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Capital Share Risk in U.S. Asset Pricing

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ABSTRACT

A single macroeconomic factor based on growth in the capital share of aggregate income exhibits significant explanatory power for expected returns across a range of equity characteristic portfolios and nonequity asset classes, with risk price estimates that are of the same sign and similar in magnitude. Positive exposure to capital share risk earns a positive risk premium, commensurate with recent asset pricing models in which redistributive shocks shift the share of income between the wealthy, who finance consumption primarily out of asset ownership, and workers, who finance consumption primarily out of wages and salaries.

CONTEMPORARY ASSET PRICING THEORY REMAINS in search of an empirically relevant stochastic discount factor (SDF) linked to the marginal utility of investors. This study presents evidence that a single macroeconomic factor based on growth in the capital share of aggregate income exhibits significant explanatory power for expected returns across a wide range of equity characteristic portfolio styles and nonequity asset classes, with positive risk price estimates of similar magnitude. These assets include equity portfolios formed from sorts on size/book-to-market, size/investment, size/operating profitability, long-run reversal, and nonequity asset classes such as corporate bonds, sovereign bonds, credit default swaps, and options.

Why should growth in the share of national income accruing to capital (hereafter the "capital share") be a source of systematic risk? After all, a mainstay of contemporary asset pricing theory is that assets are priced as if there were a representative agent, leading to an SDF based on the marginal rate of

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substitution over aggregate household consumption. Under this paradigm, the division of aggregate income between labor and capital is irrelevant for the pricing of risky securities once aggregate consumption risk is accounted for. The representative agent model is especially convenient from an empirical perspective, since aggregate household consumption is readily observed in national income data.

But there are reasons to question whether average household consumption is the appropriate source of systematic risk for the pricing of risky financial securities. Wealth is highly concentrated at the top, and limited securities market participation remains pervasive. The majority of households own no equity but even among those who do, most own very little. In particular, while just under half of households report owning stocks either directly or indirectly in 2013, the top 5% of the stock wealth distribution owns 75% of the stock market value.[1] It follows that any reasonably defined wealth-weighted stock market participation rate should be much lower than 50%, as we illustrate below. Moreover, unlike the average household, the wealthiest U.S. households earn a relatively small fraction of income as labor compensation, implying that income from the ownership of firms and financial investments, that is, capital income, finances much more of their consumption.[2] Consistent with this point, we find that the capital share is strongly positively related to the income shares of those in the top 5% to 10% of the stock market wealth distribution, but negatively related to the income shares of those in the bottom 90%.

These observations suggest a different approach to explaining return premia on risky assets. Recent inequality-based asset pricing models imply that the capital share should be a priced risk factor when risk-sharing is imperfect and wealth is concentrated in the hands of a few investors or "shareholders," while most households are "workers" who finance consumption primarily out of wages and salaries (e.g., Greenwald, Lettau, and Ludvigson (2014, GLL)). In these models, redistributive shocks that shift the share of income between labor and capital are a source of systematic risk for asset owners. In the extreme case in which workers own no risky asset shares and there is no risk-sharing between workers and shareholders, a representative shareholder who owns the entire corporate sector will have consumption in equilibrium equal to $C_t \cdot KS_t$, where C_t is aggregate (shareholder plus worker) consumption and KS_t is the capital share of aggregate income.[3] The capital share is then a source of priced risk.

[1] Source: 2013 Survey of Consumer Finances.

[2] In the 2013 SCF, the top 5% of the net worth distribution had a median wage-to-capital-income ratio of 18%, where capital income is defined as the sum of income from dividends, capital gains, pensions, net rents, trusts, royalties, and/or sole proprietorships or farms.

[3] This reasoning goes through as an approximation even if workers own a small fraction of the corporate sector and 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.

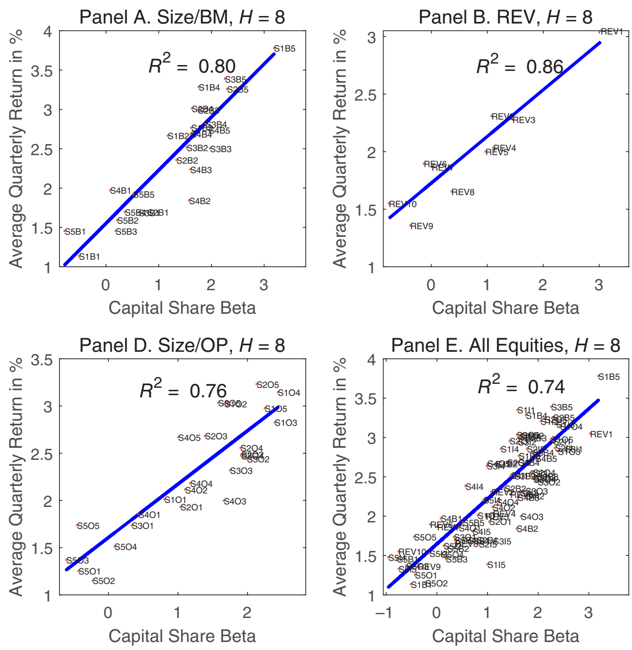

Figure 1. Capital share betas. This plot depicts betas constructed from Fama-MacBeth (1973) regressions of average returns on capital share beta for different equity characteristic portfolios or using all equity portfolios together (size/BM, REV, size/INV, and size/OP). H indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q3 to 2013Q4. (Color figure can be viewed at wileyonlinelibrary.com)

With this theoretical motivation as backdrop, in this paper we explore whether growth in the capital share is a priced risk factor for explaining cross-sections of expected asset returns. We find that an asset's exposure to short- to medium-frequency (i.e., four-to-eight quarter) fluctuations in capital share growth has strong explanatory power for the cross-section of expected returns on a range of equity characteristic portfolios as well as other asset classes. For the equity portfolios and asset classes mentioned above, we find that positive exposure to capital share risk earns a positive risk premium, with risk prices of similar magnitude across portfolio groups. A preview of the results for equity characteristic portfolios is given in Figure 1, which plots observed quarterly return premia (average excess returns) on each portfolio on the y-axis against the portfolio capital share beta for exposures of $H = 8$ quarters on the x-axis. The estimates show that the model fit is high across a variety of equity portfolio styles. (We discuss this figure further below.) Pooled estimations of the different stock portfolios considered jointly and of the stock portfolios combined with the portfolios of other asset classes also indicate that capital share risk has substantial explanatory power for expected returns. In principle, these findings could be consistent with the canonical representative agent model if aggregate consumption growth were perfectly positively correlated with capital share growth. But this is not what we find. For all but one portfolio group studied here, aggregate consumption risk measured over any horizon exhibits far lower explanatory power for the cross-section of returns and/or is not statistically significant after exposures to capital share risk are introduced.

A notable result of our analysis is that an empirical model with capital share growth as the single source of macroeconomic risk explains a larger fraction of expected returns on equity portfolios formed from size/book-to-market sorts than does the Fama-French three-factor model, an empirical specification explicitly designed to explain the large cross-sectional variation in average return premia on these portfolios (Fama and French (1993)). Moreover, the risk prices for the return-based factors SMB and HML are either significantly attenuated or driven completely out of the pricing regressions by the estimated exposure to capital share risk.

We also compare the empirical capital share pricing model studied here to two other empirical models recently documented to have explanatory power for cross-sections of expected asset returns, namely, the intermediary-based asset pricing models of Adrian, Etula, and Muir (2014, AEM) and He, Kelly, and Manela (2016, HKM). This comparison is apt because the motivations behind the inequality- and intermediary-based asset pricing theories are quite similar. Both theories are macro factor frameworks in which average household consumption is not itself an appropriate source of systematic risk for the pricing of financial securities. In the intermediary-based paradigm, intermediaries are owned by "sophisticated" or "expert" investors who are distinct from the majority of households that comprise aggregate consumption. It is reasonable to expect that sophisticated investors often coincide with wealthy asset owners and face similar if not identical sources of systematic risk. Indeed, we find that capital share growth exposure contains information for the pricing of risky securities that overlaps with that of the banking sector's equity capital ratio factor studied by HKM and the broker-dealer leverage factor studied by AEM. But the information in these intermediary balance sheet exposures is almost always subsumed in part or in whole by the capital share exposures, suggesting that the latter contain additional information about the cross-section of expected returns that is not present in the intermediary-based factor exposures.

In the last part of the paper, we provide additional evidence from household-level data that sharpens the focus on redistributive shocks as a source of systematic risk for the wealthy. First, we show that growth in the income shares of the richest stockowners (e.g., the top 10% of the stock wealth distribution) is sufficiently strongly negatively correlated with that of nonrich stockowners (e.g., the bottom 90%) that growth in the *product* of these shares with aggregate consumption is also strongly negatively correlated. This means that the inversely related component in the product operating through income shares outweighs the common component operating through aggregate consumption. While this finding is suggestive of limited risk-sharing, some income share variation between these groups is likely to be idiosyncratic and capable of being diversified away. We therefore form an estimate of the component of income share variation that represents systematic risk as the fitted values from a projection of each group's income share on the aggregate capital share. Finally, we form a proxy for the consumption of the wealthiest stockholders as the product of aggregate consumption times the top group's fitted income share. We find that estimated exposures to this proxy help explain expected return premia on the same equity characteristic portfolios that are well explained by capital share exposures.

Our investigation is related to a classic older literature emphasizing the importance for stock pricing of limited stock market participation and heterogeneity (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)). In contrast to this literature, the limited participation dimension relevant for our analysis is not shareholder versus nonshareholder, but rather investors who differ according to whether their income is earned primarily from supplying labor or from owning assets. Our results suggest the relevance of frameworks in which investors are concerned about shocks that have opposite effects on labor and capital. Such redistributive shocks play no role in the traditional limited participation literature.

A growing body of literature considers the role of redistributive shocks that transfer resources between shareholders and workers as a source of priced risk when risk-sharing is imperfect (Danthine and Donaldson (2002), Favilukis and Lin (2013, 2015, 2016), Gomez (2016), GLL, Marfe (2017)). In this literature, labor compensation is a charge to claimants on the firm and therefore a systematic risk factor for aggregate stock and bond markets. In models that combine these features with limited stock market participation, such as that in GLL, the capital share matters for risk pricing. Finally, the findings here are related to a body of evidence suggesting that the returns to human capital are negatively correlated with those to stock market wealth (Lustig and Van Nieuwerburgh (2008), Lettau and Ludvigson (2009, 2013), Chen, Favilukis, and Ludvigson (2014), GLL, Bianchi, Lettau, and Ludvigson (2016)).

We note that estimated exposures to capital share risk do not explain cross-sections of expected returns on all portfolio types. We find that these exposures have no ability to explain cross-sections of expected returns on industry portfolios, or on the foreign exchange and commodities portfolios that HKM find are well explained by their intermediary sector equity-capital ratio. Moreover, momentum portfolios present a puzzle for both the inequality-based and the intermediary-based models, since these factors often earn a negative risk price when explaining cross-sections of expected momentum returns. Exploration of this momentum-related puzzle is taken up in a separate paper (Lettau, Ludvigson, and Ma (2018)).

The rest of this paper is organized as follows. Section I discusses the data and presents preliminary analyses. Section II describes the econometric models to be estimated, while Section III discusses the results of these estimations. Section IV concludes.

I. Data and Preliminary Analysis

This section briefly describes our data. A more detailed description of the data and our sources is provided in the Internet Appendix.[4] Our sample is quarterly and unless otherwise noted spans the period 1963:Q3 to 2013:Q4 before losing observations to computing long horizon relations as described below.

