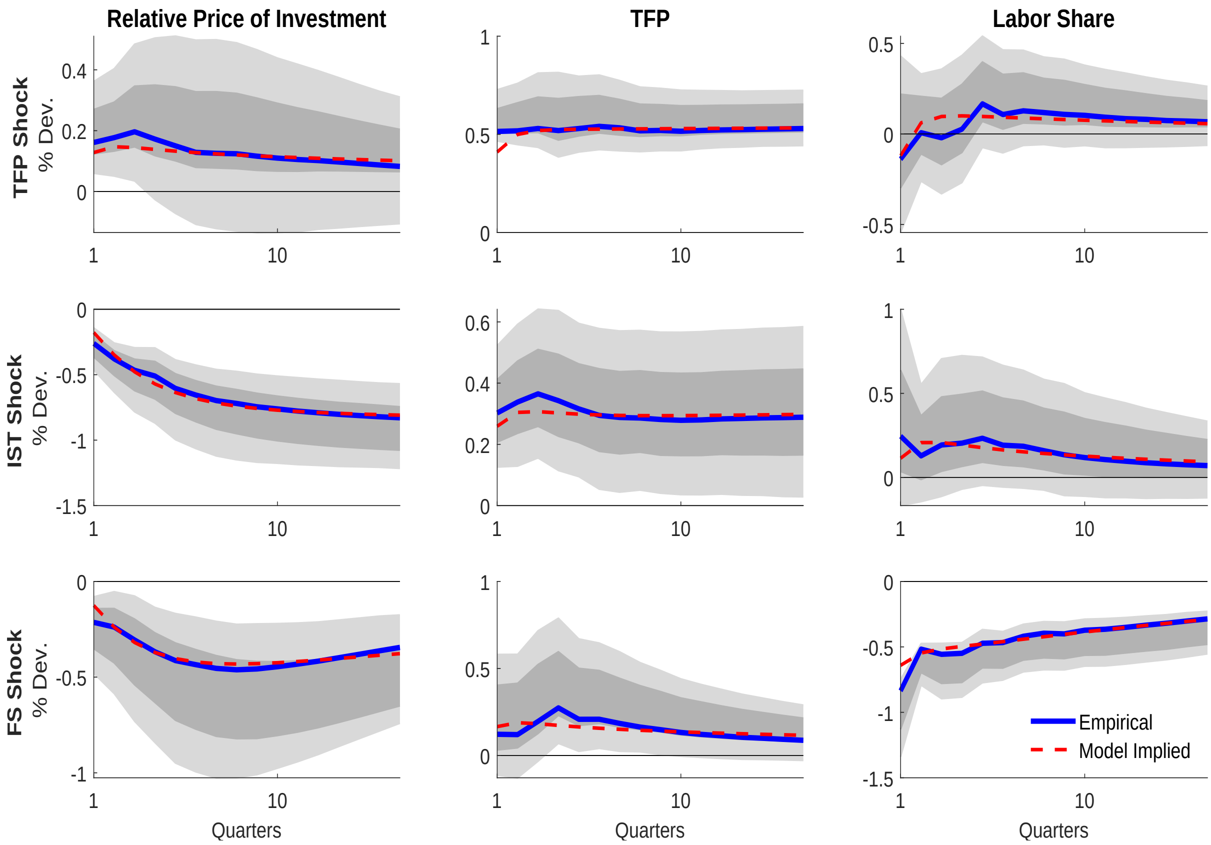
$r^{\text{ex}}_{t,t+12} = \alpha + \beta_1 g_{c,t} + \beta_2 g^{TFP}_{rc,t} + \beta_3 g^{IST}_{rc,t} + \beta_4 g^{FS}_{rc,t}$			
β_1	β_2	β_3	β_4
Panel A: AR shocks			
-4.08	1.65	**-4.66**	**6.09**
(1.51)	(2.20)	(1.83)	(2.41)
[0.01]	[0.46]	[0.01]	[0.01]
Panel B: Max-share identification			
-4.80	−1.24	−0.20	**5.17**
(1.61)	(2.40)	(2.05)	(2.28)
[0.00]	[0.61]	[0.92]	[0.03]
Panel C: VAR including profit share			
-4.98	0.54	2.09	2.37
(1.66)	(2.83)	(3.53)	(1.89)
[0.00]	[0.85]	[0.56]	[0.21]
Panel D: FS shocks orthogonal to oil shocks			
-6.20	−3.15	4.22	**3.86**
(1.78)	(2.78)	(3.18)	(1.60)
[0.00]	[0.26]	[0.19]	[0.02]
Panel E: FS shocks orthogonal to MP and FP shocks			
-5.90	−2.65	3.71	**3.71**
(1.70)	(2.81)	(3.32)	(1.72)
[0.00]	[0.35]	[0.27]	[0.03]
Panel F: Not-detrended labor share			
-5.03	1.78	−0.98	**3.93**
(1.39)	(2.53)	(2.48)	(1.73)
[0.00]	[0.48]	[0.69]	[0.03]
Panel G: Naive labor share definition			
-6.07	−3.60	5.49	**3.32**
(1.66)	(3.17)	(3.73)	(1.33)
[0.00]	[0.26]	[0.14]	[0.01]
Panel H: Stockholders vs. non-stockholders			
-6.06	−5.81	5.85	**4.19**
(1.64)	(3.99)	(4.32)	(1.64)
[0.00]	[0.15]	[0.18]	[0.01]
Panel I: Controlling for CAY			
-8.12	−3.48	3.88	**3.92**
(1.70)	(2.87)	(3.70)	(1.14)
[0.00]	[0.23]	[0.30]	[0.00]
Panel J: First differences			
-0.92	**2.30**	−1.48	**2.27**
(0.40)	(1.30)	(1.57)	(0.79)
[0.02]	[0.08]	[0.35]	[0.01]

