

NBER WORKING PAPER SERIES

HOW THE WEALTH WAS WON:
FACTORS SHARES AS MARKET FUNDAMENTALS

Daniel L. Greenwald
Martin Lettau
Sydney C. Ludvigson

Working Paper 25769
<http://www.nber.org/papers/w25769>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2019, Revised October 2023

This paper supplants an earlier paper entitled “Origins of Stock Market Fluctuations.” We are grateful to Andrew Atkeson, Simcha Barkai, John Y. Campbell, Andrea Eisfeldt, Valentin Haddad, Ralph Koijen, Edward Nelson, Annette Vissing-Jorgensen, Mindy Xiaolan, and four anonymous referees for helpful comments, as well as to seminar participants at the October 2020 NBER EF&G meeting, 2020 Women in Macro conference, the 2021 American Finance Association meetings, the January 2021 NBER Long Term Asset Management conference, the Federal Reserve Board, the Harvard University economics department, the HEC Paris finance department, the Ohio State University Fisher College of Business, the University of California Berkeley Haas School of Business, the University of Chicago Booth School of Business, the University of Michigan Ross School of Business, the University of Minnesota Carlson School, and AQR. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2019 by Daniel L. Greenwald, Martin Lettau, and Sydney C. Ludvigson. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

How the Wealth Was Won: Factors Shares as Market Fundamentals
Daniel L. Greenwald, Martin Lettau, and Sydney C. Ludvigson
NBER Working Paper No. 25769
April 2019, Revised October 2023
JEL No. G0,G12,G17

ABSTRACT

Why does the stock market rise and fall? From 1989 to 2017, the real per-capita value of corporate equity increased at a 7.2% annual rate. We estimate that 40% of this increase was attributable to a reallocation of rewards to shareholders in a decelerating economy, primarily at the expense of labor compensation. Economic growth accounted for just 25% of the increase, followed by a lower risk price (21%), and lower interest rates (14%). The period 1952 to 1988 experienced only one third as much growth in market equity, but economic growth accounted for more than 100% of it.

Daniel L. Greenwald
Kaufman Management Center
44 West Fourth Street, Office 9-97
United States
New York, New 10012
dlg340@stern.nyu.edu

Sydney C. Ludvigson
Department of Economics
New York University
19 W. 4th Street, 6th Floor
New York, NY 10002
and NBER
sydney.ludvigson@nyu.edu

Martin Lettau
Haas School of Business
University of California, Berkeley
545 Student Services Bldg. #1900
Berkeley, CA 94720-1900
and CEPR
and also NBER
lettau@haas.berkeley.edu

1 Introduction

Why does the stock market rise and fall? This question has received surprisingly little attention in the academic finance literature, which has instead concentrated on explaining expected quarterly or annual returns, often concluding that expected returns are poorly accounted for by economic fundamentals.¹ By contrast, much less effort has been devoted to understanding the drivers of the overall level of market equity over the post-war era. According to textbook theories, the stock market and the broader economy should share a common trend, implying that the same factors that boost economic growth are also the key to rising equity values over longer periods of time.² Taken together, these observations motivate the key question of this paper: can the longer-run behavior of the total value of the stock market — the cumulation of *realized* returns — be accounted for by cash flow fundamentals, even if expected returns cannot?

Some basic empirical facts serve to motivate our investigation. While the US equity market has done exceptionally well in the post-war period, this performance has been highly uneven over time, even at long horizons. For example, the real value of market equity of the US corporate sector grew at an average rate of 7.2% per annum over the last 29 years of our sample (1989:Q1 to 2017:Q4), compared to an average of merely 1.8% over the previous 23 years (1966:Q1 to 1989:Q1).³ At the same time, growth in the value of what was actually produced by the corporate sector has displayed a strikingly different temporal pattern. While real corporate net value added grew at a robust average rate of 3.8% per annum from 1966 to 1988 amid anemic stock returns, it averaged much lower growth of only 2.6% from 1989 to 2017 even as the stock market was booming. This multi-decade disconnect between growth in market equity and output presents a difficult challenge to theories in which economic growth is the key long-run determinant of market returns.

One potential resolution of this puzzle is to posit that economic fundamentals such as cash flows may be relatively unimportant for the value of market equity, with discount rates driving the bulk of growth even at long horizons. In this paper we entertain an alternative

¹For summary evidence see Cochrane (2005), Chapter 20. For a behavioral perspective, see Bordalo, Gennaioli, La Porta, and Shleifer (2019).

²This tenet goes back at least to Klein and Kosobud (1961), followed by a vast literature in macroeconomic theory that presumes balanced growth among economic aggregates over long periods of time. For a more recent variant, see Farhi and Gourio (2018).

³Real values are obtained from nominal values using the price index for Corporate Net Value Added. See Section 4 and Appendix A.1 for details on these and other data series. The subperiods we use are chosen visually to approximate structural breaks in the growth of market valuations and earnings shares, allowing for a clear demonstration of the paper’s main mechanism. However, a strength of our ultimate estimation approach is that we are able to decompose the evolution of the value of the stock market over any subperiod, making these particular choices relatively unimportant. Appendix A.14 summarizes our main results graphically using a complete set of possible brekpoints.

hypothesis: that cash flows have explained a large share of variation in realized returns at low frequencies, but that these movements have been driven by changes in factor shares rather than economic growth.

This hypothesis is motivated by an additional set of empirical facts. Within the total pool of net value added produced by the corporate sector, only a relatively small share — averaging 12.3% in our sample — accrues to the shareholder in the form of after-tax profits. Importantly, however, this share varies widely and persistently over time, fluctuating from less than 8% to nearly 20% over our sample. This suggests that swings in the profit share are strong enough to cause large and long-lasting deviations between cash flows and output. If so, growth in market equity could diverge from economic growth for an extended period of time, even when valuations are largely driven by fundamental cash flows. Indeed, while the 1989-2017 period lagged the 1966-1988 period in economic growth, it exhibited growth in real after-tax corporate *profits* of 5.1% per annum that far outpaced the average 1.4% growth of the previous period.

What role, if any, might these trends have played in the evolution of the post-war stock market? To translate these empirical facts into a quantitative decomposition of the post-war growth in market equity, we construct and estimate a model of the US equity market. Although the specification of a model necessarily imposes some structure, our approach is intended to let the data speak as much as possible. We do this by estimating a flexible parametric model of how equities are priced that allows for influence from a number of mutually uncorrelated latent factors, including not only factors driving productivity and profit shares, but also independent factors driving risk premia and risk-free interest rates.

Equity in our model is priced, not by a representative household, but by a representative shareholder, akin in the data to a wealthy household or large institutional investor. The remaining agents supply labor, but play no role in asset pricing. Shareholder preferences are subject to shocks that alter their patience and appetite for risk, driving variation in both the equity risk premium and in risk-free interest rates. Our representative shareholder consumes cash flows from firms, variation which is driven by shocks to both the total rewards generated by productive activity and to how those rewards are divided between shareholders and other claimants. Our model naturally generates operating leverage effects due to capital investment, implying that the cash flow share of output moves more than one-for-one with the earnings share (the *leverage effect*), and that cash flow growth is more volatile when the earnings share is low (the *leverage risk effect*).

We estimate the full dynamic model using state space methods, allowing us to precisely decompose the market's observed growth into these distinct component sources. The model is flexible enough to explain the entirety of the change in equity values over our sample and at

each point in time. To capture the influence of our fundamental sources at different horizons, we model each as a mixture of two stochastic processes capturing low-frequency and high-frequency variation, respectively. To discipline our estimation of these series, we confront the model with a wide range of data, including options-based measures of risk premia and long-term professional forecasts of interest rates and real output growth. Because our log-linear model is computationally tractable, we are able to account for uncertainty in both latent states and parameters using millions of Markov Chain Monte Carlo draws. We apply and estimate our model using data on the US corporate sector over the period 1952:Q1–2017:Q4.

Our objective in this paper is to develop a decomposition capable of informing and disciplining subsequent structural modeling. To do so, we measure the variation in the value of market equity that would have occurred varying a single component at a time, while holding all other components fixed. By design, this approach measures the contribution of each component source without requiring us to take a stand on the structural model that generated the stochastic innovations driving our data. This is important if the objective is to obtain a set of empirical facts against which a range of structural models can be evaluated, as opposed to obtaining a set of empirical outcomes predicated on a particular model.

Our main results may be summarized as follows. First, we find that neither economic growth, risk premia, nor risk-free interest rates has been the foremost driving force behind the market’s sharp gains over the last several decades. Instead, the single most important contributor has been a string of *factor share* shocks that reallocated the rewards of production without affecting the size of those rewards. Our estimates imply that these shocks increased profits to such an extent that they account for 40% of the market’s real per-capita increase since 1989. Decomposing the components of corporate earnings reveals that the vast majority of this increase in the profit share came at the expense of labor compensation.

Second, while equity values were also boosted since 1989 by persistent declines in the market price of risk, and in the real risk-free rate, these factors played smaller roles, contributing 21% and 14% respectively to the increase in the stock market over this period.

Third, growth in the real value of corporate sector output contributed just 26% to the increase in equity values since 1989 and 55% over the full sample. By contrast, while economic growth accounted for more than 100% of the rise in equity values from 1952 to 1988, this 37-year period created only one third of the growth in equity wealth generated over the 29 years from 1989 to the end of 2017.

Fourth, the considerable gains to holding equity over the post-war period can be in large part attributed to an unpredictable sequence of shocks, largely factor share shocks that reallocated rewards to shareholders. We estimate that 1.9pp of the post-war average annual log return on equity is attributable to this sequence of favorable shocks, rather than to

genuine ex-ante compensation for bearing risk. These results imply that the common practice of averaging return data over the post-war sample to estimate an equity risk premium would overstate the true unconditional risk premium by 34%.

We close with two important robustness tests. First, we relax our microfounded and tightly parameterized link between the earnings share and risk premia, and estimate an alternative specification where this link has an arbitrary and freely estimated strength. The results are remarkably similar to our baseline model. Second, we use a modification of the typical Campbell-Shiller decomposition to obtain alternative estimates of the role of factor shares. This decomposition is model-free and only measures direct cash flow effects, ignoring the indirect contributions through risk premia implied by our structural model. The resulting contributions are large at all plausible levels of persistence, and imply that our model estimates if anything understate these direct cash flow contributions.

All told, our results point strongly to a leading role for factor shares in driving market valuations at long horizons.

Related Literature. The empirical asset pricing literature has traditionally focused on explaining variation in expected returns or in the value of the stock market relative to dividends, often finding that discount rates play a dominant role.⁴ But as noted in Summers (1985), and still true today, surprisingly little attention has been devoted to understanding what drives the real level of the stock market over time. By focusing on the level of market equity, or the ratio of equity to output (rather than equity to dividends) we instead find a primary role for cash flow growth in driving the value of the market over time. Moreover, we find that these large cash flow contributions are largely orthogonal to growth in corporate output. While previous studies have noted an apparent disconnect between economic growth and the rate of return on stocks over long periods of time, these works have largely abstracted from models or direct evidence on the alternative forces that have driven cash flows in its place, a gap that our study is intended to fill.⁵

Our study focuses in particular on the role played by factor shares in driving the level of market equity. This focus follows most directly from Lettau and Ludvigson (2013), a purely empirical exercise that showed under a natural rotation scheme that shocks from a VAR that push labor income and asset prices in opposite directions explain much of the long-term trend in stock wealth. This approach was adapted in Greenwald, Lettau, and Ludvigson (2014), an earlier version of our work that this paper fully supplants. Greenwald,

⁴See e.g., Campbell and Shiller (1989), Cochrane (2011). See Ludvigson (2012) for a review of this empirical asset pricing literature.

⁵See e.g., Estrada (2012); Ritter (2012); Siegel (2014).

Lettau, and Ludvigson (2014) expanded on this analysis, demonstrating that a calibrated model could reproduce many of these VAR results. In contrast, the model in the current paper is both richer and more flexible in terms of its state variables and cash flow process, is directly estimated on the time series rather than calibrated, and produces a period-by-period accounting of the drivers of market equity.⁶

More broadly, our work connects to a growing body of research that considers the role of redistributive or factor-augmenting shocks in asset pricing and macroeconomic models.⁷ Our paper is particularly close to Corhay, Kung, and Schmid (2020), Eggertsson, Robbins, and Wold (2021), and Farhi and Gourio (2018), who compare calibrated steady states of macrofinancial models of production, finding large roles for rising market power in driving the high returns to equity over the last 30 years. Compared to these works, our time series approach features a simpler model of production and investment, but allows us to (i) decompose the impact of different forces at any time period and horizon, rather than between two particular “eras;” (ii) estimate potentially non-permanent degrees of persistence for our underlying fundamental factors, influencing their impact on asset prices; and (iii) formally account for parameter and latent state uncertainty in our estimates.⁸ While we view these approaches as highly complementary, they generate very different quantitative implications, which we discuss in Section 6 below.

Beyond the impact of factor shares on the level of cash flows, we study the implications of factor share risk. In contrast to traditional work that prices assets based on their exposure to aggregate consumption risk, for which changes in factor shares are neutral, we assume a representative investor who consumes firm cash flows and is therefore exposed to factor share risk.⁹ As a result, our paper is consistent with evidence in Lettau, Ludvigson, and Ma

⁶Greenwald, Lettau, and Ludvigson (2014) solves a fully nonlinear model in place of our approximate log-linear model here, demonstrating that the results in this paper are robust to allowing for these nonlinearities.

⁷See e.g., Caballero, Farhi, and Gourinchas (2017), Danthine and Donaldson (2002), Donangelo, Gourio, Kehrig, and Palacios (2019), Eisefeldt and Papanikolaou (2013), Eisefeldt and Papanikolaou (2014), Eggertsson, Robbins, and Wold (2021), Farhi and Gourio (2018), Favilukis and Lin (2016a, 2013, 2016b), Gomez (2016), Hall (2000), Marfe (2017). The factor share element of our paper is also related to a separate macroeconomic literature that examines the long-run variation in the labor share (e.g., Atkeson (2020), Barkai (2020), Karabarbounis and Neiman (2013), Koh, Santaella-Llopis, and Zheng (2020), and the theoretical study of Lansing (2015)). Our results on the redistributive role of factor shares echo those from previous studies finding that returns to human capital are negatively correlated with those to stock market wealth (Lustig and Van Nieuwerburgh (2008); Lettau and Ludvigson (2009); Chen, Favilukis, and Ludvigson (2014)), and are supported in subsequent work by Kuvshinov and Zimmermann (2021).

⁸Lansing (2021), a paper subsequent to the initial draft of our work, also fits a time-series model to match and decompose macroeconomic and financial data, emphasizing the role of sentiment.

⁹In this sense our model also relates to a classic literature emphasizing the importance for stock pricing of limited stock market participation and heterogeneity. See e.g., Mankiw (1986), Mankiw and Zeldes (1991), Constantinides and Duffie (1996), Vissing-Jorgensen (2002), Ait-Sahalia, Parker, and Yogo (2004), Guvenen (2009), and Malloy, Moskowitz, and Vissing-Jorgensen (2009).

(2019) that factor share risk is priced in the cross-section.

Through this mechanism, we also link to the broad literature that endogenizes equity risk premia based on the consumption processes of shareholders, by providing a new mechanism through the leverage risk effect.¹⁰ This mechanism shares a deep similarity to the habit specification of Campbell and Cochrane (1999), but is driven by variation in earnings relative to an external target (reinvestment), rather than by variation in aggregate consumption relative to an external target (habit). This approach thus offers novel quantitative and empirical implications for variation in risk premia over time that differ from traditional mechanisms based on aggregate consumption risk.

Last, our work relates to the literature estimating log-affine SDFs in reduced form.¹¹ These studies describe the evolution of the state variables and the SDF in purely statistical terms, for example using an estimated vector autoregression (VAR) for state dynamics. While less statistically flexible, our work features more economic structure, using separate and mutually uncorrelated fundamental components, as well as parametric restrictions on the SDF exposures obtained from theory, such as the leverage risk effect. This structure allows a much clearer interpretation of the drivers of asset prices. For example, unlike VAR-based models, which face the difficult task of transforming reduced-form residuals into identified structural shocks, our model allows us to directly read off the contribution of each latent state. We thus complement this literature by providing economic insight on the economic sources of market fluctuations, particularly the role of factor shares.

Overview. The rest of this paper is organized as follows. Section 2 displays empirical patterns in a model-free setting. Section 3 describes the theoretical model. Section 4 presents the data. Section 5 describes our estimation procedure. Section 6 presents our findings. Section 7 considers robustness and extensions. Section 8 concludes.

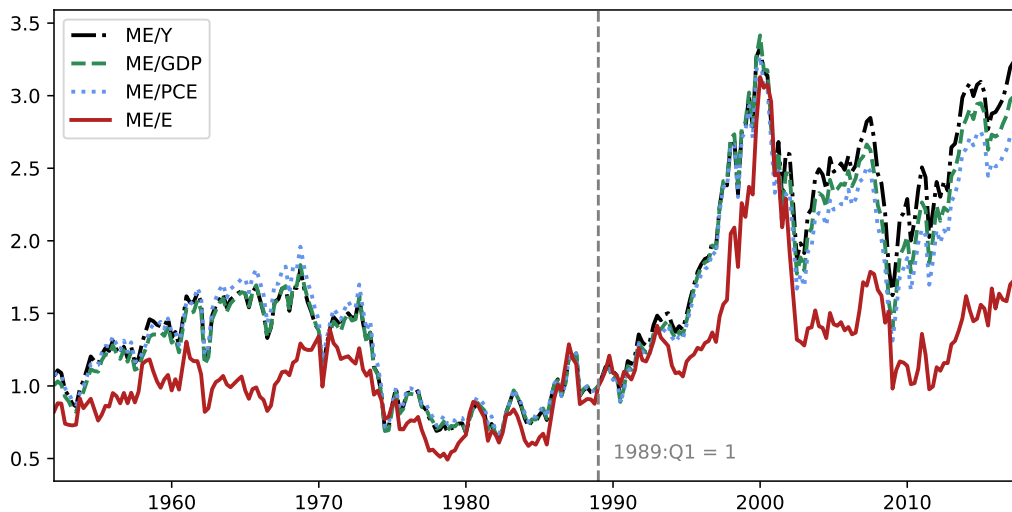
2 Time Series Patterns

Before presenting our full structural model, we first describe the basic time series patterns of equity values, output, and the earnings share in a model-free setting.

¹⁰See e.g., Bansal and Yaron (2004), Barro (2009), Campbell and Cochrane (1999), Campbell, Pflueger, and Viceira (2020), Constantinides and Duffie (1996), Wachter (2013).

¹¹See e.g., Ang and Piazzesi (2003), Bekaert, Engstrom, and Xing (2009), Dai and Singleton (2002), Duffie and Kan (1996), Lustig, Van Nieuwerburgh, and Verdellhan (2013).

Figure 1: Stock Market Ratios



Notes: To make the units comparable, each series has been normalized to unity in 1989:Q1. The sample spans the period 1952:Q1-2017:Q4. **ME**: market value of corporate equities. **Y**: corporate sector net value added. **GDP**: gross domestic product. **PCE**: personal consumption expenditures. **E**: corporate sector after-tax profits. Sources: NIPA and Flow of Funds.

2.1 Asset Pricing Patterns

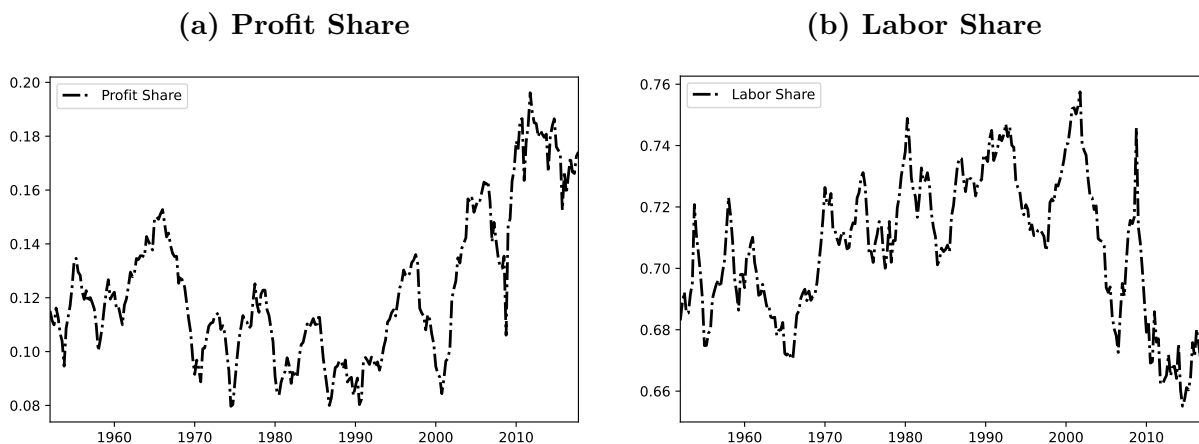
We begin by examining the co-movement between market equity and factor shares. For notation, we denote the value of market equity as “ME,” earnings (after-tax profits) as “E,” and output (net value added) as “Y.” All variables are constructed at the level of the US corporate sector, with details available in Section 4 and Appendix A.1.

To begin, Figure 1 plots the ratio of market equity to output, using our net value added measure (Y) in the denominator, as well two alternative measures of aggregate economic activity: gross domestic product (GDP) and personal consumption expenditures (PCE). Despite substantial volatility in these ratios, each is at or near a post-war high by the end of 2017. Notably, however, the ratio of market equity to earnings (ME/E) is far below its post-war high.¹² Appendix Figure A.10 shows that this result is not specific to our measure of ME/E, but holds for alternative ratios of market valuation to earnings, payout, or dividends.

This large difference between the behavior of the ratios ME/E and ME/Y stems from movements in the shares of output accruing to different factors, which are plotted in Figure

¹²It is worth noting that the ratio of market equity to earnings (ME/E) actually rises by more than 80% from 1989 to the end of our sample — a substantial increase that is nonetheless visually dwarfed by the much larger rises in the ratio of market equity to output or consumption.

Figure 2: Evolution of Factor Shares



Notes: Panel (a) displays the ratio of after-tax profits to net value added for the corporate sector, adjusted for foreign earnings, while Panel (b) displays the ratio of labor compensation to net value added for the corporate sector. See Section 4 and Appendix A.1 for details on the data construction. The sample spans the period 1952:Q1-2017:Q4.

2. Panel (a) displays the profit share (E/Y), defined as the ratio of after-tax profits to net value added for the corporate sector. This share fell substantially from the 1960s to the 1980s, declining from 15.3% in 1966:Q1 to 8.9% in 1989:Q1. From the late 1980s until the end of the sample, however, the profit share experiences extensive growth, nearly doubling to 17.4% by 2017:Q4. Panel (b) shows that these shifts are in turn made possible by a reverse pattern in labor’s share of corporate output, which rises from 67.0% in 1966:Q1 to 72.7% in 1989:Q1 before reverting to 67.7% by 2017:Q4.

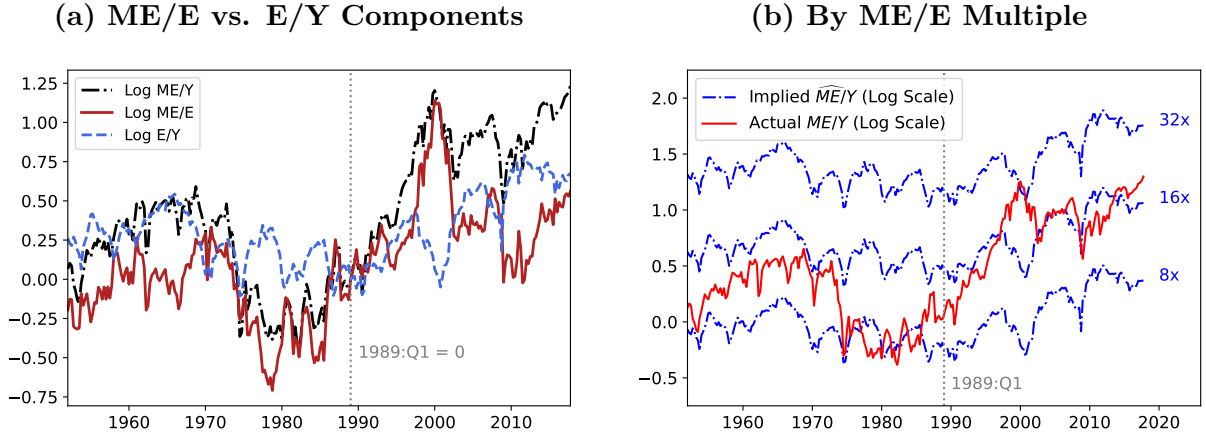
Motivated by these empirical patterns, we next study the observational links between factor shares and equity values. To begin, we decompose

$$\log\left(\frac{ME}{Y}\right) = \log\left(\frac{ME}{E}\right) + \log\left(\frac{E}{Y}\right). \quad (1)$$

This relationship, while clearly lacking causal interpretation, additively separates movements in the ratio of stock wealth to corporate output into a component driven by factor shares (E/Y) and a component driven by valuations holding fixed factor shares (ME/E).

This decomposition is presented in Panel (a) of Figure 3, normalized by subtracting a constant from each series so that each is equal to zero in 1989:Q1. The figure shows that, particularly at low frequencies, much of the variation in the ME/Y ratio is associated with movements in factor shares. In particular, movements in this component fully explain the decline in ME/Y from the mid-1960s to the late 1980s, and explain the majority of the rise in ME/Y from the late 1980s to the end of the sample. At the same time, there are also

Figure 3: Model-Free Decompositions of ME/Y



Notes: In both panels, abbreviations are defined as follows. **ME**: market value of corporate equities. **E**: corporate sector after-tax profits. **Y**: corporate sector net value added. In Panel (b), \widehat{ME} is defined according to (2), using the labeled multiple associated with each series as $\overline{ME/E}$. The sample spans 1952:Q1 to 2017:Q4.

important subperiods in which ME/Y is explained almost completely by variation in equity values relative to earnings, such as the large drop in ME/Y over the course of the 1970s, as well as the large rise in equity values during the dot-com boom of the late 1990s. Appendix A.13 presents similar decomposition showing that much of the evolution of Tobin’s Q over our sample is also associated with movement in factor shares.

Next, for an alternative decomposition of ME/Y, we compute counterfactual series

$$\widehat{ME}_t = \overline{ME/E} \times E_t. \quad (2)$$

which describe how the value of market equity would have evolved under a fixed ratio or multiple of ME to E, denoted $\overline{ME/E}$. Panel (b) of Figure 3 displays the resulting series, where movements of the actual ME/Y series *along* a given $\widehat{ME/Y}$ series correspond to movements linked to factor shares, while movements *between* the various $\widehat{ME/Y}$ series correspond to movements in ME/E holding fixed factor shares.¹³ This figure shows that essentially all of the increase in equity values relative to output from the mid-1990s to the end of the sample occur along the same $\widehat{ME/Y}$ series, pointing to the importance of factor shares in driving asset prices over this period. In contrast, most of the sharp drop in ME/Y in the mid-1970s, and much of the rise in ME/Y from the early 1980s to the mid-1990s correspond to movements between different ME/E multiples holding fixed factor shares.

In summary, the degree to which movements in the value of market equity are associated

¹³This figure is inspired by similar figures in Yardeni, Abbott, and Quintana (2023).

with changes in factor shares varies substantially over time, but appears strong over the last three decades of our sample.

2.2 Sources of Earnings Share Variation

Having examined the time series relationship between equity values and the earnings share, we turn to the drivers of the earnings share itself. To begin, we briefly present an accounting breakdown of corporate output. Beginning with gross value added, the Bureau of Economic Analysis (BEA) removes depreciation to yield net value added, which we use as our measure of output Y_t . From this, a fraction τ_t of Y_t is devoted to taxes and interest payments (as well as a catchall of “other” charges against earnings). We refer to τ_t simply as the “tax and interest” share for brevity.¹⁴ The remaining $1 - \tau_t$ share is divided between labor compensation and domestic after-tax profits (domestic earnings, E_t^D).¹⁵ We denote labor’s share of domestic value added net of taxes and interest as L_t^D , so that $E_t^D = (1 - \tau_t)(1 - L_t^D)Y_t$. Finally, firms receive some earnings from their foreign subsidiaries $E_t^F = F_t Y_t$, where F_t is the ratio of foreign earnings to domestic output, yielding the total earnings decomposition.

$$E_t = E_t^D + E_t^F = \underbrace{\left((1 - \tau_t)(1 - L_t^D) + F_t \right)}_{S_t} Y_t.$$

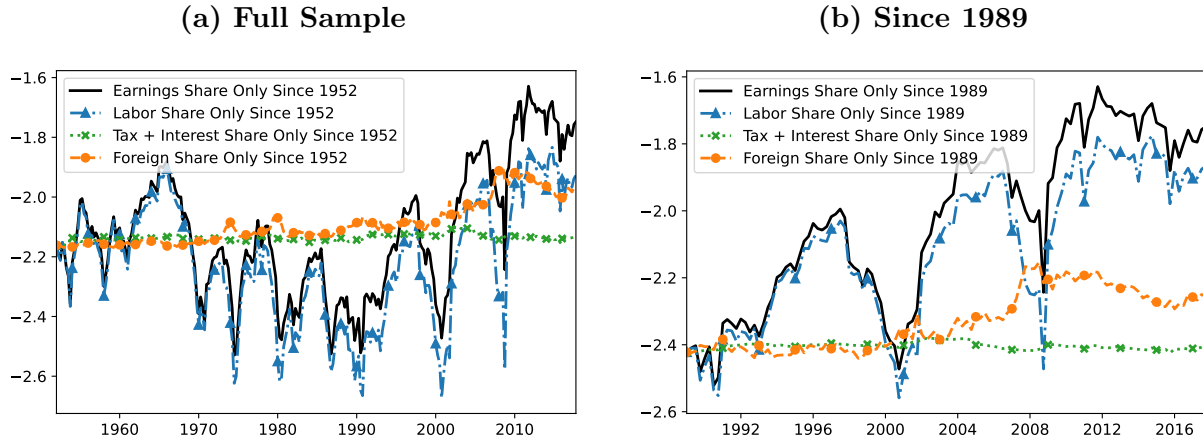
We note that, because we are working entirely within the corporate sector, this decomposition is exclusively among “unambiguous” components of income, and therefore avoids the important critique raised by Koh, Santaëulàlia-Llopis, and Zheng (2020) that many measures of factor shares depend heavily on how various “ambiguous” components of income, such as proprietor’s income, are classified.

To decompose the contributions of the various components described above we compute counterfactual series allowing a single component (τ_t , L_t^D , or F_t) to vary at a time, while holding the others fixed at their initial values. The resulting series are displayed in Figure 4. Panel (a) shows that movements in the domestic labor share L_t^D explain the vast majority

¹⁴In this accounting, the implications of firms’ financial policies for the market value of equity are taken into account in τ_t , which subtracts off net interest payments.

¹⁵We use the BEA corporate sector labor compensation data to measure $L_t^D (1 - \tau_t) Y_t$. Some researchers have questioned whether the BEA adequately accounts for all of employee compensation in the form of restricted stock or stock options (e.g., Koh, Santaëulàlia-Llopis, and Zheng (2020), Eisfeldt, Falato, and Xiaolan (2023)). To the extent that BEA labor compensation data fails to capture equity-based compensation, shifts toward this form of compensation would both reduce measured labor compensation, and increase equity values, as resources that would have been paid out are now kept inside the firm. While this would imply that movements in the profit share may partially represent changes in the form of compensation rather than redistribution, it should not affect our main result that changes in profit shares have accounted for a large share of the rise in equity values since the 1980s.

Figure 4: Role of Components in Earnings Share



Notes: The figure decomposes the corporate earnings share S_t into contributions from changes in the domestic labor share S^D , the tax and interest share τ , and the foreign share F . Each series shows the result of allowing a single component to vary, while the others are held fixed at their initial values for that period (1952:Q1 or 1989:Q1). The sample spans the period 1952:Q1-2017:Q4.

of variation in the earnings share. At lower frequencies, an upward trend in the foreign earnings share has also contributed substantially to the rise in S_t . Combined, the tax and interest shares play close to zero role.¹⁶ Panel (b) repeats this decomposition on the 1989–2017 subsample that has featured rapid increases in equity valuations. This panel shows that movements in the domestic labor share have been the dominant driver of the earnings share over this period, with the foreign share playing a smaller role, and the tax and interest share again playing close to zero role.

Taken together, these results imply that the declining domestic labor share has played the largest role in the sustained rise in the corporate earnings share. Combined with our results earlier in the section showing that most of the rise in valuations since 1989 is associated with rising earnings shares, this suggests that much of stock market gains over this period may have come at the expense of US labor compensation.