We use equity return data available from Kenneth French's Dartmouth website on 25 size/book-to-market sorted portfolios (size/BM), 10 long-run reversal portfolios (REV), 25 size/operating profitability portfolios (size/OP), and 25 size/investment portfolios (size/INV). We also use the portfolio data recently explored by HKM to investigate other asset classes, including the 10 corporate bond portfolios from Nozawa (2014) spanning 1972:Q3 to 1973:Q2 and 1975:Q1 to 2012:Q4 ("bonds"), six sovereign bond portfolios from Borri and Verdelhan (2011) spanning 1995:Q1 to 2011:Q1 ("sovereign bonds"), 54 S&P 500 index option portfolios sorted on moneyness and maturity from Constantinides, Jackwerth, and Savov (2013) spanning 1986:Q2 to 2011:Q4 ("options"), and the 20 credit default swap (CDS) portfolios constructed by HKM spanning 2001:Q2 to 2012:Q4.[5]

We define the *capital share* as $KS \equiv 1 - LS$, where LS is the *labor share* of national income. Our benchmark measure of LS_t is the labor share of the nonfarm business sector as compiled by the Bureau of Labor Statistics (BLS), measured on a quarterly basis.

There are well-known difficulties with accurately measuring the labor share. Most notable is the difficulty with separating income of sole proprietors into components attributable to labor and capital inputs. But Karabarbounis and Neiman (2013) report *trends* for the labor share, that is, changes within the corporate sector that are similar to those for sectors that include sole proprietors, such as the BLS nonfarm measure (which makes specific assumptions on how proprietors' income is proportioned). Indirect taxes and subsidies can also create a wedge between the labor and the capital shares, but Gomme and Rupert (2004) find that these do not vary much over time, so that movements in the labor share are still strongly (inversely) correlated with movements in the capital share. Thus, the main difficulties with measuring the labor share pertain to getting the *level* of the labor share right. Our results rely instead on *changes* in the labor share, and we maintain the hypothesis that they are informative about opposite-signed changes in the capital share. Figure 2 plots the rolling eight-quarter log difference in the capital share over time. This variable is volatile throughout our sample.

The empirical investigation of this paper is motivated by the inequality-based asset pricing literature discussed above. One question prompted by this literature is whether there is any evidence that fluctuations in the aggregate capital share are related in a quantitatively important way to observed income shares of wealthy households, and the latter to expected returns on risky assets.

[4] The Internet Appendix may be found in the online version of this article.

[5] We are grateful to Zhiguo He, Bryan Kelly, and Asaf Manela for making their data and code available to us.

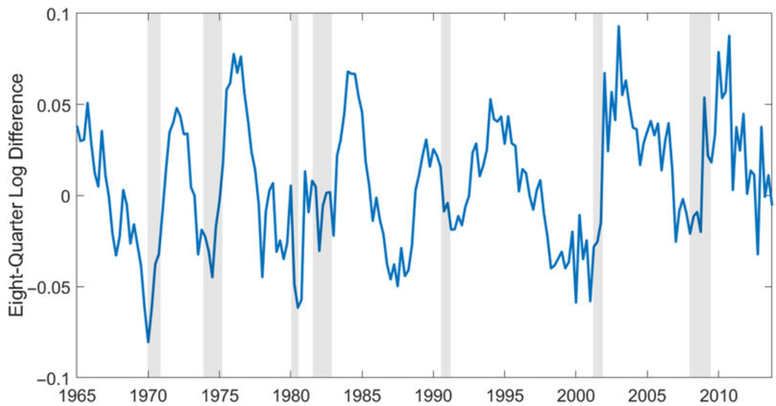

Figure 2. Capital share, eight-quarter log difference. The vertical lines correspond to NBER recession dates. The sample spans the period 1963Q3 to 2013Q4. (Color figure can be viewed at wileyonlinelibrary.com)

To address these questions, we make use of two household-level data sets that provide information on wealth and income inequality. The first is the triennial survey data from the Survey of Consumer Finances (SCF), the best source of micro-level data on household-level assets and liabilities for the United States. The SCF also provides information on income and on whether the household owns stocks directly or indirectly. The SCF is well suited to studying the wealth distribution because it includes a sample intended to measure the wealthiest households, identified on the basis of tax returns. It also has a standard random sample of U.S. households. The SCF provides weights for combining the two samples, which we use whenever we report statistics from the SCF. The 2013 survey is based on 6,015 households.

The second household level data set uses the income-capitalization method of Saez and Zucman (2016) (SZ), which combines information from income tax returns with aggregate household balance sheet data to estimate the wealth distribution across households annually.[6] This method starts with the capital income reported by households on their tax forms to the Internal Revenue Service (IRS). For each class of capital income (e.g., interest income, rents, dividends, capital gains, etc.), a capitalization factor is computed that maps total flow income reported for that class to the amount of wealth from the household balance sheet of the U.S. Financial Accounts. Wealth for a given household and year is obtained by multiplying the individual income components for that asset class by the corresponding capitalization factors. We modify the selection criteria to additionally form an estimate of the distribution of wealth and income among just those individuals who can be described as stockholders.[7] We define a stockholder in the SZ data as any individual who reports having

[6] We are grateful to Emmanuel Saez and Gabriel Zucman for making their code and data available.

[7] See the Internet Appendix for details.

nonzero income from dividends and/or realized capital gains. Note that this classification of stockholder fits the description of "direct" stockowner, but unlike the SCF, there is no way to account for indirect holdings in, for example, tax-deferred accounts. The annual data we employ span the period 1963 to 2012. We refer to these data as the "SZ data."

The empirical literature on limited stock market participation and heterogeneity has often relied on the Consumer Expenditure Survey (CEX). We do not use this survey because we wish to focus on wealthy households and there are several reasons the CEX does not provide reliable data for this purpose. First, the CEX provides an inferior measure of household-level assets and liabilities as compared to the SCF and SZ data,both of which consider samples intended to measure the wealthiest households identified from tax returns. Second, CEX answers to asset questions are often missing for more than half of the sample and much of the survey is top-coded. Third, wealthy households are known to exhibit very high nonresponse rates in surveys such as the CEX that do not have an explicit administrative tax data component that directly targets wealthy households (Sabelhaus et al. (2014)). In the last section of the paper, we consider a way to form a proxy for the top wealth households' consumption using income data.

Panel A of Table I shows the distribution of stock wealth across households, conditional on the household owning a positive amount of corporate equity. The left part of the panel reports results for stockholdings held either directly or indirectly from the SCF. [8] The right part reports the analogous results for the SZ data corresponding to direct ownership. Panel B shows the distribution of stock wealth among all households, including non–stock owners. The table shows that stock wealth is highly concentrated. Among all households, the top 5% of the stock wealth distribution owns 74.5% of the stock market according to the SCF in 2013, and 79.2% in 2012 according to the SZ data. Focusing on just stockholders, the top 5% of stockholders own 61% of the stock market in the SCF and 63% in the SZ data. Because many low-wealth households own no equity, wealth is more concentrated when we consider the entire population than when we consider only those households who own stocks.

Panel C of Table I reports the "raw" stock market participation rate from the SCF, denoted *rpr*, across years, and also a "wealth-weighted" participation rate. The raw participation rate is the fraction of households in the SCF who report owning stocks, directly or indirectly. The wealth-weighted rate takes into account the concentration of wealth. As an illustration, we compute a wealth-weighted participation rate by dividing the survey population into three groups: the top 5% of the stock wealth distribution, the rest of the stock-owning households representing $(rpr - 0.05)\%$ of the population, and the residual who own no stocks and make up $(1 - rpr)\%$ of the population. In 2013, stockholders outside the top 5% represent 46% of households, and those who hold no stocks represent 51% of households. The wealth-weighted participation rate is then

[8] For the SCF, we start our analysis with the 1989 survey. There are two earlier surveys, but the survey in 1986 is a condensed reinterview of respondents in the 1983 survey.

Table I

Distribution of Stock Market Wealth

This table reports the percentage of the stock wealth owned by the percentile group reported in the first column. Panel A is conditional on the household being a stockowner, while Panel B reports the distribution across all households. SCF stock wealth ownership is based on direct and indirect holdings of public equity, where indirect holdings include annuities, trusts, mutual funds, IRAs, Keogh Plans, other retirement accounts. Stock ownership in SZ data is based on direct stock holdings only. Panel C reports the stock market participation rate. The wealth-weighted participation rate is calculated as value-weighted ownership $\equiv 5\%(w^{5\%}) + (rpr - 0.05)\%(1 - w^{5\%}) + (1 - rpr)\%(0)$, where rpr is the raw participation rate (not in percentage points) in the first row. $w^{5\%}$ is the proportion of stock market wealth owned by top the 5% the stock wealth distribution.

Panel A: Percent of Stock Wealth, Sorted by Stock Wealth, Stockowners

SCF (indirect + direct stock holdings)

Percentile of Stock Wealth	1989	1998	2004	2013
<70%	7.80%	9.15%	8.86%	7.21%
70% to 85%	11.76%	10.95%	12.08%	11.32%
85% to 90%	8.39%	6.59%	7.88%	7.42%
90% to 95%	12.52%	11.18%	13.33%	13.40%
95% to 100%	59.56%	62.09%	57.95%	60.74%

SZ (direct stock holdings)

Percentile of Stock Wealth	1989	1998	2004	2012
<70%	23.62%	15.50%	18.93%	16.51%
70% to 85%	9.56%	9.37%	7.90%	6.91%
85% to 90%	5.91%	6.09%	4.97%	5.10%
90% to 95%	9.86%	10.69%	8.27%	8.06%
95% to 100%	51.05%	58.35%	59.93%	63.43%

Panel B: Percent of Stock Wealth, Sorted by Stock Wealth, All Households

SCF (indirect + direct stock holdings)

Percentile of Stock Wealth	1989	1998	2004	2013
<70%	0.01%	1.30%	1.35%	0.84%
70% to 85%	3.12%	7.42%	7.41%	5.92%
85% to 90%	4.19%	6.45%	6.70%	6.17%
90% to 95%	11.16%	11.28%	13.26%	12.67%
95% to 100%	81.54%	73.93%	71.21%	74.54%

SZ (direct stock holdings)

Percentile of Stock Wealth	1989	1998	2004	2013
<70%	11.32%	4.95%	8.48%	6.92%
70% to 85%	4.22%	3.76%	4.68%	3.77%
85% to 90%	4.20%	4.25%	3.86%	3.29%
90% to 95%	8.81%	9.39%	7.43%	6.71%
95% to 100%	71.44%	77.65%	75.55%	79.29%

(*Continued*)

Table I—*Continued*

Panel C: Stock Market Participation Rates, SCF					
	1989	1992	1995	1998	2001
Raw participation rate	31.7%	36.9%	40.5%	49.3%	53.4%
Wealth-weighted participation rate	13.8%	15.8%	16.4%	19.9%	23.9%
	2004	2007	2010	2013	
Raw participation rate	49.7%	53.1%	49.9%	48.8%	
Wealth-weighted participation rate	21.7%	21.1%	20.9%	20.2%	

$5\% \cdot w^{5\%} + (rpr - 0.05)\% \cdot (1 - w^{5\%}) + (1 - rpr)\% \cdot 0$, where $w^{5\%}$ is the fraction of wealth owned by the top 5%. The table shows that the raw participation rate has increased steadily over time, rising from 32% in 1989 to 49% in 2013. But the wealth-weighted rate is much lower than 49% in 2013 (equal to 20%) and has risen less over time. Note that the choice of the top 5% to measure the wealthy is not crucial; any percentage at the top can be used to illustrate how the concentration of wealth affects the intensive margin of stock market participation. The calculation shows that steady increases in stock market ownership rates do not necessarily correspond to quantitatively meaningful changes in stock market ownership patterns, underscoring the conceptual challenges to explaining equity return premia using a representative agent SDF that is a function of aggregate household consumption.

The inequality-based asset pricing literature predicts that the income shares of wealthy capital owners should vary positively with the national capital share. Table II investigates this implication by showing the output from regressions of income shares on the aggregate capital share KS_t. The regressions are carried out for households located in different percentiles of the stock wealth distribution. For this purpose, we use the SZ data, since the annual frequency provides more information than the triennial SCF, although the results are similar using either data set. To compute income shares, income Y_t^i from all sources including wages, investment income, and other for percentile group i is divided by aggregate income for the SZ population, Y_t, and regressed on the aggregate capital share KS_t.[9] The left panel of the table reports regression results for all households, while the right panel reports results for stock owners.