Notes: Results of predictive regressions for different robustness exercises, with $h = 12$.

D Model details and robustness

This appendix reports additional figures for the baseline model and discusses the details of the model robustness exercises.

Figure D.1: IRFs Matching



Notes: The figure displays the structural impulse-response functions estimated from the VAR in equation (C.1) (blue solid lines) together with the 90% and 68% confidence intervals (light-grey and dark-grey areas, respectively); and the corresponding IRFs generated by the estimated model (red-dashed lines).

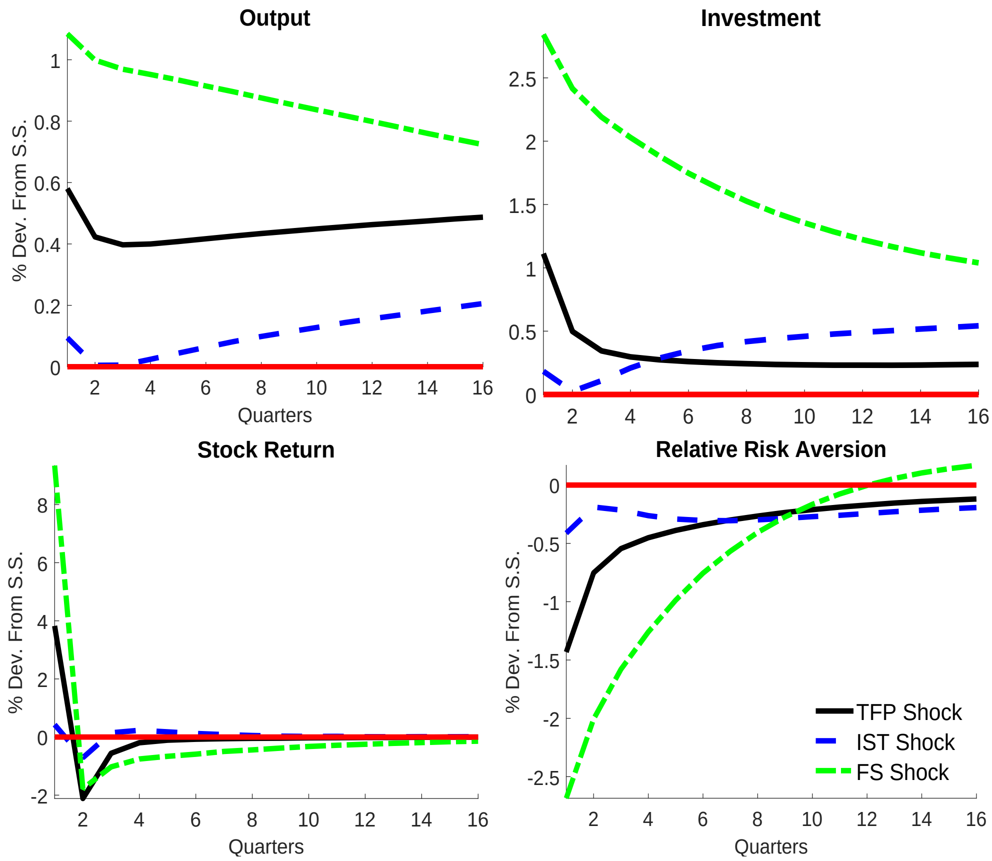
D.1 Additional results

Figures D.1 and D.2 depict, respectively, the results of the IRF-matching procedure and the IRFs of additional variables in the baseline model.

D.2 AR shocks

In this robustness exercise, we replace the VAR structure linking TFP growth, relative price of investment growth, and the labor share with the following independent

Figure D.2: Conditional dynamics - Additional variables



Notes: Output, investment, stock return, and assetholders' relative risk aversion responses to TFP, IST, and FS shocks.

univariate autoregressive processes:

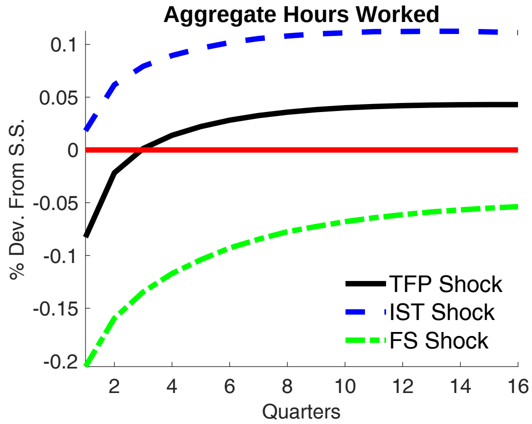
$$\Delta z_t = \rho^z \Delta z_{t-1} + \epsilon_t^z, \tag{D.1}$$

$$\Delta \mu_t = \rho^\mu \Delta \mu_{t-1} + \epsilon_t^\mu, \tag{D.2}$$