3 Model

In the previous sections, we have shown two main facts. First, the large rise in equity values relative to output from 1989 to the end of our sample occurs mainly due to a rise in profits relative to output, rather than due to a rise in equity values relative to profit. Second, the rise in profits relative to output over this period is itself primarily driven by a decline in

¹⁶This result is partially due to the separate contributions of the tax and interest shares, each of which is of moderate value, largely canceling out due to a strong negative correlation.

labor compensation relative to output.

While highly salient, these facts in isolation are not sufficient to explain the evolution of the value of market equity. Most important, they represent associations rather than causal links. Although earnings are an important fundamental for determining firm value, the fact that they rose at the same time as equity valuations tells us little about what would have happened in a counterfactual world where profit shares had not increased. Instead, measuring the contribution of a given change in factor shares on asset prices requires estimates of (i) the degree to which firm cash flows move with firm profits; (ii) the persistence of that change, as transitory changes to cash flows will move asset prices by less than highly persistent ones; and (iii) how changes in factor shares influence the risk prices used to map cash flows into asset values. Moreover, even an attempt at measuring these quantities for factor shares would not yield a complete picture of what has moved equity values over time, which must produce a consistent story reconciling movements in factor shares with other fundamental forces driving valuations.

To address these points, we present a structural model that provides a comprehensive decomposition of movements in market equity into their fundamental components over time. Throughout this exposition, lowercase letters denote variables in logs, while bolded symbols represent vectors or matrices.

Demographics The economy is populated by a representative firm that produces aggregate output, and two types of households. The first type are “shareholders” who typify owners of most equity wealth in the US (i.e., wealthy households or institutional investors). Their income consists of cash flows (payouts) from firms, and may borrow and lend among themselves in the risk-free bond market. The second type are hand-to-mouth “workers” who finance consumption out of wages and salaries, and do not trade in financial markets. This choice is motivated by empirical observation: the top 5% of the stock wealth distribution owns 76% of the stock market value and earns a relatively small fraction of income from labor compensation, while around half of households have no ownership of stocks at all.¹⁷

Productive Technology Output is produced under a constant returns to scale process:

$$Y_t = A_t N_t^\alpha K_t^{1-\alpha}, \quad (3)$$

¹⁷See Lettau, Ludvigson, and Ma (2019). In the 2016 SCF, the median household in the top 5% of the stock wealth distribution had \$2.97 million in nonstock financial wealth. By comparison, households with no equity holdings had median nonstock financial wealth of \$1,800, while all households (including equity owners) in the bottom 95% of the stock wealth distribution had median nonstock financial wealth of \$17,480.

where A_t represents total factor productivity (TFP), N_t is the aggregate labor endowment (hours times a productivity factor) and K_t is input of capital, respectively. Workers inelastically supply labor to produce output. We assume that both capital and labor productivity grow deterministically at a gross rate $\bar{G} = \exp(\bar{g})$. Hours of labor supplied are fixed and normalized to unity, so $N_t = \bar{G}^t$. These assumptions imply

$$Y_t = A_t(\bar{G}^t K_0)^\alpha (\bar{G}^t)^{1-\alpha} = A_t \bar{G}^t K_0^\alpha \quad (4)$$

where K_0 is the fixed initial value of the capital stock. We assume a stochastic process for TFP, denoted $\tilde{g}_{t+1} = \Delta \log A_{t+1}$. We note that \bar{g} represents the unconditional average for output growth, or deterministic trend, while \tilde{g}_t is a mean-zero variable representing deviations from that trend.

Factor Shares Once output is produced, it is divided among the various factors of production and other entities. We define earnings (after-tax profits) as $E_t = S_t Y_t$, where the *earnings share* S_t represents the fraction of total output that accrues to shareholders in the form of earnings, arising from both foreign and domestic operations. The remaining fraction $1 - S_t$ of output accrues to workers in the form of labor compensation, to the government in the form of tax payments, and to debtholders in the form of interest payments. In our estimation, we assume an exogenous process for S_t that does not directly distinguish between shifts in these components, but note that our results in Section 2.2 imply that most variation in S_t is driven by the labor share of domestic value added. Although we do not directly microfound variation in S_t , we note that it would be isomorphic to stochastic variation in α in a model where workers are paid their marginal product.

Investment and Payout Technology. We assume that attaining balanced growth in capital requires the firm to invest a fixed fraction ω of its output beyond replacing depreciated capital. We view this as a parsimonious approximation to a richer model with time-varying investment, which allows us to solve the model in closed form without tracking the capital stock or solving the optimal investment problem.¹⁸ While this abstracts from the volatility and cyclicity of the investment-output ratio at high frequencies, this type of transitory variation should have only modest effects on driving the value of forward-looking equity. Instead, we show in Section 6.3 that our parsimonious assumption closely reproduces the observed variation in cash flows at the low frequencies essential to our core results.

¹⁸Jermann (1998) demonstrates that generating realistic asset pricing moments in production economies requires very large investment adjustment costs. Our investment process can be seen as a limiting case in which any deviation from a constant investment-output ratio is infinitely costly.

Shareholders receive the portion of earnings not reinvested as cash flows:

$$C_t = E_t - \omega Y_t = (S_t - \omega)Y_t. \quad (5)$$

The variable C_t represents net payout, defined as net dividend payments minus net equity issuance. It encompasses any cash distribution to shareholders including share repurchases, which have become a primary method for returning cash to shareholders in the US. For brevity, we refer to these payments simply as “cash flows.”

Importantly, (5) implies that the volatility of cash flow growth is amplified relative to earnings share growth — a form of operating leverage. For example, if $\omega = 6\%$, then an increase in the earnings share S_t from 12% to 18% increases the cash flow share from 6% to 12%. As a result, proportional growth in the cash flow share (100%) is twice as large as in the earnings share (50%), a phenomenon that we call the *leverage effect*. We note that this leverage effect should hold on average even if the reinvestment share is not exactly constant, so long as investment at long horizons is proportional to output rather than earnings.

Preferences. Let C_{it}^s denote the consumption of an individual stockholder indexed by i at time t . Identical shareholders maximize the function

$$U_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \prod_{k=0}^t \beta_k u(C_{it}^s), \quad u(C_{it}^s) = \frac{(C_{it}^s)^{1-x_{t-1}}}{1-x_{t-1}}. \quad (6)$$

This specification effectively corresponds to time separable power utility preferences with a time-varying price of risk x_t , and a time-varying time discount factor β_t . Since shareholders perfectly insure idiosyncratic risk, shareholder consumption C_{it} is identically equal to aggregate cash flows C_t .¹⁹ Because firm cash flows are only a subset of total economy-wide consumption, shocks to S_t shift shareholder consumption, and are a source of systematic risk for asset owners. This implication has been explored by Lettau, Ludvigson, and Ma (2019) who study risk pricing in a large number of cross-sections of return premia.

Aggregating over shareholders, equities are priced by the stochastic discount factor (SDF) of a representative shareholder, derived in Appendix A.4, that takes the form

$$M_{t+1} = \hat{\beta}_t \left(\frac{C_{t+1}}{C_t} \right)^{-x_t}. \quad (7)$$

¹⁹This need not imply that individual shareholders are hand-to-mouth households. They may trade an arbitrary set of assets with each other, including a complete set of state contingent contracts. Because they perfectly share idiosyncratic risk with other shareholders, they each consume per capita aggregate shareholder cash flows C_t at equilibrium. See Appendix A.2 for a stylized model.

where $\hat{\beta}_t$ is a scaled version of β_t defined in Appendix equation (A.5). This specification is a generalization of the SDFs considered in previous work, such as Campbell and Cochrane (1999) or Lettau and Wachter (2007). As in these models, the preference shifters $(x_t, \hat{\beta}_t)$ are taken as exogenous processes that are the same for each shareholder.

We specify the risk price x_t as an independent stochastic process. While in the model this term specifically represents variation in risk aversion, in practice it may also serve as an estimation residual that captures variation in equity values not directly accounted for by our framework, such as institutional frictions or changes in stock market participation.

Shareholder preferences are also subject to exogenous shifts in the time discount factor $\hat{\beta}_t$. As is well known, applying a realistic level of variation in the risk price while holding the time discount factor fixed would generate counterfactually high volatility in the risk-free rate. Instead, following Ang and Piazzesi (2003), we specify $\hat{\beta}_t$ as

$$\hat{\beta}_t = \frac{\exp(-\delta_t)}{\mathbb{E}_t \exp(-x_t \Delta c_{t+1})}$$

where Δc_{t+1} represents log cash flow growth. This specification implies $\mathbb{E}_t M_{t+1} = \exp(-\delta_t)$, ensuring that the log risk-free rate is equal to the exogenous stochastic process δ_t at all times, regardless of the values for the other state variables of the economy.

3.1 Model Solution and Parameterization

Exogenous Processes. Our model has four sets of exogenous processes that drive $s_t, x_t, \delta_t,$ and \tilde{g}_t , respectively. We specify each process as the sum of two independent AR(1) processes:

$$\begin{aligned} s_t &= \bar{s} + \mathbf{1}'\tilde{\mathbf{s}}_t, & \tilde{\mathbf{s}}_{t+1} &= \mathbf{\Phi}_s \tilde{\mathbf{s}}_t + \boldsymbol{\varepsilon}_{s,t+1}, & \boldsymbol{\varepsilon}_{s,t+1} &\stackrel{\text{iid}}{\sim} N(0, \boldsymbol{\Sigma}_s), \\ x_t &= \bar{x} + \mathbf{1}'\tilde{\mathbf{x}}_t, & \tilde{\mathbf{x}}_{t+1} &= \mathbf{\Phi}_x \tilde{\mathbf{x}}_t + \boldsymbol{\varepsilon}_{x,t+1}, & \boldsymbol{\varepsilon}_{x,t+1} &\stackrel{\text{iid}}{\sim} N(0, \boldsymbol{\Sigma}_x), \\ \delta_t &= \bar{\delta} + \mathbf{1}'\tilde{\boldsymbol{\delta}}_t, & \tilde{\boldsymbol{\delta}}_{t+1} &= \mathbf{\Phi}_\delta \tilde{\boldsymbol{\delta}}_t + \boldsymbol{\varepsilon}_{\delta,t+1}, & \boldsymbol{\varepsilon}_{\delta,t+1} &\stackrel{\text{iid}}{\sim} N(0, \boldsymbol{\Sigma}_\delta), \\ \tilde{g}_t &= \mathbf{1}'\tilde{\mathbf{g}}_t, & \tilde{\mathbf{g}}_{t+1} &= \mathbf{\Phi}_g \tilde{\mathbf{g}}_t + \boldsymbol{\varepsilon}_{g,t+1}, & \boldsymbol{\varepsilon}_{g,t+1} &\stackrel{\text{iid}}{\sim} N(0, \boldsymbol{\Sigma}_g), \end{aligned}$$

where $\tilde{\mathbf{s}}_t, \tilde{\mathbf{x}}_t, \tilde{\boldsymbol{\delta}}_t,$ and $\tilde{\mathbf{g}}_t$ are 2×1 vectors, all terms denoted $\mathbf{\Phi}$ or $\boldsymbol{\Sigma}$, are 2×2 diagonal matrices, and tildes indicate that variables are demeaned. While these AR(1) processes are unbounded, in principle allowing for implausible values, we verify in Section 6.1 that earnings shares in excess of unity effectively never occur, while negative levels of the risk price are uncommon and are not estimated to have occurred over our sample.

We choose a two-component mixture for each process to capture variation at different frequencies. Since equity gives its owners access to profits for the lifetime of the firm, it is a

heavily forward-looking asset that is much more influenced by persistent rather than transitory fluctuations in fundamentals. Our mixture specification allows the model to capture both low frequency movements that have greater impact on equity prices, as well as higher frequency movements that have a smaller impact on equity prices but may nonetheless drive much of the variation in the observable series. Correspondingly, we refer to the components of each latent state vector as the low-frequency or high-frequency component, so that e.g., $\tilde{\mathbf{s}}_t = (s_{LF,t}, s_{HF,t})'$ and $\text{diag}(\Phi_s) = (\phi_{s,LF}, \phi_{s,HF})$ with $\phi_{s,LF} > \phi_{s,HF}$.

Stacking this system yields a transition equation for the economy's state vector \mathbf{z}_t :

$$\mathbf{z}_{t+1} = \Phi \mathbf{z}_t + \boldsymbol{\varepsilon}_{t+1}, \quad \boldsymbol{\varepsilon}_t \stackrel{\text{iid}}{\sim} N(0, \Sigma) \quad (8)$$

where

$$\mathbf{z}_t = \begin{bmatrix} \tilde{\mathbf{s}}_t \\ \tilde{\mathbf{x}}_t \\ \tilde{\boldsymbol{\delta}}_t \\ \tilde{\mathbf{g}}_t \end{bmatrix}, \quad \Phi = \begin{bmatrix} \Phi_s & 0 & 0 & 0 \\ 0 & \Phi_x & 0 & 0 \\ 0 & 0 & \Phi_\delta & 0 \\ 0 & 0 & 0 & \Phi_g \end{bmatrix}, \quad \boldsymbol{\varepsilon}_t = \begin{bmatrix} \boldsymbol{\varepsilon}_{s,t} \\ \boldsymbol{\varepsilon}_{x,t} \\ \boldsymbol{\varepsilon}_{\delta,t} \\ \boldsymbol{\varepsilon}_{g,t} \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \Sigma_s & 0 & 0 & 0 \\ 0 & \Sigma_x & 0 & 0 \\ 0 & 0 & \Sigma_\delta & 0 \\ 0 & 0 & 0 & \Sigma_g \end{bmatrix}. \quad (9)$$

Log-Linearization. We seek a specification that allows an analytical, log-linear solution for the price-dividend ratio. This solution requires three approximations: (i) a log-linear approximation of the equity return, (ii) a log-linear approximation of cash flow growth, and (iii) a second-order perturbation of the log SDF that allows for linear terms in the states and shocks, as well as interactions between the states and shocks. We summarize these approximations below, with full detail relegated to the appendix.

First, we approximate the return on equity

$$R_{t+1} = \frac{P_{t+1} + C_{t+1}}{P_t}$$

where P_t denotes total market equity, i.e., price per share times shares outstanding. Following Campbell and Shiller (1989), we approximate the log return as

$$r_{t+1} = \kappa_0 + \kappa_1 p c_{t+1} - p c_t + \Delta c_{t+1} \quad (10)$$

where $p c_t = \ln(P_t/C_t)$, $\kappa_1 = \exp(\bar{p}c) / (1 + \exp(\bar{p}c))$, $\kappa_0 = \ln(\exp(\bar{p}c) + 1) - \kappa_1 \bar{p}c$, and $\bar{p}c$ is the average value of $p c_t$.

Second, we log-linearize the log cash flow to output ratio $c_t - y_t = \log(S_t - \omega)$ to obtain

$$c_t - y_t \simeq \bar{c}y + \xi(s_t - \bar{s}), \quad \xi \equiv \frac{\bar{S}}{\bar{S} - \omega}$$

where $\bar{c}y = \log(\bar{S} - \omega)$, and \bar{S} is the average value of S_t . Differencing this relation yields

$$\Delta c_t = \xi \Delta s_t + \Delta y_t. \quad (11)$$

Importantly, for $\omega > 0$ we have $\xi > 1$, so that changes in profit share map more than one-for-one into cash flows, preserving the leverage effect discussed above.

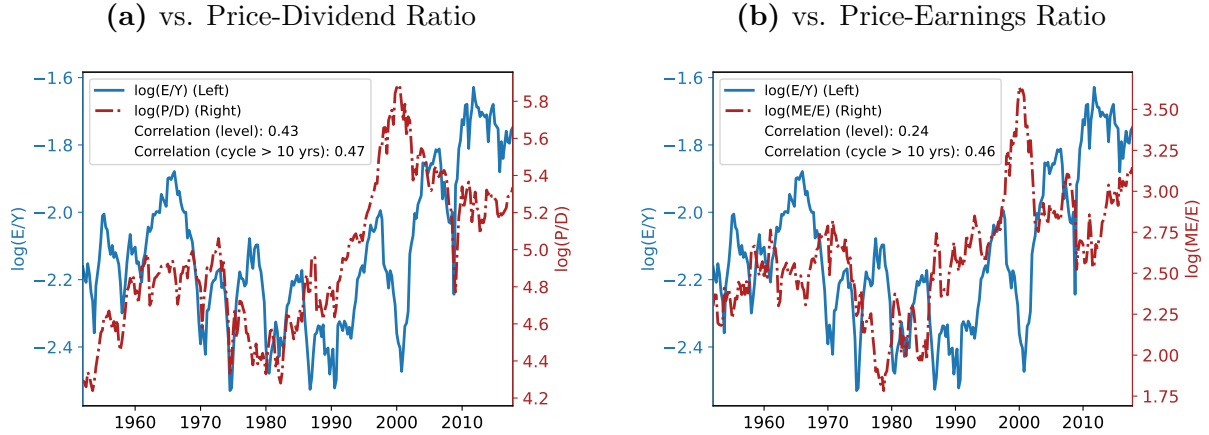
Last, we approximate our nonlinear SDF (7) using a perturbation around the steady state that includes terms linear in \mathbf{z}_t and $\boldsymbol{\varepsilon}_{t+1}$, as well as interactions between \mathbf{z}_t and $\boldsymbol{\varepsilon}_{t+1}$. While the complete solution and derivation can be found in the appendix, we present here the more intuitive form

$$\log M_{t+1} \simeq -\delta_t - \mu_t - \underbrace{x_t (\xi \Delta s_{t+1} + \Delta y_{t+1})}_{\text{baseline cash flow risk}} + \underbrace{\bar{x} \xi (\xi - 1) (\mathbb{E}_t[s_{t+1}] - \bar{s}) \Delta s_{t+1}}_{\text{leverage risk effect}} \quad (12)$$

where μ_t is implicitly set to ensure a log risk-free rate of δ_t . The “baseline cash flow risk” term represents the price of risk x_t times the change in cash flows under the approximation (11). The final *leverage risk effect* term is a second-order interaction, representing the fact that the same shock to the earnings share $\varepsilon_{s,t+1}$ has a larger proportional impact on cash flows when the current (and thus expected) earnings share is low. For example, if we again assume $\omega = 6\%$, then increasing the earnings share from 8% to 10% would increase the cash flow share of output by 100% (from 2% to 4%), while the same proportional increase in the earnings share from 16% to 20% would only increase the cash flow share of output by 40% (from 10% to 14%). The leverage risk effect captures this phenomenon, causing the SDF to load more negatively on changes in profit shares when the expected profit share is low.

The specification (12) implies that changes in the profit share influence market valuations by affecting both cash flows and risk premia. We view this risk premium channel as strongly supported by the data. Figure 5 displays time-series variation in the corporate sector log earnings share of output, $e_t - y_t$, alongside either the Center for Research in Securities Prices (CRSP) log price-dividend ratio $p_t - d_t$, or the log of the corporate sector price-earnings ratio ME/E, denoted $p_t - e_t$. The figure shows that these variables are positively correlated, particularly at lower frequencies. For example, the correlation between $e_t - y_t$ and $p_t - d_t$ is 47% for band-pass filtered components of the series that retain fluctuations with cycles greater than 10 years.

Figure 5: Earnings Share and Valuations



Notes: $\log(E/Y)$ denotes the logarithm of the after-tax profit (earnings) share of output for the corporate sector. $\log(ME/E)$ is the log of the market equity-to-earnings ratio. $\log(P/D)$ is the log of the CRSP price-dividend. Each plot presents the correlation between the series in levels, as well as the correlation of the components of each series with cycles of at least 10 years, obtained using the random walk band-pass filter of Christiano and Fitzgerald (1999). The sample spans the period 1952:Q1-2017:Q4.

A model with no correlation between the the earnings share and the price or quantity of risk would instead unambiguously predict that $p_t - c_t$ and $p_t - e_t$ should be negatively correlated with the profit share. Because shocks to the profit share revert over time, they influence prices (discounted forward-looking cash flows) less than current cash flows, resulting in a negative correlation between the earnings share and the ratio of price to cash flows. The positive correlation observed in the data instead implies that persistently high earnings shares must coincide with a decline in expected future returns, so that valuation ratios rise even as the earnings share is rationally expected to decline in the future.²⁰

Equilibrium Stock Market Values. The first-order-condition for optimal shareholder consumption implies the following Euler equation:

$$\frac{P_t}{C_t} = \mathbb{E}_t \exp \left[m_{t+1} + \Delta c_{t+1} + \ln \left(\frac{P_{t+1}}{C_{t+1}} + 1 \right) \right]. \quad (13)$$

We conjecture a solution to (13) taking the form

$$pc_t = A_0 + \mathbf{A}'_s \tilde{\mathbf{s}}_t + \mathbf{A}'_\delta \tilde{\boldsymbol{\delta}}_t + \mathbf{A}'_x \tilde{\mathbf{x}}_t + \mathbf{A}'_g \tilde{\mathbf{g}}_t \quad (14)$$

²⁰If shocks to the earnings share improved shareholder fundamentals permanently, these shocks would drive prices up proportionally with earnings, leaving valuation ratios unaffected and the correlation zero.

where $pc_t = \log(P_t/C_t)$ is the log price to cash-flow ratio. The solution, derived in Appendix A.3, implies that the coefficients on these state variables take the form

$$\begin{aligned}\mathbf{A}'_s &= -\xi \left[\mathbf{1}'(\mathbf{I} - \Phi_s) - (\mathbf{1}'\Sigma_s\mathbf{1})\Gamma' \right] \left[(\mathbf{I} - \kappa_1\Phi_s) - \kappa_1\xi\Sigma_s\mathbf{1}\Gamma' \right]^{-1} \\ \mathbf{A}'_x &= - \left[\left(\xi^2(\mathbf{1}'\Sigma_s\mathbf{1}) + \mathbf{1}'\Sigma_g\mathbf{1} + \kappa_1\xi(\mathbf{A}'_s\Sigma_s\mathbf{1}) \right) \mathbf{1}' \right] (\mathbf{I} - \kappa_1\Phi_x)^{-1} \\ \mathbf{A}'_\delta &= -\mathbf{1}'(\mathbf{I} - \kappa_1\Phi_\delta)^{-1} \\ \mathbf{A}'_g &= \mathbf{1}'\Phi_g(\mathbf{I} - \kappa_1\Phi_g)^{-1}\end{aligned}$$

where the leverage risk effect is captured by the term

$$\Gamma' = \bar{x}\xi(\xi - 1)\mathbf{1}'\Phi_s. \quad (15)$$

The signs of the elements of \mathbf{A}'_s depend on the values of Γ . As discussed above, were $\Gamma = 0$, the elements of \mathbf{A}_s would also be negative, yielding a counterfactual negative correlation between the earnings share and pc_t , with the correlation approaching zero as the persistences of both earnings share components approach unity. In contrast, when the leverage risk effect is active, we have $\Gamma > 0$, lessening or reversing this counterfactual negative correlation.

Turning to the other components, the elements of \mathbf{A}_x and \mathbf{A}_δ are all negative, implying that an increase in the risk-free rate or an increase in the price of risk x_t at any frequency reduces the price-cash flow ratio, as either event increases the rate at which future payouts are discounted. The size of these effects depends on the persistences of the risk-free rate and risk price processes, as captured by Φ_δ and Φ_x , with more persistent shocks translating into larger effects. Last, \mathbf{A}_g inherits its sign from Φ_g . For example, if $\text{diag}(\Phi_g) > 0$ then high current growth predicts high future growth, increasing future cash flows and hence current asset prices relative to current cash flows, leading to a positive loading $\mathbf{A}_g > 0$.

We show in Appendix A.3, the model's log equity premium is given by

$$\log \mathbb{E}_t [R_{t+1}/R_{f,t}] = (\Psi_s + \Psi_g) x_t - \Psi_s \Gamma' \tilde{\mathbf{s}}_t \quad (16)$$

where $\Psi_s \equiv \xi(\mathbf{1}'\Sigma_s\mathbf{1}) + \kappa_1\xi(\mathbf{A}'_s\Sigma_s\mathbf{1})$ is a measure of average earnings share risk, which arises directly through cash flows (first term), as well as the covariance of the earnings share with the pc ratio (second term), and $\Psi_g \equiv (\mathbf{1}'\Sigma_s\mathbf{1}) + \kappa_1\xi(\mathbf{A}'_g\Sigma_g\mathbf{1})$ is the corresponding measure of output growth risk. Equation (16) shows that the equity premium is the sum of two terms: (i) product of the price of risk and the average total cash flow risk, including both earnings share and output risk, and (ii) time variation in the risk premium due to e.g., higher earnings share risk when $\tilde{\mathbf{s}}_t$ is low, via the leverage risk effect.

4 Data

We next describe our data sources, with full details available in Appendix A.1. Our data consist of quarterly observations spanning the period 1952:Q1 to 2017:Q4. We construct all of our data series at the level of the US corporate sector. This choice stands in contrast to previous work, which has typically compared trends in aggregate measures of output and the labor share against trends in the value of public equity. A weakness of this existing approach is that BEA data on output and the labor share are not limited to the publicly traded sector and cover a far broader swath of the economy. This creates the potential for confounding compositional effects over time if publicly traded firms have experienced different shifts in their profit share or productivity compared to non-public firms. Moreover, Koh, Santaaulàlia-Llopis, and Zheng (2020) find that measures of the profit and labor share based on these aggregates are highly sensitive to how “ambiguous” income is classified as either labor or capital income, posing additional measurement challenges.

In contrast, we construct all of our series at the same level — the US corporate sector — to avoid these compositional effects. As discussed above, our data also have the advantage of “unambiguously” classifying income, using the terminology of Koh, Santaaulàlia-Llopis, and Zheng (2020), sidestepping any need to classify the ambiguous portion of national income. At the same time, this approach requires that equity value includes non-public firms. While the vast majority of our equity value measure stems from public firms, it is broader than that used in most existing work, and may exhibit slight differences as a result.²¹

For our estimation, we use observations on seven data series: the log share of domestic output accruing to earnings (the earnings share), denoted $ey_t = e_t - y_t$; a measure of the log short-term real interest rate, denoted $r_{f,t}$; growth in output for the corporate sector as measured by growth in corporate net value added, denoted Δy_t ; professional survey forecasts of average future real risk-free rates and future real GDP growth over the next 40Q, denoted $\bar{\delta}_t^{40}$ and \bar{g}_t^{40} , respectively; the log market equity to output ratio for the corporate sector, denoted $py_t = p_t - y_t$; and a proxy for the market risk premium, denoted rp_t .

Our motivation behind this choice of series is as follows. The series ey_t , $r_{f,t}$ and Δy_t pin down the values of s_t , δ_t , and \tilde{g}_t in the model at each date. The series $\bar{\delta}_t^{40}$ and \bar{g}_t^{40} ensure that the model correctly allocates between low-frequency and high-frequency components of the risk-free rate and output growth to match the expected long-term forecasts of these variables in addition to their levels. The series py_t ensures that the model is able to fully

²¹The Flow of Funds separately tracks public and private (“closely held”) equity for the US corporate sector from 1996:Q4 onward. Over this subsample, public equity makes up 83% of total corporate equity on average. The remaining 17% is a mix of 11.5% of private S-corporation equity, and 6.5% of private C-corporation equity.

explain movements in market equity in each period, while the risk premium estimate rp_t provides additional discipline for the risk price process.

We next construct these series in the data. Our earnings share measure ey_t is equal to the ratio of total corporate earnings to domestic net value added. To compute total corporate earnings, we combine corporate domestic after-tax profits from the National Income and Product Accounts (NIPA) with data on corporate foreign direct investment income from the BEA’s International Transaction Accounts. The domestic after-tax profits represent domestic net value added, net of domestic labor compensation, taxes, and interest payments. Foreign earnings represent equity income from directly held foreign subsidiaries. Because this foreign income data is only available from 1982 on, we impute this series over the full sample using NIPA data on total foreign income (direct and indirect) as a proxy, which provides an extremely close fit over the overlapping period (see Appendix A.1 for details).

Subtracting net interest payments to form our measure of earnings helps us overcome an important challenge regarding the accounting of financial liabilities. By definition, market equity is equal to the enterprise value of the firm, plus its financial assets, minus its liabilities, with all terms measured at market value. However, the market values of liabilities such as firm debt are not available in our data. To the extent that the present value of financial assets and liabilities are approximated by the present value of their remaining interest payments, as would be the case if assets and liabilities are perpetually rolled over, removing net interest payments from our cash flows effectively subtracts the market value of net liabilities and adds the market value of net financial assets, exactly as required. While this approximation is imperfect, and in particular ignores the timing of financial transactions, we believe it is superior to the alternative of relying on book values.²² In practice, deviations due to this form of approximation error will likely be attributed to the estimated contribution of the risk price, which effectively serves as a residual in our estimation.

Our real risk-free rate measure $r_{f,t}$ is the 3-month Treasury Bill (T-Bill) yield net of expected inflation, which is computed using an ARMA(1,1) model.²³ Our real risk-free rate forecast $\bar{\delta}_t^{40}$ is the mean Survey of Professional Forecasters (SPF) expectation of the average annualized 3-month T-Bill return over the next ten years (BILL10) less the mean

²²Davydiuk, Richard, Shaliastovich, and Yaron (2023) provide an alternative methodology in which the market values of liabilities are imputed using bond pricing data. While this approach appears effective and appealing, it is relatively involved and beyond the scope of this paper.

²³We note that while our real short rate series uses our ARMA(1,1) forecast to move from nominal to real rates, making our results potentially dependent on this particular model, our long-term risk-free rate forecast series directly uses professional forecasts of long-term inflation to map from nominal to real rates. Since these long-term forecasts have a greater influence on our measured persistence of risk-free rates, we do not believe our main results on long-term contributions of real risk-free rates to equity valuations should be particularly sensitive to this choice.

SPF expectation of annualized Consumer Price Index (CPI) inflation over the same period (CPI10).²⁴ Our output growth measure Δy_t is the change in log real net value added for the corporate sector from NIPA, while our 40Q output growth forecast \bar{g}_t^{40} is the 10-year real GDP growth forecast from the Survey of Professional Forecasters (GDP10). Because these forecasts may be biased on average, for example due to differences in CPI inflation and the Corporate NVA deflator used in this paper, we allow each forecast to differ on average from the corresponding model object by parameters denoted ν_δ and ν_g , respectively, which we estimate below. Our equity-output ratio py_t is the log ratio of the market value of corporate equity from the Flow of Funds to corporate net value added from NIPA.

For our observable measure of the risk premium (rp_t), we use the SVIX-based estimate derived by Martin (2017), who documents that a wide range of representative agent asset pricing theories fail to explain the high-frequency variation in the risk premium implied by options data, even if they are broadly consistent with the lower-frequency variation suggested by variables like the price-dividend ratio or cay_t (Lettau and Ludvigson, 2001).²⁵ Since our model allows for mixture processes, the risk premium we estimate is capable of simultaneously accounting for both these higher- and lower-frequency types of variation.

Last, we compute corporate payouts as the net dividends minus net equity issuance for the corporate sector. Importantly, other than indirectly in the calibration of ξ below, we do not use this payout data in our estimation. This choice is motivated by the observation that payouts are a function of current and future earnings, as well as transitory factors that affect the timing with which they are paid out, subject to an intertemporal budget constraint. These two sources of variation have very different implications for future payouts. A rise in payouts due to a persistent rise in earnings implies that higher payouts today also forecast larger payouts in the future, paid by a more profitable corporate sector. In contrast, a rise in payouts holding profitability fixed implies that the corporate sector is exhausting resources it could have paid out at a later date, forecasting *smaller* payouts in the future.

As a result, variation driven purely by the timing of payouts adds noise to the fundamental forecasts of profitability and its associated payouts that are our key objects of interest. This problem can be severe when estimating a model of equity pricing, since observed variation in the timing of payouts is large and subject to extreme swings due to temporary factors such as changes in tax law that are likely unrelated to economic fundamentals.²⁶ Thus, direct

²⁴We thank our discussant Annette Vissing-Jorgenson for this suggestion.

²⁵Martin (2017) uses options data to compute a lower bound on the equity risk premium, then argues that this lower bound is tight and is therefore a good measure of the true risk premium on the stock market.

²⁶For a recent example, see NIPA Table 4.1, which shows an unusually large 2018:Q1 increase in net dividends received from the rest of the world by domestic businesses, generating a very large decline in net payout. BEA has indicated that these unusual transactions reflect the effect of changes in the US tax law attributable to the Tax Cut and Jobs Act of 2017 that eliminated taxes for US multinationals on repatriated

use of these data as cash flows would require extensive investigation to align what is being measured with the desired theoretical input. For these reasons, we consider earnings to be a better indicator of future payouts and fundamental equity value than current payouts, and verify ex-post that our model reproduces the path of net dividends in Section 6.3.