The information in both panels is potentially relevant for our investigation. The wealthiest shareholders are likely to be affected by a movement in the labor share because corporations pay all of their employees more or less, not just the minority who own stocks. The regression results on the left panel speak directly to this question and show that movements in the capital share are strongly *positively* related to the income shares of those in the top 10% of the stock wealth distribution and strongly *negatively* related to the income shares

[9] We use the average of the quarterly observations on KS_t over the year corresponding to the year for which the income share observation in the SZ data is available.

Table II

Regressions of Income Shares on the Capital Share

This table presents regressions of income shares on the capital shares. The groups refer to the percentiles of the stock wealth distribution. * and ** indicate statistical significance at the 10% and 5% level, respectively. $\frac{Y_t^i}{Y_t}$ is the income share for group i. KS is the capital share. OLS t-statistics are reported in parentheses. The sample spans the period 1963Q3 to 2013Q4. OLS regression $\frac{Y_t^i}{Y_t} = \varsigma_0^i + \varsigma_1^i KS_t + \varepsilon_t$

All Households				Stock Owners			
Group	$\widehat{\varsigma}_0^i$	$\widehat{\varsigma}_1^i$	R^2	Group	$\widehat{\varsigma}_0^i$	$\widehat{\varsigma}_1^i$	R^2
<90%	1.18**	−1.13**	0.61	<90%	1.24**	−1.27**	0.49
	(23.60)	(−8.65)			(17.36)	(−6.82)	
95% to 100%	−0.24**	1.08**	0.61	95% to 100%	−0.28**	1.20**	0.53
	(−5.10)	(8.65)			(−4.47)	(7.34)	
99% to 100%	−0.24**	0.82**	0.62	99% to 100%	−0.27**	0.93**	0.59
	(−6.71)	(8.88)			(−6.16)	(8.25)	
99.9% to 100%	−0.16**	0.48**	0.65	99.9% to 100%	−0.17**	0.54**	0.63
	(−7.91)	(9.41)			(−7.61)	(9.13)	
90% to 100%	−0.18**	1.13**	0.61	90% to 100%	−0.24**	1.27**	0.49
	(−3.54)	(8.64)			(−3.32)	(6.82)	

of those in the bottom 90% of the stock wealth distribution. Indeed, this single variable explains 61% of the variation in the income shares of the top 10% group (63% of the top 1%) and is strongly statistically significant with a t -statistic greater than eight. These R^2 statistics are quite high considering that some of the income variation in these groups can still be expected to be idiosyncratic and uncorrelated with aggregate variables. The right panel shows the same regression output for the shareholder population only. The capital share is again strongly positively related to the income share of stock owners in the top 10% of the stock wealth distribution and strongly statistically significant, while it is negatively related to the income share of stock owners in the bottom 90%. The capital share explains 55% of the top 1%'s income share, 48% of the top 10%, and 50% of the bottom 90%. These results underscore the extent to which most households, even those who own some stocks, are better described as "workers" whose share of aggregate income shrinks when the capital share grows.

Of course, the resources that support the consumption of each group contain both common and idiosyncratic components. Figure 3 provides one piece of evidence on how these components evolve over time. The top panel plots annual observations on the gross growth rate of $C_t \frac{Y_t^i}{Y_t}$ for the top 10% and bottom 90% of the stock owner stock wealth distribution, where C_t is aggregate consumption for the corresponding year measured from the National Income and Product Accounts and $\frac{Y_t^i}{Y_t}$ is computed from the SZ data for the two groups ($i = top$ 10, $bottom$ 90). The bottom panel plots the same measure on quarterly data using the fitted values $\widehat{\frac{Y_t^i}{Y_t}}$ from the right-hand-panel regressions in Table II,

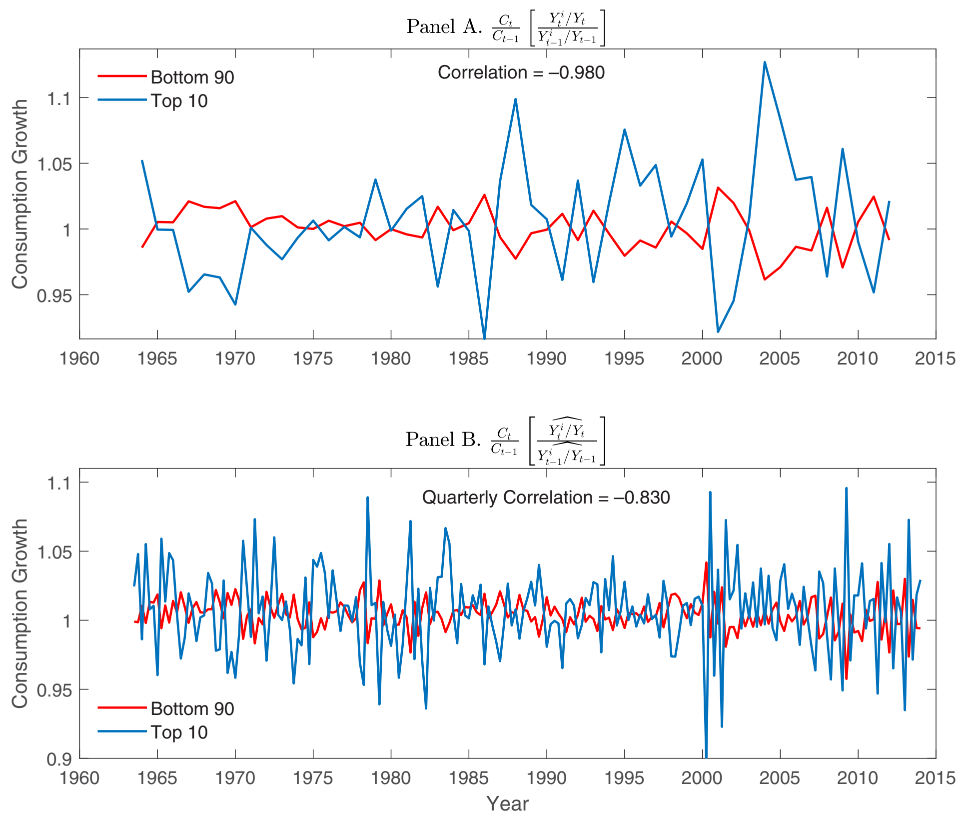

Figure 3. Growth in aggregate consumption times income share. Panel A plots annual observations on the annual value of $\frac{C_t}{C_{t-1}}[\frac{Y_t^i/Y_t}{Y_{t-1}^i/Y_{t-1}}]$ corresponding to the years for which the SZ data are available. Y_t^i/Y_t is shareholders' income share for group i calculated from the SZ data. Panel B reports quarterly observations on quarterly values of $\frac{C_t}{C_{t-1}}[\frac{\widehat{Y_t^i/Y_t}}{\widehat{Y_{t-1}^i/Y_{t-1}}}]$ using the mimicking income share factor $\widehat{Y_t^i/Y_t} = \widehat{\alpha}^i + \widehat{\beta}^i KS_t$. The annual SZ data spans the period 1963 to 2012. The quarterly sample spans the period 1963Q3 to 2013Q4. (Color figure can be viewed at wileyonlinelibrary.com)

which are based on the subsample of households that report having income from stocks.[10] Growth in the product $C_t\frac{Y_t^i}{Y_t}$ is much more volatile for the top 10% than the bottom 90% of the stock owner stock wealth distribution, but both panels of the figure display a clear negative comovement between the two groups. Using the raw data, the correlation is -0.97. In the quarterly data, it is -0.85. Thus, the common component in this variable, captured by

[10] Specifically, $\widehat{\frac{Y_t^i}{Y_t}}$ is constructed using the estimated intercepts $\widehat{\varsigma}_0^i$ and slope coefficients $\widehat{\varsigma}_1^i$ from these regressions along with quarterly observations on the capital share to generate quarterly observations on fitted income shares $\widehat{\frac{Y_t^i}{Y_t}}$.

aggregate consumption growth, is more than offset by the negatively correlated component driven by their inversely related income shares, a finding suggestive of imperfect risk-sharing between the two groups.

II. Econometric Model

This section describes the econometric models we consider. Throughout the paper, we use the superscript "o" to denote the true value of a parameter and "hats" to denote estimated values.

A. SDF and Beta Representation

Our main analysis is based on estimation of SDF models with familiar no-arbitrage Euler equations taking the form

$$\mathbb{E}\left[M_{t+1}R^e_{jt+1}\right] = 0, \tag{1}$$

or equivalently,

$$\mathbb{E}\left(R^e_{jt+1}\right) = \frac{-\mathrm{cov}\left(M_{t+1}, R^e_{t+1}\right)}{\mathbb{E}(M_{t+1})}, \tag{2}$$

where M_{t+1} is a candidate SDF and R^e_{jt+1} is the excess return on an asset j held by the investor with marginal rate of substitution M_{t+1} at time $t+1$. The excess return is defined as $R^e_{j,t} \equiv R_{j,t} - R_{f,t}$, where $R_{j,t}$ denotes the gross return on asset j, with $R_{f,t}$ a risk-free asset return that is uncorrelated with M_{t+1}.

In this paper, we consider a stylized limited participation endowment economy in which wealth is concentrated in the hands of a few investors, or "shareholders," while most households are "workers" who finance consumption out of wages and salaries. We suppose that workers own no risky asset shares and consume their labor earnings. There is no risk-sharing between workers and shareholders. In this case, a representative shareholder who owns the entire corporate sector and earns no labor income will then have consumption in equilibrium that is equal to $C_t \cdot KS_t$, where C_t is aggregate (shareholder plus worker) consumption and KS_t is the capital share of aggregate income.[11] These features of the model follow GLL. We denote $C_t \cdot KS_t = C_{st}$, where "s" denotes shareholder.

To evaluate such a framework empirically, the econometrician could start by considering an especially simple limited participation SDF in which the capital share plays a role via its influence on the richest shareholders' consumption:

$$M_{t+1} = \delta\left(\frac{C_{st+1}}{C_{st}}\right)^{-\gamma}. \tag{3}$$

[11] This statement presumes a closed economy. See the section on "A Stylized Model of Asset Owners and Workers" in the Internet Appendix.

In the above, δ may be interpreted as a subjective time-discount factor and γ as a coefficient of relative risk aversion. Note that worker consumption plays no role in the SDF since workers do not participate in risky asset markets. In the endowment economy, the capital share is equal in equilibrium to the consumption share of shareholders. In this case (3) collapses to a simple power utility model over C_{st}, which has an approximate linear factor specification taking the form

$$M_{t+1} \approx b_0 - b_1\left(\frac{C_{t+1}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+1}}{KS_t} - 1\right), \tag{4}$$

with $b_0 = 1 + \ln(\delta)$ and $b_1 = b_2 = \gamma$. Denote the vector $f \equiv (\frac{C_{t+1}}{C_t} - 1, \frac{KS_{t+1}}{KS_t} - 1)'$ and $b = (b_1, b_2)'$. Equations (2) and (4) together imply a representation in which expected returns are a function of factor risk exposures, or betas β_j', and factor risk prices λ:

$$\begin{aligned} \mathbb{E}\left(R^e_{jt+1}\right) &= \lambda_0 + \beta_j'\lambda, \\ \beta_j' &= \text{cov}(f, f')^{-1}\text{cov}\left(f, R^e_{jt+1}\right) \\ \lambda &= \mathbb{E}(M_t)^{-1}\text{cov}(f, f')b. \end{aligned} \tag{5}$$

Below we use the three-month Treasury bill (T-bill) rate to proxy for a risk-free rate. The parameter λ_0 (the same in each return equation) is included to account for a "zero beta" rate if there is no true risk-free rate (or quarterly T-bills are not an accurate measure of the risk-free rate).