$$\log(ls_t) = \rho^{ls} \log(ls_{t-1}) + \epsilon_t^{ls}, \tag{D.3}$$

with $\epsilon_t^j \sim N(0, \sigma^j)$, $j \in \{z, \mu, ls\}$. The parameters ρ^j and σ^j are set equal to their empirical counterparts estimated over the sample 1982Q3-2017Q4, which are $\rho^z = 0.09$, $\sigma^z = 0.0063$, $\rho^\mu = 0.48$, $\sigma^\mu = 0.0041$, $\rho^{ls} = 0.94$, and $\sigma^{ls} = 0.0095$. All other parameters are kept at their baseline values.

Figure D.3: Conditional dynamics - Robustness - Hours worked



Notes: Aggregate hours response to TFP, IST, and FS shocks in the model robustness with non-assetholders' flexible labor supply.

D.3 Flexible labor

In this model extension, we allow non-assetholders to flexibly adjust their supply of labor. To this end, we assume that non-assetholders' intertemporal utility is:

$$\mathrm{E}_t \sum_{i=0}^{\infty} \beta^i \left\{ \frac{\left[c_{t+i}^{na} - \chi_c^{na} h_{t+i}^{na}\right]^{1-\sigma}}{1-\sigma} - G_{t+i}^{1-\sigma} \psi^{na} \frac{\left(n_{t+i}^{na}\right)^{1+\phi^{na}}}{1+\phi^{na}} \right\}, \tag{D.4}$$

where ψ^{na} is a preference weight pinning down steady-state hours worked, ϕ^{na} controls the (inverse) Frisch elasticity, and the term $G_{t+i}^{1-\sigma}$ affecting the disutility of work is introduced to allow for a balanced-growth path (following Mertens and Ravn, 2011).