Measurement Issues. Beyond the “ambiguous income” issue discussed above, Koh, Santaèulàlia-Llopis, and Zheng (2020) and Atkeson (2020) note that long-term trends in factor shares appear to depend heavily on the accounting treatment of intangible investment. We provide evidence in Appendix A.11 that our results on the role of factor shares should be robust to these concerns for two reasons. First, this critique largely applies to factor shares of *gross* value added, whereas we measure factor shares of *net* value added, which Koh, Santaèulàlia-Llopis, and Zheng (2020) note are much less sensitive to these assumptions, and deliver more conservative measures of the long-term rise in profit shares. Second, to the extent that various accounting treatments differ, we show that these differences mostly appear in the first half of the sample. Over the post-1989 subsample where we estimate the largest role for factor shares, all measures of the earnings share display very similar changes. As a result, we believe our earnings share measures, and our resulting estimates of the contribution of factor shares to equity values, are robust to these important concerns.

We also consider the influence of multinational profit shifting on our core data measures. Our main analysis uses BEA data on the US corporate sector that may be affected by changes in the formal location of corporate headquarters or profits. For example, Guvenen, Mataloni Jr, Rassier, and Ruhl (2022) document that US firms appear to shift their profits to their foreign subsidiaries to reduce their tax burden. Because we include both domestic and foreign subsidiary profits in our main profit share measure, this should not influence our main results. However, to the extent that part of the rise in profit share that we attribute to foreign earnings in Section 2.2 may actually represent increases in the domestic profit share that have been shifted overseas for accounting purposes, we may understate the contribution of the domestic labor share in driving our results.

Relatedly, Bertaut, Bressler, and Curcuru (2021) show that some US firms also change their nationality for tax reasons, for example by using corporate inversions. Because firms formally relocating away from the US would drop out of the US corporate sector according to the BEA, these switches could influence our data series. However, since taxes are paid on corporate profits, the firms with the greatest incentive to relocate are those with the highest profits. If these firms have selected *out* of our US sample over time, it should only bias our measured rise in the profit share — and its contribution to the growth in equity profits from their affiliates abroad.

values — downward. Beyond this intuition, we directly check in Appendix A.12 whether our key BEA measures line up with equivalents constructed from Compustat, which may be less affected by these nominal changes in location. Appendix Figure A.7 shows that ratios of market equity to earnings from our BEA data align closely with those from Compustat, and confirms that if anything our earnings share measures are conservative.²⁷

5 Estimation

Our model is parameterized by a vector of primitive parameters

$$\boldsymbol{\theta} = \left(\omega, \bar{s}, \bar{\delta}, \bar{x}, \bar{g}, \nu_\delta, \nu_g, \text{diag}(\boldsymbol{\Phi}_s)', \text{diag}(\boldsymbol{\Phi}_x)', \text{diag}(\boldsymbol{\Phi}_\delta)', \text{diag}(\boldsymbol{\Phi}_g)', \right. \\ \left. \text{diag}(\boldsymbol{\Sigma}_s)', \text{diag}(\boldsymbol{\Sigma}_x)', \text{diag}(\boldsymbol{\Sigma}_\delta)', \text{diag}(\boldsymbol{\Sigma}_g)' \right)'$$

With the exception of a small group of parameters, discussed below, these primitive parameters are freely estimated using Bayesian methods with flat priors.

To estimate our model, we relate our state vector \mathbf{z}_t to our observable series $\mathcal{Y}_t = (ey_t, r_{ft}, \bar{r}_{f,t}^{40}, \Delta y_t, \bar{g}_t^{40}, py_t, rp_t)'$ using the linear measurement equation

$$\mathcal{Y}_t = \mathbf{H}_t \mathbf{z}_t + \mathbf{b}_t \tag{17}$$

where the full structure for \mathbf{H}_t and \mathbf{b}_t can be found in Appendix A.5. Since our model has more shocks in $\boldsymbol{\varepsilon}_t$ than observable series in \mathcal{Y}_t , the model is able to explain all of the variation in our observable series, allowing us to estimate (17) without measurement error. We note that the coefficient matrix \mathbf{H}_t and vector \mathbf{b}_t depend on t because some of our observable data series are not available for the full sample. In particular, the samples for the real rate forecast $\bar{\delta}_t^{40}$ and real output growth forecast \bar{g}_t^{40} span 1992:Q1 - 2017:Q1, with one observation every 4Q, while the sample for the SVIX risk premium rp_t is available for each quarter of 1996:Q1 - 2012:Q1, both of which are shorter than our full sample period 1952:Q1 - 2017:Q4. As a result, the state-space estimation uses different measurement equations to include observations for these series when they are available, and exclude them when they are missing (see Appendix A.5 for details). Combined, (8) and (17) describe the full state space system used for estimation.

We estimate the parameters of the model as follows. Given a vector of primitive param-

²⁷While we would ideally directly validate our measure of the profit share, this would require a measure of value added to use in the denominator. This is not directly computable in Compustat, which does not separate out expenses on intermediate goods. Instead, since mismeasurement of the E/Y ratio should lead to corresponding mismeasurement of the ME/E ratio, we choose to validate this second metric instead.

eters θ , we construct our state space system using (8) and (17). We then use the Kalman filter to compute the log likelihood $L(\theta)$, which is equivalent to the posterior under our flat priors, up to a restriction that ensures the correct ordering of our low-frequency and high-frequency processes.²⁸ To sample draws of θ from the parameter space Θ we use a random walk Metropolis-Hastings (RWMH) algorithm (see Appendix A.5 for further details).

Given our parameter draws, we employ the simulation smoother of Durbin and Koopman (2002) to compute one draw of the latent states $\{\mathbf{z}_t^j\}$ for $t = 1, \dots, T$ for each parameter draw $\{\theta^j\}$, yielding a distribution of latent state paths that characterize the model’s uncertainty over its latent state estimates. Given our lack of measurement error, each latent state path perfectly matches the growth in market equity Δp_t over time and at each point in time, a property we exploit when calculating our growth decompositions below.

Calibrated Parameters. We calibrate, rather than estimate, four parameters. The first three are the average growth rate of net value added g , the average log profit share \bar{s} , and the average real risk-free rate $\bar{\delta}$. Since these represent the means of our observable series, we take the conservative approach of fixing them equal to their sample means. We do this to avoid a potential estimation concern: because some of our series are very persistent, the estimation might otherwise have a wide degree of freedom in setting steady state values that are far from the observed sample means. At quarterly frequency, we obtain the values $g = 0.552\%$, $\bar{s} = -2.120$ (corresponding to a share in levels of 12.01%), and $\bar{\delta} = 0.278\%$.

The final calibrated parameter is $\xi = \frac{\bar{S}}{\bar{S}-\omega}$, which relates payout growth to earnings growth according to (11), and can also be pinned down directly by sample means. Since $C_t = (S_t - \omega)Y_t$, we can rearrange and take sample averages of both sides to obtain $\omega = \bar{S} - \frac{\bar{C}}{\bar{Y}}$. Computing \bar{S} as the mean of the total profit to domestic output ratio and $\frac{\bar{C}}{\bar{Y}}$ as the mean of the payout to output ratio observed in the data yields the value $\xi = 1.890$. We further test and validate this parameter and its implications for cash flows in Sections 6.3 and 6.6.

6 Results

6.1 Parameter Estimates

We begin with a discussion of the estimated parameter values. Table 1 presents the estimates of our primitive parameters based on the posterior distribution obtained with flat priors.

²⁸The latent state space includes components that differ according to their degree of persistence. With flat priors, a penalty to the likelihood is required to ensure that the low-frequency component has greater persistence than the higher frequency component. This is accomplished using a prior density that is equal to zero if $\phi_{(\cdot),LF} \leq \phi_{(\cdot),HF}$ for any relevant component of the state vector, and is constant elsewhere.

Table 1: Parameter Estimates

Variable	Symbol	Median	5%	95%	Mode
Risk Price Mean	\bar{x}	6.9123	5.4526	8.6252	6.6601
Factor Share (LF) Pers.	$\phi_{s,LF}$	0.9907	0.9703	0.9985	0.9907
Factor Share (LF) Vol.	$\sigma_{s,LF}$	0.0166	0.0091	0.0305	0.0150
Factor Share (HF) Pers.	$\phi_{s,HF}$	0.8810	0.8272	0.9188	0.9006
Factor Share (HF) Vol.	$\sigma_{s,HF}$	0.0524	0.0450	0.0573	0.0534
Risk Price (LF) Pers.	$\phi_{x,LF}$	0.9892	0.9815	0.9960	0.9925
Risk Price (LF) Vol.	$\sigma_{x,LF}$	0.6566	0.3963	1.0460	0.5345
Risk Price (HF) Pers.	$\phi_{x,HF}$	0.6912	0.5530	0.7943	0.6757
Risk Price (HF) Vol.	$\sigma_{x,HF}$	2.3427	1.7213	3.1908	2.3496
Risk-Free (LF) Pers.	$\phi_{\delta,LF}$	0.9650	0.9526	0.9803	0.9630
Risk-Free (LF) Vol.	$\sigma_{\delta,LF}$	0.0010	0.0007	0.0013	0.0010
Risk-Free (HF) Pers.	$\phi_{\delta,HF}$	0.8445	0.7713	0.8925	0.8394
Risk-Free (HF) Vol.	$\sigma_{\delta,HF}$	0.0017	0.0015	0.0019	0.0017
Output Growth (LF) Pers.	$\phi_{g,LF}$	0.9588	0.9203	0.9840	0.9653
Output Growth (LF) Vol.	$\sigma_{g,LF}$	0.0009	0.0005	0.0017	0.0008
Output Growth (HF) Pers.	$\phi_{g,HF}$	0.2496	0.1663	0.3301	0.2469
Output Growth (HF) Vol.	$\sigma_{g,HF}$	0.0144	0.0134	0.0155	0.0144
Forecast Mean Adjustment (δ)	ν_{δ}	0.0018	-0.0007	0.0043	0.0017
Forecast Mean Adjustment (g)	ν_g	0.0061	0.0018	0.0104	0.0064

Notes: The table reports parameter estimates from the posterior distribution. All parameters are reported at quarterly frequency. The sample spans the period 1952:Q1-2017:Q4.

Several results are worth highlighting.

First, the persistence parameters of the low-frequency components of the state variables are of immediate interest, since they determine the role of each latent variable in driving market equity values over longer periods of time. Table 1 shows that the earnings share and risk price contain highly persistent components, with median estimates of $\phi_{s,LF} = 0.991$ and $\phi_{x,LF} = 0.989$, respectively. In contrast, the low-frequency risk-free rate and output growth processes are substantially less persistent, with median values $\phi_{\delta,LF} = 0.965$ and $\phi_{g,LF} = 0.959$, respectively. In part because more persistent processes have stronger influence on equity values in our model, we will find that the risk-free rate and output growth generally play smaller roles in driving equity values among these components.

For a more complete look at the estimated persistence of our stochastic processes, Figure 6 compares the autocorrelations of the latent states in the model and data.²⁹ To account for

²⁹We include all four observable series that are available over the full sample. We omit the SPF real rate and real output growth forecasts and the SVIX risk premium, all of which are available only on a much

small sample bias, the model autocorrelations are obtained from 10,000 simulations, each the length of the data sample, taken from 10,000 equally spaced parameter draws from our MCMC estimation.³⁰ Our model-generated autocorrelations generally match their data equivalents well, especially at the longer lags that are more important for asset prices.

In both model and data, the autocorrelations of output growth decay rapidly to zero, whereas the autocorrelations for the earnings share, the risk-free rate, and the log ME-to-output ratio start decline gradually as the lag order increases, consistent with more persistent processes. Panels (b) and (d) show that the model’s typical autocorrelations are close to, but slightly understate, their sample counterparts for both the earnings share and the equity-output ratio at long horizons. Since the strength of the earnings share’s effect on valuations increases with its persistence, this implies that our results on the role of the earnings share are, if anything, conservative. Panel (c) shows that the autocorrelations of the risk-free rate converge to zero by quarterly lag 40 in both model and data, and display much less persistence than the equity-output ratio, suggesting that the risk-free rate process is not persistent enough to explain much of the variation in the ME-to-output ratio at long horizons.

Turning to the risk price, Table 1 shows that our median estimate of the average risk price is only $\bar{x} = 6.912$. Because shareholders in our model consume corporate cash flows that are much more volatile than aggregate consumption, our model is able to reproduce a large equity risk premium without high levels of aversion to risk or ambiguity.³¹

Next, returning to the discussion in Section 3.1, the correlation between the pc ratio and the earnings share components depends on the strength of the leverage risk effect, which is in turn determined by our model parameters. Our median estimate is $A'_s = (-0.32, -1.69)$, with the entries corresponding to the low-frequency and high-frequency components, respectively. Thus, the effect of the leverage risk effect is not to change the sign of the loading of pc on the earnings share components, which remain negative, but instead to merely dampen these coefficients toward zero. This adjustment brings the correlation of the earnings share and pc ratio closer to the data pattern displayed in Figure 5, but again implies a conservative estimate of the influence of the earnings share on risk premia.

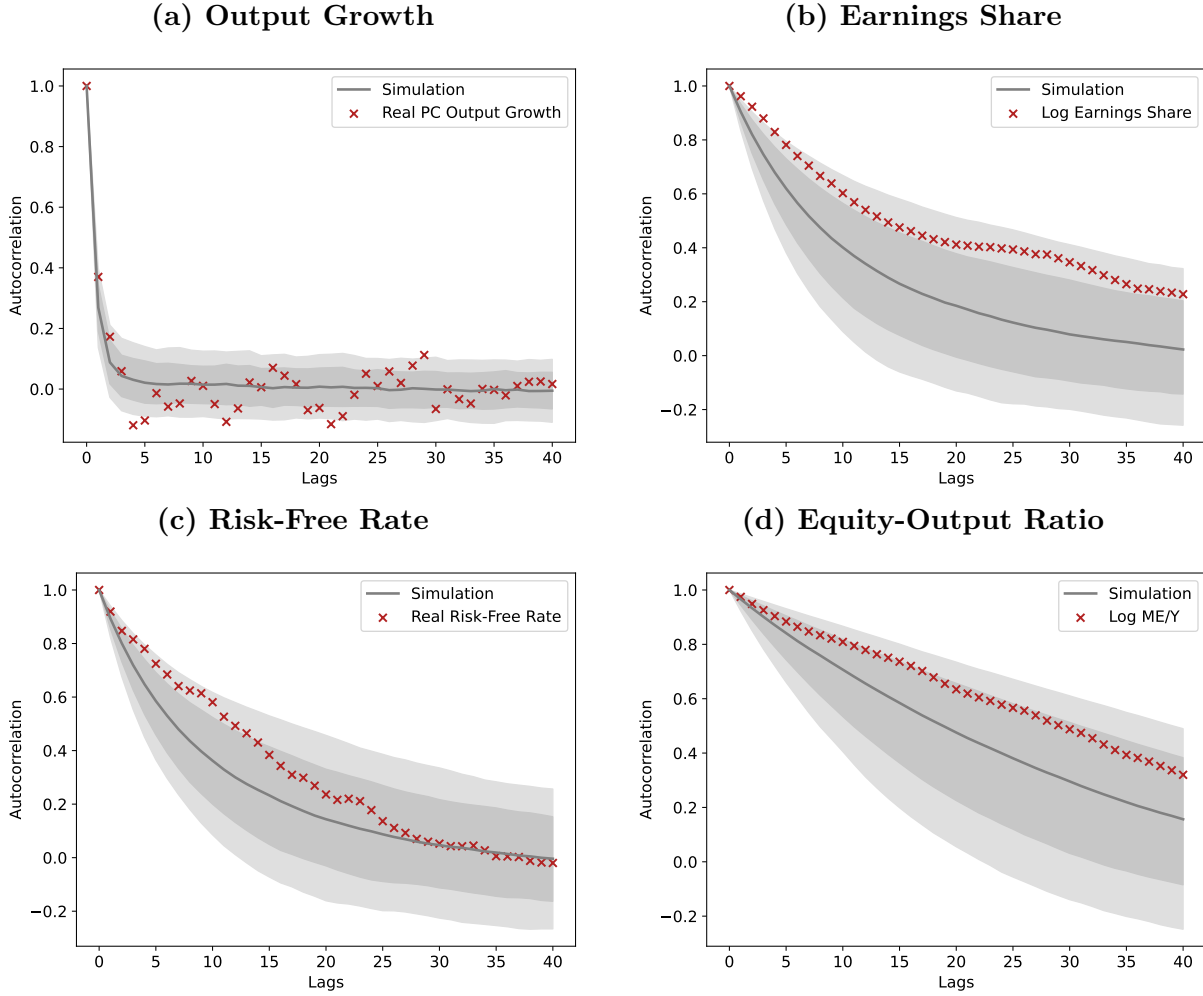
Last, we check whether our linear processes generate implausible or unlikely values for our latent states. For the earnings share process S_t , the estimated parameters imply that earnings shares in excess of unity never occur, meaning that the probability is indistinguishable from

shorter sample, and are therefore unsuitable for computing longer autocorrelations.

³⁰“Equally spaced” means sampled at regular intervals from the Markov Chain. Because the parameter draws in the original Markov Chain are highly serially correlated, this resampling dramatically speeds up computation time with little loss of fidelity in characterizing the distribution of parameters.

³¹We note that this estimate may be influenced by our parsimonious investment process, and might differ in an environment with a time-varying investment-output ratio correlated with output growth.

Figure 6: Observable Autocorrelations



Notes: The figure compares the data autocorrelations for the observable variables available over the full sample, compared to the same statistics from the model. For the model equivalents, we use 10,000 evenly spaced parameter draws from our MCMC chain, and for each compute the autocorrelations from a simulation the same length as the data. The center line displays the simulation median, while the dark and light gray bands represent 66.7% and 90% credible sets, respectively. The sample spans the period 1952:Q1-2017:Q4.

zero. For example, at the parameter mode, the unconditional distribution of the earnings share is 12.8 standard deviations away from unity. For the risk price process x_t , the estimated parameters imply that a negative risk price can occur, with unconditional probability equal to 10.9% at the parameter mode. This occurs because explaining the level and volatility of asset prices requires a risk price that is both low on average (since investors face substantial cash flow risk) and volatile (since pc ratios exhibit large movements at high frequency). In a nonlinear model, this could be obtained with a non-negative but highly skewed risk price process, as in Greenwald, Lettau, and Ludvigson (2014), an earlier version of this paper. In

the current paper, however, we use a linear specification that enables tractable time series estimation. As a result, the required combination of high volatility and low mean makes some probability of negative values unavoidable. These negative values do not cause any extreme behavior in our linearized model, but simply imply that agents sometimes price assets in a highly confident or overoptimistic manner. Regardless, our latent state point estimates do not imply negative risk premia at any point in our sample (see Appendix Figure A.4).

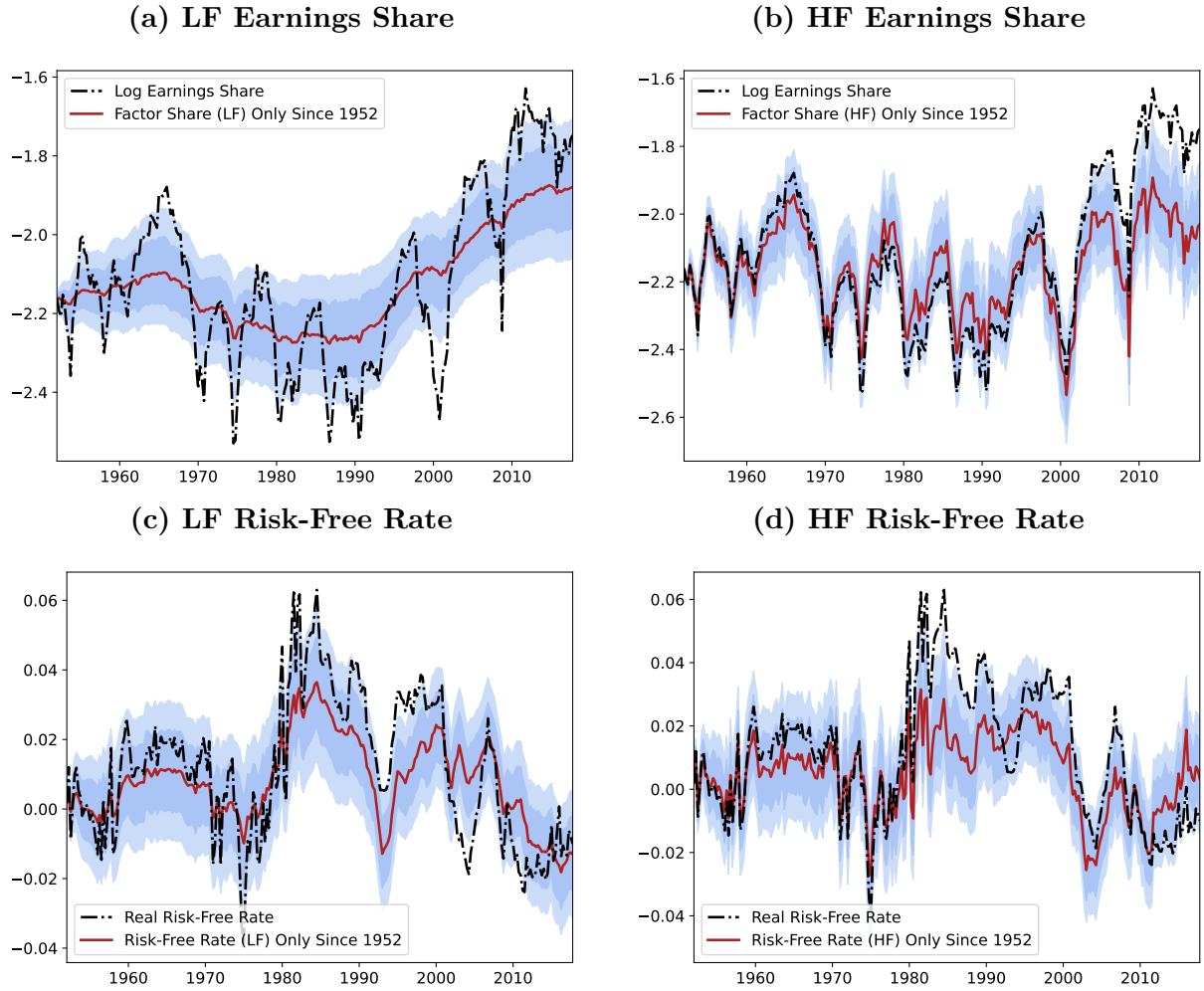
6.2 Latent State Estimates

Figure 7 displays our model’s decomposition of the earnings share s_t and real risk-free rate δ_t into their low- and high-frequency components. Similar decompositions for our remaining observables can be found in Appendix Figure A.11. Each panel plots the observable series, alongside the variation attributable to a single frequency subcomponent, holding the other fixed. In all of our decomposition figures throughout the paper, the red solid line shows the median outcome over our parameter and latent state estimates, while the shaded areas are 66.7% and 90% credible sets accounting for both parameter and latent state uncertainty.

Panels (a) and (b) show time-variation in the log earnings share ey_t over our sample, along with the portion of this variation attributable to the low- and high-frequency factor share components $s_{LF,t}$ and $s_{HF,t}$. This decomposition by frequency is central to our asset pricing results, since forward looking equity prices in our model respond strongly to movements in the low-frequency component, while movements in the high-frequency component are too transitory to have a large effect. As a result, it is critical that these components accurately decompose the true data series, and are not biased by the model’s need to match asset prices. Reassuringly, Figure (a) shows that the estimated low-frequency component accurately tracks the slow moving trend in the earnings share series.

Panels (c) and (d) similarly show the evolution of the risk-free rate over time, along with the estimated contributions of its low-frequency and high-frequency components. From the data series it is clear that, although real rates are low toward the end of our sample, they are not unusually so by historical standards, with real rates at similarly low levels at several points in the 1950s and late 1970s. The series also appears far from a unit root, with these swings reverting relatively quickly. This stands in sharp contrast to the time series for *nominal* interest rates, which features a highly persistent trend in inflation, demonstrating the importance of using real rates. The low frequency component $\delta_{LF,t}$ captures the underlying trend and drives most of the variation in 10-year real risk-free rate forecasts, while the high-frequency component $\delta_{HF,t}$ largely captures more short-lived fluctuations.

Figure 7: Latent State Components



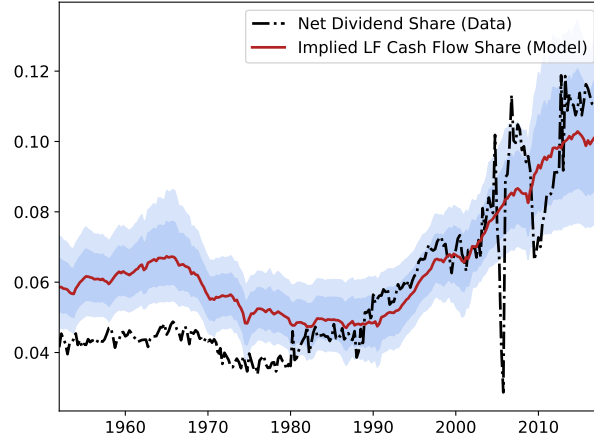
Notes: The figure exhibits the observed profit share along with the model-implied variation in the series attributable to the low-frequency and high-frequency components of \tilde{s}_t . The red center line corresponds to the median of the distribution of outcomes, accounting for both parameter and latent state uncertainty, while the dark and light blue bands correspond to 66.7% and 90% credible sets, respectively. The sample spans the period 1952:Q1-2017:Q4. Corresponding plots for additional observables can be found in Appendix Figure A.11.

6.3 Dynamics of Cash Flows

A crucial intermediate step between the evolution of the earnings share and the resulting implications for asset prices is the transmission from earnings to cash flows (corporate payouts), particularly at the low frequencies that are key to equity pricing.

In the model, the low-frequency component of the payout-output ratio can be defined as

Figure 8: Low Frequency Cash Flow Share, Model vs. Data



Notes: Net Dividend Share is the ratio of net dividends to net value added for the corporate sector (source: Flow of Funds). Implied LF Cash Flow Share is equal to $cy_{LF,t}$ in equation (18). The red line represents the median outcome over our estimates, while the dark and light blue bands represent 66.7% and 90% confidence intervals, respectively. The sample spans the period 1952:Q1-2017:Q4.

the portion of its variation driven by the low-frequency component of the earnings share:

$$cy_{LF,t} = \overline{cy} + \xi \tilde{s}_{LF,t}. \quad (18)$$

In the data, the low-frequency component of payouts is less obviously defined. However, a simple and effective decomposition can be obtained by dividing total payouts into its two subcomponents: net dividends and net repurchases. Appendix Figure A.3 shows that net dividends form a stable and highly persistent series that accounts for the vast majority of the long-term movement in payouts, both over the full sample and since 1989. In contrast, net repurchases are extremely volatile but much less persistent, explaining little long-term variation. In light of this, we use the ratio of net dividends to output as our empirical counterpart to the low-frequency component of the corporate payout share in the model.

We display these low-frequency cash flow components in Figure 8. This figure shows an excellent fit between the two series at low frequencies, particularly over the period since 1989, and one that if anything understates net dividend growth over the full sample and our main post-1989 subsample. These results imply that while (11) is clearly a parsimonious approximation of the actual path of cash flows — abstracting from changes in financial leverage through debt, cyclical variation in the investment share of output, and changes in payout policy — it is highly effective at capturing the core variation in cash flows over our

sample, providing strong support for our ultimate findings for equity values. Further details on payouts in the model and data can be found in Appendix A.7.

6.4 Dynamics of Equity Values

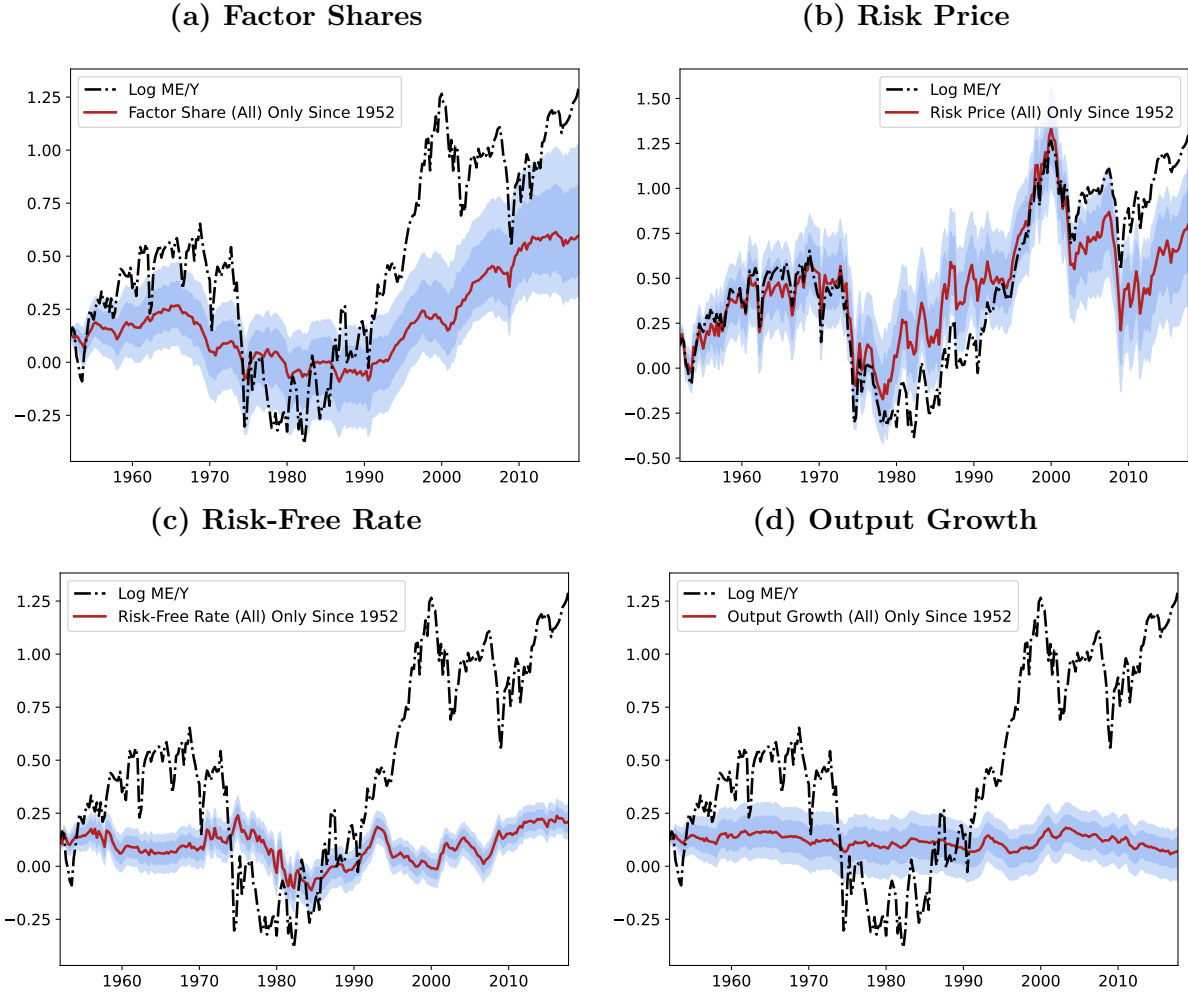
With the estimation of the latent states and analysis of implied cash flows complete, we next present their contribution to the evolution of market equity over our sample, displayed in Figure 9. Each panel displays the log equity-to-output ratio py_t , alongside the variation in py_t attributable to a single latent component, holding the others fixed at their initial value in 1952:Q1. We note that this decomposition is additive, so that the contributions in the four panels, if demeaned by the average value of the data, would add exactly to the true demeaned data series.

Beginning with the top row, Panel (a) displays the overall contribution of the profit share process s_t , including both low-frequency and high-frequency components. The figure shows that movements in factor shares explain much of the low-frequency variation in equity values, particularly over the last three decades of the sample. This series shows much less variation at high frequencies despite the high variability of $s_{HF,t}$ — which Figure 7 Panel (b) shows is volatile and drives a large portion of earnings share dynamics — since these more transitory movements in profits have weaker effects on forward-looking asset prices (see Appendix Figure A.12). As a result, the influence of factor shares on asset prices is dominated by its low-frequency component, demonstrating the importance of estimating our latent state processes at multiple frequencies.

Next, Panel (b) displays the contribution of the risk price process x_t . These secular variations in the risk price drive most variation in valuations at at high and medium frequencies, as well as much of the lower-frequency trend in the first half of the sample. In particular, this component explains nearly all of the large short-run swings in equity values over our sample, including the technology boom/bust of the late 1990s and early 2000s, and the crash following the 2008 financial crisis. However, movements in the risk price fail to explain much of the overall rise in equity valuations over the last three decades, with little upward trend in this series between the late 1980s and the end of the sample.