B. Longer-Horizon Betas

A common approach to estimating equations such as (5) is to run a cross-sectional regression of average returns on estimates of the risk exposures $\beta_j' = (\beta_{jC,1}, \beta_{jKS,1})'$, where β_j' are obtained from a first-stage time-series regression of excess returns on factors,[12]

$$R^e_{j,t+1,t} = a_j + \beta_{jC,1}(C_{t+1}/C_t) + \beta_{jKS,1}(KS_{t+1}/KS_t) + u_{j,t+1,t}, \quad t = 1, 2 \ldots T. \tag{6}$$

The above equation uses the more explicit notation $R^e_{j,t+1,t}$ to denote the one-period return on asset j from the end of t to the end of $t+1$.[13] Equation (6) is used to estimate one-period betas, denoted by β_j'.

[12] Restrictions on the SDF coefficients of multiple factors, such as $b_1 = b_2$, require restrictions on the λ in the cross-sectional regression. We address this issue in the next section.

[13] The specification of factors in terms of gross versus net growth rates is immaterial and only affects the units of the time-series coefficients.

The gross H-period excess return on asset j from the end of t to the end of $t+H$ is denoted $R^e_{j,t+H,t}$.[14] Longer horizon risk exposures $\beta'_{jH} = (\beta_{jC,H}, \beta_{jKS,H})'$ may be estimated from a regression of longer-horizon returns on longer-horizon factors, that is,

$$R^e_{j,t+H,t} = a_j + \beta_{jC,H}(C_{t+H}/C_t) + \beta_{jKS,H}(KS_{t+H}/KS_t) + u_{j,t+H,t}, \quad t = 1, 2 \ldots T. \tag{7}$$

There are at least two circumstances under which longer-horizon betas β'_{jH} may be useful for explaining one-period expected return premia. First, the factors on the right-hand side of (6) could be measured with transitory error. Second, the econometrician's simple SDF (3) could be misspecified and omit additional risk factors that do not appear in (3). In both circumstances, estimates of multiperiod risk exposures could be closer to the true one-period exposures than are estimates of the one-period risk exposures.

A preexisting literature points out that measurement error in macroeconomic data can affect the estimation of asset pricing models. This literature focuses largely on how measurement error in consumption can influence tests of the Consumption CAPM. Daniel and Marshall (1997) show that long-horizon consumption growth can help explain the equity premium puzzle if quarterly consumption is contaminated by transitory measurement error. Parker and Julliard (2004) point to measurement error as motivation for their use of long-horizon consumption growth, and Kroencke (2017) studies methods to undo the smoothing-type filters that data collection agencies appear to apply to different components of aggregate consumption. Our framework differs somewhat from the models in these papers. Instead of using consumption growth, our model is based on the capital share (or one minus the labor share), which unlike consumption is a ratio of two macroeconomic series. Each of these series, labor compensation in the numerator and value added in the denominator, are likely to be measured with error, leaving the magnitude of the effect on the ratio unclear. But smoothing filters, of the type emphasized by Kroencke (2017), for example, would contribute to positive autocorrelation in the growth of both the numerator and the denominator of the labor share. Except in knife-edge cases in which these effects exactly cancel, such a smoothing procedure would contribute to the negative autocorrelation in the capital share growth rate that is observed in the data. In this case, the use of long-horizon betas could provide a

[14] The gross multiperiod (long-horizon) return from the end of t to the end of $t+H$ is denoted $R_{j,t+H,t}$,

$$R_{j,t+H,t} \equiv \prod_{h=1}^{H} R_{j,t+h},$$

and the gross H-period excess return is denoted

$$R^e_{j,t+H,t} \equiv \prod_{h=1}^{H} R_{j,t+h} - \prod_{h=1}^{H} R_{f,t+h}.$$

simple method for undoing measurement error in capital share growth caused by smoothing filters.

An alternative reason for focusing on longer-horizon betas is that the simple SDF (3) is likely to be misspecified because it misses some additional risk factors. A growing body of evidence using equity options data suggests the existence of a volatile but highly transitory component in equity market risk premia that is at odds with a range of consumption-based models, even those that generate a time-varying market risk premium (e.g., see the evidence in Bollerslev, Tauchen, and Zhou (2009), Andersen, Fusari, and Todorov (2013), and Martin (2017)). The time-variation in market risk premia generated by standard consumption-based models is much less volatile and much more persistent than that suggested by options data.

With this evidence in mind, suppose that the econometrician presumes that the SDF takes the form (3) but the true SDF instead takes the form

$$M_{t+1} = \delta_t \left(\frac{C_{st+1}}{C_{st}} \right)^{-\gamma} \left(\frac{G_{t+1}}{G_t} \right)^{-\chi}, \tag{8}$$

where χ is a parameter and G_{t+1} are any additional components of the SDF that contribute to volatility in priced risk but are unobserved to the econometrician.[15] Since any such unknown factors would be omitted from the right-hand side of (6) by the econometrician, their presence could bias estimates of risk exposures on the included factors such as capital share growth in (6). In particular, if positive exposure to an omitted factor earns a risk premium, estimates of risk exposures on the included factors in (6) will tend to be biased downward whenever the omitted factor is negatively correlated with the included factor. If the omitted source of risk is more transitory than the included source of risk, this bias can be mitigated by estimating longer-horizon betas rather than one-period betas. The Internet Appendix gives a specific parametric example and simulation in repeated finite samples of this phenomenon that show that a substantial downward bias in estimated one-period capital share betas may be attenuated by estimating the longer-horizon relationships in (7). In essence, estimates of the long-horizon relationships filter out the higher frequency "noise" generated by a more transitory omitted factor that is the source of the bias in the estimated one-period exposures.

These examples motivate us to investigate whether *multi*quarter, that is, H-period, estimated risk exposures from regressions such as (7) explain cross-sections of *one*-period (quarterly) expected return premia $\mathbb{E}(R^e_{j,t+1})$. Note that the point of estimating longer-horizon risk exposures in the first stage is not to examine how they affect longer-horizon expected return premia $\mathbb{E}(R^e_{j,t+H,t})$ in

[15] Following GLL, volatility in G_{t+1} need not translate into unrealistic volatility in the risk-free rate if the parameter δ_t varies over time in a manner that generalizes to nonnormal functions the familiar compensating Jensen's term that appears in lognormal models of the SDF (e.g., Campbell and Cochrane (1999) and Lettau and Wachter (2007)). In the above, a specification for δ_t that renders the risk-free rate constant, for example, is $\delta_t = \frac{\exp(-r_f)}{E_t[D_{t+1}/D_t]}$, where $D_{t+1} \equiv (\frac{C_{st+1}}{C_{st}})^{-\gamma}(\frac{G_{t+1}}{G_t})^{-\chi}$ and r_f is a parameter.

the cross-section.[16] Rather, the point is to obtain a more accurate estimate of the true one-period exposures, which can be used to explain one-period expected return premia $\mathbb{E}(R^e_{j,t+1,t})$ in the cross-section. For the linearized SDF model (4), this may be implemented by running time-series regressions of the form (7) to obtain $\widehat{\beta}'_{jH} = (\widehat{\beta}_{jC,H}, \widehat{\beta}_{jKS,H})$, and then running a second-pass cross-sectional regression of the form

$$\mathbb{E}\big(R^e_{j,t}\big) = \lambda_0 + \widehat{\beta}_{j,C,H}\lambda_{C,H} + \widehat{\beta}_{j,KS,H}\lambda_{KS,H} + \epsilon_j, \quad j = 1, 2 \ldots .N, \tag{9}$$

where $j = 1, \ldots, N$ indexes the asset with quarterly excess return $R^e_{j,t}$.

Although in principle aggregate consumption growth plays a role as a risk factor in (4), we focus on the more parsimonious SDF model that depends only on capital share growth. We do so because, as shown below, the capital share is the most important empirical component of $C_t KS_t$ for explaining cross-sections of asset returns, while the aggregate consumption component is relatively unimportant. For this parsimonious specification, we use a univariate time-series regression of H-period excess returns on H-period capital share growth to estimate $\widehat{\beta}_{j,KS,H}$ and a cross-sectional regression to estimate the risk price $\lambda_{KS,H}$:

$$\mathbb{E}\big(R^e_{j,t}\big) = \lambda_0 + \widehat{\beta}_{j,KS,H}\lambda_{KS,H} + \epsilon_j, \quad j = 1, 2 \ldots .N. \tag{10}$$

In the above equations, t represents a quarterly time period, and $\lambda_{\cdot,H}$ are the H-period risk price parameters to be estimated. We refer to the joint time-series and cross-sectional regression approach as the "two-pass" regression approach, even though both equations are estimated jointly in one Generalized Method of Moments (GMM, Hansen (1982)) system as detailed in the Internet Appendix.

Although we employ the linear SDF specifications as our baseline, we also conduct a GMM estimation that applies the approach just discussed to the nonlinear SDF version of (4). In this case, the moment conditions upon which the estimation is based are given by

$$\mathbb{E}\begin{bmatrix} \mathbf{R}^e_t - \lambda_0 \mathbf{1}_N + \frac{(M_{t+H,t} - \mu_H)\mathbf{R}^e_{t+H,t}}{\mu_H} \\ M_{t+H,t} - \mu_H \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ 0 \end{bmatrix}, \tag{11}$$

where

$$M_{t+H,t} = \delta^H \left[\left(\frac{C_{t+H}}{C_t} \right)^{-\gamma} \left(\frac{KS_{t+H}}{KS_t} \right)^{-\gamma} \right].$$

For the reasons discussed above, this nonlinear estimation again implements the approach of using H-period empirical covariances between excess returns $\mathbf{R}^e_{t+H,t}$ and the SDF $M_{t+H,t}$ to explain one-period (quarterly) average return premia $\mathbb{E}(\mathbf{R}^e_t)$ in the cross-section. Details of this estimation are given in the Internet Appendix and will be commented on below.

[16] This observation does not rule out the possibility that $\widehat{\beta}_{b,H}$ also explains cross-sections of expected H-period returns as well as one-period returns.

In the final empirical analysis of the paper, we explicitly connect aggregate capital share fluctuations to fluctuations in the income shares of rich versus nonrich stockowners using SZ household-level data to investigate whether a proxy for the consumption of wealthy stockholders is priced in our asset return data. This investigation is described below.

For all estimations above, we report an $\overline{R}^2$ for the cross-sectional block of moments as a measure of how well the model explains the cross-section of quarterly returns.[17] Bootstrapped confidence intervals for the $\overline{R}^2$ are reported. Also reported are the root-mean-squared pricing errors (*RMSE*) as a fraction of the root-mean-squared return (*RMSR*) on the portfolios being priced, that is,

$$RMSE \equiv \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\mathbb{E}\left(R_j^e\right) - \widehat{R}_j^e\right)^2}, \quad RMSR \equiv \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\mathbb{E}\left(R_j^e\right)\right)^2},$$

where R_j^e refers to the excess return of portfolio j and $\widehat{R}_j^e = \widehat{\lambda}_0 + \widehat{\beta}'_{j,H}\widehat{\lambda}_H$. Finally, in keeping with our acknowledgment that capital share risk is an incomplete description of the true SDF, we use statistics for model comparison such as the Hansen-Jagannathan distance measure (HJ-distance, Hansen and Jagannathan (1997)) that explicitly recognize model misspecification.

III. Results

This section presents empirical results. We begin with a preliminary analysis of the relative importance of aggregate consumption growth versus capital share growth in linearized SDF model (4).