Relative to the baseline model, two more first-order conditions need to be considered:

$$\lambda_t^{na} = \left(c_t^{na} - \chi_c^{na} h_t^{na}\right)^{-\sigma}, \tag{D.5}$$

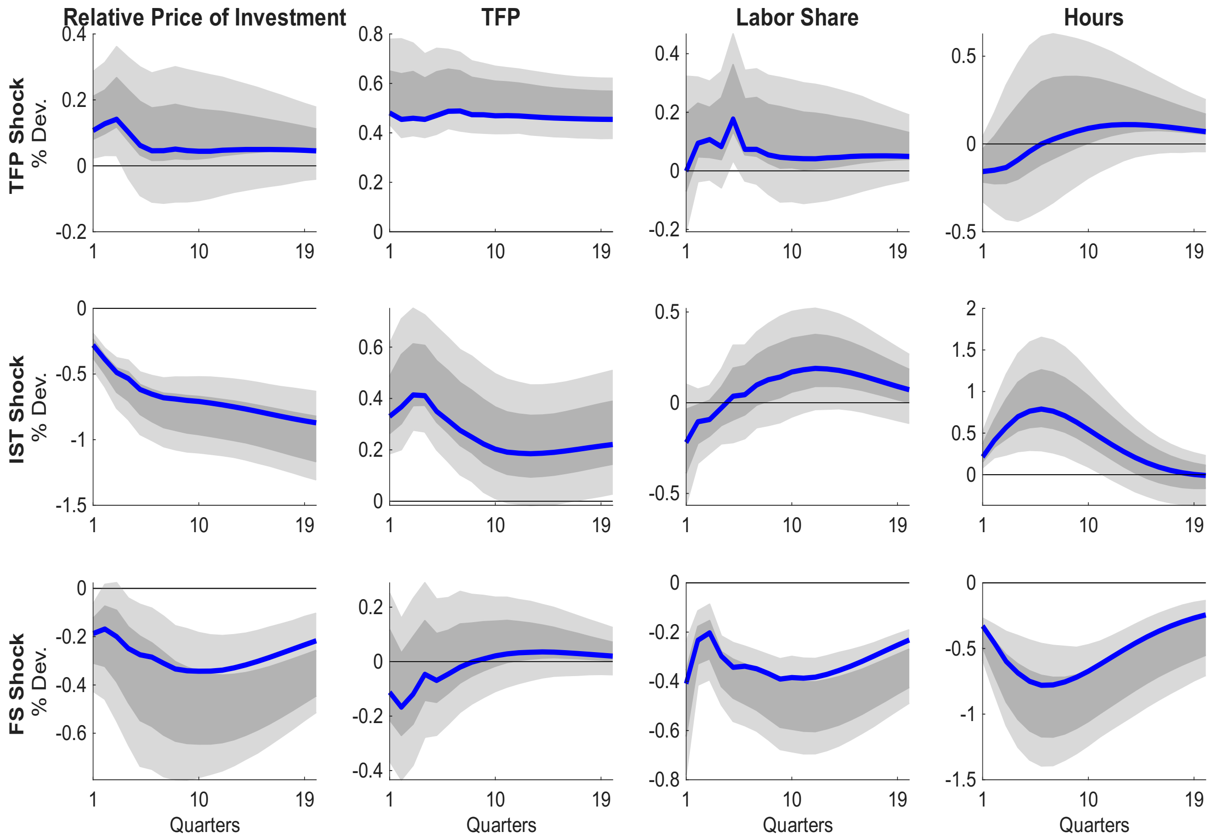
$$\lambda_t^{na} w_t = \psi^{na} G_t^{1-\sigma} \left(n_t^{na}\right)^{\phi^{na}}, \tag{D.6}$$

with the first one determining non-assetholders' marginal utility of consumption and the second one their optimal supply of labor.