Panel (c) shows the contribution of the risk-free rate process δ_t . Our estimates attribute a relatively modest role to risk-free rate variation in explaining equity valuations over our sample. While the contribution of risk-free rates is nontrivial, particularly from the mid-1970s to mid-1990s, and around the 2008 crisis, these results stand in contrast to alternative works that attribute a dominant role to risk-free rates. This occurs due to our relatively low estimated persistence for the risk-free rate process, a topic we return to in Section 6.7.

Figure 9: Market Equity-Output Ratio Decomposition

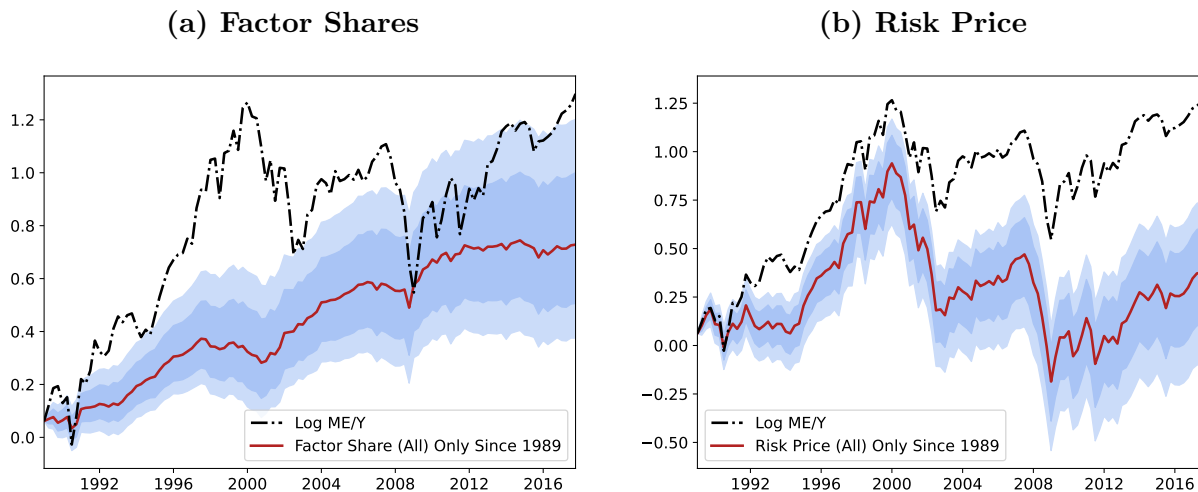


Notes: This figure exhibits the observed market equity-to-output series along with the model-implied variation in the series attributable to each of our latent components. The red center line corresponds to the median of the distribution of outcomes, accounting for both parameter and latent state uncertainty, while the dark and light blue bands correspond to 66.7% and 90% credible sets, respectively. The sample spans the period 1952:Q1-2017:Q4.

Last, Panel (d) shows that deviations from trend output growth have played a minimal role in driving equity valuations relative to output over our sample. We note that this result measures only the contribution of the \tilde{g}_t factor in driving market valuations *relative* to output, as we show in Section 6.5 below that output growth has played a larger role in driving the *level* of equity valuations over our sample.

To clarify the contributions since 1989 — the portion of the sample with extremely high growth in both equity valuations and earnings shares — Figure 10 plots the contributions of factor shares and the risk price, respectively, for this subsample. This figure shows that the

Figure 10: Market Equity-Output Ratio Decomposition: 1989 - 2017 Subsample



Notes: This figure exhibits the observed market equity-to-output series along with the model-implied variation in the series attributable to certain latent components over the subsample 1989:Q1 - 2017:Q4. The left panel displays the combined contribution of the earnings share \bar{s}_t while the right panel displays the combined contribution of the risk price components \bar{x} . The red center line corresponds to the median of the distribution of outcomes, accounting for both parameter and latent state uncertainty, while the dark and light blue bands correspond to 66.7% and 90% credible sets, respectively.

prime driver of valuations over this period is the rising profit share. Movements in the risk price explain much of the cyclical variation, but fail to capture the overall upward trend.

6.5 Growth Decompositions

In this section, we summarize the contributions of the different components over our sample. As in Figure 9, we compute the contribution of each component using the counterfactual growth in equity values allowing that component to vary while holding all others fixed at their initial values. By construction, these components sum to 100% of the observed variation in equity values, since our latent state estimates perfectly match the observed log market equity-to-output ratio py_t as well as output growth Δy_t at each point in time.

Table 2 presents the decompositions for the total change in the log ratio of market equity to corporate NVA ($p_t - y_t$) in Panel A and the log of real market equity (p_t) in Panel B. These decompositions are either computed over the whole sample or over the subperiod before or since 1989.³² The year 1989 separating the two subperiods is chosen visually due to the sharp change in the growth trend of profit shares around this date. However, we

³²The growth decompositions for the log level of real market equity p_t are computed by adding back the cumulated growth Δy_t in real per-capita output (net value added) to the growth Δpy_t . Since Δy_t is deflated by the implicit price deflator for net value added, the decomposition for p_t pertains to the value of per-capita market equity deflated by the implicit NVA price deflator.

Table 2: Growth Decomposition

Contribution	1952-2017	1952-1988	1989-2017
<i>Panel A: Decomposition of Market Equity / NVA</i>			
Total	222.41%	-10.29%	244.30%
Factor Share (s_t)	41.51%	149.61%	54.15%
	[15.61%, 75.36%]	[381.84%, -58.34%]	[24.96%, 89.21%]
Orth. Risk Price (x_t)	56.90%	-218.97%	28.06%
	[22.44%, 85.08%]	[36.72%, -496.98%]	[-7.37%, 58.02%]
Risk-Free Rate (δ_t)	6.92%	136.14%	19.26%
	[0.10%, 14.20%]	[228.75%, 54.19%]	[13.40%, 26.09%]
Real PC Output Growth (\tilde{g}_t)	-5.33%	33.22%	-1.47%
	[-16.92%, 4.98%]	[168.03%, -86.06%]	[-8.85%, 5.86%]
<i>Panel B: Decomposition of Real PC Market Equity</i>			
Total	1277.12%	150.36%	429.70%
Factor Share (s_t)	18.53%	-17.69%	40.16%
	[6.97%, 33.64%]	[-45.16%, 6.90%]	[18.51%, 66.16%]
Orth. Risk Price (x_t)	25.40%	25.90%	20.81%
	[10.02%, 37.98%]	[-4.34%, 58.78%]	[-5.47%, 43.03%]
Risk-Free Rate (δ_t)	3.09%	-16.10%	14.29%
	[0.04%, 6.34%]	[-27.05%, -6.41%]	[9.94%, 19.35%]
Real PC Output Growth ($g + \tilde{g}_t$)	52.98%	107.90%	24.75%
	[47.81%, 57.59%]	[91.95%, 122.00%]	[19.27%, 30.19%]

Notes: The table presents the growth decompositions for the real per-capita value of market equity. The row “Total” displays the total growth in market equity over this period, either scaled by NVA or in levels. The remaining rows report the share of this overall growth explained by each component, obtained by measuring the difference in implied growth between the data and a counterfactual path in which that variable is held fixed at its initial value for the relevant subsample. To ensure an additive decomposition, we measure the share of total growth explained in logs. The reported statistics are means over shares computed from 10,000 equally spaced parameter draws from our MCMC chain. Below each set of means in brackets are the 5th and 95th percentiles over the same distribution, providing a 90% credible set that accounts for both parameter and latent state uncertainty. Further decompositions into low-frequency and high-frequency components can be found in Appendix Tables A.2 and A.3. The sample spans the period 1952:Q1-2017:Q4.

note that a major advantage of our approach is that our quarter-by-quarter estimates allow decompositions of any possible subperiod, making this choice much less important than for steady state analyses that depend crucially on how the different eras are defined. To this end, Appendix A.14 presents relative contributions from all possible start dates to the end of the sample, showing that the strength of the factor share contribution is generally large and stable outside of the dot-com boom and the post-2010 era.

Panel A decomposes the growth in the ratio of market equity to output, corresponding to our results in Figures 9 and 10.³³ Our results show that the majority (54%) of the large rise in this ratio since 1989, and 42% of the overall rise since 1952, is explained by rising profit shares, pointing to a leading role for this factor in driving equity valuations. Since 1989, both risk prices and risk-free rates have played smaller but nontrivial roles, explaining 28% and 19%, respectively, while output growth played a negligible role (-1%). Over the full sample, only risk prices are important among factors other than profit shares, explaining 57% of growth, compared to just 7% for risk-free rates and -5% for output growth.

Panel B recomputes this decomposition for the log level of real per-capita asset prices p_t , without scaling by output. As a result, cumulated output growth from both trend growth (g) and deviations from trend (\tilde{g}_t) will now contribute to growth in p_t by increasing underlying production and cash flows. We find that, from 1989 to 2017, output growth explained only 25% of the rise in the value of market equity, showing that the vast majority of the huge valuation gains over this 29-year period were due to factors other than economic productivity. In fact, the contribution of rising profit shares alone (40%) is 60% larger than the contribution of output growth.

These patterns may be contrasted against the previous subsample, from 1952 to 1988, when economic growth accounted for 107% of the rise in the stock market, while factor share movements contributed negatively to the market's rise. These findings underscore a striking aspect of post-war equity markets: in the longer 37-year subsample for which equity values grew comparatively slowly, economic growth propelled the market, while factor shares played a negative role. However, the market experienced close to three times greater growth in value in the shorter period from 1989 to 2017, when factor share shocks reallocated rewards to shareholders even as economic growth slowed.

Combining these periods, we find that output growth explains only 53% of total log growth in market equity over the full sample despite being the only non-stationary variable in our model, demonstrating the importance of non-output factors even over a horizon as long as 66 years. Factor shares explained 19% of the full sample rise, while the declining risk price contributed 25%, and real interest rates contributed a much smaller 3%.

6.6 Asset Pricing Moments

Up to this point, our model estimates have decomposed the contributions of various forces over our data sample. At the same time, the observed sample is only a single realization of

³³We focus on the full sample and subsample since 1989, since the 1952 to 1989 subsample shows close to zero growth, making the decomposition uninformative.

Table 3: Asset Pricing Moments

Variable	Unconditional		Fitted		Data	
	Mean	StD	Mean	StD	Mean	StD
Log Equity Return	6.405	17.845	8.276	16.626	8.934	15.949
Log Risk-Free Rate	1.074	1.748	1.111	1.933	1.111	1.933
Log Excess Return	5.331	17.939	7.166	16.595	7.458	16.679
Log Price-Payout Ratio	3.387	0.425	3.235	0.358	3.385	0.470
Log Earnings Growth	2.188	8.922	2.819	11.911	2.819	11.911
Log Payout Growth	2.185	16.019	3.374	20.880	4.597	30.049
Log Earnings Share Growth	-0.004	8.290	0.624	10.459	0.624	10.459
Log Payout Share Growth	-0.008	15.674	1.180	19.662	2.403	28.309

Notes: All statistics are computed for annual (continuously compounded) data and reported in units of percent. For annualization, returns, earnings, and payouts are summed over the year in levels. Log growth of earnings, payouts, the earnings share, the payout share, and the price-payout ratio are computed using these annual sums of earnings and payouts, as well as Q4 equity prices from each year. “Unconditional” numbers represent averages across 10,000 simulations of the model of the same size as our data sample. “Fitted” numbers use the estimated latent states fitted to observed data in our historical sample. The sample spans the period 1952:Q1-2017:Q4.

possible paths. We now use the model to compare the observed asset pricing moments over our sample to the unconditional distributions of these moments implied by the model.

The results can be seen in Table 3. The columns labeled “Unconditional” report averages across 10,000 simulations of the model, evaluated at 10,000 equally spaced parameter draws from our MCMC chains, each using a sample length equal to that of our historical sample. Next, the columns labeled “Fitted” compute moments using draws of the estimated latent states conditional on the actual historical sample, computed using the disturbance smoother. Finally, the columns labeled “Data” report the actual sample moments of our observed data series. Note that the “Fitted” and “Data” moments are identical by construction for the risk-free rate, earnings growth, and earnings share growth, because we use these series as observables and fit their behavior exactly over the sample with no measurement error.

For series not matched by construction, Table 3 shows that the fitted moments are close to the data. Importantly, the model’s operating leverage effect allows it to match the fact that both the mean and volatility of growth in the log payout share $c_t - y_t$ are substantially higher than the corresponding moments for growth in the log earnings share $e_t - y_t$.³⁴ At the same time, the fact that our Fitted mean payout growth slightly understates the data

³⁴While the volatility is scaled upward by exactly $\xi = 1.890$ in the model’s quarterly simulations, this ratio differs in Table 3 due to our conversion of the data to annual frequency.

suggests that our calibration for ξ is conservative, and that our model is not overstating the impact of the leverage effect. This small understatement of cash flow growth leads the fitted log excess return (7.2%) to marginally understate its data counterpart (7.5%).

Turning to risk premia, Table 3 shows that the model’s unconditional average log excess equity return is 5.3% per annum. This moment represents the mean risk premium implied by our parameter estimates, reflecting compensation for bearing risk in the stock market. By contrast, the mean *fitted* excess stock market return is 7.2%, which reflects not only ex-ante risk compensation, but also the effect of unexpected realizations of shocks over our sample.

This difference between our fitted and unconditional mean excess returns implies that high returns to holding equity in the post-war period have been driven in large part by a highly unusual sample, one characterized by a long string of factor share shocks that redistributed rewards from productive activity toward shareholders. Our estimates imply that 1.9pp per annum of the post-war mean log return on stocks in excess of a T-Bill rate is attributable to these and other realized shocks, leading the average realized excess return to overstate the true unconditional equity risk premium by 34%.³⁵ These findings imply substantial bias from the common practice of using the sample mean excess return as an estimate of the average equity risk premium, even over this 66-year post-war period.³⁶

Last, we note that in our estimation, the observable measure of the risk premium rp_t we use is the SVIX-implied risk premium from Martin (2017). Technically speaking, this series is a lower bound on the true risk premium, and not an exact point estimate of it. Although Martin (2017) provides statistical evidence that the lower bound is tight, holding with or close to equality, this measure might understate the true risk premium, perhaps contributing to our result that excess returns exceeded their unconditional average over our sample.

To address this, Appendix A.15 presents an extension of the model in which the SVIX-implied measure rp_t is allowed to deviate on average from the true model risk premium. After estimating this model, we find that it cannot reject that the bias is zero (meaning that the lower bound holds with equality), while the median estimate of this bias implies that the SVIX measure is *higher* on average than the true risk premium — the opposite of our original concern. Similarly, the implied gaps between realized and unconditional excess returns, while slightly lower than in our baseline estimates, remain substantial and are statistically indistinguishable from our baseline. For these reasons, we believe our results are not driven by the use of the SVIX lower bound as our measure of the risk premium.

³⁵As alternative to taking means over our 10,000 simulations, we could compute sample medians. In this case, the gap would be even larger, with median fitted excess returns of 7.2% per annum exceeding median unconditional realized returns of 4.9% by 2.3pp, or 47% of the unconditional median.

³⁶Avdis and Wachter (2017) arrive at a similar conclusion using a different estimation methodology.

6.7 Interest Rate Persistence

Our results differ from contemporaneous papers such as Corhay, Kung, and Schmid (2020), Eggertsson, Robbins, and Wold (2021), and Farhi and Gourio (2018). While these papers find a crucial role for falling interest rates in driving the increase in asset prices over recent decades, we find that interest rates account for only 14% of stock market growth since 1989. Moreover, Corhay, Kung, and Schmid (2020) and Farhi and Gourio (2018) conclude that risk premia have risen over this period, while Appendix Figure A.4 shows that we estimate risk premia to have fallen to historically low levels by the end of our sample.

These differing results stem from the different estimation approaches behind them. While we estimate our model directly on the time series, allowing for shocks to enter with a variety of estimated persistences, the papers cited above measure changes across steady states, in which parameters can change only permanently. As a result, these papers interpret the observed drop in risk-free rates as a permanent shift, causing major changes in how long-term cash flows are discounted, and leading to a huge increase in market value. Since the implied increase in market value from this permanent fall risk-free rates is even larger than the actual increase in the data, Corhay, Kung, and Schmid (2020) and Farhi and Gourio (2018) infer that risk premia must have risen to match the realized growth in asset prices.

In contrast, our model views changes in interest rates as far from permanent, with a median estimate of their low-frequency quarterly persistence of 0.965. As a result, investors in our model did not believe that interest rates would remain permanently high in the 1980s, nor did they expect them to remain permanently low at the end of our sample, dampening the effect of falling rates on the value of market equity. This smaller contribution from interest rates allows us to match the observed rise in asset prices in an environment with falling risk premia. In particular, we show in Appendix A.8 that our model implies equity premia that have been falling for decades, and that by 2017:Q4 had reached lows previously seen only during the tech boom in 2000 and the twin housing/equity booms in 2006.

To confirm that it is our estimated levels of persistence, and not some other variation in model structure, that cause these differences, we present in Appendix A.9 a counterfactual version of our model in which all movements in risk-free rates are effectively permanent. Under this counterfactual model, we find that falling risk-free rates would have an enormous effect on asset prices, explaining 74% of the rise in the value of market equity from 1989 to 2017. At the same time, our estimated positive contribution to ME/Y from falling risk prices and risk premia in Table 2 becomes a negative contribution reflecting rising risk prices and risk premia in our counterfactual. Thus, our model is able to reproduce the findings of e.g., Farhi and Gourio (2018) and Corhay, Kung, and Schmid (2020) if we force the model

to use a near-permanent process for risk-free rates.

These results show that the persistence of risk-free rates is central to determining their importance for equity values. We view our less-persistent estimates, and therefore our findings, as strongly preferred by the data. Recall that, because we include the 10-year SPF real rate forecast as an observable, our estimates of the risk-free rate process match this forecast in each period in which it is available. Since we also match the current real short rate, our model matches the expected persistence of real interest rates as perceived by forecasters at each point in time. This strong discipline allows us to precisely estimate the risk-free rate persistence, which we can bound far from unity. This can be seen visually in Figure 6, as the sample autocorrelation of our real risk-free rate series decreases rapidly with the lag order, decreasing by half within the first 15 quarters and falling close to zero at the 10-year horizon — a pattern inconsistent with a process dominated by permanent changes. Our model is able to match this pattern well, and does not understate the autocorrelation at long horizons.

At the same time, we note that in our model, the contribution of risk-free rates is restricted to variation in the short rate orthogonal to the other components. As such, it does not account for any indirect effects on term premia, risk premia, or cash flows, that may accompany shocks to the risk-free rate. In practice, monetary policy may have a large influence on term premia (e.g., Gürkaynak, Sack, and Swanson (2005)), the equity market risk premium (e.g., Bianchi, Lettau, and Ludvigson (2022); Bianchi, Ludvigson, and Ma (2022)) and potentially on forecasts of future cash flows (e.g., Nakamura and Steinsson (2018)). Such correlations would allow for large impacts on prices in our model even if the direct effect through the risk-free rate channel were limited.³⁷

To study the strength of this channel for term premia, we investigate how well our model is able to explain variation in long real bond yields in the data. Since our definition of the risk-free rate component is restricted to the path of short rates, it is possible that time-varying term premia beyond the scope of our model could be influencing the value of other long-maturity assets like equities. In this case, the model would attribute such movements to changes in the risk price, leading to a potentially different interpretation of our risk price results. Nonetheless, while we do not directly target long bond yields in our estimation of the model, we show in Appendix A.10 that the model provides a good fit for the evolution of 10-year TIPS yields at low frequencies, implying that these uncaptured portions of term premia may be small in practice.

A final caveat to these results is that they are based on the backward-looking statistical

³⁷For example, our findings are not directly comparable to those in Bianchi, Lettau, and Ludvigson (2022), who find evidence of a low-frequency component in interest rates driven by monetary policy, since the monetary policy component they uncover is correlated with risk-premium variation, whereas we identify only the mutually uncorrelated components of risk-free rate and equity premium variation.

properties of risk-free rates in the historical data, during which time interest rate fluctuations did not appear statistically permanent. If the economy had instead undergone a structural break, with interest rates changing much more persistently than in the past, our model might understate the effect of such a change. Regardless, this type of misattribution would primarily affect the estimated contribution of the risk price, which effectively serves as our residual, and should be largely orthogonal to our core results on the role of factor shares, which are heavily disciplined by their own data series. We confirm this in Appendix A.9, showing that the estimated contribution of factor shares is nearly identical to our baseline estimates, even in our counterfactual where risk-free rates are effectively permanent.

7 Robustness

To close our results, we examine the robustness of our main finding on the role of factor shares to our key modeling and calibration assumptions.

7.1 Robustness: The Leverage Risk Effect

For our first set of robustness checks, we relax the tight parametric link between factor shares and risk premia that stems from our microfounded leverage risk effect, captured in our model solution by the term $\xi(\xi - 1)$ in equation (15). To do this, we solve an “Estimated Risk” model in which we instead define Γ using

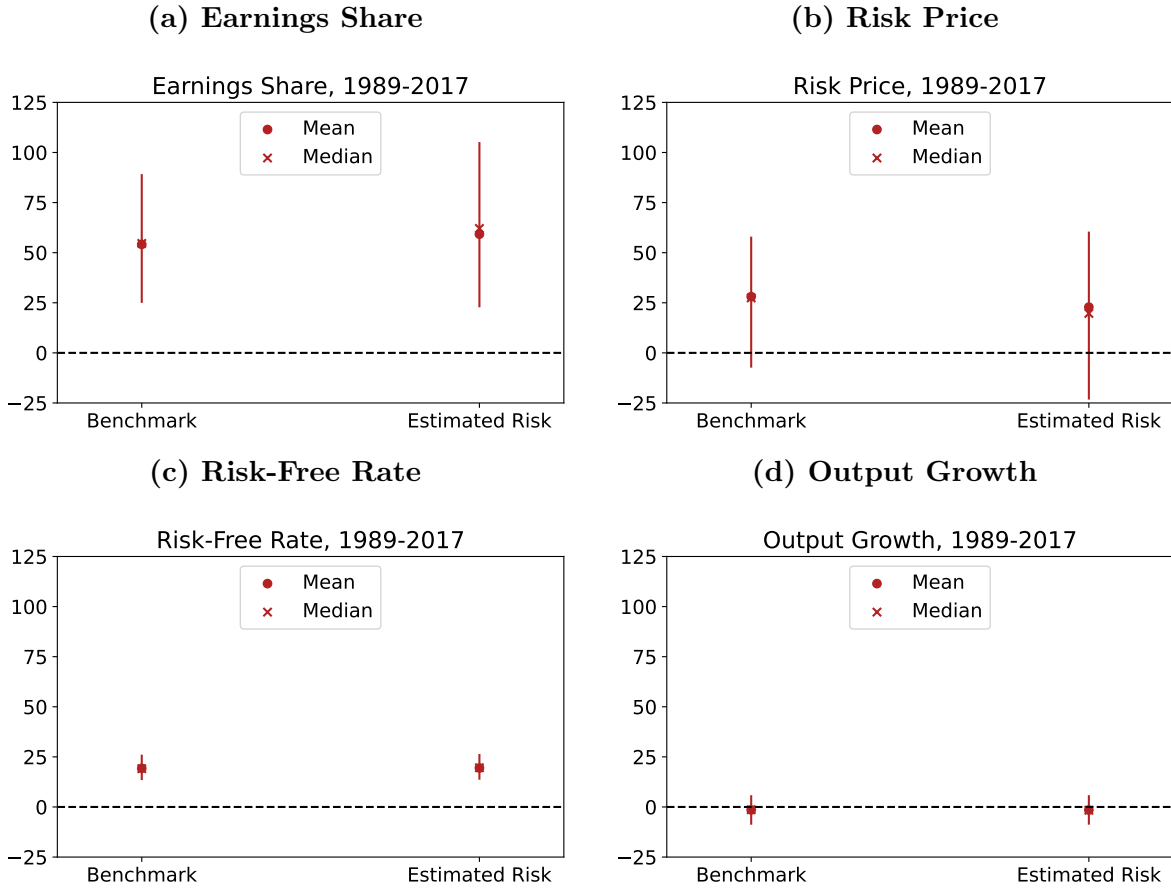
$$\Gamma' = \bar{x}\lambda\mathbf{1}'\Phi_s \tag{19}$$

where λ is a new parameter to be estimated. This unrestricted specification nests our benchmark model for $\lambda = \xi(\xi - 1)$, and nests a model without any leverage risk effect for $\lambda = 0$. We repeat our estimation procedure described in Section 5 for the unrestricted model, with no restriction on λ other than $\lambda \geq 0$.³⁸ Thus, to the extent that our benchmark assumptions regarding the leverage risk effect are misspecified, the Estimated Risk model is able to weaken or shut down these effects to better match the data.

We find that our parameter estimates from the Estimated Risk model are supportive of our baseline model and far from rejecting it. In our baseline model, our theory and calibration imply the exact value $\lambda = 1.683$. In our Estimated Risk model, the median value of λ , now freely estimated, is 1.567, with a range of [0.350, 2.841] from the 5th to 95th

³⁸This assumption avoids a numerical issue where the MCMC chain can get “stuck” in a local maximum with $\lambda \rightarrow -\infty$, even though these points have low likelihood and are far from a global maximum. In practice, our estimates are far from this lower bound, so this assumption has minimal impact on our results.

Figure 11: Model Comparison, Contributions to ME/Y



Notes: These figures plot the growth decompositions for the real value of market equity under alternative model specifications, with each panel corresponding to a different fundamental component, and the different lines in each panel corresponding to alternative models. Growth decompositions are obtained by measuring the difference in implied growth of py_t between the data and a counterfactual path in which that variable is held fixed at its initial value for the relevant subsample. To ensure an additive decomposition, we measure the share of total growth explained in logs. Each model reports the mean and median in red, while error bars span from the 5th to 95th percentiles.

percentiles. Thus, we freely estimate values of λ that are close to (and clearly cannot reject) the implied value from our restricted baseline model.

More important than the value of λ itself is its impact on our main results. To this end, Figure 11 compares the estimated contributions to the rise in market equity valuations since 1989 across our Benchmark and Estimated Risk models. The figure shows that this more flexible specification delivers a decomposition nearly identical to the Benchmark model. Although the error bars on the Estimated Risk model are slightly wider, likely due to the inclusion of an additional free parameter, the point estimates and general ranges are highly

similar. To be precise, the Estimated Risk model delivers average contributions to $p_t - y_t$ from 1989 to 2017 of (59%, 23%, 19%, -2%) for the earnings share, risk price, risk-free rate, and output growth respectively, compared to equivalent values of (54%, 28%, 19%, -1%) for the Benchmark model. Because the model was free to choose an arbitrary strength for the influence of the earnings share on risk premia, these highly similar results, featuring a slightly stronger contribution of factor shares, provide strong quantitative support for our specification of the leverage risk effect.

7.2 Robustness: Cash Flows vs. Risk Premia

For our final set of results, we decompose the contribution of the earnings share into the components driven by the change in cash flows vs. the change in the risk premium, then consider robustness to alternative degrees of earnings share persistence. We begin with the workhorse decomposition of Campbell and Shiller (1989) for the price-payout ratio:

$$pc_t = \text{const} + \mathbb{E}_t \sum_{j=0}^{\infty} \kappa_1^j \Delta c_{t+j+1} - \mathbb{E}_t \sum_{j=0}^{\infty} \kappa_1^j r_{t+j+1}.$$

Since the log ME/Y ratio py_t is equal to the sum $pc_t + cy_t$, we can apply a single restriction — our loglinear approximation for the cash flow share of output (11) — to obtain³⁹

$$py_t = \text{const} + \underbrace{\xi s_t + \xi \mathbb{E}_t \sum_{j=0}^{\infty} \kappa_1^j \Delta s_{t+j+1}}_{\text{direct cash flow component} = py_t^{CF}} + \mathbb{E}_t \sum_{j=0}^{\infty} \kappa_1^j \Delta y_{t+j+1} - \mathbb{E}_t \sum_{j=0}^{\infty} \kappa_1^j r_{t+j+1}. \quad (20)$$

The term in braces represents the contribution of the earnings share process s_t to the log ratio of market equity to output, directly through cash flows, while ignoring any influence on risk premia. In our structural model, this component, which we denote py_t^{CF} is given by

$$py_t^{CF} = \xi \left\{ \bar{s} + \mathbf{1}' \left[\mathbf{I} - \mathbf{1}'(\mathbf{I} - \Phi_s)(\mathbf{I} - \kappa^1 \Phi_s)^{-1} \right] \tilde{\mathbf{s}}_t \right\}. \quad (21)$$

We can therefore compare the growth of py_t^{CF} and py_t to compute the contribution of growth in the log ME/Y ratio explained by the direct cash flow effect.

The results are displayed in Table 4. Under our Benchmark model estimates, the direct change in cash flows explains 31% of the rise in the py ratio since 1989. Since our mean estimate of the total contribution of earnings share changes to py (rather than to p as

³⁹We thank our discussant, Valentin Haddad, for this helpful suggestion.

Table 4: Comparison, Share of ME/Y Explained (1989 - 2017)

	AR(1) Models (by ϕ_s)				
	Bench.	0.980	0.990	0.995	1.000
Cash Flow Contribution	31.09%	28.71%	45.08%	62.68%	102.15%

Notes: This table displays the share of the growth in the log market equity to output ratio explained by the implied contributions of the earnings share via cash flows, defined as $(py_{2017:Q4}^{CF} - py_{1989:Q1}^{CF}) / (py_{2017:Q4} - py_{1989:Q1})$, where py is the log ratio of market equity to output, and py^{CF} is the direct cash-flow component.

presented in Table 2) is 54%, these results imply that 57% of our overall earnings share contribution in the Benchmark model is due to the direct influence on cash flows, with the remaining share due to the influence on risk premia through the leverage risk effect.

While these results already imply that the direct cash flow component is an important driver of market equity over this period, with a magnitude similar to total economic growth, these results may understate the direct cash flow contribution, as the Benchmark model appears to understate the empirical autocorrelation of factor shares. This can be seen in Figure 6 Panel (b), which shows that small sample autocorrelations from our model simulations lie below the true sample autocorrelations on average at all lag orders, including the longest.

This downward bias in persistence estimates is common in statistical applications, and is not straightforward to correct in our baseline model.⁴⁰ Instead, we provide results from a simpler parametric specification to demonstrate the strength of the cash flow effect at plausible levels of bias-corrected persistence. In place of our full structural model, we approximate s_t by a simpler AR(1) process

$$s_{t+1} = (1 - \phi_s)\bar{s} + \phi_s s_t + \varepsilon_{s,t+1}$$

which implies $\mathbb{E}_t \Delta s_{t+j+1} = -(1 - \phi_s)\phi_s^j s_t$. Substituting, solving for the geometric sum, and omitting all terms not entering our “direct cash flow component” above, we obtain the following expression for py_t^{CF} under the AR(1) specification:

$$py_t^{CF} = \xi \left[1 + \left(\frac{1 - \phi_s}{1 - \kappa_1 \phi_s} \right) \right] s_t.$$

⁴⁰Because the model has freedom to allocate between the low-frequency and high-frequency components, manually increasing the persistence of the low-frequency component, or even both components, can lead to the model assigning more variation to the high-frequency component, leaving the overall results unchanged.

For given parameter choices of ϕ_s , ξ , and κ_1 , we can thus directly evaluate the contribution of the earnings share over time, without taking a stand on the remaining blocks of the model. We obtain ξ and κ_1 directly from the data, using $\xi = 1.890$, as explained above, and calibrating $\kappa_1 = \exp(\bar{pc}) / \exp(\bar{pc} + 1)$, where we obtain $\bar{pc} = 4.823$ as the average of our log price-to-payout ratio from our sample.⁴¹

The implied contributions since 1989:Q1 are reported in Table 4 for a range of possible persistences: $\phi_s \in \{0.98, 0.99, 0.995, 1.000\}$. Appendix Figure A.14 shows that the implied py_t^{CF} series are reasonable, and track the true py_t series relatively well over time, even at the higher persistence values, providing support for the specification. Table 4 shows that the direct cash flow contribution is nontrivial even for a persistence of 0.98 — the OLS estimate of the AR(1) persistence — while a unit root profit share process would explain more than 100% of the rise in the log ME/Y ratio over this period.

The question then becomes which persistence value is most appropriate. A bootstrap bias corrected AR(1) estimate yields $\phi_s = 0.990$ (see Appendix Section A.6), which corresponds to nearly half of the rise in the log ME/Y ratio being explained through the direct cash flow channel. For equity values, however, the autocorrelation at the first lag is not as important as at longer lags. Appendix Figure A.15 reproduces the simulated autocorrelation plots from Figure 6 for these AR(1) models, showing that even more persistent processes, such as $\phi = 0.995$, or even a unit root, provide a better fit of the observed longer autocorrelation pattern for s_t . Although the empirical autocorrelations in the data decay substantially with the lag order, our simulation results indicate that this is an endemic feature of sample autocorrelations given our sample size, even for extremely persistent or unit root processes, and an augmented Dickey-Fuller test fails to reject the presence of a unit root in s_t (p -value 0.164). From our results in Table 4, a persistence of 0.995 or higher would imply direct cash flow contributions in excess of 60% over the 1989 - 2017 period.