A. The Relative Importance of $\frac{C_{t+H}}{C_t}$ versus $\frac{KS_{t+H}}{KS_t}$

As discussed above, we investigate whether H-quarter risk exposures explain quarterly expected return premia in the cross-section. For the linearized SDF with $C_t \cdot KS_t = C_{st}$, this is tantamount to examining whether covariances of

[17] This measure is defined as

$$R^2 = 1 - \frac{\mathrm{var}_c\left(\mathbb{E}\left(R_j^e\right) - \widehat{R}_j^e\right)}{\mathrm{var}_c\left(\mathbb{E}\left(R_j^e\right)\right)}$$

$$\widehat{R}_j^e = \widehat{\lambda}_0 + \underbrace{\widehat{\beta}'_{j,H}}_{1\times K}\underbrace{\widehat{\lambda}_H}_{K\times 1},$$

where K are the number of factors in the asset pricing mode, var_c denotes the cross-sectional variance, $\widehat{R}_j^e$ is the average return premium predicted by the model for asset j, and "hats" denote estimated parameters.

H-period excess returns $R^e_{t+H,t}$ with the H-period linearized SDF $M_{t+H,t}$, where

$$M_{t+H,t} \equiv b_0 - b_1\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+H}}{KS_t} - 1\right) \tag{12}$$

have explanatory power for one-period expected return premia $\mathbb{E}(R^e_{j,t+1,t})$. Although specification (12), which follows from (3), restricts the coefficients $b_1 = b_2 = \gamma$, it need not follow that the two factors are equally *priced* in the cross-section. That is, $\lambda_{C,H}$ in (9) could be much smaller than $\lambda_{KS,H}$, in which case capital share risk would be a more important determinant of the cross-section of expected returns than aggregate consumption risk, despite their equally weighted presence in the linearized SDF. To see why, observe that the factor risk prices $\lambda_H = (\lambda_{C,H}, \lambda_{KS,H})'$ are related to the SDF coefficients b_1 and b_2 according to

$$\lambda_H = \mathbb{E}\big(M_{t+H,t}\big)^{-1}\mathrm{cov}\big(f_H, f_H'\big)b, \tag{13}$$

where $f_H = (\frac{C_{t+H}}{C_t} - 1, \frac{KS_{t+H}}{KS_t} - 1)'$ and $b = (b_1, b_2)'$. Equation (13) shows that, even if $b_1 = b_2 \neq 0$, $\lambda_{C,H}$ will be smaller than $\lambda_{KS,H}$ whenever consumption growth is less volatile than capital share growth and the two factors are not too strongly correlated.

We use GMM to estimate the elements of $\mathrm{cov}(f_H, f_H')$ along with the parameters b, while restricting $b_1 = b_2$ and using data on the same cross-sections of asset returns employed in the main investigation of the next section. Doing so provides estimates of the risk prices λ_H from (13). The following results are reported in the Internet Appendix, for $H = 4$ and $H = 8$ quarters. First, in Table IA.I, estimates of $\mathrm{cov}(f_H', f_H)$ show that consumption growth is much less volatile than capital share growth while the off-diagonal elements of $\mathrm{cov}(f_H', f_H)$ are small. As a consequence, estimates of $\lambda_{C,H}$ from (13) using data on different asset classes and equity characteristic portfolios are in most cases several times smaller than those of $\lambda_{KS,H}$ despite $b_1 = b_2$. The exception to this are estimates using options data for $H = 8$. Note that if aggregate consumption growth were constant, we would have $\lambda_{C,H} = 0$ no matter what the value of $b_1 = b_2$. This reasoning together with the foregoing result suggests that an approximate empirical SDF that eliminates consumption growth altogether is likely to perform almost as well as one that includes it.

Second, comparing Table IA.II, which reports the GMM restricted parameter estimates of $b_1 = b_2$ (denoted b in the table) for explaining quarterly expected return premia when both H-period consumption and capital share growth are included as risk factors, and Table IA.III, which reports the same estimates when b_1 is restricted to zero, effectively eliminating consumption growth from the SDF, the results show that little is lost in terms of cross-sectional explanatory power or pricing errors by estimating a model with b_1 constrained to zero. By contrast, as can be seen in Table IA.IV, restricting b_2 to zero, that is, dropping capital share growth from the linearized SDF, makes a big difference for the cross-sectional fit, which is typically far lower than the previous two cases.

Given these results, we use the more parsimonious SDF that depends only on capital share growth, that is, $M_{t+H,t} = b_0 - b_2(\frac{KS_{t+H}}{KS_t} - 1)$, referred to hereafter as the *capital share* SDF as our baseline empirical model. This is estimated with a univariate time-series regression to obtain $\widehat{\beta}_{j,KS,H}$ combined with the cross-sectional regression (10) to explain quarterly expected return premia. Of course, if risk-sharing between shareholders and workers were perfect, capital share growth should not appear in the SDF at all (i.e., $b_2 = 0$) and *only* growth in aggregate consumption should be priced in the cross-section once the betas for both variables are included. But the results just reported show that this is not what we find. The results are therefore strongly supportive of a model with limited participation and imperfect risk-sharing between workers and shareholders.

B. A Parsimonious Capital Share SDF

This subsection presents our main results on whether capital share risk is priced in the cross-section when explaining expected returns on a range of equity styles and nonequity asset classes. This is followed by subsections reporting results that control for the betas of empirical pricing factors from other models, statistical significance of our estimated beta spreads, and tests that directly use the distribution of income shares and wealth from the household-level SZ data. In all cases, we characterize sampling error by computing block bootstrap estimates of the finite sample distributions of the estimated risk prices and cross-sectional $\overline{R}^2$, from which we report 95% confidence intervals for these statistics. The bootstrap procedure corrects for the "first-stage" estimate of the risk exposures $\widehat{\beta}$ as well as the serial dependence of the data in the time-series regressions used to compute the risk exposures. The Internet Appendix provides a description of the bootstrap procedure.

Panels A to E of Table III report results from estimating the cross-sectional regressions (10) on four distinct equity characteristic portfolio groups size/BM, REV, size/INV, size/OP, and a pooled estimation of the many different stock portfolios jointly. To give a sense of which portfolio groups are most mispriced in pooled estimation, Panel F reports the $RMSE_i/RMSR_i$ for each group i computed from pooled estimation on the "All Equities" characteristic portfolios. Panels G to J report results from estimating the cross-sectional regressions on portfolios of four nonequity asset classes, including, bonds, sovereign bonds, options, and CDS. Finally, Panel K reports these results for the pooled estimation on the many different stock portfolios with the portfolios of other asset classes. For each portfolio group, and for $H = 4$ and 8 quarters, we report the estimated capital share factor risk prices $\widehat{\lambda}_{KS,H}$ and the $\overline{R}^2$ with 95% confidence intervals for these statistics in square brackets, along with the $RMSE/RMSR$ for each portfolio group in the final row.

Turning first to the equity characteristic portfolios, Table III shows that the risk price for capital share growth is positive and strongly statistically significant in each of the cross-sections considered, as indicated by the 95%

Table III

Expected Return-Beta Regressions

This table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrapped 95% confidence intervals are reported in square brackets. Panel F reports the $RMSE_i/RMSR_i$ attributable to group i named in the column. The pricing error is defined as $RMSR_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}(\mathbb{E}(R^e_{ji}))^2}$, where R^e_{ji} refers to the return of portfolio j in group i and $RMSE_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}(\mathbb{E}(R^e_{ji}) - \widehat{R}^e_{ji})}$, where $\widehat{R}^e_{ji} = \widehat{\lambda}_0 + \widehat{\beta}'_{ji,H}\widehat{\lambda_H}$. The sample spans the period 1963Q3 to 2013Q4.

$\mathbb{E}(R^e_{j,t}) = \lambda_0 + \lambda'_H\beta_H + \epsilon_j$, Estimates of Factor Risk Prices λ_H						
Equity Portfolios						
	Panel A: Size/BM		Panel B: REV		Panel C: Size/INV	
H	4	8	4	8	4	8
Constant	0.65	1.55	0.83	1.73	0.92	1.70
	[0.01, 1.23]	[1.39, 1.71]	[0.35, 1.32]	[1.62, 1.84]	[0.20, 1.54]	[1.50, 1.90]
$\frac{KS_{t+H}}{KS_t}$	0.74	0.68	0.63	0.41	0.61	0.55
	[0.42, 1.08]	[0.53, 0.83]	[0.33, 0.92]	[0.30, 0.50]	[0.27, 0.96]	[0.37, 0.74]
$\bar{R}^2$	0.51	0.80	0.70	0.86	0.39	0.62
	[0.13, 0.77]	[0.52, 0.91]	[0.17, 0.91]	[0.68, 0.96]	[0.03, 0.70]	[0.29, 0.81]
$\frac{RMSE}{RMSR}$	0.19	0.12	0.11	0.08	0.19	0.16
	Panel D: Size/OP		Panel E: All Equities		Panel F: All Equities $\frac{RMSE_i}{RMSR_i}$	
H	4	8	4	8	4	8
Constant	0.60	1.61	0.74	1.65	Size/BM: 0.19	0.13
	[0.26, 0.94]	[1.46, 1.77]	[0.45, 1.01]	[1.56, 1.74]		
$\frac{KS_{t+H}}{KS_t}$	0.70	0.57	0.68	0.57	REV: 0.12	0.11
	[0.54, 0.87]	[0.45, 0.71]	[0.54, 0.83]	[0.49, 0.66]		
$\bar{R}^2$	0.78	0.76	0.58	0.74	Size/INV: 0.19	0.16
	[0.48, 0.89]	[0.42, 0.90]	[0.28, 0.73]	[0.51, 0.84]		
$\frac{RMSE}{RMSR}$	0.12	0.12	0.17	0.14	Size/OP: 0.20	0.16

(Continued)

Table III—*Continued*

$\mathbb{E}(R^e_{j,t}) = \lambda_0 + \lambda'_H \beta_H + \epsilon_j$, Estimates of Factor Risk Prices λ_H						
Other Asset Classes						
	Panel G: Bonds		Panel H: Sovereign Bonds		Panel I: Options	
H	4	8	4	8	4	8
Constant	0.43	0.23	−0.32	0.16	0.56	3.68
	[0.35, 0.51]	[0.13, 0.32]	[−1.08, 0.34]	[−1.00, 1.62]	[0.10, 1.07]	[1.35, 6.11]
$\frac{KS_{t+H}}{KS_t}$	0.82	0.57	1.41	1.18	1.87	1.80
	[0.59, 1.03]	[0.40, 0.72]	[0.88, 1.93]	[0.20, 2.19]	[1.43, 2.35]	[0.83, 2.76]
$\bar{R}^2$	0.86	0.89	0.79	0.32	0.95	0.81
	[0.32, 0.96]	[0.34, 0.96]	[0.44, 0.99]	[0.20, 0.99]	[0.32, 0.99]	[0.01, 0.95]
$\frac{RMSE}{RMSR}$	0.17	0.15	0.18	0.33	0.18	0.34

	Panel J: CDS		Panel K: All Assets	
H	4	8	4	8
Constant	−0.24	−0.16	0.39	1.34
	[−0.36, −0.11]	[−0.22, −0.09]	[−0.91, 0.63]	[0.81, 1.72]
$\frac{KS_{t+H}}{KS_t}$	1.26	0.77	0.83	0.63
	[0.84, 1.71]	[0.64, 0.89]	[0.71, 1.21]	[0.63, 0.96]
$\bar{R}^2$	0.84	0.94	0.78	0.44
	[0.17, 0.97]	[0.68, 0.99]	[0.28, 0.79]	[0.42, 0.84]
$\frac{RMSE}{RMSR}$	0.34	0.20	0.25	0.41

bootstrapped confidence interval, which includes only positive values for $\widehat{\lambda}_{KS}$ that are bounded well away from zero. Exposure to this single macroeconomic factor explains a large fraction of the cross-sectional variation in return premia on these portfolios. For $H = 4$ and $H = 8$, the cross-sectional $\overline{R}^2$ statistics are 51% and 80%, respectively, for size/BM, 70% and 86% for REV, 39% and 62% for size/INV, and 78% and 76% for size/OP. The $\overline{R}^2$ statistics remain sizable for all three portfolio groups even after taking into account sampling uncertainty and small-sample biases. And, while the 95% bootstrap confidence intervals for the cross-sectional (adjusted) $\overline{R}^2$ statistics are fairly wide in some cases, especially for $H = 4$, for $H = 8$ most show relatively tight ranges around high values, that is, [52%, 91%], [68%, 96%], [29%, 81%], and [42%, 90%] for size/BM, REV, size/INV, and size/OP, respectively. The interval for all equities combined is [51%, 84%]. Moreover, the estimated risk prices are similar across the different equity portfolio characteristic groups. This is reflected in the finding that the pooled estimation on the different equity portfolios combined retains substantial explanatory power with an $\overline{R}^2$ equal to 0.74% and a risk price estimate from the pooled "All Equities" group that is about the same magnitude as those estimated on the individual portfolio groups. Panel F, which shows the $RMSE_i/RMSR_i$ for each equity portfolio group i, shows that the pricing errors are all very similar as a fraction of the mean squared expected returns on each group.