While the baseline calibration is kept unchanged, three additional parameters need to be calibrated. First, we set ψ^{na} so that non-assetholders work 33% of their time-endowment (normalized to 1) in the steady-state.[7] Second, we fix the Frisch elasticity to 1, a standard value in the macroeconomics literature. Finally, we set the habit intensity $\chi_c^{na} = 0.50$. By affecting the strength of the wealth effect, this parameter controls

[7] Assetholders' steady-state hours are set accordingly, so that aggregate hours worked are also 0.33.

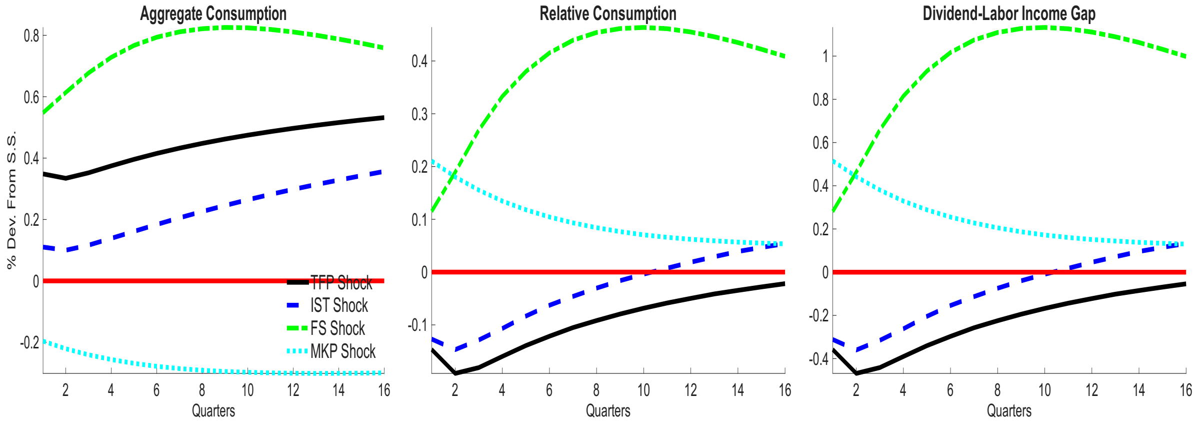
Figure D.4: IRFs from VAR augmented with aggregate hours worked



Notes: The figure displays the impulse-response functions estimated from the VAR in equation (C.1) extended to include hours worked.

the sign of the response of hours worked. As depicted in Figure D.3, this calibration implies a significantly negative (positive) response of aggregate hours worked to FS (IST) shocks, while the response to TFP shocks is more muted and overshoots after an initially negative response. Thus, in line with Francis and Ramey (2005), the combination of habits and capital adjustment costs generates a negative response of hours to TFP shocks even with flexible prices. Furthermore, these findings are qualitatively consistent with the dynamics implied by our VAR setup when extended to include (quadratically detrended) hours worked (as reported in the last column of Figure D.4). Our identification scheme implies that hours respond more strongly to IST than TFP shocks (in line with Fisher, 2006). Furthermore, FS shocks reduce hours worked while expanding economic activity (as shown in Figures 4 and E.1). Thus, these shocks do not generate the typical business-cycle comovement between output, consumption, investment, and hours worked (Gali, 1999; Francis and Ramey, 2005), in line with the idea that they do not constitute the major drivers of aggregate fluctuations. However,

Figure D.5: Conditional dynamics - Mechanism - Robustness - Markup shocks



Notes: Responses of aggregate consumption, relative consumption, and dividend-to-labor income ratio to TFP, IST, FS, and markup shocks in the model robustness with markup shocks.

the responses of the relative price of investment, TFP, and the labor share remain qualitatively similar to the baseline setup.