Overall, this analysis implies that under minimal assumptions — that investment is proportional to output, not earnings, and that the earnings share follows a simple AR(1) process — the data are consistent with a strong direct effect of the earnings share on the value of market equity over the last three decades, and that our benchmark estimates if anything provide a lower bound on this contribution.⁴²

⁴¹This value of κ_1 differs slightly from our baseline results, in which κ_1 is pinned down by the equilibrium pd ratio in the model.

⁴²These simpler models, while providing robustness, are not a complete substitute for our full structural model. First, they only account for the contribution of a single component (factor shares) that is restricted to influencing cash flows and not risk premia, whereas our full model provides an internally consistent decomposition of the full change in equity values among multiple fundamental factors. Moreover, because AR(1) models do not distinguish between low-frequency and high-frequency components, they feature excessive volatility in the implied contribution of factor shares at higher frequencies. While these simpler models

8 Conclusion

In this paper, we investigate the causes of rising equity values over the post-war period. We do this by estimating a flexible parametric model of how equities are priced that allows for influence from a number of mutually uncorrelated latent components, while at the same time inferring what values those components must have taken over our sample to explain the data. The identification of mutually uncorrelated components and the specification of a log linear model allow us to precisely decompose the observed market growth into distinct component sources at each point in time.

We confront our model with data on equity values, output, the earnings share of output, interest rates, and a measure of the conditional equity premium implied by options data. We find that the high returns to holding equity over the post-war era have been attributable in large part to an unpredictable string of factor share shocks that reallocated rewards away from labor compensation and toward shareholders. Indeed, our estimates suggest that at least 1.9pp of the post-war average annual log equity return in excess of a short-term interest rate is attributable to this string of reallocative shocks, rather than to genuine compensation for bearing risk. This estimate implies that the sample mean log excess equity return overstates the true risk premium by 34%.

Factor share shocks alone would have driven a 95% increase in the value of real per-capita market equity since 1989, explaining 40% of actual log growth over this period. Equity values were modestly boosted since 1989 by persistently declining interest rates and a decline in the price of risk, which contributed 14% and 21%, respectively. But growth in the real value of aggregate output contributed just 25% since 1989 and just 53% over the full sample. By contrast, economic growth was overwhelmingly important for rising equity values from 1952 to 1988, where it explained over 100% of the market's rise. Still, this 37-year period generated only one third the growth in equity wealth created in the 29 years since 1989. In this sense, factor shares, far more than economic growth, have been the preponderant measure of fundamental value in the stock market over the last three decades.

References

Ait-Sahalia, Yacine, Jonathan A. Parker, and Motohiro Yogo. 2004. "Luxury Goods and the Equity Premium." *Journal of Finance* 59:2959–3004.

Ang, Andrew and Monika Piazzesi. 2003. "A No-Arbitrage Vector Autoregression of Term Structure

may deliver reasonable results over particular periods, especially at longer horizons where the low-frequency component should dominate, they may deliver inaccurate results over shorter horizons or even longer spans that begin or end in a period with large deviations of the high-frequency component in either direction.

- Dynamics With Macroeconomic and Latent Variables.” *Journal of Monetary Economics* 50:745–787.
- Atkeson, Andrew. 2020. “Alternative facts regarding the labor share.” *Review of Economic Dynamics* 37:S167–S180.
- Avdis, Efstathios and Jessica A Wachter. 2017. “Maximum Likelihood Estimation of the Equity Premium.” *Journal of Financial Economics* 125 (3):589–609.
- Bansal, Ravi and Amir Yaron. 2004. “Risks for the Long-Run: A Potential Resolution of Asset Pricing Puzzles.” *Journal of Finance* 59 (4):1481–1509.
- Barkai, Simcha. 2020. “Declining labor and capital shares.” *The Journal of Finance* 75 (5):2421–2463.
- Barro, Robert J. 2009. “Rare Disasters, Asset Prices, and Welfare Costs.” *American Economic Review* 99 (1):243–64.
- Bekaert, Geert, Eric Engstrom, and Yuhang Xing. 2009. “Risk, Uncertainty, and Asset Prices.” *Journal of Financial Economics* 91 (1):59–82.
- Bertaut, Carol, Beau Bressler, and Stephanie Curcuru. 2021. “Globalization and the Reach of Multinationals Implications for Portfolio Exposures, Capital Flows, and Home Bias.” *Journal of Accounting and Finance* 21 (5):92–104.
- Bianchi, Francesco, Martin Lettau, and Sydney C Ludvigson. 2022. “Monetary policy and asset valuation.” *The Journal of Finance* 77 (2):967–1017.
- Bianchi, Francesco, Sydney C Ludvigson, and Sai Ma. 2022. “Belief distortions and macroeconomic fluctuations.” *American Economic Review* 112 (7):2269–2315.
- Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer. 2019. “Diagnostic expectations and stock returns.” *The Journal of Finance* 74 (6):2839–2874.
- Caballero, Ricardo J, Emmanuel Farhi, and Pierre-Olivier Gourinchas. 2017. “Rents, technical change, and risk premia accounting for secular trends in interest rates, returns on capital, earning yields, and factor shares.” *American Economic Review* 107 (5):614–20.
- Campbell, John Y. and John H. Cochrane. 1999. “By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior.” *Journal of Political Economy* 107:205–251.
- Campbell, John Y, Carolin Pflueger, and Luis M Viceira. 2020. “Macroeconomic drivers of bond and equity risks.” *Journal of Political Economy* 128 (8):3148–3185.
- Campbell, John Y. and Robert J. Shiller. 1989. “The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors.” *Review of Financial Studies* 1 (3):195–228.
- Chen, Xiaohong, Jack Favilukis, and Sydney C. Ludvigson. 2014. “An Estimation of Economic Models with Recursive Preferences.” *Quantitative Economics* 4 (1):39–83.
- Christiano, Lawrence J. and Terry J. Fitzgerald. 1999. “The Band-Pass Filter.” Federal Reserve Bank of Cleveland Working Paper 9906.

- Cochrane, John H. 2005. *Asset Pricing, Revised Edition*. Princeton, NJ: Princeton University Press.
- . 2011. “Discount Rates.” *Journal of Finance*, forthcoming American Finance Association Presidential Speech.
- Constantinides, George M. and Darrell Duffie. 1996. “Asset Pricing With Heterogeneous Consumers.” *Journal of Political Economy* 104:219–40.
- Corhay, Alexandre, Howard Kung, and Lukas Schmid. 2020. “Competition, markups, and predictable returns.” *The Review of Financial Studies* 33 (12):5906–5939.
- Dai, Qiang and Kenneth Singleton. 2002. “Expectation Puzzles, Time-Varying Risk Premia, and Affine Models of the Term Structure.” *Journal of Financial Economics* 63:415–441.
- Danthine, Jean-Pierre and John B. Donaldson. 2002. “Labour Relations and Asset Returns.” *Review of Economic Studies* 69 (1):41–64.
- Davydiuk, Tetiana, Scott Richard, Ivan Shaliastovich, and Amir Yaron. 2023. “How Risky Are US Corporate Assets?” *The Journal of Finance* 78 (1):141–208.
- Donangelo, Andres, Francois Gourio, Matthias Kehrig, and Miguel Palacios. 2019. “The cross-section of labor leverage and equity returns.” *Journal of Financial Economics* 132 (2):497–518.
- Duffie, Darrell and Rui Kan. 1996. “A yield-factor model of interest rates.” *Mathematical finance* 6 (4):379–406.
- Durbin, James and Siem Jan Koopman. 2002. “A simple and efficient simulation smoother for state space time series analysis.” *Biometrika* 89 (3):603–616.
- Eggertsson, Gauti B, Jacob A Robbins, and Ella Getz Wold. 2021. “Kaldor and Piketty’s facts: The rise of monopoly power in the United States.” *Journal of Monetary Economics* 124:S19–S38.
- Eisfeldt, Andrea L, Antonio Falato, and Mindy Z Xiaolan. 2023. “Human capitalists.” *NBER Macroeconomics Annual* 37 (1):1–61.
- Eisfeldt, Andrea L and Dimitris Papanikolaou. 2013. “Organization capital and the cross-section of expected returns.” *The Journal of Finance* 68 (4):1365–1406.
- . 2014. “The value and ownership of intangible capital.” *American Economic Review* 104 (5):189–94.
- Estrada, Javier. 2012. “Blinded by growth.” *Journal of Applied Corporate Finance* 24 (3):19–25.
- Farhi, Emmanuel and François Gourio. 2018. “Accounting for Macro-Finance Trends: Market Power, Intangibles, and Risk Premia.” *Brookings Papers on Economic Activity* :147.
- Favilukis, Jack and Xiaoji Lin. 2013. “The Elephant in the Room: The Impact of Labor Obligations on Credit Risk.” <https://sites.google.com/site/jackfavilukis/WageCreditRisk.pdf>.
- . 2016a. “Does wage rigidity make firms riskier? Evidence from long-horizon return predictability.” *Journal of Monetary Economics* 78:80–95.

- . 2016b. “Wage rigidity: A quantitative solution to several asset pricing puzzles.” *The Review of Financial Studies* 29 (1):148–192.
- Gelman, Andrew, Hal S Stern, John B Carlin, David B Dunson, Aki Vehtari, and Donald B Rubin. 2013. *Bayesian Data Analysis*. Chapman and Hall/CRC.
- Gomez, Matthieu. 2016. “Asset prices and wealth inequality.” Unpublished paper: Princeton. <http://www.princeton.edu/~mattg/files/jmp.pdf>.
- Greenwald, Daniel, Martin Lettau, and Sydney C. Ludvigson. 2014. “Origins of Stock Market Fluctuations.” National Bureau of Economic Research Working Paper No. 19818.
- Gürkaynak, Refet S., Brian Sack, and Eric Swanson. 2005. “The sensitivity of long-term interest rates to economic news: evidence and implications for macroeconomic models.” *The American Economic Review* 95 (1):425–436.
- Güvenen, Fatih, Raymond J Mataloni Jr, Dylan G Rassier, and Kim J Ruhl. 2022. “Offshore profit shifting and aggregate measurement: Balance of payments, foreign investment, productivity, and the labor share.” *American Economic Review* 112 (6):1848–1884.
- Güvenen, M. Fatih. 2009. “A Parsimonious Macroeconomic Model for Asset Pricing.” *Econometrica* 77 (6):1711–1740.
- Haario, Heikki, Eero Saksman, Johanna Tamminen et al. 2001. “An Adaptive Metropolis Algorithm.” *Bernoulli* 7 (2):223–242.
- Hall, Robert E. 2000. “E-Capital: The Link Between the Stock Market and the Labor Market in the 1990s.” *Brookings Papers on Economic Activity* 2:73–118.
- Herbst, Edward and Frank Schorfheide. 2014. “Sequential Monte Carlo Sampling for DSGE Models.” *Journal of Applied Econometrics* 29 (7):1073–1098.
- Jermann, Urban. 1998. “Asset Pricing in Production Economies.” *Journal of Monetary Economics* 41 (2):257–275.
- Karabarbounis, Loukas and Brent Neiman. 2013. “The Global Decline of the Labor Share.” *Quarterly Journal of Economics* 129 (1):61–103.
- Klein, Lawrence R and Richard F Kosobud. 1961. “Some econometrics of growth: Great ratios of economics.” *The Quarterly Journal of Economics* 75 (2):173–198.
- Koh, Dongya, Raül Santaeulàlia-Llopis, and Yu Zheng. 2020. “Labor share decline and intellectual property products capital.” *Econometrica* 88 (6):2609–2628.
- Kuvshinov, Dmitry and Kaspar Zimmermann. 2021. “The Big Bang: Stock Market Capitalization in the Long Run.” *Journal of Financial Economics* .
- Lansing, Kevin J. 2015. “Asset pricing with concentrated ownership of capital and distribution shocks.” *American Economic Journal: Macroeconomics* 7 (4):67–103.
- . 2021. “Replicating Business Cycles and Asset Returns with Sentiment and Low Risk Aversion.”

- Lettau, Martin and Sydney C. Ludvigson. 2001. “Consumption, Aggregate Wealth and Expected Stock Returns.” *Journal of Finance* 56 (3):815–849.
- . 2009. “Euler Equation Errors.” *The Review of Economic Dynamics* 12 (2):255–283.
- Lettau, Martin and Sydney C Ludvigson. 2013. “Shocks and Crashes.” In *National Bureau of Economics Research Macroeconomics Annual: 2013*, vol. 28, edited by Jonathan Parker and Michael Woodford. Cambridge and London: MIT Press, 293–354.
- Lettau, Martin, Sydney C. Ludvigson, and Sai Ma. 2019. “Capital Share Risk in U.S. Asset Pricing.” *The Journal of Finance* 74 (4):1753–1792.
- Lettau, Martin and Jessica A. Wachter. 2007. “Why is Long-Horizon Equity Less Risky? A Duration Based Explanation of the Value Premium.” *Journal of Finance* LXII (1):55–92.
- Ludvigson, Sydney C. 2012. “Advances in Consumption-Based Asset Pricing: Empirical Tests.” In *Handbook of the Economics of Finance Vol. II*, edited by George Constantinides, Milton Harris, and Rene Stulz. North Holland, Amsterdam: Elsevier Science B.V., 799–906.
- Lustig, Hanno and Stijn Van Nieuwerburgh. 2008. “The Returns on Human Capital: Good News on Wall Street is Bad News on Main Street.” *Review of Financial Studies* 21:2097–2137.
- Lustig, Hanno, Stijn Van Nieuwerburgh, and Adrien Verdelhan. 2013. “The wealth-consumption ratio.” *Review of Asset Pricing Studies* 3 (1):38–94.
- Malloy, Christopher J., Tobias J. Moskowitz, and Annette Vissing-Jorgensen. 2009. “Long-run Stockholder Consumption Risk and Asset Returns.” *Journal of Finance* 64:2427–2479.
- Mankiw, N. Gregory. 1986. “The Equity Premium and the Concentration of Aggregate Shocks.” *Journal of Financial Economics* 17:97–112.
- Mankiw, N. Gregory and Stephen P. Zeldes. 1991. “The Consumption of Stockholders and Non-stockholders.” *Journal of Financial Economics* 29 (1):97–112.
- Marfe, Roberto. 2017. “Income insurance and the equilibrium term structure of equity.” *The Journal of Finance* 72 (5):2073–2130.
- Martin, Ian. 2017. “What is the Expected Return on the Market?” *The Quarterly Journal of Economics* 132 (1):367–433.
- Nakamura, Emi and Jón Steinsson. 2018. “High-frequency identification of monetary non-neutrality: the information effect.” *The Quarterly Journal of Economics* 133 (3):1283–1330.
- Ritter, Jay R. 2012. “Is Economic Growth Good for Investors? 1.” *Journal of Applied Corporate Finance* 24 (3):8–18.
- Siegel, Jeremy J. 2014. *Stocks for the Long Run: The Definitive Guide to Financial Market Returns and Long-term Investment Strategies*. New York, NY: McGraw Hill, 5 ed.
- Summers, Lawrence H. 1985. “On economics and finance.” *The Journal of Finance* 40 (3):633–635.
- Vissing-Jorgensen, Annette. 2002. “Limited Asset Market Participation and Intertemporal Substitution.” *Journal of Political Economy* 110 (4):825–853.

Wachter, Jessica. 2013. "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Activity?" *Journal of Finance* 68:987–1035.

Yardeni, Edward, Joe Abbott, and Mali Quintana. 2023. "Stock Market Indicators: S&P 500 Blue Angels Dividend Yields." Working Paper, Yardeni Research Inc.

Appendix: For Online Publication

A.1 Data Description

Corporate Equity. Our measure of market equity for the corporate sector is constructed as follows. To begin, we compute unadjusted corporate equity as the sum of corporate equity for the nonfinancial corporate sector (series LM103164103 from table B.103) plus corporate equity for the financial corporate sector (series LM793164105 from table L.108). However, because exchange traded funds and closed end funds form a component of financial corporate equity, while themselves holding large amounts of corporate equity, there is potential for double counting. To avoid this, we remove shares outstanding in exchange traded funds (series LM564090005 from table L.124) and closed end funds (series LM554090005 from table L.123) from unadjusted corporate equity to form our benchmark measure of market equity. Source: Federal Reserve Board.

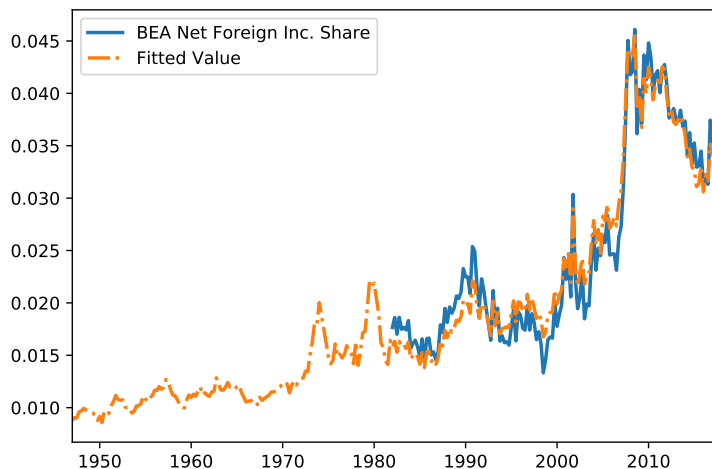
Foreign Earnings. Total earnings is the sum of domestic after-tax profits from NIPA and earnings of US multinational enterprises on their overseas operations. Total earnings are defined as a share of domestic net-value-added for the corporate sector. (See the next subsection for the sources of domestic data.)

$$\begin{aligned} E_t &= S_t Y_t \\ &= (S_t^D Z_t + F_t) Y_t. \end{aligned}$$

In the above, F_t is the foreign profit share of domestic output. The measure of foreign profits in the numerator of F_t is based on data from Table 4.2 of the US International Transactions in Primary Income on Direct Investment, obtained from BEA's International Data section. We refer to this simply as corporate "direct investment." Specifically, these data are from the "income on equity" row 2 of Direct investment income on assets, asset/liability basis. Note that US direct investment abroad is ownership by a US investor of at least 10 percent of a foreign business, and so excludes household portfolio investment. This series is available from 1982:Q1 to the present. To extend this series backward, we first take data on net foreign receipts from abroad (Corporate profits with IVA and CCA_{adj} from BEA NIPA Table 1.12. (A051RC) or from Flow of Funds (FOF) Table F.3 (FA096060035.Q less corporate profits with IVA and CCA_{adj}, domestic industries from BEA NIPA Table 1.14 (A445RC)), which is available from the post-war period onward. This series includes portfolio investment income of households as well as direct investment, but its share of domestic

net-value-added for the corporate sector is highly correlated with the foreign direct investment share of net-value-added. We regress the direct investment share of net-value-added on the foreign receipts share of domestic net-value-added and then use the fitted value from this regression as the measure of F_t in data pre-1982. Because the portfolio income component is relatively small, the fit of this regression is high, as seen in Figure A.1, which compares the fitted series with the actual series over the post-1982 period.

Figure A.1: Net Foreign Income Share: Data vs. Fitted value



Notes: The sample spans the period 1952:Q1-2018:Q2.

Domestic Variables: Corp. Net Value Added, Corp. Labor Compensation, Corp. After-Tax Profits, Taxes, and Interest. Define domestic corporate earnings E_t^D as

$$E_t^D = S_t^D (1 - \tau_t) NVA_t,$$

which is equivalent to

$$E_t^D = \left[1 - \underbrace{\frac{LC_t}{ATP_t + LC_t}}_{\text{Labor share of labor+profit}} \right] (1 - \tau_t) NVA_t.$$

Data for the net value added (NVA) comes from NIPA Table 1.14 (corporate sector series codes A457RC1 and A438RC1). We use per capita real net value added, deflated by the implicit price deflator for net value added. After tax profits (ATP) for the domestic sector come from NIPA Table 1.14 (corporate sector series code: W273RC1). Corporate sector

labor compensation (LC) for the domestic sector is from Table 1.14 (series code A442RC). The domestic after-tax profit share ($ATPS$) of NVA is identically equal to

$$\begin{aligned}
 ATPS &= \frac{ATP}{ATP + LC} \frac{ATP + LC}{NVA} = \underbrace{\frac{ATP}{ATP + LC}}_{=S_t^D} \frac{NVA - (\text{taxes and interest})}{NVA} \\
 &= S_t^D \left[1 - \underbrace{\left(\frac{\text{taxes and interest}}{NVA} \right)}_{=\tau_t} \right] \\
 &= S_t^D Z_t,
 \end{aligned}$$

where S_t^D is the domestic after-tax profit share of combined profit plus labor compensation, “taxes and interest” is the sum of taxes on production and imports less subsidies (W325RC1), net interest and miscellaneous payments (B471RC1), business current transfer payments (Net) (W327RC1), and taxes on corporate income (B465RC1). Source: Bureau of Economic Analysis.

Corporate Payouts. We define corporate payouts as net dividends minus net equity issuance for the corporate sector. Net dividends is the sum of nonfinancial corporate net dividends (series FA106121075 from Table F.103) and financial corporate net dividends (series FA796121073 from Table F.3). Net equity issuance is the sum of nonfinancial corporate net equity issuance (series FA103164103 from Table F.103) and financial corporate net equity issuance (series FA793164105 from Table F.108). As with the market value of equity, we again remove flows related to exchange traded funds and closed end funds to avoid double counting. To this end, we add back in net equity issuance for exchange traded funds (series FA564090005 from Table F.124) and closed end funds (series FA554090005 from Table F.123). We also adjust net dividends to remove the influence of these funds. Since these series are not directly available, we assume that they comprise a fraction of financial corporate sector net dividends equal to the ratio of equity in these funds to total financial corporate sector equity. We then remove this approximate measure from corporate payouts. In summary, our corporate payouts measure can be summarized as

$$\begin{aligned}
 \text{Payout} &= \text{Nonfinancial Net Dividends} + \text{Financial Net Dividends} \\
 &\quad - \text{Nonfinancial Net Equity Issuance} - \text{Financial Net Equity Issuance} \\
 &\quad + \text{ETF Net Equity Issuance} + \text{Closed End Net Equity Issuance}
 \end{aligned}$$

$$- \underbrace{(\text{Financial Net Dividends}) \times \left(\frac{\text{ETF} + \text{Closed End Equity}}{\text{Financial Equity}} \right)}_{\text{Approximate ETF} + \text{Closed End Net Dividends}}.$$

Since all of these variables are computed at annual rates, we divide by four to convert to quarterly payouts.

Price Deflators. Implicit price deflator and GDP deflator. A chain-type price deflator for the nonfinancial corporate sector (NFCS) is obtained implicitly by dividing the net value added of nonfinancial corporate business by the chained real dollar net value added of nonfinancial corporate business from NIPA Table 1.14. This index is used to deflate net value added of the corporate sector. There is no implicit price deflator available for the whole corporate sector, so we use deflator for the non-financial corporate sector instead. The GDP deflator is used to construct a real returns and a real interest (see below). GDPDEF is retrieved from FRED. Our source is the Bureau of Economic Analysis.

Interest Rate. The nominal risk-free rate is measured by the 3-Month Treasury Bill rate, secondary market rate. We take the (average) quarterly 3-Month Treasury bill from FRED (code: TB3MS). A real rate is constructed by subtracting the fitted value from a regression of GDP deflator inflation onto lags of inflation from the nominal rate. Our source is the board of governors of the Federal Reserve System and the Bureau of Economic Analysis.

Risk Premium Measure. Our measure of the risk premium comes from Martin (2017). This paper uses option data to compute a lower bound on the equity risk premium, then argues that this lower bound is in fact tight, and a good measure of the true risk premium on the stock market. We obtain this series from the spreadsheet `epbound.xls` on Ian Martin's website, which corresponds to the value

$$EPBound_{t \rightarrow T} = 100 \times \left(R_{f,t} SVIX_{t \rightarrow T}^2 - 1 \right)$$

which is equivalent to the bound on the annualized net risk premium, in percent. To translate these measures to our model's quarterly frequency, we use the risk premium measure computed over the next three months. We then convert this variable into a log return, average it over the quarter, and label it rp_t .

Survey Data on Expected Average Risk-Free Rate For the average short-term expected nominal interest rate, we use the mean forecast from the Survey of Professional

Forecasters for variable BILL10, which is the 10-year annual-average forecast for returns on 3-month Treasury bills. We subtract from this the mean forecast for variable CPI10, the 10-year annual-average forecast of inflation, to obtain a survey forecast for the average real rate over the next ten years.

A.2 A Stylized Model of Workers and Shareholders

We consider a stylized limited participation endowment economy in which wealth is concentrated in the hands of a few asset owners, or “shareholders,” while most households are “workers” who finance consumption out of wages and salaries. The economy is closed. Workers own no risky asset shares and consume their labor earnings. There is no risk-sharing between workers and shareholders. A representative firm issues no new shares and buys back no shares. Cash flows are equal to output minus a wage bill,

$$C_t = Y_t - w_t N_t,$$

where w_t equals the wage and N_t is aggregate labor supply. The wage bill is equal to Y_t times a time-varying labor share α_t ,

$$w_t N_t = \alpha_t Y_t \implies C_t = (1 - \alpha_t) Y_t. \quad (\text{A.1})$$

We rule out short sales in the risky asset:

$$\theta_t^i \geq 0.$$

Asset owners not only purchase shares in the risky security, but also trade with one another in a one-period bond with price at time t denoted by q_t . The real quantity of bonds is denoted B_{t+1} , where $B_{t+1} < 0$ represents a borrowing position. The bond is in zero net supply among asset owners. Asset owners could have idiosyncratic investment income ζ_t^i , which is independently and identically distributed across investors and time. The gross financial assets of investor i at time t are given by

$$A_t^i = \theta_t^i (V_t + C_t) + B_t^i.$$

The budget constraint for the i th investor is

$$\begin{aligned} C_t^i + B_{t+1}^i q_t + \theta_{t+1}^i V_t &= A_t^i + \zeta_t^i \\ &= \theta_t^i (V_t + C_t) + B_t^i + \zeta_t^i, \end{aligned} \quad (\text{A.2})$$

where C_t^i denotes the consumption of investor i .

A large number of identical nonrich workers, denoted by w , receive labor income and do not participate in asset markets. The budget constraint for the representative worker is therefore

$$C^w = \alpha_t Y_t. \quad (\text{A.3})$$

Equity market clearing requires

$$\sum_i \theta_t^i = 1.$$

Bond market clearing requires

$$\sum_i B_t^i = 0.$$

Aggregating (A.2) and (A.3) and imposing both market clearing and (A.1) implies that aggregate (worker plus shareholder) consumption C_t^{Agg} is equal to total output Y_t . Aggregating over the budget constraint of shareholders shows that their consumption is equal to the capital share times aggregate consumption C_t^{Agg} :

$$C_t^S = C_t = \underbrace{(1 - \alpha_t)}_{KS_t} C_t^{Agg}.$$

A representative shareholder who owns the entire corporate sector will therefore have consumption equal to $C_t^{Agg} \cdot KS_t$. This reasoning goes through as an approximation if workers own a small fraction of the corporate sector even if there is some risk-sharing in the form of risk-free borrowing and lending between workers and shareholders, as long as any risk-sharing across these groups is imperfect. While individual shareholders can smooth out transitory fluctuations in income by buying and selling assets, shareholders as a whole are less able to do so since purchases and sales of any asset must net to zero across all asset owners.

A.3 Model Solution

This section provides details on our model solution, as well as derivations and formulas for additional model outputs of interest.

A.4 Deriving the Stochastic Discount Factor

Taking derivatives of equation (6), the stochastic discount factor (intertemporal marginal rate of substitution) is given by

$$M_{t+1} = \beta_t \frac{C_{t+1}^{-x_t}}{C_t^{-x_{t-1}}}. \quad (\text{A.4})$$

Defining

$$\hat{\beta}_t = \beta_t C_t^{-(x_t - x_{t-1})} \quad (\text{A.5})$$

and substituting into (A.4) yields (7).

A.4.1 Perturbation Details.

The derivation of the perturbed stochastic discount factor (12) follows here. We seek a perturbation of the terms determining the risk exposure of the SDF, the nonlinear expression $\tilde{m}_{t+1} = -x_t \Delta c_{t+1}$. Our perturbation includes terms linear in both the state vector \mathbf{z}_t , the shock vector $\boldsymbol{\varepsilon}_{t+1}$, and interactions between the two, while omitting all other higher-order terms. While our solution could handle terms quadratic in \mathbf{z}_t , they would be irrelevant since the term μ_t would implicitly offset them in all states. On the other hand, terms quadratic in $\boldsymbol{\varepsilon}_{t+1}$ would influence the solution, but would break our solution methodology.

To derive the perturbed stochastic discount factor, we first express \hat{m}_t in terms of the current period's states and next period's shocks:

$$\hat{m}_{t+1} = -x_t \left\{ \log \left[\exp \left(\bar{s} + \mathbf{1}' (\boldsymbol{\Phi}_s \tilde{\mathbf{s}}_t + \boldsymbol{\varepsilon}_{s,t+1}) \right) - \omega \right] - \log \left[\exp \left(\bar{s} + \mathbf{1}' \tilde{\mathbf{s}}_t \right) - \omega \right] + \bar{g} + \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1} \right\}.$$

Evaluating the derivatives of this expression with respect to shocks and states, we obtain

$$\begin{aligned} \frac{\partial \hat{m}_{t+1}}{\partial \tilde{\mathbf{x}}_t} &= -\Delta c_{t+1} \mathbf{1}' \\ \frac{\partial \hat{m}_{t+1}}{\partial \tilde{\mathbf{s}}_t} &= -x_t \left\{ \left(\frac{S_{t+1}}{S_{t+1} - \omega} \right) \mathbf{1}' \boldsymbol{\Phi} - \left(\frac{S_t}{S_t - \omega} \right) \mathbf{1}' \right\} \\ \frac{\partial \hat{m}_{t+1}}{\partial \boldsymbol{\varepsilon}_{s,t+1}} &= -x_t \left(\frac{S_{t+1}}{S_{t+1} - \omega} \right) \mathbf{1}' \\ \frac{\partial \hat{m}_{t+1}}{\partial \boldsymbol{\varepsilon}_{y,t+1}} &= -x_t \\ \frac{\partial^2 \hat{m}_{t+1}}{\partial \boldsymbol{\varepsilon}_{s,t+1} \partial \tilde{\mathbf{x}}_t} &= -\mathbf{1} \left(\frac{S_{t+1}}{S_{t+1} - \omega} \right) \mathbf{1}' \\ \frac{\partial^2 \hat{m}_{t+1}}{\partial \boldsymbol{\varepsilon}_{s,t+1} \partial \tilde{\mathbf{s}}_t} &= x_t \mathbf{1} \left(\frac{S_{t+1}}{S_{t+1} - \omega} \right) \left(\frac{\omega}{S_{t+1} - \omega} \right) \mathbf{1}' \boldsymbol{\Phi}_s \end{aligned}$$

We therefore approximate

$$\begin{aligned} \hat{m}_{t+1} &\simeq -\bar{x} \bar{g} - \bar{g} \mathbf{1}' \tilde{\mathbf{x}}_t - \bar{x} \xi \mathbf{1}' (\boldsymbol{\Phi}_s - I) \tilde{\mathbf{s}}_t - \bar{x} \xi \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} - \bar{x} \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1} \\ &\quad - \tilde{\mathbf{x}}_t' \mathbf{1} \xi \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} + \tilde{\mathbf{s}}_t' \boldsymbol{\Phi}_s' \bar{x} \xi (\xi - 1) \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} - \tilde{\mathbf{x}}_t' \mathbf{1} \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1} \end{aligned}$$

$$= \dots - (x_t \xi - \bar{x} \xi (\xi - 1) (\mathbf{1}' \Phi_s \tilde{s}_t)) \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} - x_t \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1}$$

where the omitted terms are known at time t , and whose exact values are thus irrelevant to our solution as they will be directly offset by the implicitly defined μ_t . Combining this result with the identity

$$\mathbb{E}_t[s_{t+1}] = \bar{s} + \mathbf{1}' \Phi_s \tilde{s}_t$$

and rearranging yields (12).