A caveat with the results above is that the estimated zero-beta rates λ_0 are large for some cross-sections, a result suggestive of misspecification. (The numbers are multiplied by 100 in the table.) However, estimation of the full nonlinear SDF shows that these zero-beta parameters are often half as large or smaller than those reported above for the linear SDF models. We discuss this further below.

Turning to the nonequity asset classes (corporate bonds, sovereign bonds, options, and CDS), we find that the risk prices for the capital share betas are again positive and strongly statistically significant in each case. For $H = 4$, the capital share beta explains 86% of the cross-sectional variation in expected returns on corporate bonds, 79% on sovereign bonds, 95% on options, and 84% on CDS. For $H = 8$, the fit is similar with the exception of sovereign bonds, where the $\overline{R}^2$ is lower at 32%. The magnitudes of the risk prices are somewhat larger on average for these asset classes than they are for the equity characteristic portfolios, but they remain roughly in the same ballpark. This is reflected in the finding that the pooled estimation on "All Assets," which combines the many different stock portfolios with the portfolios of other asset classes, retains substantial explanatory power, with an $\overline{R}^2$ equal to 78% for $H = 4$. For $H = 8$, the $\overline{R}^2$ from this pooled estimation is lower, at 44%, in part because the fit for sovereign bonds is lower for this horizon.

Figures 1 and 4 depict these results. Figure 1 focuses on the equity characteristic portfolios and plots observed quarterly return premia (average excess returns) on each portfolio on the y-axis against the portfolio capital share beta

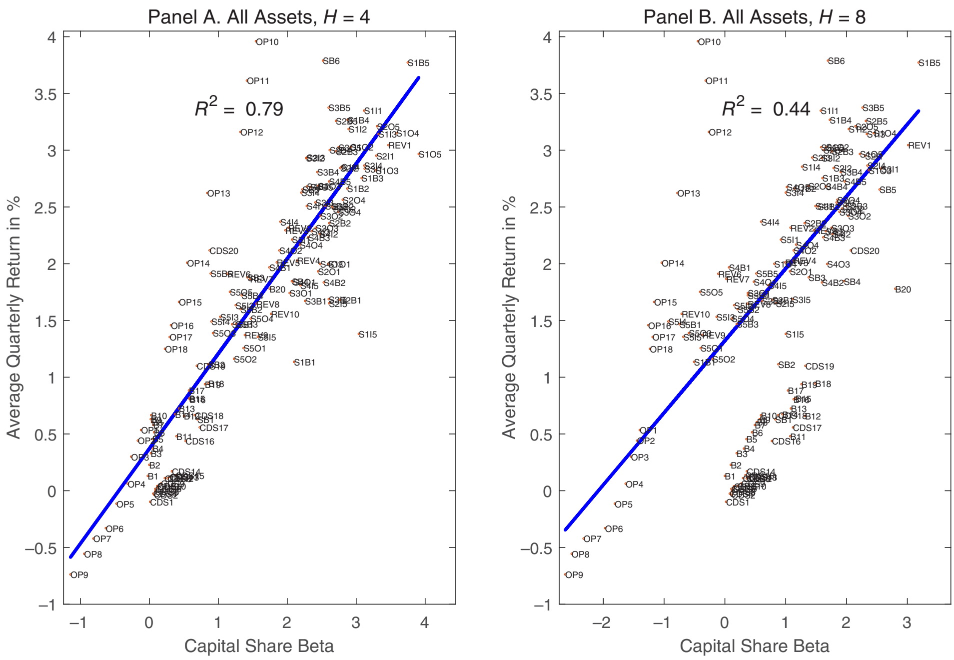

Figure 4. Capital share betas. This figure plots betas constructed from Fama-MacBeth (1973) regressions of average returns on capital share beta using all assets (size/BM, REV, size/INV, size/OP, plus bonds, sovereign bonds, CDS, and options). H indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q3 to 2013Q4. (Color figure can be viewed at wileyonlinelibrary.com)

for exposures of $H = 8$ quarters on the x-axis. The solid lines show the fitted return implied by the model using the single capital share beta as a measure of risk. Size/BM portfolios are denoted $SiBj$, where i, $j = 1, 2, \ldots, 5$, with $i = 1$ the smallest size category and $i = 5$ the largest, while $j = 1$ denotes the lowest BM category and $j = 5$ the largest. Analogously, size/INV portfolios are denoted $SiIj$, size/OP portfolios are denoted $SiOj$, and REV portfolios are denoted $REVi$.

Figure 1 shows that the largest spread in returns on size/BM portfolios is found by comparing the high- and low-BM portfolios in the smaller size categories. Value spreads for the largest $S = 5$ or $S = 4$ size category are much smaller. This underscores the importance of using double-sorted (on the basis of size and BM) portfolios for studying the value premium in U.S. data. The betas for size/BM portfolios line up strongly with return spreads for the smaller-sized portfolios, but the model performs least well for larger stock portfolios, for example, $S4B2$ and $S4B3$, where the return spreads are small. At the same time, the model fits the extreme high and extreme low portfolio returns almost perfectly for both sets of portfolios. Observations for the high-return $S1B5$ and low-return $S1B1$ portfolios lie almost exactly on the fitted lines. Thus, capital share exposure explains virtually 100% of the maximal return obtainable from a long-short strategy designed to exploit these spreads. Moreover, exposure to capital share risk alone produces virtually no pricing error for the challenging $S1B1$ "micro cap" growth portfolio that Fama and French (2015) find is most troublesome for their new five-factor model. The pooled estimation for "All Equities" shows a similar result. Finally, the figure shows that the spread in betas for all sets of portfolios is large. For example, the spread in the capital share betas between $S1B5$ and $S1B1$ is 3.5 compared to a spread in returns of 2.6% per quarter. Thus, these findings are not a story of tiny risk exposures multiplied by large risk prices.

Figure 4 provides an analogous plot for the pooled estimation that combines the many different equity portfolios with the portfolios from the other asset classes. The results show that the option portfolios are the least well priced in the estimations with $H = 4$, while CDS and sovereign bonds are less well priced when $H = 8$. In contrast, the micro cap $S1B1$ and most equity portfolios remain well priced in the pooled estimation on all assets.

It is worth emphasizing that the estimates of $\lambda_{KS,H}$ reported in Table III imply reasonable levels of risk aversion. These estimates, which use the two-pass regression approach, are very close to the estimates of $\lambda_{KS,H}$ obtained from estimating the model $M_{t+H,t} = b_0 - b_2(\frac{KS_{t+H}}{KS_t} - 1)$ using GMM and restriction (13). (The GMM estimates of $\lambda_{KS,H}$ for each portfolio group are given in Table IA.V of the Internet Appendix.) For example, for the size/BM portfolio group, the two-pass regression approach produces $\widehat{\lambda}_{KS,H} = 0.74$ and $\widehat{\lambda}_{KS,H} = 0.68$ for $H = 4$ and 8, respectively, while the GMM approach produces $\widehat{\lambda}_{KS,H} = 0.74$ and $\widehat{\lambda}_{KS,H} = 0.69$. Moreover, the GMM estimates of $\lambda_{KS,H}$ correspond to estimates of b_2 equal to 10.1 and 4.9 for $H = 4$ and $H = 8$, respectively. Bearing in mind that b_2 should equal γ according to the theoretical model, these results demonstrate that the estimates of $\lambda_{KS,H}$ reported in Table III are consistent with plausible levels of risk aversion.

We close this section by briefly commenting on the results for the nonlinear SDF estimation (equation (11)), which are reported in Table IA.VI. Several observations are worth noting. First, the estimates of the (constant) risk-aversion parameter γ imply reasonable values that monotonically decline with H from $\gamma = 9.2$ at $H = 4$ to $\gamma = 4.2$ at $H = 8$. (These values are also very close to those obtained when estimating the linearized specifications; see Table IA.III of the Internet Appendix.) The finding that estimates of risk aversion γ decline with horizon H is consistent with a model in which low-frequency capital share exposures capture sizable systematic cash-flow risk for investors, such that fitting return premia does not require an outsized risk-aversion parameter. Second, estimates of measures of cross-sectional fit are similar to those for the linear SDF specifications. Third, estimates of the zero-beta term λ_0 are in almost all cases much smaller than those for the linear SDF and typically not statistically distinguishable from zero (the intercept values reported in the table are multiplied by 100). The smaller values can occur if higher-order terms that are omitted from the linear SDF specification contain a common component across assets, thereby biasing the estimate of the zero-beta constant upward in the second-stage regression.

C. Controlling for Other Pricing Factors

In this section, we consider whether the explanatory power of capital share risk is merely proxying for exposure to other risk factors. To address this question, we include estimated betas from several alternative factor models and explore whether the information in our capital share beta is captured by other pricing models by estimating cross-sectional regressions that include the betas from competing models together with the capital share betas. For example, we estimate a baseline Fama-French (1993) three-factor specification that takes the form,

$$E(R^e_{j,t}) = \lambda_0 + \widehat{\beta}_{j,KS,H}\lambda_{KS} + \widehat{\beta}_{j,MKT}\lambda_{MKT} + \widehat{\beta}_{j,SMB}\lambda_{SMB} + \widehat{\beta}_{j,HML}\lambda_{HML} + \epsilon_{j,t}$$

and then include $\widehat{\beta}_{j,KS,H}$ as an additional regressor. Analogous specifications are estimated controlling for the intermediary-based factor exposures, that is, the beta for the leverage factor, $LevFac_t$, advocated by AEM, or the beta for the banking sector's equity-capital ratio advocated by HKM, which we denote $EqFac_t$ in this paper. The betas for the alternative models are estimated in the same way as in the original papers introducing these risk factors.

For size/BM, we compare the model to the Fama-French (1993) three-factor model, which uses the market excess return $R^e_{m,t}$, SMB_t, and HML_t as factors, an empirical specification explicitly designed to explain the large cross-sectional variation in average return premia on these portfolios. We also consider the intermediary SDF model of AEM using their broker-dealer leverage factor $LevFac_t$ and the intermediary SDF model of HKM using their banking equity-capital ratio factor $EqFac_t$ jointly with the market excess return $R^e_{m,t}$, which HKM argue is important to include. In all cases, we compare the betas from these models to capital share betas for horizons of $H = 8$ quarters. Because the number of factors varies widely across these models, we rank competing specifications according to a Bayesian Information Criterion (BIC) that adjusts for the number of free factor risk prices λ chosen to minimize the pricing errors. The smaller is the BIC criterion, the more preferred is the model.