D.4 Markup shocks

Finally, we consider an extension of the baseline model that allows for monopolistically competitive firms and price markup fluctuations. The introduction of markups alters factor prices as follows:

$$w_t = \frac{(1-\alpha_t)y_t}{\xi_t n}, \tag{D.7}$$

$$r_t^k = \frac{\alpha_t y_t}{\xi_t k_t}, \tag{D.8}$$

and implies that the labor share now is defined as $ls_t = (1-\alpha_t)/\xi_t$, where ξ_t denotes the price markup, which follows:

$$\xi_t = \xi \exp(\nu_t), \tag{D.9}$$

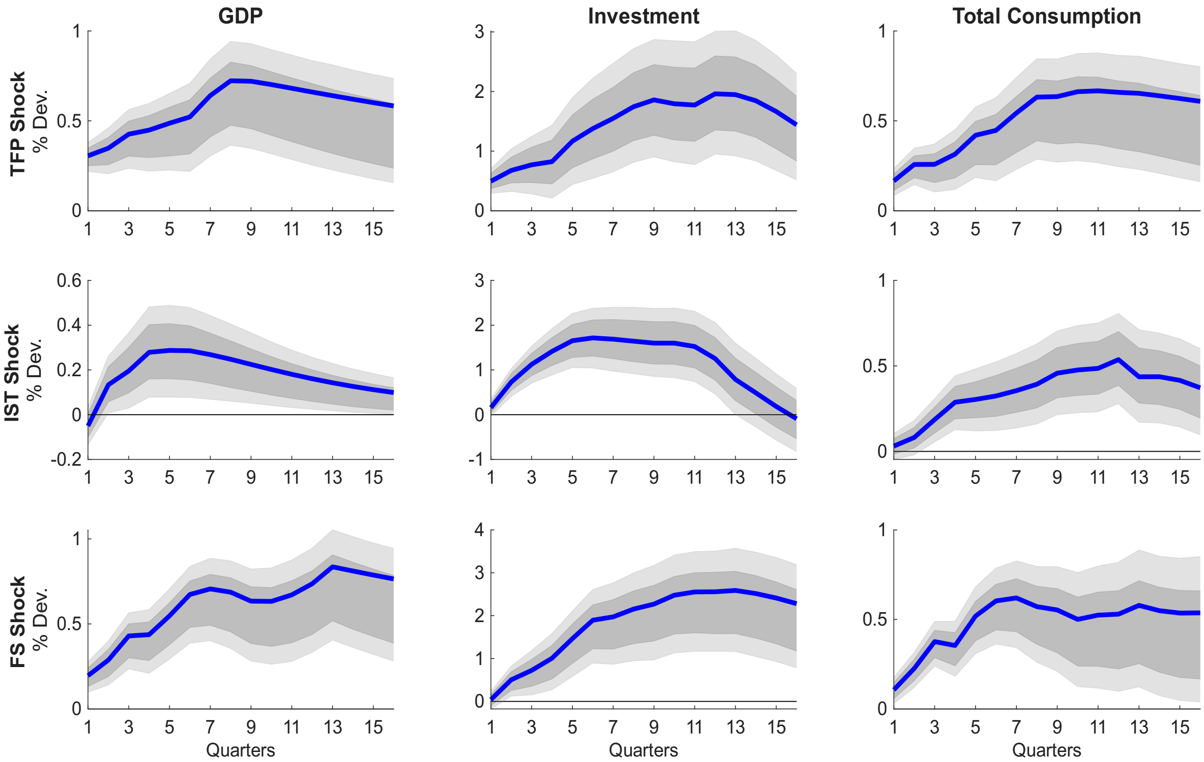
$$\nu_t = \rho^\nu \nu_{t-1} + \epsilon_t^\nu. \tag{D.10}$$

The calibration of $\xi = 1.27$, $\rho^\nu = 0.93^{1/4}$, and $\sigma^\nu = 0.0025$ follows Corhay et al. (2022), expressed in quarterly terms. Moreover, to highlight the impact of markup shocks on real allocations, we abstract from financial leverage ($\theta = 0$), given that the Modigliani-Miller theorem holds in our framework. The other parameters are kept at the baseline values.