A.4.2 Price-Payout Ratio

This section derives the coefficients of the main asset pricing equation (14). To begin, define for convenience the variables

$$\begin{aligned} u_{t+1} &= \log(PC_{t+1} + 1) - pc_t \\ q_{t+1} &= m_{t+1} + \Delta c_{t+1} \end{aligned}$$

so that $m_{t+1} + r_{t+1} = u_{t+1} + q_{t+1}$. Applying the log linear approximation to $\log(PC_{t+1} + 1)$ and substituting in our guessed functional form (14) yields

$$\begin{aligned} u_{t+1} &= \log(PC_{t+1} + 1) - pd_t \\ &= \kappa_0 + \kappa_1 \left(A_0 + \mathbf{A}'_s \tilde{s}_{t+1} + \mathbf{A}'_x \tilde{x}_{t+1} + \mathbf{A}'_\delta \tilde{\delta}_{t+1} + \mathbf{A}'_g \tilde{g}_{t+1} \right) \\ &\quad - \left(A_0 + \mathbf{A}'_s \tilde{s}_t + \mathbf{A}'_x \tilde{x}_t + \mathbf{A}'_\delta \tilde{\delta}_t + \mathbf{A}'_g \tilde{g}_{t+1} \right) \\ &= \kappa_0 + (\kappa_1 - 1) A_0 + \mathbf{A}'_s (\kappa_1 \Phi_s - \mathbf{I}) \tilde{s}_t + \mathbf{A}'_x (\kappa_1 \Phi_x - \mathbf{I}) \tilde{x}_t + \mathbf{A}'_\delta (\kappa_1 \Phi_\delta - \mathbf{I}) \tilde{\delta}_t + \mathbf{A}'_g (\kappa_1 \Phi_g - \mathbf{I}) \tilde{g}_t \\ &\quad + \kappa_1 \mathbf{A}'_s \boldsymbol{\varepsilon}_{s,t+1} + \kappa_1 \mathbf{A}'_x \boldsymbol{\varepsilon}_{x,t+1} + \kappa_1 \mathbf{A}'_\delta \boldsymbol{\varepsilon}_{\delta,t+1} + \kappa_1 \mathbf{A}'_g \boldsymbol{\varepsilon}_{g,t+1}. \end{aligned}$$

Now turning to q_{t+1} , we can expand the expression to yield

$$q_{t+1} = -\delta_t - \mu_t + \xi \mathbb{E}_t \Delta s_{t+1} + \mathbb{E}_t \Delta y_{t+1} + (1 - \gamma_{s,t}) \xi \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} + (1 - x_t) \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1}$$

where

$$\begin{aligned} \gamma_{s,t} &= x_t - \bar{x} (1 - \xi) (\mathbb{E}_t[s_{t+1}] - \bar{s}) \\ &= \bar{x} + \mathbf{1}' \tilde{x}_t - \bar{x} (1 - \xi) \mathbf{1}' \Phi_s \tilde{s}_t \\ &= \bar{x} + \mathbf{1}' \tilde{x}_t + \Gamma' \tilde{s}_t. \end{aligned}$$

for

$$\mathbf{\Gamma}' \equiv -\bar{x}(1 - \xi)\mathbf{1}'\mathbf{\Phi}_s.$$

Next, we apply our fundamental asset pricing equation $0 = \log \mathbb{E}_t [q_{t+1} + u_{t+1}]$, which under lognormality implies

$$0 = \mathbb{E}_t[q_{t+1}] + \mathbb{E}_t[u_{t+1}] + \frac{1}{2}\text{Var}_t(q_{t+1}) + \frac{1}{2}\text{Var}_t(u_{t+1}) + \text{Cov}(q_{t+1}, u_{t+1}).$$

These moments can be calculated as

$$\begin{aligned} \mathbb{E}_t[q_{t+1}] &= -\delta_t - \mu_t + g - \xi\mathbf{1}'(\mathbf{I} - \mathbf{\Phi}_s)\tilde{\mathbf{s}}_t + \mathbf{1}'\mathbf{\Phi}_g\tilde{\mathbf{g}}_t \\ \mathbb{E}_t[u_{t+1}] &= \kappa_0 + (\kappa_1 - 1)A_0 + \mathbf{A}'_s(\kappa_1\mathbf{\Phi}_s - \mathbf{I})\tilde{\mathbf{s}}_t + \mathbf{A}'_x(\kappa_1\mathbf{\Phi}_x - \mathbf{I})\tilde{\mathbf{x}}_t \\ &\quad + \mathbf{A}'_\delta(\kappa_1\mathbf{\Phi}_\delta - \mathbf{I})\tilde{\mathbf{\delta}}_t + \mathbf{A}'_g(\kappa_1\mathbf{\Phi}_g - \mathbf{I})\tilde{\mathbf{g}}_t \\ \text{Var}_t(q_{t+1}) &= (1 - \gamma_{s,t})^2\xi^2(\mathbf{1}'\mathbf{\Sigma}_s\mathbf{1}) + (1 - x_t)^2(\mathbf{1}'\mathbf{\Sigma}_g\mathbf{1}) \\ \text{Var}_t(u_{t+1}) &= \kappa_1^2\left(\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{A}'_s + \mathbf{A}'_x\mathbf{\Sigma}_x\mathbf{A}'_x + \mathbf{A}'_\delta\mathbf{\Sigma}_\delta\mathbf{A}'_\delta + \mathbf{A}'_g\mathbf{\Sigma}_g\mathbf{A}'_g\right) \\ \text{Cov}_t(q_{t+1}, u_{t+1}) &= \kappa_1\xi(1 - \gamma_{s,t})\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{1} + \kappa_1(1 - x_t)\mathbf{A}'_g\mathbf{\Sigma}_g\mathbf{1} \end{aligned}$$

Substituting, we obtain

$$\begin{aligned} 0 &= -\bar{\delta} + g + \kappa_0 + (\kappa_1 - 1)A_0 + \frac{1}{2}\left((1 - 2\bar{x})\xi^2(\mathbf{1}'\mathbf{\Sigma}_s\mathbf{1}) + (1 - 2\bar{x})(\mathbf{1}'\mathbf{\Sigma}_g\mathbf{1})\right) \\ &\quad + \frac{1}{2}\kappa_1^2\left(\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{A}'_s + \mathbf{A}'_x\mathbf{\Sigma}_x\mathbf{A}'_x + \mathbf{A}'_\delta\mathbf{\Sigma}_\delta\mathbf{A}'_\delta + \mathbf{A}'_g\mathbf{\Sigma}_g\mathbf{A}'_g\right) \\ &\quad + \kappa_1\xi(1 - \bar{x})\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{1} + \kappa_1(1 - \bar{x})\mathbf{A}'_g\mathbf{\Sigma}_g\mathbf{1} \\ &\quad + \left[\mathbf{A}'_s(\kappa_1\mathbf{\Phi}_s - \mathbf{I}) - \xi\mathbf{1}'(\mathbf{I} - \mathbf{\Phi}_s) - \xi^2(\mathbf{1}'\mathbf{\Sigma}_s\mathbf{1})\mathbf{\Gamma}'_s - \kappa_1\xi(\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{1})\mathbf{\Gamma}'_s\right]\tilde{\mathbf{s}}_t \\ &\quad + \left[\mathbf{A}'_x(\kappa_1\mathbf{\Phi}_x - \mathbf{I}) - \xi^2(\mathbf{1}'\mathbf{\Sigma}_s\mathbf{1})\mathbf{1}' - (\mathbf{1}'\mathbf{\Sigma}_g\mathbf{1})\mathbf{1}' - \kappa_1\xi(\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{1})\mathbf{1}' - \kappa_1(\mathbf{A}'_g\mathbf{\Sigma}_g\mathbf{1})\mathbf{1}'\right]\tilde{\mathbf{x}}_t \\ &\quad + \left[\mathbf{A}'_\delta(\kappa_1\mathbf{\Phi}_\delta - \mathbf{I}) - \mathbf{1}\right]\tilde{\mathbf{\delta}}_t \\ &\quad + \left[\mathbf{A}'_g(\kappa_1\mathbf{\Phi}_g - \mathbf{I}) + \mathbf{1}'\mathbf{\Phi}_g\right]\tilde{\mathbf{g}}_t \end{aligned}$$

Applying the method of undetermined coefficients now yields the solutions

$$\begin{aligned} \mathbf{A}'_s &= -\left[\xi\mathbf{1}'(\mathbf{I} - \mathbf{\Phi}_s) - \xi^2(\mathbf{1}'\mathbf{\Sigma}_s\mathbf{1})\mathbf{\Gamma}'_s\right]\left[(\mathbf{I} - \kappa_1\mathbf{\Phi}_s) - \kappa_1\xi\mathbf{\Sigma}_s\mathbf{1}\mathbf{\Gamma}'_s\right]^{-1} \\ \mathbf{A}'_x &= -\left[\left(\xi^2(\mathbf{1}'\mathbf{\Sigma}_s\mathbf{1}) + (\mathbf{1}'\mathbf{\Sigma}_g\mathbf{1}) + \kappa_1\xi(\mathbf{A}'_s\mathbf{\Sigma}_s\mathbf{1})\right)\mathbf{1}'\right](\mathbf{I} - \kappa_1\mathbf{\Phi}_x)^{-1} \\ \mathbf{A}'_\delta &= -\mathbf{1}'(\mathbf{I} - \kappa_1\mathbf{\Phi}_\delta)^{-1} \\ \mathbf{A}'_g &= \mathbf{1}'\mathbf{\Phi}_g(\mathbf{I} - \kappa_1\mathbf{\Phi}_g)^{-1} \end{aligned}$$

while the constant term must solve

$$\begin{aligned}
0 &= -\bar{\delta} + g + \kappa_0 + (\kappa_1 - 1)A_0 + \frac{1}{2} \left((1 - 2\bar{x})\xi^2(\mathbf{1}'\Sigma_s\mathbf{1}) + (1 - 2\bar{x})(\mathbf{1}'\Sigma_g\mathbf{1}) \right) \\
&\quad + \frac{1}{2}\kappa_1^2 \left(\mathbf{A}'_s\Sigma_s\mathbf{A}'_s + \mathbf{A}'_x\Sigma_x\mathbf{A}_x + \mathbf{A}'_\delta\Sigma_r\mathbf{A}_\delta + \mathbf{A}'_g\Sigma_g\mathbf{A}_g \right) \\
&\quad + \kappa_1\xi(1 - \bar{x})\mathbf{A}'_s\Sigma_s\mathbf{1} + \kappa_1(1 - \bar{x})\mathbf{A}'_g\Sigma_g\mathbf{1}.
\end{aligned} \tag{A.6}$$

A.4.3 Equilibrium Selection

The parameters κ_0 and κ_1 determine the steady state *pc* (price-payout ratio), which depends on A_0 . But since κ_0 and κ_1 are both themselves nonlinear functions of A_0 , the equilibrium condition (A.6) is also nonlinear, leading to the possibility that multiple solutions, or no solution, exists. In fact, we confirm that both of these outcomes can occur numerically.

Typically we find that multiple solutions occur due to the following type of nonmonotonicity. First, for low or moderate values of the price-dividend ratio, the right hand side of (A.6) is decreasing in A_0 . The intuitive mechanism here is that as the price-dividend ratio is increasing, average returns are decreasing, pushing typical values of $m_{t+1} + r_{t+1}$ downward.

However, for larger values of A_0 , the right hand side of (A.6) can begin increasing in A_0 . This occurs because A_0 begins to influence κ_1 and hence the covariance of m_{t+1} and r_{t+1} , improving the risk properties of the asset, and increasing $E_t \exp(m_{t+1} + r_{t+1})$. We view this mechanism as unrealistic and likely driven by the log-linear approximation rather than the actual underlying economics. Moreover, these solutions often feature very high and unreasonable values of the price dividend ratio.

Given these considerations, we address the problem of multiple solutions by constructing our solution algorithm so that it will seek the lowest solution. In practice, this is done by using Newton's method, beginning at a very low initial guess for the price-dividend ratio, which reliably finds the first (lowest) intersection between the right hand side of (A.6) and zero.

A.4.4 Expected Returns

Combining the relations

$$\begin{aligned}
0 &= \log \mathbb{E}_t[M_{t+1}R_{t+1}] \\
&= \mathbb{E}_t[m_{t+1}] + \mathbb{E}_t[r_{t+1}] + \frac{1}{2}\text{Var}_t(m_{t+1}) + \frac{1}{2}\text{Var}_t(r_{t+1}) + \text{Cov}_t(m_{t+1}, r_{t+1}) \\
-r_{f,t} &= \log \mathbb{E}_t[M_{t+1}] \\
&= \mathbb{E}_t[m_{t+1}] + \frac{1}{2}\text{Var}_t(m_{t+1})
\end{aligned}$$

and rearranging, we obtain

$$\begin{aligned}\log \mathbb{E}_t[R_{t+1}/R_{f,t}] &= \mathbb{E}_t[r_{t+1}] + \frac{1}{2}\text{Var}_t(r_{t+1}) - r_{f,t} \\ &= -\text{Cov}_t(m_{t+1}, r_{t+1}).\end{aligned}$$

Since

$$\begin{aligned}r_{t+1} &= \text{const}_t + \underbrace{\kappa_1 \left(\mathbf{A}'_s \boldsymbol{\varepsilon}_{s,t+1} + \mathbf{A}'_x \boldsymbol{\varepsilon}_{x,t+1} + \mathbf{A}'_\delta \boldsymbol{\varepsilon}_{\delta,t+1} + \mathbf{A}'_g \boldsymbol{\varepsilon}_{g,t+1} \right)}_{pc \text{ growth}} + \underbrace{\xi \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} + \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1}}_{\text{cash flow growth}} \\ m_{t+1} &= \text{const}_t - \gamma_{s,t} \mathbf{1}' \boldsymbol{\varepsilon}_{s,t+1} - x_t \mathbf{1}' \boldsymbol{\varepsilon}_{g,t+1}\end{aligned}$$

we obtain

$$\text{Cov}_t(m_{t+1}, r_{t+1}) = -\gamma_{s,t} (\kappa_1 \mathbf{A}'_s + \xi \mathbf{1}') \boldsymbol{\Sigma}_s \mathbf{1} - x_t (\kappa_1 \mathbf{A}'_g + \mathbf{1}') \boldsymbol{\Sigma}_g \mathbf{1}$$

Substituting for $\gamma_{s,t}$ and rearranging yields (16).

A.4.5 Forecasting Real Rates

This section derives our 40Q average real rate forecast in the model. As an intermediate step, note that for a given matrix A , the geometric sum, assuming it converges, is equal to

$$\sum_{j=0}^{\infty} A^j = I + A \sum_{j=0}^{\infty} A^j$$

which implies

$$\sum_{j=0}^{\infty} A^j = (I - A)^{-1}.$$

Similarly the partial sum can be obtained as

$$\begin{aligned}\sum_{j=0}^{N-1} A^j &= \sum_{j=0}^{\infty} A^j - \sum_{j=N}^{\infty} A^j = \sum_{j=0}^{\infty} A^j - A^N \left(\sum_{j=0}^{\infty} A^j \right) = (I - A)^{-1} - (I - A)^{-1} A^N \\ &= (I - A)^{-1} (I - A^N).\end{aligned}$$

Applying this to our interest rate forecast, we have

$$\bar{\delta}_t^N = \frac{1}{N} \sum_{j=0}^{N-1} \mathbb{E}_t \delta_{t+j} = \bar{\delta} + \frac{1}{N} \mathbf{1}' \sum_{j=0}^{N-1} \mathbb{E}_t \tilde{\boldsymbol{\delta}}_{t+j}.$$

Since our law of motion for δ implies $\mathbb{E}_t \tilde{\delta}_{t+j} = \Phi_\delta^j \tilde{\delta}_t$, we can substitute to obtain

$$\begin{aligned} \bar{\delta}_t^N &= \bar{\delta} + \frac{1}{N} \mathbf{1}' \left(\sum_{j=0}^{N-1} \Phi_\delta^j \right) \tilde{\delta}_t \\ &= \bar{\delta} + \frac{1}{N} \mathbf{1}' (\mathbf{I} - \Phi_\delta)^{-1} (\mathbf{I} - \Phi_\delta^N) \tilde{\delta}_t \end{aligned}$$

where the last line follows from our partial geometric sum formula above.

A symmetric argument shows that the average forecasted growth rate over the next N quarters is given by

$$\bar{g}_t^N = \bar{g} + \frac{1}{N} \mathbf{1}' (\mathbf{I} - \Phi_g)^{-1} (\mathbf{I} - \Phi_g^N) \tilde{g}_t$$

A.4.6 Bond Pricing

We can represent our model in the form

$$\log M_{t+1} = -\delta_t - \frac{1}{2} \Lambda_t' \Sigma \Lambda_t - \Lambda_t' \varepsilon_{t+1}$$

where

$$\begin{aligned} \Lambda_t &= \Lambda_0 + \Lambda_1 \mathbf{z}_t \\ &= \underbrace{\begin{bmatrix} \xi \bar{x} \\ 0 \\ 0 \\ \bar{x} \end{bmatrix}}_{\Lambda_0} + \underbrace{\begin{bmatrix} -\bar{x} \xi (\xi - 1) \mathbf{1}' \Phi_s & \xi \mathbf{1}' & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \mathbf{1}' & 0 & 0 \end{bmatrix}}_{\Lambda_1} \underbrace{\begin{bmatrix} \tilde{s}_t \\ \tilde{x}_t \\ \tilde{\delta}_t \\ \tilde{g}_t \end{bmatrix}}_{\mathbf{z}_t}. \end{aligned}$$

To price a zero-coupon bond of maturity n , we guess that the log bond price $p_{n,t}$ takes the functional form

$$p_{n,t} = A_n + B_n' \mathbf{z}_t.$$

This guess is trivially verified for $n = 0$, with $p_{0,t} = 0$ implying the initialization $A_0 = 0$, $B_0' = 0$. To prove by induction, assume the claim holds for n . Then we have

$$p_{n+1,t} = \log E_t \exp \left\{ -\delta_t - \frac{1}{2} \Lambda_t' \Sigma \Lambda_t - \Lambda_t' \varepsilon_{t+1} + A_n + B_n' \Phi_z \mathbf{z}_t + B_n' \varepsilon_{t+1} \right\}$$

$$\begin{aligned}
&= \log E_t \exp \left\{ -\delta_t - \frac{1}{2} \Lambda_t' \Sigma \Lambda_t + (B_n' - \Lambda_t') \varepsilon_{t+1} + A_n + B_n' \Phi_z z_t \right\} \\
&= \log E_t \exp \left\{ -\delta_0 - \delta_1' z_t - \frac{1}{2} \Lambda_t' \Sigma \Lambda_t + (B_n' - \Lambda_t') \varepsilon_{t+1} + A_n + B_n' \Phi_z z_t \right\} \\
&= -\delta_0 - \delta_1' z_t - \frac{1}{2} \Lambda_t' \Sigma \Lambda_t + \frac{1}{2} B_n' \Sigma B_n - B_n' \Sigma \Lambda_t + \frac{1}{2} \Lambda_t' \Sigma \Lambda_t + A_n + B_n' \Phi_z z_t \\
&= -\delta_0 - \delta_1' z_t + \frac{1}{2} B_n' \Sigma B_n - B_n' \Sigma \Lambda_0 - B_n' \Sigma \Lambda_1 z_t + A_n + B_n' \Phi_z z_t \\
&= \left(-\delta_0 + \frac{1}{2} B_n' \Sigma B_n - B_n' \Sigma \Lambda_0 + A_n \right) + (-\delta_1' - B_n' \Sigma \Lambda_1 + B_n' \Phi_z) z_t
\end{aligned}$$

which implies

$$\begin{aligned}
A_{n+1} &= -\delta_0 + \frac{1}{2} B_n' \Sigma B_n - B_n' \Sigma \Lambda_0 + A_n \\
B_{n+1}' &= -\delta_1' - B_n' \Sigma \Lambda_1 + B_n' \Phi_z.
\end{aligned}$$

This both completes the proof and provides the recursion used to compute long-term real bond prices in our model.

A.5 Estimation Details

This section provides additional details on our state space specification and estimation procedure.

Measurement Equation. To construct measurement equation, we relate our observed series to the model's primitive parameters and latent state variables using the following system of equations:

$$\begin{aligned}
ey_t &= \mathbf{1}' \mathbf{s}_t \\
r_{f,t} &= \mathbf{1}' \boldsymbol{\delta}_t \\
\bar{\delta}_t^{40} &= \frac{1}{40} \sum_{j=0}^{40-1} \mathbb{E}_t \delta_{t+j} = \bar{\delta} + \frac{1}{40} \mathbf{1}' (I - \Phi_\delta)^{-1} (I - \Phi_\delta^{40}) \tilde{\boldsymbol{\delta}}_t + \nu_\delta \\
\Delta y_t &= \bar{g} + \mathbf{1}' \tilde{\mathbf{g}}_t \\
\bar{g}_t^{40} &= \frac{1}{40} \sum_{j=0}^{40-1} \mathbb{E}_t \tilde{g}_t = \bar{g} + \frac{1}{40} \mathbf{1}' (I - \Phi_g)^{-1} (I - \Phi_g^{40}) \tilde{\mathbf{g}}_t + \nu_g \\
py_t &= pc_t + cy_t \\
&= \bar{p}y + (\mathbf{A}'_s + \xi') \tilde{\mathbf{s}}_t + \mathbf{A}'_\delta \tilde{\boldsymbol{\delta}}_t + \mathbf{A}'_x \tilde{\mathbf{x}}_t + \mathbf{A}'_g \tilde{\mathbf{g}}_t
\end{aligned}$$

$$rp_t = (\Psi + \sigma_a^2) (\bar{x} + \mathbf{1}'\tilde{\mathbf{x}}_t) - \Psi\Gamma'\tilde{\mathbf{s}}_t.$$

where $cy_t = c_t - y_t$, and $\overline{py} = A_0 + \bar{c} + \boldsymbol{\xi}'\bar{\mathbf{s}}$.⁴³ For the real risk-free rate forecast ($\bar{\delta}_t^{40}$), the parameter ν_δ allows for an average difference between the model and data forecasts due to the different inflation series used (CPI for the forecasts vs. the GDP deflator for the model), as well as any average bias among the forecasts. We correspondingly allow the bias term ν_g for the real output forecast.⁴⁴

Time Variation in State Space. To begin, we provide additional details on time variation in our state space measurement equation (17). Because some of our data series are not available in all periods, the exact measurement equation we use will vary with time. In periods when all of our series are available, our measurement equation takes the form

$$\begin{bmatrix} ey_t \\ r_{ft} \\ \bar{\delta}_t^{40} \\ \Delta y_t \\ \bar{g}_t^{40} \\ py_t \\ rp_t \end{bmatrix} = \begin{bmatrix} H_{ey} \\ H_{rf} \\ H_{rf,40} \\ H_y \\ H_{g,40} \\ H_{py} \\ H_{rp} \end{bmatrix} \mathbf{z}_t + \begin{bmatrix} b_{ey} \\ b_{rf} \\ b_{rf,40} \\ b_y \\ b_{g,40} \\ b_{py} \\ b_{rp} \end{bmatrix}$$

where each of the H terms represents the row of the measurement matrix mapping the current state \mathbf{z} into the time-varying portion of each observable, and each of the b terms represents a constant.

In periods where certain series are not available, we simply omit the relevant H terms. For instance, in periods when our risk premium measure rp_t is not available (before 1996:Q1 or after 2012:Q1), we apply the alternative measurement equation

$$\begin{bmatrix} ey_t \\ r_{ft} \\ \bar{\delta}_t^{40} \\ \Delta y_t \\ \bar{g}_t^{40} \\ py_t \end{bmatrix} = \begin{bmatrix} H_{ey} \\ H_{rf} \\ H_{rf,40} \\ H_y \\ H_{g,40} \\ H_{py} \end{bmatrix} \mathbf{z}_t + \begin{bmatrix} b_{ey} \\ b_{rf} \\ b_{rf,40} \\ b_y \\ b_{g,40} \\ b_{py} \end{bmatrix}$$

⁴³We note that Δa_t is exactly pinned down by the observation equation for Δy_t .

⁴⁴A full derivation of the formulas for $\bar{\delta}_t^{40}$ and \bar{g}_t^{40} can be found in Appendix A.4.5.

which omits the H and b terms related to the risk premium. A completely analogous adjustment is used in periods when the risk-free rate forecast $\bar{\delta}_t^{40}$ or real output growth forecast \bar{g}_t^{40} are not available.

MCMC Details. We next describe the procedure used to obtain the parameter draws. First, because some of our variables are bounded by definition (e.g., volatilities cannot be negative), we define a set of parameter vectors satisfying these bounds denoted Θ . We exclude parameters outside of this set, which formally means that we apply a Bayesian prior

$$p(\boldsymbol{\theta}) = \begin{cases} \text{const} & \text{for } \boldsymbol{\theta} \in \Theta \\ 0 & \text{for } \boldsymbol{\theta} \notin \Theta \end{cases}$$

Our restrictions on Θ are as follows: all volatilities (σ) and the average risk price \bar{x} are bounded below at zero. All persistence parameters (ϕ) are bounded between zero and unity.

With these bounds set, we can evaluate the posterior by

$$\pi(\boldsymbol{\theta}) = L(y|\boldsymbol{\theta})p(\boldsymbol{\theta}).$$

so that the posterior is simply proportional to the likelihood over Θ and is equal to zero outside of Θ .

To draw from this posterior, we use a Random Walk Metropolis Hastings algorithm. We initialize the first draw $\boldsymbol{\theta}_0$ at the mode, and then iterate on the following algorithm:

1. Given $\boldsymbol{\theta}_j$, draw a proposal $\boldsymbol{\theta}^*$ from the distribution $\mathcal{N}(\boldsymbol{\theta}_j, c\boldsymbol{\Sigma}_\theta)$ for some scalar c and matrix $\boldsymbol{\Sigma}_\theta$ defined below.

2. Compute the ratio

$$\alpha = \frac{\pi(\boldsymbol{\theta}^*)}{\pi(\boldsymbol{\theta}_j)}.$$

3. Draw u from a Uniform $[0, 1]$ distribution.

4. If $u < \alpha$, we accept the proposed draw and set $\boldsymbol{\theta}_{j+1} = \boldsymbol{\theta}^*$. Otherwise, we reject the draw and set $\boldsymbol{\theta}_{j+1} = \boldsymbol{\theta}_j$.

For the covariance term, we initialize $\boldsymbol{\Sigma}_\theta$ to be the inverse Hessian of the log likelihood function at the mode. Once we have saved 10,000 draws, we begin updating $\boldsymbol{\Sigma}_\theta$ to be the sample covariance of the draws to date, following Haario, Saksman, Tamminen et al. (2001), with the matrix re-computed after every 1,000 saved draws. For the scaling parameter c ,

we initialize it at $2.4/\text{length}(\boldsymbol{\theta})$ as recommended in Gelman, Stern, Carlin, Dunson, Vehtari, and Rubin (2013). To target an acceptance rate for our algorithm of 25%, we adapt the approach of Herbst and Schorfheide (2014) in updating

$$c_{new} = c_{old} \cdot \left(0.95 + 0.1 \frac{\exp(16(x - 0.25))}{1 + \exp(16(x - 0.25))} \right)$$

after every 1,000 saved draws, where c_{old} is the pre-update value of c .

With these methods in place, we compute our estimation results in ten independent chains, each containing 550,000 draws of $\boldsymbol{\theta}$. We discard the first 50,000 draws from each chain as burn-in, leaving 5,000,000 parameter draws. Since these draws are highly serially correlated, we increase computational efficiency in most applications by using every 500th draw, leaving a total of 10,000 draws over which our margins of parameter uncertainty are computed.

A.6 Bootstrap Bias Correction

The bootstrap bias corrected estimate for the AR(1) model of the log earnings share is computed as follows. First, we run the regression

$$s_t = a + \phi s_{t-1} + \varepsilon_{s,t} \tag{A.7}$$

to obtain the estimates $\hat{a}^{OLS}, \hat{\phi}^{OLS}$. We then bootstrapping many samples from the data generating process

$$s_t^j = \hat{a}^{OLS} + \hat{\phi}^{OLS} s_{t-1}^j + \tilde{\varepsilon}_{s,t}^j$$

where residuals $\tilde{\varepsilon}_{s,t}^j$ are drawn with replacement from $\{\varepsilon_{s,t}\}$. For each j in 100,000 simulations, we repeat the regression (A.7) to obtain estimates $\hat{a}^j, \hat{\phi}^j$, which we average to obtain the estimates $\hat{a}^{boot}, \hat{\phi}^{boot}$. The approximate bias is computed as $\hat{\phi}^{OLS} - \hat{\phi}^{boot}$, implying that the corrected persistence estimator is obtained as

$$\hat{\phi}^* = \hat{\phi}^{OLS} + \left(\hat{\phi}^{OLS} - \hat{\phi}^{boot} \right).$$

For example suppose that every time we run OLS there is a downward bias of 0.05. The true data has persistence 0.95, so the OLS on historical data measures 0.9, while OLS on data simulated using our OLS estimate of 0.9 yields an average estimate of 0.85. In this case the corrected coefficient is $\hat{\phi}^* = 0.9 + (0.9 - 0.85) = 0.9 + 0.05 = 0.95$.

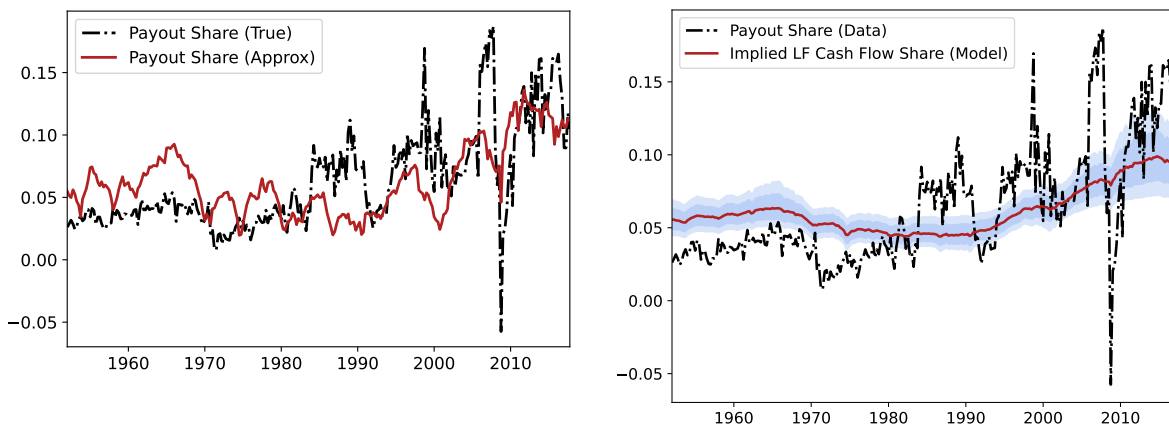
A.7 Additional Detail: Model-Implied Cash Flows

This section provides additional detail on the comparison of implied cash flows in the model to payouts actually observed in the data. Because our model obtains implied cash flows from earnings, using (5), or its log-linear approximation (11), rather than using actual payout data, it is important to check that these series are sufficiently close.

Figure A.2 Panel (a) displays the model-implied cash flow share of output against the actual payout share from the data. The figure shows that the series line up moderately well, particularly toward the end of the sample, and that the model-implied series is able to reproduce a large rise in payouts over the second half of the sample. At the same time, the two series display nontrivial discrepancies at higher frequencies. Panel (b) compares the total payout share to the implied low-frequency component computed as in Figure 8, showing again that we capture but slightly understate the low-frequency rise in this series.

Figure A.2: Cash Flow Share, Implied vs. Data

(a) Model Implied CFs vs. All Payouts **(b) Model Low Freq. CFs vs. All Payouts**



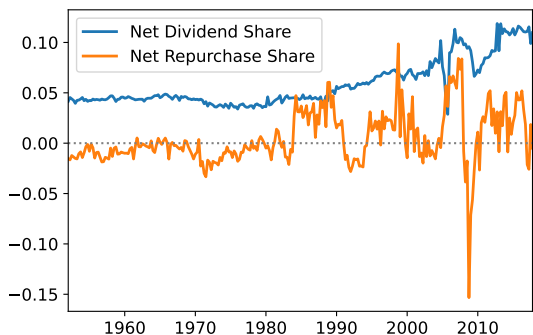
Notes: The left panel compares the implied cash flow series used by our model $C_t = (S_t - \omega)E_t$, compared to the true corporate payout series in the data. The implied series takes S_t and E_t directly from the data, and uses the calibrated value $\omega = 0.0601$ consistent without our calibration of ξ . The right panel compares total payout share in the data to the model's implied low-frequency payout share computed as in Figure 8

To focus in further on the lower-frequency trend in cash flows, we split our payout data into its two component series: net dividends, and net repurchases (i.e., the negative of net equity issuance), displayed in Figure A.3. Panel (a) displays the raw series, showing that the net dividend share is always positive and exhibits slow and persistent dynamics, while the net repurchase share is close to zero on average and fluctuates wildly at high frequencies. Although repurchases have become an increasingly important form of payout, they largely

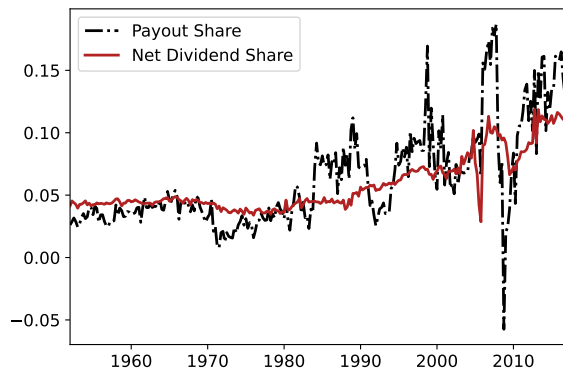
cancel out with issuance of new equity, yielding a series without a major discernible trend. As a result, Panel (b) shows that we can effectively treat the net dividend share as a good measure of the low-frequency trend in payouts, with the exception of the transitory downward spike in net dividends during the financial crisis.