Table IV reports results that control for the Fama-French (1993) factor betas. The first set of results forms the relevant benchmark by showing how these models perform on their own. Against this benchmark, the results in Panel A of Table IV for size/BM portfolios show that the capital share risk model generates pricing errors that are lower than the Fama-French (1993) three-factor model. The *RMSE/RMSR* pricing errors are 12% for the capital share model and 15% for the Fama-French (1993) three-factor model. The cross-sectional $\overline{R}^2$ for the capital share model is 0.80, as compared to 0.69 for the Fama-French (1993) three-factor model. Panel B shows that a similar

Table IV

Fama-Macbeth Regressions Using Fama-French Three-Factor Betas

This table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrapped 95% confidence intervals are reported in square brackets. The sample spans the period 1963Q3 to 2013Q4.

$\mathbb{E}(R^e_{j,t}) = \lambda_0 + \lambda'_H \beta_H + \epsilon_j$, Estimates of Factor Risk Prices λ_H, $H = 8$							
Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	SMB_t	HML_t	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
Panel A: Size/BM							
1.55	0.68				0.80	0.12	−283.41
[1.39, 1.71]	[0.53, 0.83]			[0.52, 0.91]			
3.63		−1.96	0.70	1.35	0.69	0.15	−268.12
[1.19, 5.99]		[−4.30, 0.41]	[0.40, 1.01]	[0.76.1.90]	[0.54, 0.89]		
3.57	0.50	−2.04	0.22	0.24	0.84	0.10	−282.29
[1.91, 5.39]	[0.33, 0.74]	[−4.01, −0.61]	[−0.10, 0.45]	[−0.37, 0.72]	[0.67, 0.94]		
Panel B: All Equities							
1.65	0.57				0.74	0.14	−966.12
[1.56, 1.74]	[0.49, 0.66]				[0.51, 0.84]		
3.02		−1.28	0.67	1.37	0.68	0.15	−943.11
[2.02, 4.06]		[−2.30, −0.30]	[0.52, 0.83]	[1.00, 1.74]	[0.58, 0.81]		
2.89	0.39	−1.25	0.25	0.40	0.78	0.12	−970.29
[2.13, 3.94]	[0.28, 0.52]	[−2.45, −0.67]	[0.04, 0.39]	[−0.10, 0.73]	[0.60, 0.86]		

comparison holds for the pooled estimation on all four types of equity characteristic portfolios.

When the capital share beta is included together with the betas from the Fama-French (1993) model in the cross-sectional regression, the risk prices on the exposures to SMB_t and HML_t fall by large magnitudes. For example, the risk price for HML_t declines 82% from 1.35 to 0.24. Moreover, the 95% confidence intervals are far wider for these risk prices, which now include values around zero. By contrast, the risk price for the capital share beta retains its strong explanatory power and most of its magnitude. According to the BIC criterion, the single capital share risk factor performs better than the three-factor model in explaining these portfolios. A similar finding holds for the pooled regression on "All Equities" (Panel B). It is striking that a single macroeconomic risk factor drives out better measured return-based factors that were designed to explain these portfolios.

Table V compares the pricing power of the capital share model to the intermediary-based models for the four equity characteristic portfolios, as well as the pooled estimation on all equity portfolios, jointly. For the most part, the intermediary models do well on their own, and we reproduce the main findings of these studies. For all portfolio types, however, the capital share risk model has the lowest pricing errors, lowest BIC criterion, and highest $\overline{R}^2$. When we include the capital share beta together with the betas for these factors, we find that the risk prices for the intermediary factors are either significantly attenuated or driven out of the pricing regressions by the estimated exposure to capital share risk. This is especially true of the equity-capital ratio factor $EqFac_t$, where the confidence intervals are wide and include zero after the capital share beta is included, while the risk price for the capital share beta retains its strong explanatory power and most of its magnitude in all cases. These findings suggest that the information contained in the intermediary balance sheet factors for risk pricing is largely subsumed by the information contained in capital share growth.

Table VI further compares the capital share model's explanatory power for cross-sections of expected returns on the nonequity asset classes with the HKM intermediary model, which was also employed to study a broad range of nonequity classes. As shown above, the risk price for the capital share beta is positive and statistically significant in the nonequity portfolio case, explaining 89% of the cross-sectional variation in expected returns on corporate bonds, 81% on options, 94% on CDS, and 32% on sovereign bonds. In a separate regression, the risk prices for the betas of $EqFac_t$ and $R^e_{m,t}$ are positive and have strong explanatory power for each of these groups, consistent with what HKM report. But when we include the capital share betas along with the betas of $EqFac_t$ and $R^e_{m,t}$, we find that the risk prices for exposures to $EqFac_t$ become negative when pricing corporate bonds and CDS, and statistically insignificant when pricing every category except options. In contrast, the capital share risk price remains positive and strongly significant in each case. When pricing options, both the capital share beta and those for $EqFac_t$ and $R^e_{m,t}$ retain independent

Table V

Fama-Macbeth Regressions Using Intermediary Model Betas: Equities

This table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrapped 95% confidence intervals are reported in square brackets. The sample spans the period 1963Q3 to 2013Q4.

$\mathbb{E}(R^e_{j,t}) = \lambda_0 + \lambda'_H \beta_H + \epsilon_j$, Estimates of Factor Risk Prices λ_H, $H = 8$

Panel A: Size/BM

Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
1.55	0.68				0.80	0.12	−283.41
[1.39, 1.71]	[0.53, 0.83]				[0.52, 0.91]		
0.89			13.91		0.66	0.16	−270.41
[1.39, 1.71]			[10.23, 17.67]		[0.37, 0.90]		
1.24	0.50		4.96		0.82	0.11	−284.67
[0.49, 1.53]	[0.32, 0.70]		[1.36, 8.64]		[0.62, 0.92]		
0.48		1.19		6.88	0.49	0.20	−258.63
[−1.16, 2.05]		[−0.18, 2.59]		[3.22, 10.53]	[0.19, 0.85]		
3.19	0.62	−1.53		−2.72	0.81	0.13	−279.07
[1.85, 4.53]	[0.43, 0.82]	[−2.68, −0.38]		[−5.91, 0.48]	[0.56, 0.92]		

Panel B: REV

Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
1.73	0.41				0.86	0.08	−124.54
[1.62, 1.84]	[0.30, 0.50]				[0.68, 0.96]		
1.44			6.53		0.01	0.21	−104.63
[0.37, 2.69]			[−3.52, 15.55]		[−0.12, 0.78]		
1.86	0.42		−1.73		0.85	0.07	−122.80
[1.14, 2.13]	[0.26, 0.49]		[−4.33, 2.86]		[0.68, 0.97]		
0.71		1.10		4.23	0.79	0.08	−120.86
[−0.05, 1.43]		[0.41, 1.88]		[3.03, 5.70]	[0.54, 0.98]		
0.86	0.20	0.92		2.32	0.76	0.10	−116.75
[−0.32, 2.08]	[−0.02, 0.42]	[−0.15, 2.03]		[−0.91, 5.64]	[0.56, 0.98]		

(Continued)

Table V—*Continued*

Panel C: Size/INV							
Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
1.70	0.55				0.62	0.16	−272.08
[1.50, 1.90]	[0.37, 0.74]				[0.29, 0.81]		
0.59			18.06		0.52	0.16	−272.03
[−0.01, 1.20]			[13.29, 22.75]		[0.40, 0.92]		
0.97	0.32		10.33		0.70	0.13	−276.07
[−0.02, 1.34]	[0.08, 0.49]		[6.12, 16.45]		[0.45, 0.92]		
1.35		0.46		7.51	0.60	0.16	−269.89
[0.17, 2.46]		[−0.55, 1.46]		[4.56, 10.40]	[0.33, 0.92]		
2.28	0.30	−0.58		2.37	0.73	0.14	−277.09
[1.11, 3.38]	[0.12, 0.49]	[−1.57, 0.43]			[0.48, 0.92]		
				[−0.91, 5, 64]			

Panel D: Size/OP							
Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
1.61	0.57				0.76	0.12	−286.55
[1.46, 1.77]	[0.45, 0.71]				[0.42, 0.90]		
0.62			16.83		0.58	0.16	−272.43
[0.02, 1.18]			[12.26, 21.47]		[0.37, 0.91]		
1.42	0.50		2.69		0.76	0.12	−283.83
[0.68, 1.88]	[0.34, 0.74]		[−2.89, 6.27]		[0.44, 0.89]		
1.45		0.36		4.60	0.11	0.23	−255.09
[−0.16, 3.02]		[−1.06, 1.77]		[0.98, 8.29]	[−0.05, 0.61]		
2.47	0.43	−0.85		−0.23	0.60	0.17	−270.80
[1.21, 3.73]	[0.24, 0.61]	[−1.95, 0.26]		[−3.26, 2.77]	[0.23, 0.85]		

(Continued)

Table V—*Continued*

Panel E: All Equities							
Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
1.65	0.57				0.74	0.14	−966.12
[1.56, 1.74]	[0.49, 0.66]				[0.51, 0.84]		
0.80			15.03		0.59	0.17	−927.89
[0.49, 1.12]			[12.77, 17.38]		[0.44, 0.86]		
1.24	0.43		5.70		0.77	0.13	−975.12
[0.70, 1.30]	[0.32, 0.52]		[4.03, 8.25]		[0.57, 0.87]		
1.20		0.59		5.55	0.43	0.20	−904.68
[0.51, 1.87]		[−0.02, 1.19]		[3.99, 7.09]	[0.26, 0.71]		
2.54	0.41	−0.85		−0.17	0.70	0.16	−949.95
[1.87, 3.20]	[0.31, 0.51]	[−1.43, −0.27]		[−1.80, 1.50]	[0.48, 0.82]		

Table VI

Fama-Macbeth Regressions Using Intermediary Model Betas: Other Asset Classes

This table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrapped 95% confidence intervals are reported in square brackets. The sample spans the period 1970Q1 to 2012Q4.

$\mathbb{E}(R^e_{i,t}) = \lambda_0 + \lambda'_H \beta_H + \epsilon_i$, Estimates of Factor Risk Prices λ_H, $H = 8$

Constant	$\frac{KS_{t+H}}{KS_t}$	$EqFac_t$	$R^e_{m,t}$	$\bar{R}^2$	$\frac{RMSE}{RMSR}$	BIC
Panel A: Bonds						
0.23	0.57			0.89	0.15	−262.49
[0.13, 0.32]	[0.40, 0.72]			[0.34, 0.96]		
0.41		7.56	1.43	0.82	0.19	−249.97
[0.28, 0.54]		[4.16, 10.94]	[−0.25, 3.06]	[0.43, 0.95]		
0.20	0.50	−1.80	1.31	0.84	0.16	−257.26
[0.07, 0.33]	[0.18, 0.81]	[−5.34, 1.74]	[−0.43, 2.97]	[0.27, 0.95]		
Panel B: Sovereign Bonds						
0.16	1.18			0.32	0.33	−54.91
[−1.00, 1.62]	[0.20, 2.19]			[0.20, 0.99]		
0.34		7.05	1.24	0.68	0.20	−59.45
[−0.58, 1.34]		[2.77, 11.50]	[−2.63, 5.37]	[0.05, 0.99]		
−1.33	1.11	4.07	3.44	0.74	0.15	−62.84
[−2.73, 0.06]	[0.46, 1.73]	[−2.46, 10.49]	[0.61, 6.32]	[0.37, 0.99]		
Panel C: Options						
3.68	1.80			0.81	0.34	−178.57
[1.35, 6.11]	[0.83, 2.76]			[0.01, 0.95]		
−1.11		22.42	2.81	0.99	0.09	−222.10
[−2.40, 0.29]		[18.62, 26.62]	[1.18, 4.34]	[0.78, 0.99]		
5.36	0.73	15.08	−4.40	0.98	0.10	−221.04
[2.52, 8.21]	[0.29, 1.24]	[10.62, 19.60]	[−7.16, −1.61]	[0.75, 0.99]		
Panel D: CDS						
−0.16	0.77			0.94	0.20	−263.27
[−0.22, −0.09]	[0.64, 0.89]			[0.68, 0.99]		
−0.39		11.08	1.11	0.63	0.50	−224.44
[−0.63, −0.12]		[6.39, 16.61]	[−2.94, 6.16]	[0.20, 0.95]		
−0.06	0.93	−3.17	−0.60	0.94	0.20	−256.54
[−0.18, 0.06]	[0.66, 1.19]	[−6.61, 0.28]	[−2.68, 1.46]	[0.71, 0.99]		

statistical explanatory power. However, for both models, the magnitudes of the estimated risk prices when estimated on the option portfolios are somewhat larger than those estimated on the other portfolios. For example, compared to the estimations on the size/BM portfolios, the estimated options risk price for KS growth (alone) is a bit over twice as large, while that for $EqFac_t$ is more than three times as large. When all three betas are included to explain the cross-section of option returns, the risk price for KS growth is about the same as it is for explaining size/BM, while that for $EqFac_t$ is still more than twice as large.