E Validating the mechanism: Additional evidence

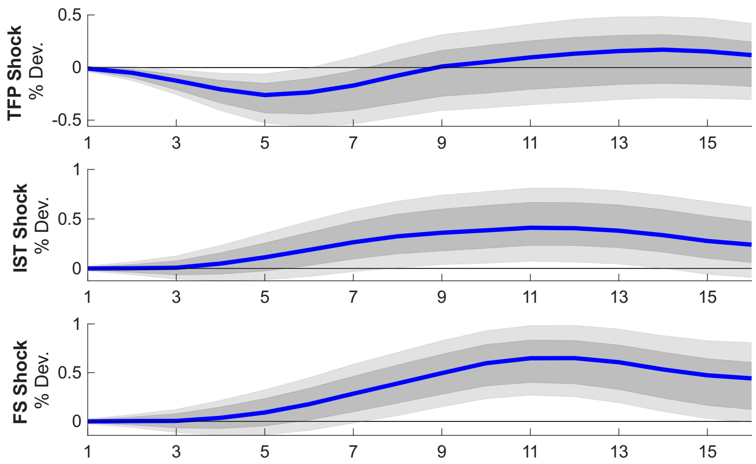
This appendix reports the additional results discussed in Section 5.

Figure E.1: Empirical conditional dynamics - Macro Variables



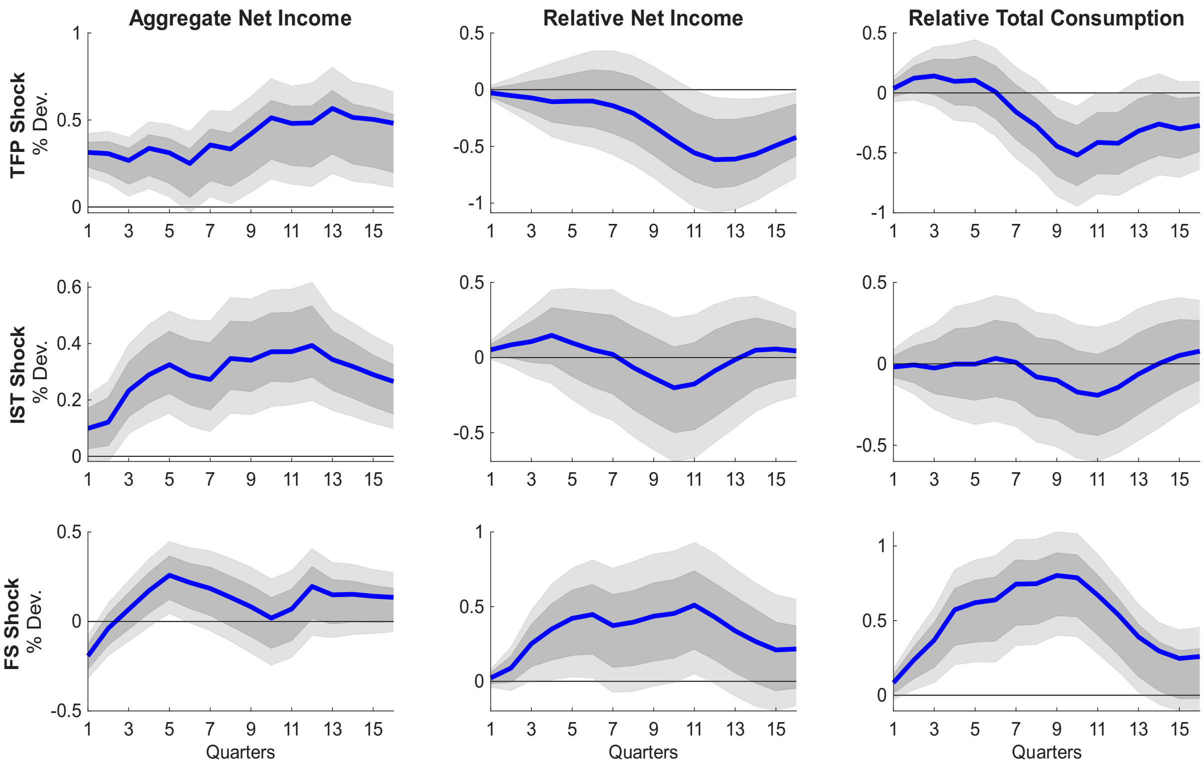
Notes: The figure displays the IRFs of GDP, investment, and total consumption. Total consumption is measured as the sum of non-durables, services, and durable expenditures.