Figure A.3: Payout Data Components

(a) Net Dividend vs. Net Repurchase Shares



(b) Payout Share vs. Net Dividend Share



Notes: Panel (a) separately displays the two components of total payout: the net dividend share (equal to (net dividends) / (net value added) for the corporate sector) and the net repurchase share ((-1) × (net equity issuance) / (net value added) for the corporate sector). Panel (b) compares the net dividend share as just defined to the payout share (payouts / (net value added) for the corporate sector, where payouts are net dividends minus net equity issuance). Source: Flow of Funds.

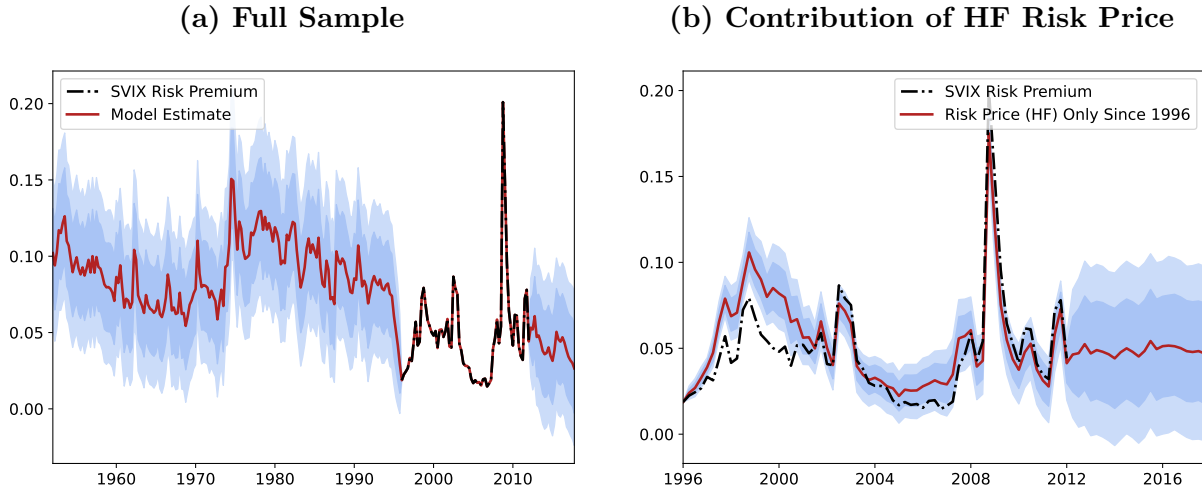
With the net dividend share as a proxy for the low-frequency trend in the payout share in the data, we can compare it to its counterpart in the model. This can be computed using (11) as

$$cy_{LF,t} = \overline{cy} + \xi \tilde{s}_{LF,t}. \quad (\text{A.8})$$

The resulting series is displayed alongside the net dividend share in Figure 8. Unlike the implied series for cy_t in Figure A.2, which can be computed directly from the data given ξ , computing $cy_{LF,t}$ depends on the decomposition of the earnings share into its low-frequency and high-frequency components, and therefore on the model's parameter and latent state estimates. This leads to uncertainty in our estimate, characterized by the blue error bands, while the median is plotted in red.

Figure 8 shows that the model's implied low frequency component cash flows delivers an excellent fit of the net dividend share in the data. The fit is particularly good over the subsample since 1989 on which our main results are based, and does not overstate the growth in payouts. The main discrepancy between the series is the transitory downward spike in

Figure A.4: Estimated Risk Premium and Risk Price Component



Notes: Panel (a) plots the estimated risk premium over the sample along with the risk premium implied by the SVIX, available for the subperiod 1996:Q1-2012Q1. Panel (b) plots the component of the risk-premium driven only by the high-frequency orthogonal risk price along with the risk premium implied by the 3-month SVIX. The label “Only Since” followed by a date describes a counterfactual path where a single component is allowed to vary, while all other components of the risk premium were held fixed from that date on. The red center line corresponds to the median of the distribution of outcomes, accounting for both parameter and latent state uncertainty, while the dark and light blue bands correspond to 66.7% and 90% credible sets, respectively. The period 1996:Q1-2012:Q1 in Panel (a) lacks bands because our estimation procedure ensures that the risk premium matches the data exactly for each quarter of this subsample. The sample spans the period 1952:Q1-2017:Q4.

the data during the financial crisis, which is not really representative of the low-frequency trend, and in fact was more severe in the net dividends data than in the overall payout data, likely due to a slowdown in equity issuance at this time.

In summary, these results provide strong support for our model’s approximate cash flow series (11). Although the implied and data series differ at high frequencies, these discrepancies largely reflect the timing of payouts, and should not play a huge role in equity pricing. At the same time, the model is highly effective at capturing the underlying trend in payouts through its low-frequency component, providing an excellent fit for the data.

A.8 Dynamics of the Equity Premium

In addition to decomposing the growth in market equity, our model also estimates a time series for the equity risk premium, shown in Figure A.4. Panel (a) plots our overall estimated risk premium, which is affected by both the orthogonal risk price component x_t and by s_t through the leverage risk effect. Panel (b) shows our estimate of the equity premium variation that is attributable to only the high-frequency component of the orthogonal risk price

component, $x_{HF,t}$. Both panels superimpose the equity premium implied by the three-month SVIX over the subperiod for which the latter is available, from 1996:Q1-2012:Q1.

Two points are worth noting. First, with the exception of the spike upward during the financial crisis of 2008-2009, Panel (a) shows that the estimated equity premium has been declining steadily over the past several decades and is quite low by historical standards at the end of the sample. By 2017:Q4, the estimates imply that the equity premium reached the record low values it had attained previously only in two episodes: at the end of the tech boom in 1999-2000, and at the end of the twin housing/equity booms in 2006. Second, Panel (b) shows that the estimation assigns to the high-frequency orthogonal risk price component, $x_{HF,t}$, virtually all of the variation in the risk premium implied by the options data, while the remaining variation is ascribed to both the lower frequency component of the risk price, and to the earnings share via the leverage risk effect. The overall risk premium is therefore influenced by a trending low-frequency component and a volatile high frequency component, consistent with the findings of Martin (2017).

On a more technical note, some of our confidence bands for the equity premium in Panel (a) fall below zero. This lack of a zero lower bound is due to our use of a tractable model that, due to its linear approximations, does not feature an extreme shift at zero in which investors refuse to hold equity. Instead, investor behavior in our model under negative risk prices or risk premia is consistent with investors occasionally behaving in a very confident or optimistic manner. A nonlinear model, as used in a precursor superseded by this paper, Greenwald, Lettau, and Ludvigson (2014), provides similar results in a nonlinear environment that precludes negative risk premia. In any case, we note that our point estimates for the risk premium are never negative, and that these are uncommon, even accounting for parameter and latent state uncertainty.

A.9 Counterfactual: Near-Permanent Risk-Free Rate

To better understand what drives the difference between our results and papers finding larger impacts of falling interest rates on the value of market equity, we consider a counterfactual economy in which we force the persistence of risk-free rates to be near-permanent.

To do this, we begin with our parameter draws θ from our estimation procedure, and then update each parameter draw in two ways. First, we set $\phi_{\delta,LF} = 0.999$ so that the low-frequency component of the risk-free rate takes on near-permanent persistence, we set $\sigma_{\delta,HF} = 0$, which forces the model to attribute all variation in risk-free rates to the low-frequency component. Combined, these assumptions ensure that all interest rate movements in the model have near-permanent persistence. Using this updated set of parameter draws,

we use the Kalman filter and disturbance smoother to obtain the distribution of latent states over our data sample. Given these latent states, we can decompose movements in the value of market equity into its various components, as in Table 2, for our counterfactual economy.

The resulting counterfactual decomposition is displayed in Table A.1. We focus on the results for the 1989 – 2017 subsample (right column), since this represents the period with the greatest movement in interest rates, as well as the period where we observe the large influence of factor shares that form our main results. In contrast to our baseline results in Table 2, our counterfactual decomposition shows massive influence of risk-free rates, which now explain the vast majority of growth in equity values over this period, and 100% of the increase in the ratio of market equity to output. This larger contribution of risk-free rates is offset by a decline in asset values from falling prices of risk and risk premia, which differs from a positive contribution from falling prices of risk in our benchmark model. Last, we observe that measured contribution of factor shares is largely unaffected, and is only slightly lower than observed in Table 2.

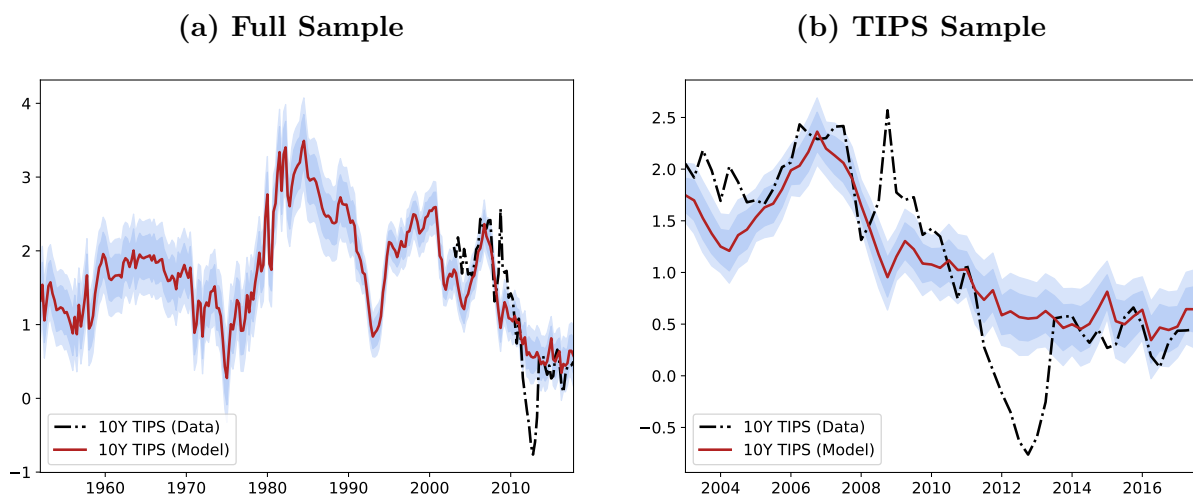
These results imply two important takeaways. First, these results show that our model, if forced to use a near-permanent risk-free rate process, can reproduce the findings of e.g., Farhi and Gourio (2018) and Corhay, Kung, and Schmid (2020), who consider permanent changes in interest rates, and find that they lead to huge movements in asset prices that have been offset by falling risk premia. The fact that we are able to recover these results if we apply these papers’ implicit persistence parameters implies that our difference in results is not due to our model’s assumptions or structure, but instead stems directly from our estimated persistence parameters for the risk-free rate, which the data imply are far from permanent.

Second, this exercise confirms that the question of whether risk-free rates played a large or small role in driving equity valuations since the 1980s is largely orthogonal to our main results on the contribution of factor shares, which is nearly identical across our baseline and counterfactual decompositions, despite large changes to the contributions of other components. Instead, these results show that alternative assumptions on the role of risk-free rates instead influences the measured role of risk prices and risk premia.

A.10 Model-Implied Real Bond Rates

In this section, we compare the implied rates on long real bonds (TIPS) in the model and data. Figure A.5 displays 10-year real bond yields in the model alongside 10-year TIPS yields in the data (details on this computation can be found in Appendix A.4.6). To allow for the fact that TIPS are computed using CPI inflation while our real rates are computed

Figure A.5: 10-Year TIPS Yields, Model vs. Data



Notes: These plots compare the yields on ten-year real bonds in model and data. The data measure is obtained from the Federal Reserve Board of Governors (FRED code: FII10). The model value is obtained using the bond pricing formulas in Appendix A.4.6. The red line displays the mean estimate taken over 10,000 equally spaced parameter draws, while the light and dark blue bands represent 67% and 90% confidence intervals, respectively. The left panel displays the full sample period 1952:Q1-2017:Q4, while the right panel displays the 2003:Q1-2017:Q4 subsample on which the TIPS data is available.

using the GDP deflator, as well as for the possibility that 10-year TIPS may include term or liquidity premia on average, we add a constant to our model-implied TIPS rate, equal to 0.61%, so that our model-implied and actual TIPS rates have the same mean over the subsample over which TIPS data are available (2003:Q1 - 2017:Q4). Panel (a) displays the full sample, while Panel (b) zooms in on the 2003:Q1 - 2017:Q4 TIPS subsample.

Comparing the series in Figure A.5 shows that the general trajectory of the model-implied TIPS yields closely matches the data. Model and data yields display similar overall declines over the sample, equal to 1.22% and 1.55% from 2003:Q1 (the start of the TIPS sample) to 2017:Q3, respectively. Similarly, model and data yields exhibit falls of 1.65% and 1.85% from the 2006:Q3 (the TIPS peak, outside of a brief spike during the financial crisis) to 2017:Q4, respectively. Although Panel (b) shows some deviations between model and data — in particular a failure of the model to capture a dip in rates between 2012 and 2013 — these results show that the model explains most movements in real long-term bonds at the 10-year horizon, despite the fact that these data are not a target of the estimation.

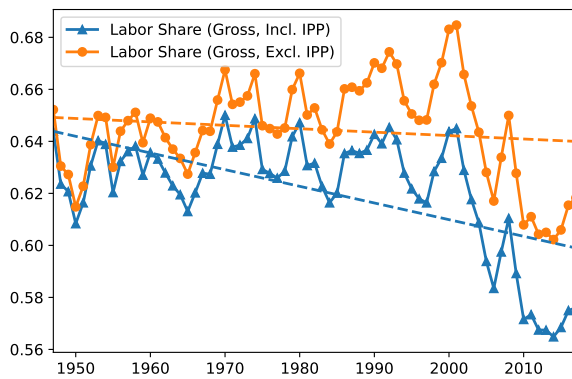
A.11 Intangible Accounting

As pointed out by Koh, Santaaulàlia-Llopis, and Zheng (2020), the BEA has changed its treatment of intangible investments over time, which can influence measured factor shares.

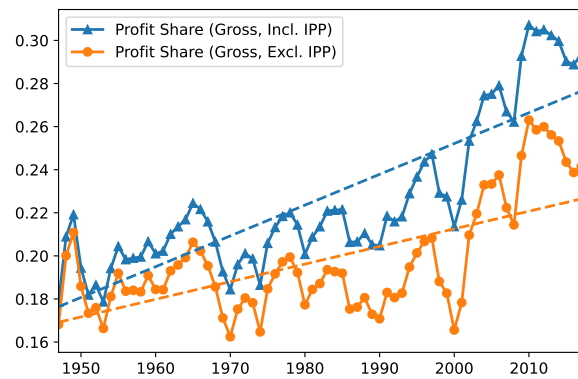
In particular, while intangible investments were considered intermediate expenses prior to 1999 (and “expensed” or removed from gross or net value added), they are now considered investments, meaning that value added (and hence profits or operating surplus) must be increased to maintain the accounting identity that value added is equal to factor payments plus investments.

Figure A.6: Factor Shares Accounting for Investment

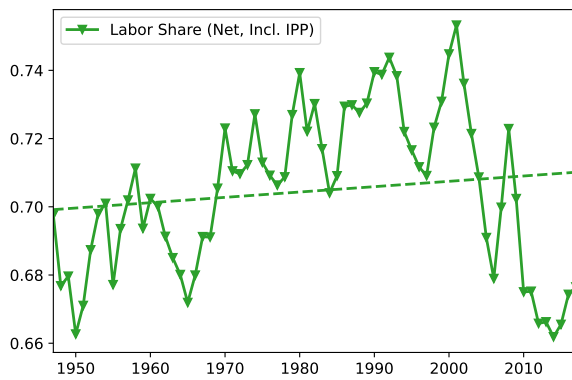
(a) Labor Share



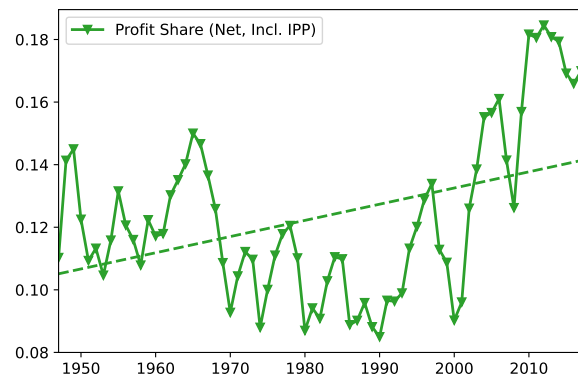
(b) Profit Share



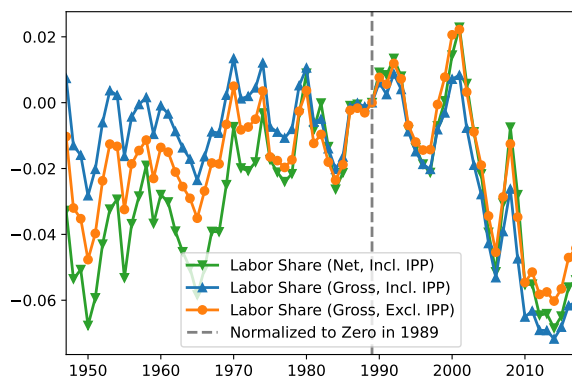
(c) Labor Share



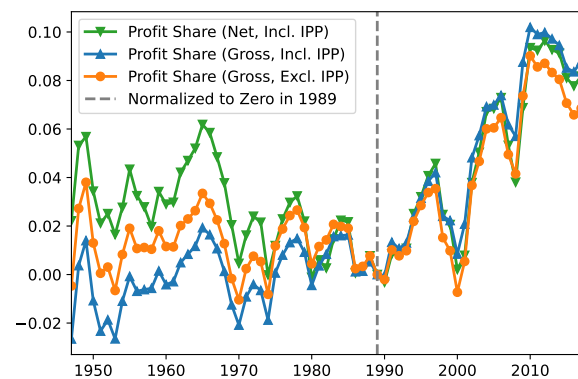
(d) Profit Share



(e) Labor Share



(f) Profit Share



Our data sample, covering the entire corporate sector, differs slightly from that used by Koh, Santaaulàlia-Llopis, and Zheng (2020) and Atkeson (2020), who consider the non-financial corporate sector only. However, we are able to reproduce the core data patterns in our sample, with the key patterns displayed in Figure A.6. To begin, Panel (a) shows that labor’s share of gross NVA including and excluding IPP, defined by

$$\text{Labor Share (Gross Incl. IPP)} = \frac{\text{Labor Compensation}}{\text{Gross Value Added}}$$

$$\text{Labor Share (Gross Excl. IPP)} = \frac{\text{Labor Compensation}}{\text{Gross Value Added} - \text{IPP Investment}}$$

where labor compensation and gross value added (GVA) come from NIPA Table 11.4, and IPP investment is defined as intangible corporate investment from BEA Fixed Asset Table 4.7. As can be seen, removing IPP investment from the denominator reduces and nearly eliminates the downward trend in the labor share of gross NVA over this period.

Panel (b) displays a similar comparison for the profit share, using the definitions

$$\text{Profit Share (Gross Incl. IPP)} = \frac{\text{Domestic After-Tax Profit} + \text{Foreign Profit}}{\text{Gross Value Added}}$$

$$\text{Profit Share (Gross Excl. IPP)} = \frac{\text{Domestic After-Tax Profit} + \text{Foreign Profit} - \text{IPP}}{\text{Gross Value Added} - \text{IPP Investment}}.$$

Note in this case that the IPP investment must be removed from both the numerator and denominator. As can be seen, the choice of whether to include or expense IPP also has an important influence on profit share growth, with the “Excl. IPP” version displaying a lower trend over the sample.

Since our definition of the profit share does not remove IPP, one therefore might be concerned that we are taking the least conservative measure, which potentially overstates the rise in the profit share over time. However, this concern is much less serious when considering that our paper does not actually use shares of gross value added (i.e., the series plotted in Panels (a) and (b)), but rather shares of *net value added*, which is equal to gross value added minus depreciation. As noted in Koh, Santaaulàlia-Llopis, and Zheng (2020), shares of net value are much less sensitive to this definitional choice, since IPP investment and depreciation take similar magnitudes, largely canceling out. To show this, Panels (c) and (d) display shares of net value added, defined by

$$\text{Labor Share (Net Incl. IPP)} = \frac{\text{Labor Compensation}}{\text{Net Value Added}}$$

$$\text{Profit Share (Net Incl. IPP)} = \frac{\text{Domestic After-Tax Profit} + \text{Foreign Profit}}{\text{Net Value Added}}.$$

These panels show that the labor share of net value added does not contain this potentially spurious downward trend over the sample, and looks closer to the gross version excluding (i.e., expensing) IPP. Similarly, the profit share of net value added displays trend growth closer to the gross version excluding IPP, implying that our definition should not be aggressively overstating growth in the profit share.

Last, we note that these definitional differences are much smaller over the second half of the sample, over which we obtain our sharpest results. Panels (e) and (f) display the three definitions for each share (gross including IPP, gross excluding IPP, and net including IPP), with a constant removed so that each series is equal to zero in 1989. These figures show that the definitions are largely irrelevant to the path of labor and profit shares since 1989, during the period when we claim the largest influence of changes in factor shares. While these figures do indicate a more substantial influence of these definitions on the evolution of profit shares earlier in the sample, we note that our chosen series (the profit share of net value added) rises the least over the full sample, and in that sense can be considered the most conservative option.

In summary, while the question of how to deal with IPP investment remains an important one, our choice to use shares of net value added should be robust to these definitional concerns, which in any case have little influence in the post-1989 sample where we find the largest role of factor shares.

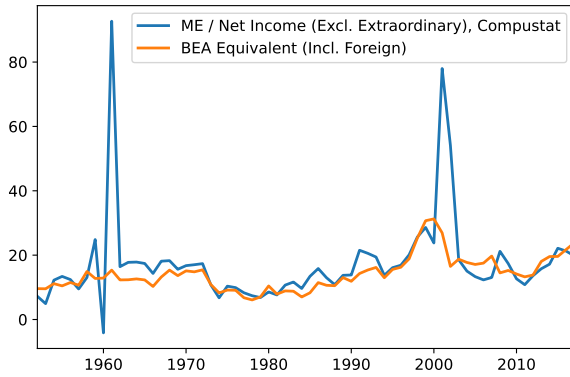
A.12 Robustness: BEA vs. Compustat

This section compares the ratio of market equity to profits in our BEA data for the US corporate sector to the corresponding measures in merged CRSP/Compustat data. We compute the value of market equity as the closing share prices times the number of shares outstanding in CRSP monthly data. We then merge the CRSP data with Compustat's North America Fundamentals Annual table using the provided linking table, and keep the last observation of each year to form an annual panel. We then sum over market equity and our various profit measures in each year, and divide to form our ratios. The profit measures we consider are: (i) earnings, equal to "Profits After Tax" in the BEA data, and "Net Income before Extraordinary Items" (code: IB) in the Compustat data; (ii) EBITDA, equal to "Net Operating Surplus" in the BEA data and "EBITDA" in the Compustat data (code: EBITDA); and (iii)

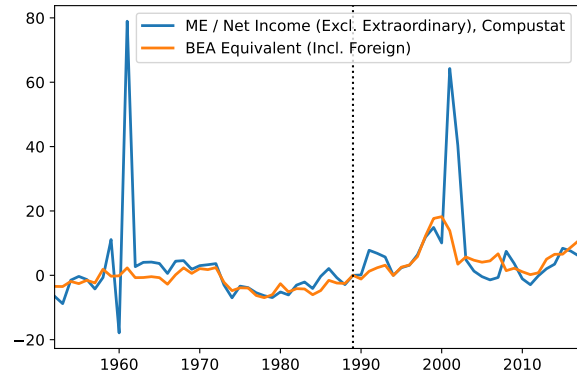
Figure A.7 displays the resulting comparison. For each row, the left panel compares

Figure A.7: Earnings Share and Valuations

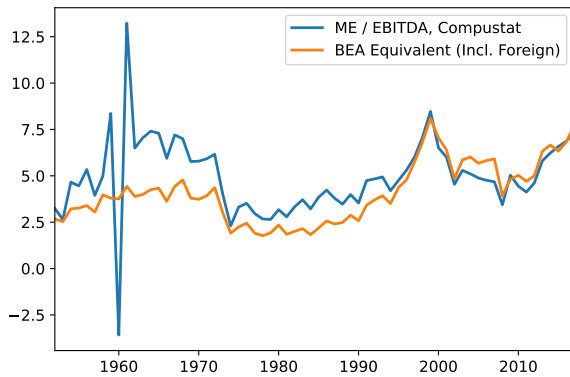
(a) ME/Earnings



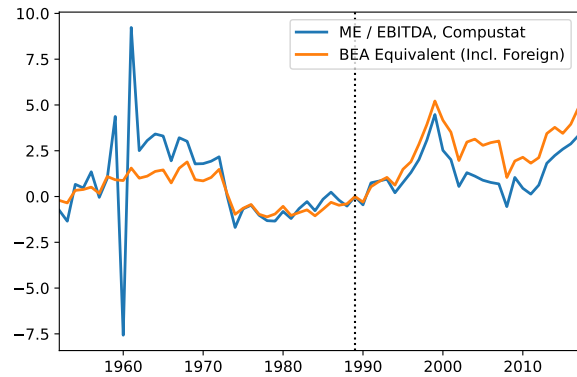
(b) ME/Earnings (Norm. 1989 = 0)



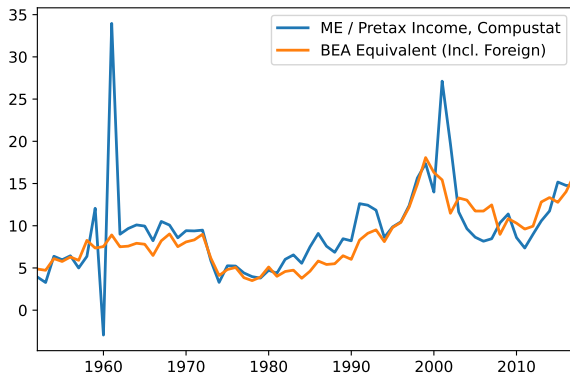
(c) ME/EBITDA



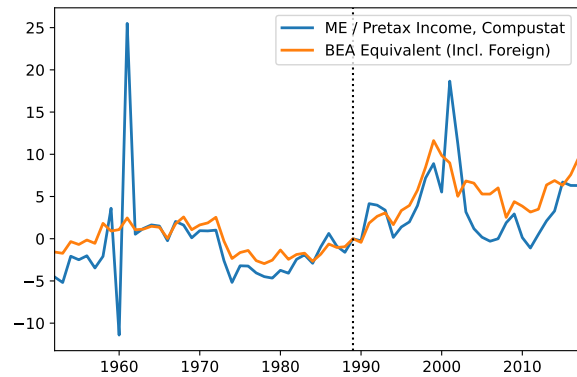
(d) ME/EBITDA (Norm. 1989 = 0)



(e) Pretax Income



(f) Pretax Income (Norm. 1989 = 0)



Notes: The sample spans the period 1952:Q1-2017:Q4.

the series in levels while the right panel normalizes both the BEA and Compustat series to be equal to zero in 1989, to more easily contrast the growth since this date. The top row uses earnings as the denominator, measured as profits after tax in the BEA data (including foreign earnings, as described in the main text), and as net income before extraordinary

expenses (“IB”) in Compustat. The series match very closely outside of some large spikes in the Compustat data, displaying very similar growth since 1989.

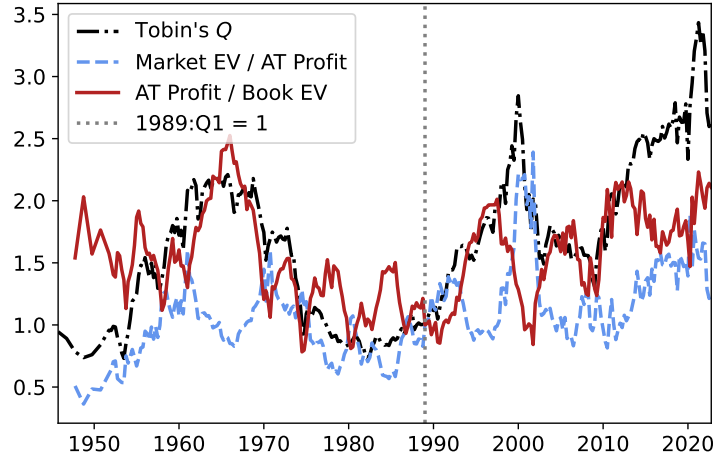
The second row uses EBITDA as the denominator (“Net Operating Surplus” in the BEA data, “EBITDA” in Compustat), while the third row uses pretax income (“Corporate Profits” in the BEA data, “PI” in Compustat). Both BEA series include foreign earnings as described in the main text. These series also match closely, and lack the extreme spikes in the Compustat data. To the extent that they differ, the ratio of ME to profit rises slightly more in the BEA data since 1989. This implies that the profit share likely rises by less in the BEA data compared to the Compustat data over this period, implying that our measures of the profit share are likely conservative.

Table A.1: Counterfactual Decomposition, Near-Permanent Risk-Free Rates

Contribution	1952-2017	1952-1988	1989-2017
<i>Panel A: Decomposition of Market Equity / NVA</i>			
Total	222.41%	-10.29%	244.30%
Factor Share (s_t)	39.67%	123.08%	49.46%
	[16.13%, 69.82%]	[344.68%, -105.00%]	[24.14%, 79.80%]
Orth. Risk Price (x_t)	41.58%	-807.36%	-46.89%
	[11.33%, 66.44%]	[-488.81%, -1126.79%]	[-82.22%, -15.79%]
Risk-Free Rate (δ_t)	23.82%	761.55%	100.04%
	[17.66%, 30.77%]	[983.56%, 564.60%]	[74.17%, 129.20%]
Real PC Output Growth (\tilde{g}_t)	-5.07%	22.73%	-2.61%
	[-16.46%, 5.12%]	[150.15%, -93.93%]	[-9.87%, 4.33%]
<i>Panel B: Decomposition of Real PC Market Equity</i>			
Total	1277.12%	150.36%	429.70%
Factor Share (s_t)	17.71%	-14.56%	36.68%
	[7.20%, 31.16%]	[-40.76%, 12.42%]	[17.91%, 59.18%]
Orth. Risk Price (x_t)	18.56%	95.48%	-34.77%
	[5.06%, 29.66%]	[57.81%, 133.26%]	[-60.97%, -11.71%]
Risk-Free Rate (δ_t)	10.63%	-90.07%	74.19%
	[7.88%, 13.73%]	[-116.32%, -66.77%]	[55.00%, 95.82%]
Real PC Output Growth ($g + \tilde{g}_t$)	53.09%	109.10%	23.91%
	[48.01%, 57.65%]	[94.07%, 122.93%]	[18.52%, 29.05%]

Notes: The table presents the growth decompositions for the real per-capita value of market equity under our counterfactual model with near-permanent risk-free rates. The row “Total” displays the total growth in market equity over this period, in levels. The remaining rows report the share of this overall growth explained by each component, obtained by measuring the difference in implied growth between the data and a counterfactual path in which that variable is held fixed at its initial value for the relevant subsample. To ensure an additive decomposition, we measure the share of total growth explained in logs. The reported statistics are means over shares computed from 10,000 equally spaced parameter draws from our MCMC chain. Below each set of means in brackets are the 5th and 95th percentiles over the same distribution, providing a 90% credible set that accounts for both parameter and latent state uncertainty. The sample spans the period 1952:Q1-2017:Q4.