Figure E.2: Empirical conditional dynamics - Assetholders' population share



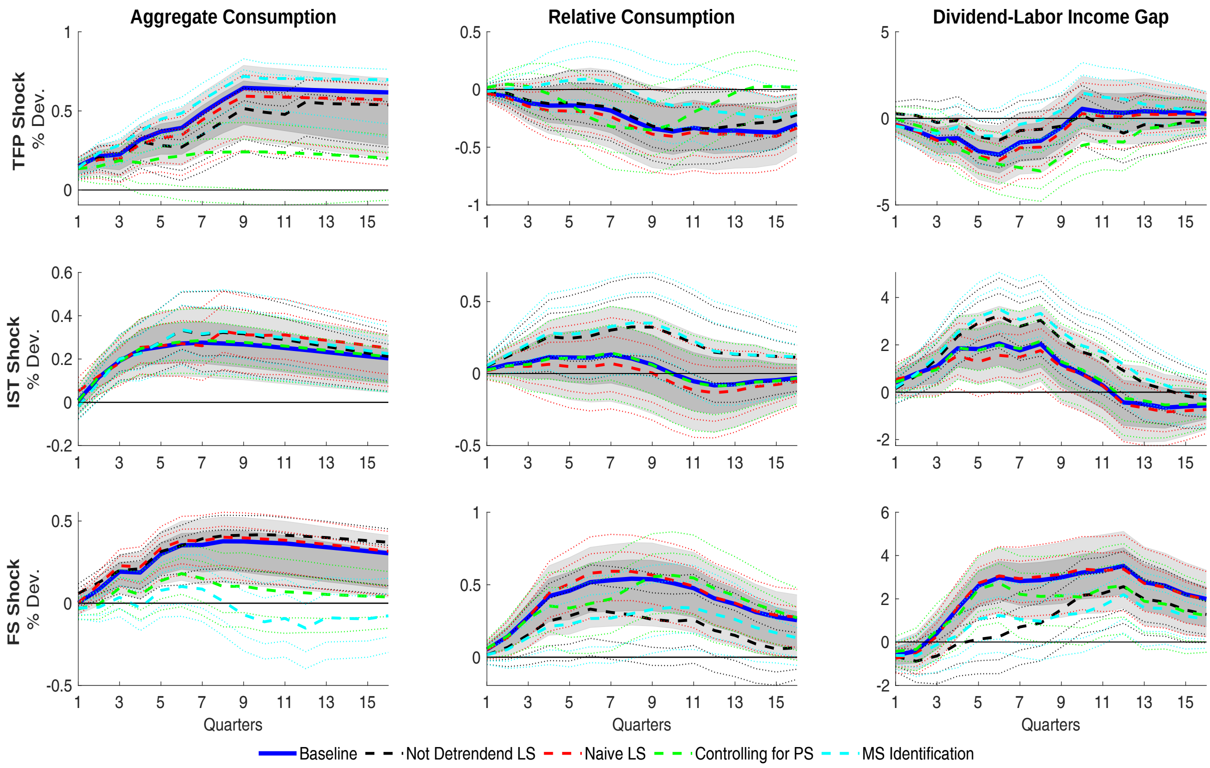
Notes: The figure displays the IRF of the assetholders' population share.

Figure E.3: Empirical conditional dynamics - Net income and total consumption



Notes: The figure displays the IRFs of aggregate after-tax income, relative after-tax income, and relative total consumption. Total consumption is measured as the sum of non-durables, services, and durable expenditures.

Figure E.4: Empirical conditional dynamics - Mechanism - Robustness



Notes: The figure displays the IRFs of aggregate consumption, relative consumption, and after-tax dividend-to-labor income ratio for different robustness exercises. Responses are computed for the baseline case (blue-solid line) and for the alternative setups where the shocks are identified from the VAR: with the not-detrended labor share (black-dashed line); with the naive definition of the labor share (red-dashed line); augmented with the profit share (green-dashed line); with a max-share, rather than long-run, identification scheme (cyan-dashed line).

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