Figure A.8: Tobin's Q Decomposition



Notes: Tobin's Q is computed from the Flow of Funds as the ratio of market value of assets to book value of assets in the nonfinancial corporate sector. Market value of nonfinancial assets is computed as the sum of liabilities (FL104190005), corporate equities (LM103164103), and foreign direct investment (LM103192105), net of financial assets (FL104090005). Book value of nonfinancial assets is obtained as the nonfinancial assets series LM102010005. AT profit is equal to after-tax profits of the corporate sector, computed as in Section 4.

A.13 Link to Tobin's Q

In this appendix, we study the model-free associations between factor shares and Tobin's Q . To understand how our work can help explain the sources of movements in Q , we can decompose Tobin's Q into two components:

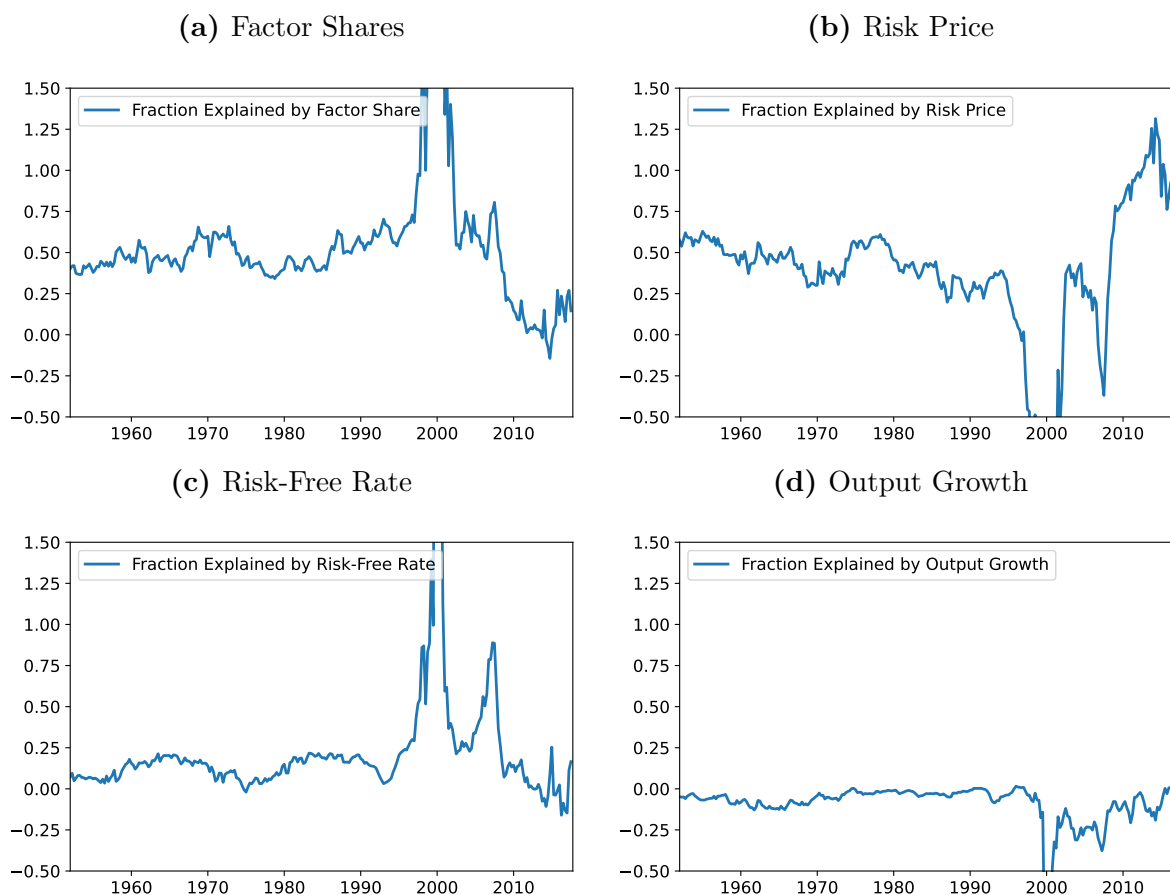
$$Q = \frac{MV}{BV} = \frac{MV}{E} \times \frac{E}{BV} \quad (\text{A.9})$$

where MV and BV represent market and book value, and E represents our measure of after-tax corporate profits. Essentially, our factor share mechanism can be viewed as operating through the E/BV term (similar to ROA or ROE), while the remaining forces in the model influencing discount rates, risk premia, and news about future cash flows operate through the MV/E term.

Figure A.8 displays Tobin's Q computed from the Flow of Funds, alongside its two components in equation (A.9), with all series normalized to one in 1989:Q1, as in Figure 1. The figure shows that changes in profit shares explain a substantial portion of movements in Tobin's Q , accounting for much of the variation from the mid-1950s to mid-2010s, outside of the early 2000s. Thus, the data suggest that variation in factor shares have provided an important quantitative contribution to Tobin's Q over our sample.

A.14 Alternative Breakpoints

Figure A.9: Contributions to ME/NVA Varying Start Date



Notes: This figure presents the median estimated share of the rise in ME/Y explained by each component from each date to the end of the sample. Contributions are computed as in Table 2 with the exception that we present medians rather than means over our parameter draws.

While we focus on a particular set of breakpoints in the paper, one advantage of our estimation approach is that we can compute contributions of each factor over any time period. To this end, we have added Figure A.9, which displays the median estimated fraction explained by each of our components from each date to the end of our sample. As can be seen, the overall share explained by factor shares is substantial and relatively stable until the mid-1990s. After this, it briefly exceeds 100%, largely due to the remaining growth in ME/NVA to the end of the sample (the denominator in the fraction explained) approaching zero at the peak of the dot-com boom. Last, toward the very end of the sample, the contribution drops toward zero as the earnings share stagnates from around 2010 to the end of our sample.

For the other series, we see that the risk price similarly explains a large and stable share of

total remaining ME/NVA growth through the mid-1990s, then experiences the same volatility due to a low denominator, and finally becomes the dominant driver of growth in ME/NVA from roughly 2010 onward. The risk-free rate has a small and stable contribution through the mid-1990s, experiences the same volatility around 2000, and also regains a dominant role briefly around the financial crisis, as falling risk-free rates around this time played a substantial role in boosting asset prices. Last, the share explained by output growth is close to zero for most of the sample, but becomes nontrivially negative toward the end of the sample due to falling output growth forecasts.

A.15 Robustness: SVIX Lower Bound

This section addresses concerns that our use of a lower bound for the risk premium, instead of a point estimate, is influencing our result that realized excess returns exceeded typical excess returns or risk premia over our sample. In this section, we extend the model estimated an alternative version of the model that adds a constant bias term to our measurement equation for the risk premium, so that

$$rp_t = rp_t^{model} + \nu_{rp}. \quad (\text{A.10})$$

In words, this equation states that the SVIX-implied lower bound for the equity risk premium in the data (rp_t), is equal to the actual risk premium in the model (rp_t^{model}) plus a constant. Thus, to the extent that the SVIX lower bound is not tight, the model is free to set $\nu_{rp} < 0$. Of course, this only addresses the degree to which the lower bound is not tight on average, rather than period-by-period, but since this average is the key to our main results on the overall difference between expected and realized returns, we believe this implementation is appropriate and has the benefit of being highly parsimonious.

Turning to our estimation results, our median estimate of ν_{rp} over our parameter draws is actually *positive* (+75bp annually), implying that the SVIX risk premium is actually larger on average than the model risk premium. Incorporating parameter uncertainty, our 5th and 95th percentile estimates range from the SVIX risk premium understating the true risk premium by 205bp annually, to overstating it by 373bp annually. In summary, our parameter estimates from this unrestricted model imply that our baseline assumption that the lower bound is tight ($\nu_{rp} = 0$) cannot be rejected, and the model appears to have no preference for setting $\nu_{rp} < 0$ even at the point estimates.

Given these results, we unsurprisingly find that the model estimating the risk premium bias term ν_{rp} in (A.10) produces results very similar to those of our baseline model in terms of our main growth decomposition. In terms of the asset pricing results, we find that this model does deliver a slightly smaller average gap between expected and realized returns, equal to 1.5pp compared to 1.9pp under our baseline model, or median gaps of 2.0pp and 2.3pp, respectively. These differences are small and statistically indistinguishable at standard confidence levels. Further, because they are mostly obtained in models with $\nu_{rp} > 0$, which violates the definition of the SVIX risk premium as a lower bound, we do not put particular weight on the fact that they are slightly smaller than our baseline estimates. As a result, we conclude that our results are robust to this concern, and are not being driven by differences between the lower bound and the actual risk premium.

A.16 Additional Tables and Figures

Table A.2: Decomposition of Market Equity / NVA by Subcomponent

Contribution	1952-2017	1952-1988	1989-2017
Total	222.41%	-10.29%	244.30%
Factor Share (s_t)	41.51%	149.61%	54.15%
	[15.61%, 75.36%]	[381.84%, -58.34%]	[24.96%, 89.21%]
$s_{LF,t}$	39.19%	134.59%	49.25%
	[11.70%, 74.65%]	[390.89%, -108.25%]	[18.87%, 85.88%]
$s_{HF,t}$	2.32%	15.03%	4.89%
	[-0.78%, 6.56%]	[54.01%, -15.78%]	[0.68%, 11.16%]
Orth. Risk Price (x_t)	56.90%	-218.97%	28.06%
	[22.44%, 85.08%]	[36.72%, -496.98%]	[-7.37%, 58.02%]
$x_{LF,t}$	56.69%	-222.93%	27.86%
	[22.62%, 85.23%]	[34.32%, -506.13%]	[-7.68%, 58.21%]
$x_{HF,t}$	0.21%	3.96%	0.20%
	[-4.93%, 5.52%]	[60.49%, -50.22%]	[-4.65%, 5.16%]
Risk-Free Rate (δ_t)	6.92%	136.14%	19.26%
	[0.10%, 14.20%]	[228.75%, 54.19%]	[13.40%, 26.09%]
$\delta_{LF,t}$	7.22%	114.78%	16.99%
	[-2.01%, 16.78%]	[232.84%, 0.56%]	[8.84%, 25.27%]
$\delta_{HF,t}$	-0.30%	21.36%	2.27%
	[-2.81%, 2.26%]	[58.92%, -8.76%]	[-0.28%, 5.72%]
Real PC Output Growth (\tilde{g}_t)	-5.33%	33.22%	-1.47%
	[-16.92%, 4.98%]	[168.03%, -86.06%]	[-8.85%, 5.86%]
$\tilde{g}_{HF,t}$	0.09%	-4.64%	0.33%
	[-0.08%, 0.29%]	[-2.15%, -7.81%]	[0.16%, 0.55%]
$\tilde{g}_{LF,t}$	-5.42%	37.86%	-1.80%
	[-17.10%, 5.06%]	[174.61%, -82.77%]	[-9.30%, 5.66%]

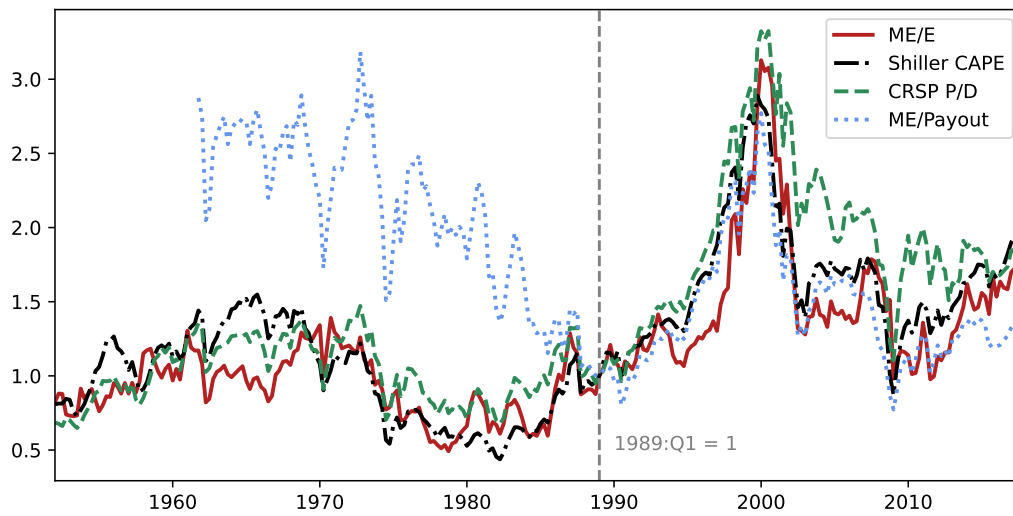
Notes: The table presents the growth decompositions for the real per-capita value of market equity, corresponding to Panel A of 2. The row “Total” displays the total growth in the ratio of market equity to corporate net value added over this period, in levels. The remaining rows report the share of this overall growth explained by each component, obtained by measuring the difference in implied growth between the data and a counterfactual path in which that variable is held fixed at its initial value for the relevant subsample. To ensure an additive decomposition, we measure the share of total growth explained in logs. The reported statistics are means over shares computed from 10,000 equally spaced parameter draws from our MCMC chain. Below each set of means in brackets are the 5th and 95th percentiles over the same distribution, providing a 90% confidence interval. The sample spans the period 1952:Q1-2017:Q4.

Table A.3: Decomposition of Market Equity by Subcomponent

Contribution	1952-2017	1952-1988	1989-2017
Total	1277.12%	150.36%	429.70%
Factor Share (s_t)	18.53%	-17.69%	40.16%
	[6.97%, 33.64%]	[-45.16%, 6.90%]	[18.51%, 66.16%]
$s_{LF,t}$	17.49%	-15.92%	36.53%
	[5.22%, 33.32%]	[-46.23%, 12.80%]	[13.99%, 63.69%]
$s_{HF,t}$	1.04%	-1.78%	3.63%
	[-0.35%, 2.93%]	[-6.39%, 1.87%]	[0.50%, 8.27%]
Orth. Risk Price (x_t)	25.40%	25.90%	20.81%
	[10.02%, 37.98%]	[-4.34%, 58.78%]	[-5.47%, 43.03%]
$x_{LF,t}$	25.30%	26.37%	20.66%
	[10.10%, 38.04%]	[-4.06%, 59.86%]	[-5.69%, 43.17%]
$x_{HF,t}$	0.09%	-0.47%	0.15%
	[-2.20%, 2.46%]	[-7.15%, 5.94%]	[-3.45%, 3.83%]
Risk-Free Rate (δ_t)	3.09%	-16.10%	14.29%
	[0.04%, 6.34%]	[-27.05%, -6.41%]	[9.94%, 19.35%]
$\delta_{LF,t}$	3.22%	-13.57%	12.60%
	[-0.90%, 7.49%]	[-27.54%, -0.07%]	[6.55%, 18.74%]
$\delta_{HF,t}$	-0.13%	-2.53%	1.69%
	[-1.26%, 1.01%]	[-6.97%, 1.04%]	[-0.21%, 4.25%]
Real PC Output Growth ($g + \tilde{g}_t$)	52.98%	107.90%	24.75%
	[47.81%, 57.59%]	[91.95%, 122.00%]	[19.27%, 30.19%]

Notes: The table presents the growth decompositions for the real per-capita value of market equity, corresponding to Panel B of Table 2. The row “Total” displays the total growth in the ratio of market equity to corporate net value added over this period, in levels. The remaining rows report the share of this overall growth explained by each component, obtained by measuring the difference in implied growth between the data and a counterfactual path in which that variable is held fixed at its initial value for the relevant subsample. To ensure an additive decomposition, we measure the share of total growth explained in logs. The reported statistics are means over shares computed from 10,000 equally spaced parameter draws from our MCMC chain. Below each set of means in brackets are the 5th and 95th percentiles over the same distribution, providing a 90% confidence interval. The sample spans the period 1952:Q1-2017:Q4.

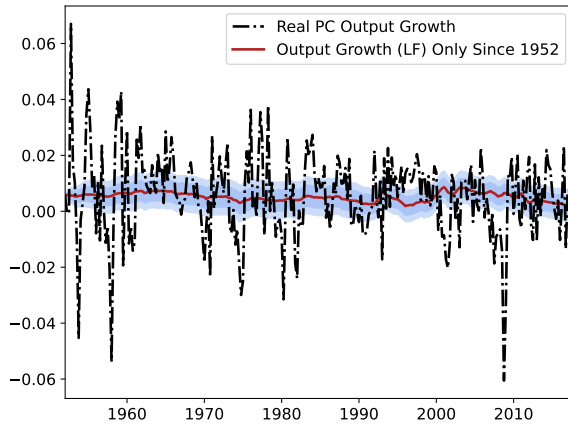
Figure A.10: Stock Market Ratios, Continued



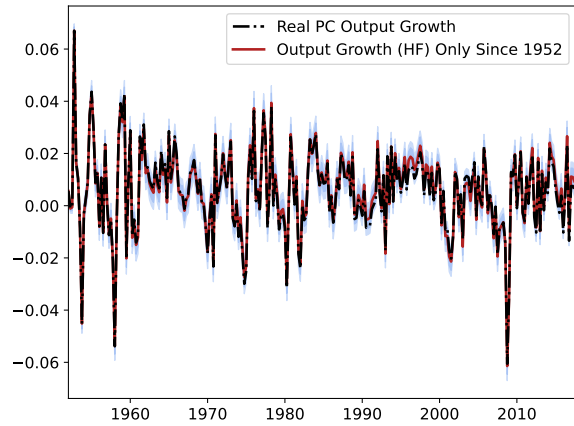
Notes: To make the units comparable, each series has been normalized to unity in 1989:Q1. The sample spans the period 1952:Q1-2017:Q4. **ME**: market value of corporate equities. **E**: corporate sector after-tax profits. **Shiller CAPE**: the Cyclical Adjusted Price/Earnings ratio of Robert Shiller. **CRSP P/D**: the ratio of prices to a 4Q rolling sum of dividends for the CRSP value-weighted average. Sources: NIPA, the Flow of Funds, Robert Shiller, CRSP.

Figure A.11: Latent State Components, Additional Series

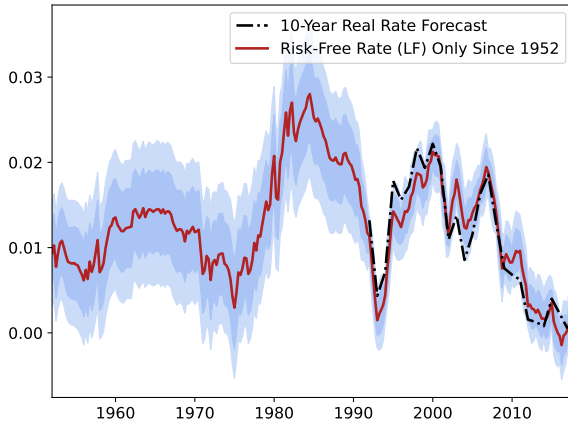
(a) Output Growth (LF)



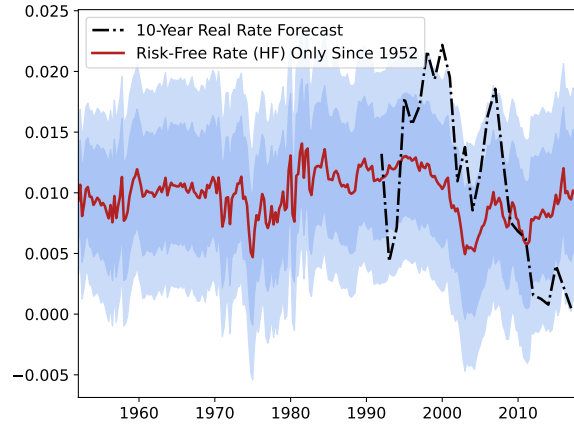
(b) Output Growth (HF)



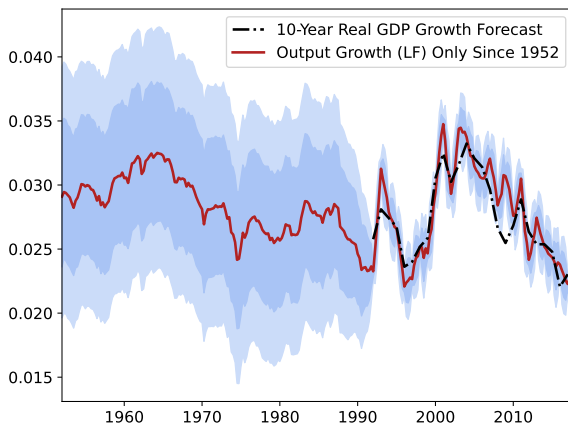
(c) 10-Year Real Rate Forecast (LF)



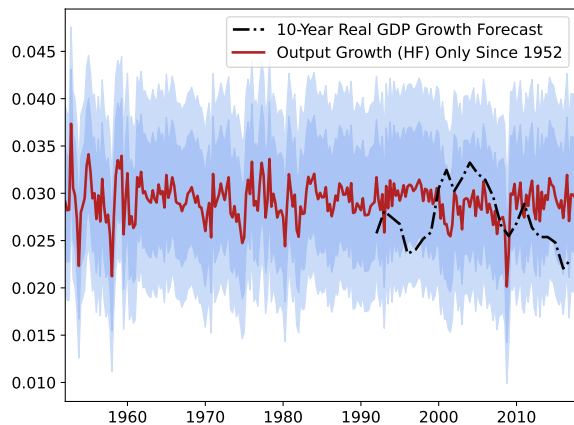
(d) 10-Year Real Rate Forecast (HF)



(e) 10-Year Real GDP Gr. Forecast (LF)

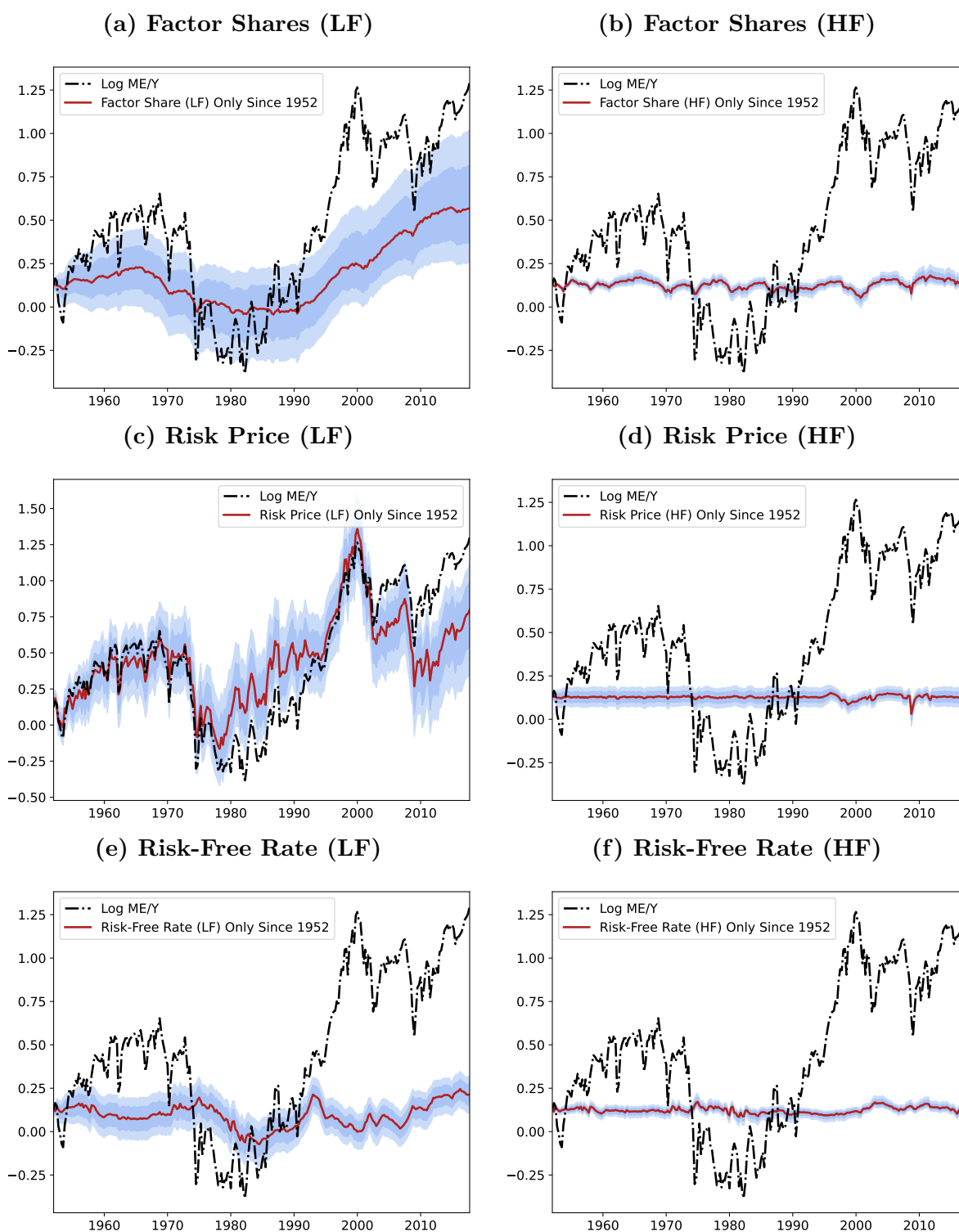


(f) 10-Year Real GDP Gr. Forecast (HF)



Notes: The figure displays the observed real per capita output growth series along with the model-implied variation in the series attributable to the low-frequency and high-frequency components of either δ_t or \tilde{g}_t , depending on the series. The red center line corresponds to the median of the distribution of outcomes, accounting for both parameter and latent state uncertainty, while the dark and light blue bands correspond to 66.7% and 90% credible sets, respectively. The sample spans the period 1952:Q1-2017:Q4.

Figure A.12: Market Equity-Output Ratio Decomposition by Subcomponent



Notes: This figure exhibits the observed market equity-to-output series along with the model-implied variation in the series attributable to certain latent components. The red center line corresponds to the median of the distribution of outcomes, accounting for both parameter and latent state uncertainty, while the dark and light blue bands correspond to 66.7% and 90% credible sets, respectively. The sample spans the period 1952:Q1-2017:Q4.

Figure A.13: Model-Implied Forecasts

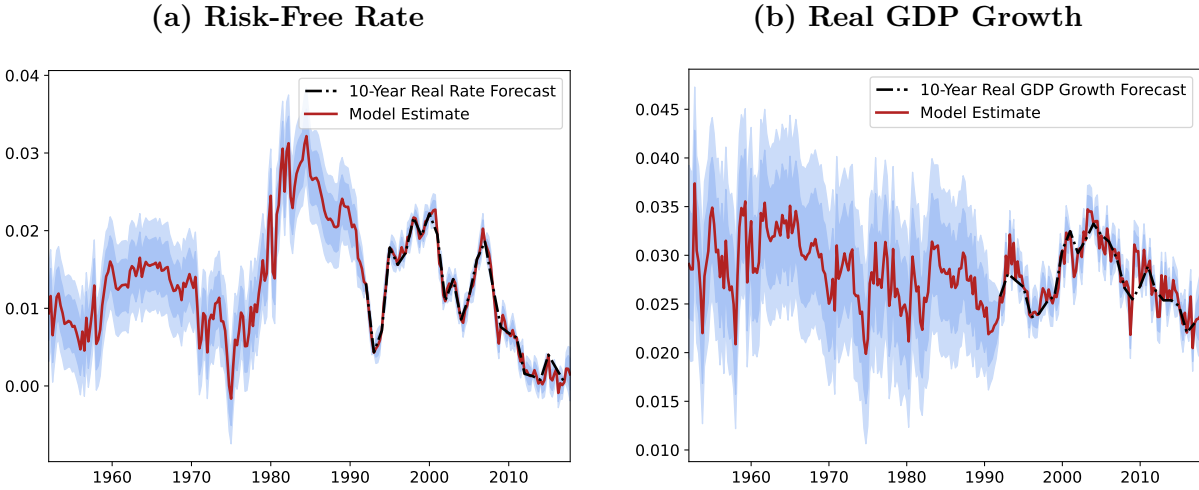
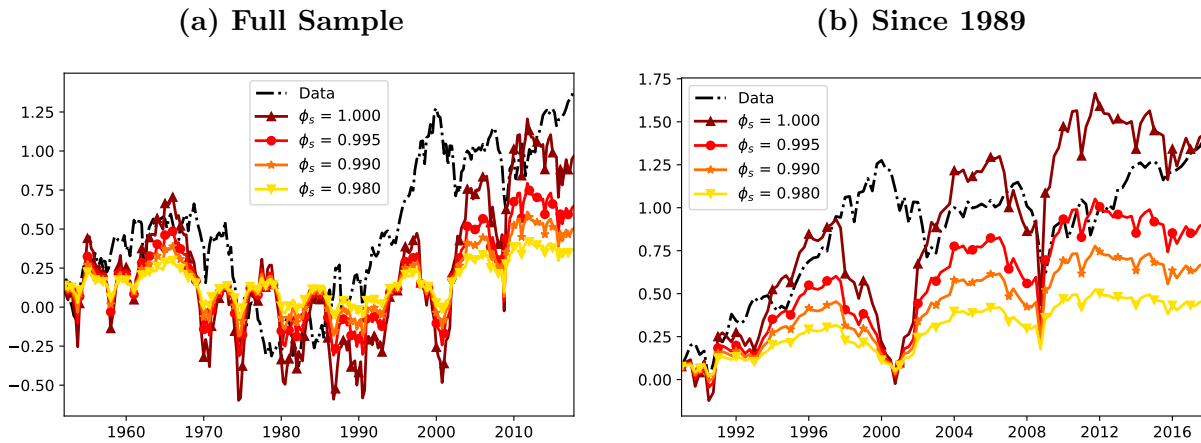


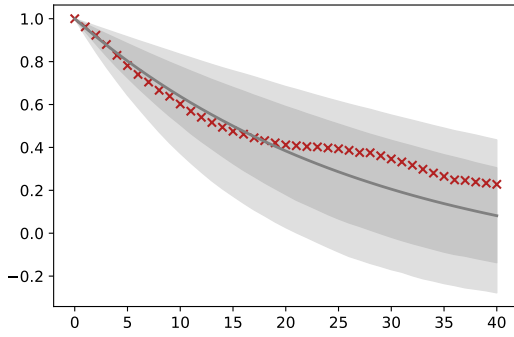
Figure A.14: Implied Contributions, AR(1) Models



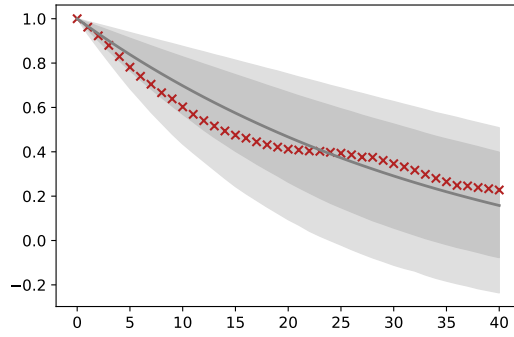
Notes: This figure superimposes the implied contributions of the earnings share to the log market equity to output ratio via cash flows measured as in equation (20), over the earnings share data. Each implied contribution is computed by adding the difference in the right hand side of (20) to the initial value of py_t at the start of the relevant subsample.

Figure A.15: Simulated Autocorrelations, AR(1) Models

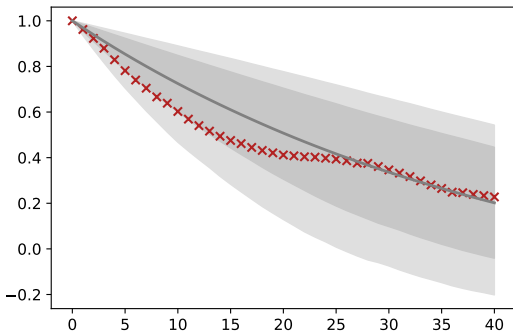
(a) $\phi_s = 0.98$



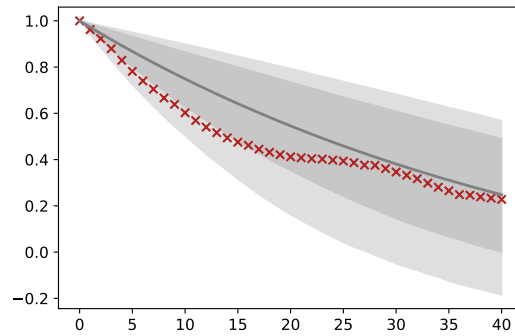
(b) $\phi_s = 0.99$



(c) $\phi_s = 0.995$



(d) $\phi_s = 1$



Notes: The figure compares the data autocorrelations for the observable variables available over the full sample, compared to the same statistics from the simplified AR(1) models described in Section 7. For the model equivalents, we compute autocorrelations from each of 10,000 simulations the same length as the data, drawn with the persistence parameter found in that panel's title. The center line corresponds to the mean of these autocorrelations, while the dark and light gray bands represent 66.7% and 90% credible sets, respectively. The sample spans the period 1952:Q1-2017:Q4.