D. Spreads between the Betas

Figures 1 and 4 show large spreads in the estimated capital share betas between the high- and low-return portfolios in each asset group. These findings suggest that the explanatory power of capital share risk exposure for the cross-section of expected asset returns is not the product of tiny risk exposures multiplied by large risk prices. A potential concern, however, is that the estimated betas may be imprecisely measured, so that the spreads are not statistically significant. To address this concern, we compute the spread in capital share betas between the highest and lowest average quarterly return portfolio for each portfolio group, along with the 95% bootstrapped confidence interval for the spread. For comparison, we also report the same numbers for the spread in the Fama-French (1993) factor betas and the intermediary-based factor betas. For the size/BM portfolio group, we separately analyze the largest attainable value premium (the spread in returns/betas between the $S1B5$ and $S1B1$ portfolios) and the largest attainable size premium (the spread in returns/betas between the $S1B5$ and $S5B5$ portfolios). To facilitate comparison across models, all factors are standardized to unit variance before performing the calculation.[18] The results are reported in Table VII.

Panel A of Table VII presents the spreads in betas for the value premium. The spread in capital share betas when $H = 4$ is slightly smaller than that of the HML beta, but is more than two times larger than the HML beta spread when $H = 8$ (for $H = 8$ quarters, the capital share beta spread is 0.13, vs. 0.06 for the HML beta spread, 0.041 for the $EqFac$ beta spread, and 0.015 for the $LevFac$ beta spread). For all models except $LevFac$, these spreads are statistically different from zero, as indicated by the 95% confidence intervals for the spreads that exclude zero. Panel B presents the analogous results for the size premium. The spread in the $H = 8$ quarter capital share betas corresponding to the size premium is 0.093, versus 0.076 for the SMB beta spread, 0.002 for the $EqFac$ beta spread, and 0.005 for the $LevFac$ beta spread. In this case, the spreads in the capital share and SMB betas are statistically significant, while those for $EqFac$ and $LevFac$ are statistically insignificant.

Panels C to J of Table VII present results for the other eight portfolio groups and can be summarized as follows.[19] There are three sets of portfolios for which the spread in capital share betas between the high and low average

[18] For this reason, the units of the betas are smaller than those in Figures 1 and 4.

[19] The numbers in Panel F for “All Equities” are identical to those in Panel A for the value premium because the spread in average returns between the $S1B5$ and $S1B1$ portfolios is largest for the “All Equities” category.

Table VII

Beta Spread

This table reports the spread in betas between the highest and lowest average return portfolio for each portfolio group. β^{High} denotes the highest average return portfolio beta, and β^{low} denotes the lowest average return portfolio beta. In the case of size/BM portfolios, these are separated into spreads along the value dimension (value spread) and size dimension (size spread) where, for example, $S1B5$ denotes the highest return portfolio along the value dimension, which is the portfolio in the smallest size category and largest book-to-market category. Bootstrapped 95% confidence intervals are reported in square brackets.

Equity

Panel A: 25 Size/BM Portfolios (Value Spread)

	$KS\ (H=4)$	$KS\ (H=8)$	$LevFac$	$EqFac$	HML
$\beta^{S1B5} - \beta^{S1B1}$	0.043	0.129	0.015	0.041	0.056
	[−0.00, 0.06]	[0.06, 0.15]	[0.00, 0.03]	[0.02, 0.06]	[0.04, 0.07]

Panel B: 25 Size/BM Portfolios (Size Spread)

	$KS\ (H=4)$	$KS\ (H=8)$	$LevFac$	$EqFac$	SMB
$\beta^{S1B5} - \beta^{S5B5}$	0.075	0.093	0.005	0.002	0.076
	[0.03, 0.09]	[0.02, 0.12]	[−0.01, 0.02]	[−0.02, 0.02]	[0.07, 0.09]

Panel C: REV

	$KS\ (H=4)$	$KS\ (H=8)$	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.054	0.119	0.001	0.041	0.057	0.035
	[0.01, 0.07]	[0.06, 0.16]	[−0.02, 0.02]	[0.01, 0.07]	[0.04, 0.07]	[0.02, 0.05]

Panel D: Size/INV

	$KS\ (H=4)$	$KS\ (H=8)$	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.041	0.082	0.010	0.018	0.086	0.031
	[−0.02, 0.07]	[−0.00, 0.13]	[−0.01, 0.03]	[0.01, 0.03]	[0.08, 0.10]	[0.02, 0.05]

Panel E: Size/OP

	$KS\ (H=4)$	$KS\ (H=8)$	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.055	0.082	0.005	−0.015	0.064	−0.003
	[0.03, 0.07]	[0.03, 0.12]	[−0.01, 0.02]	[−0.04, 0.01]	[0.06, 0.07]	[−0.02, 0.01]

Panel F: All Equities

	$KS\ (H=4)$	$KS\ (H=8)$	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.043	0.129	0.015	0.041	−0.019	0.056
	[−0.00, 0.06]	[0.06, 0.15]	[0.00, 0.03]	[0.02, 0.06]	[−0.03, −0.01]	[0.04, 0.07]

(*Continued*)

Table VII—*Continued*

Other Asset Classes

Panel G: Bonds

HML	KS ($H=4$)	KS ($H=8$)	$LevFac$	$EqFac$	SMB	
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.043	0.093	0.000	0.018	0.007	0.019
	[0.01, 0.06]	[0.02, 0.11]	[−0.02, 0.01]	[−0.00, 0.04]	[−0.00, 0.01]	[0.01, 0.03]

Panel H: Sovereign Bonds

	KS ($H=4$)	KS ($H=8$)	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.046	0.037	0.004	0.049	0.007	0.026
	[−0.04, 0.13]	[−0.11, 0.12]	[−0.06, 0.06]	[0.00, 0.08]	[−0.02, 0.03]	[−0.00, 0.06]

Panel I: Options

	KS ($H=4$)	KS ($H=8$)	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.057	0.071	−0.01	0.022	0.004	0.018
	[−0.00, 0.09]	[−0.04, 0.12]	[−0.05, 0.02]	[−0.01, 0.05]	[−0.01, 0.02]	[−0.00, 0.03]

Panel J: CDS

	KS ($H=4$)	KS ($H=8$)	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	0.030	0.075	−0.013	0.015	0.003	0.006
	[0.00, 0.05]	[0.03, 0.09]	[−0.03, −0.00]	[−0.00, 0.03]	[−0.01, 0.02]	[−0.01, 0.02]

return portfolios for each group are quantitatively sizable but not statistically significant. These are size/INV, sovereign bonds, and options. However, the spreads in HML, SMB, $EqFac$, and $LevFac$ betas are also insignificant for two of these (sovereign bonds and options), and smaller in magnitude than the capital share beta spread. Focusing on the size/INV portfolio group, the spread in SMB betas is of the same magnitude as the spread in $H = 8$ quarter capital share betas but, in contrast to the spread in capital share betas, statistically significant. For the five remaining portfolios groups (REV, size/OP, "All Equities," bonds, and CDS), the spread in capital share betas is several times larger than the spreads in HML, SMB, $EqFac$, and $LevFac$ betas and statistically significant. For the "All Equities" portfolio group, only the spreads in $H = 8$ capital share betas, $EqFac$ betas, and HML betas are statistically significant, with the largest spread of 0.129 identified with the capital share betas, followed by 0.056 for the HML beta spread and 0.041 for the $EqFac$ beta spread. For size/OP, only the spreads in the capital share betas (for both $H = 4, 8$) and in the SMB betas are statistically significant, with the $H = 8$ capital share beta spread 1.3 times as large as the SMB beta spread. For corporate bonds, the spread in $H = 8$ capital share betas is 4.9 times larger than the model with the next largest spread (the HML beta), while the spreads in all other betas are statistically insignificant. Finally, for the CDS portfolio group, only the spread in $H = 8$ capital share betas is statistically significant, and it is five times larger than the model with the next largest spread (the *EqFac* beta). Taken together, these results indicate that the capital share exposures consistently exhibit large spreads for a range of portfolio groups and compare favorably relative to competing models, even when taking into account sampling error.

E. An SDF Based on Household-Level Data

A core hypothesis of this investigation is that an SDF based on the marginal utility of the wealthiest households is more likely to be relevant for the pricing of risky securities than one based on that of the average household. Accordingly, in the final empirical analysis of the paper we explicitly connect capital share variation to fluctuations in the micro-level income shares of rich and nonrich stock owners using SZ household-level data. The SZ household-level income and wealth data are especially advantageous for this purpose because they are of high quality and detailed. Moreover, as discussed above, reliable household-level consumption data are unavailable for the wealthy. We therefore use the SZ household-level income and wealth data to construct a proxy for the consumption growth and SDF of rich stockowners.

To motivate this exercise, first note that the consumption of a representative stock owner in the i^{th} percentile of the stock wealth distribution can be tautologically expressed as $C_t\theta_t^i$, where θ_t^i is the i^{th} percentile's consumption share in period t. We do not observe $C_t\theta_t^i$ because reliable observations on θ_t^i are unavailable for wealthy households. We do observe reliable estimates of income shares, $\frac{Y_{it}}{Y_t}$, however, and a crude estimate of the i^{th} percentile's consumption could be constructed as $C_t\frac{Y_{it}}{Y_t}$. But, since some of the variation in $\frac{Y_{it}}{Y_t}$ across percentile groups is likely to be idiosyncratic, capable of being insured against and therefore not priced, a better measure would be one that isolates the systematic risk component of the income share variation. Given imperfect insurance between workers and capital owners, the inequality-based literature discussed above implies that fluctuations in the aggregate capital share should be a source of nondiversifiable income risk to which investors are exposed. We therefore form an estimate of the component of income share variation for the i^{th} percentile that represents systematic risk by replacing observations on $\frac{Y_{it}}{Y_t}$ with the fitted values from a projection of $\frac{Y_{it}}{Y_t}$ on KS_t. (Note that this is not the same as using KS_t itself as a risk factor.) That is, we ask whether betas for the H-period growth in $C_t\widehat{\frac{Y_t^i}{Y_t}}$ are priced, where $\widehat{Y_t^i/Y_t} = \widehat{\varsigma}_0^i + \widehat{\varsigma}_1^i(KS_t)$ are quarterly observations on fitted income shares from the i^{th} percentile. The parameters $\widehat{\varsigma}_0^i$ and $\widehat{\varsigma}_1^i$ are the estimated intercepts and slope coefficients from the regressions of income shares on the capital share reported in the right panel of Table II pertaining to households that are stockholders. We refer to $C_t\widehat{\frac{Y_t^i}{Y_t}}$ as a proxy for the i^{th} percentiles consumption. Finally, we focus on $i = top$ 10% of the stock

Table VIII
Top Income Shares and the Cross-Section

The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrapped 95% confidence intervals are reported in square brackets. The factor is $\frac{C_t}{C_{t-1}}[\frac{\widehat{Y_t^{>10\%}/Y_t}}{\widehat{Y_{t-1}^{>10\%}/Y_{t-1}}}]$ using the mimicking SZ data income share factor $\widehat{Y_t^{>10\%}/Y_t} = \widehat{\varsigma}_0^{>10\%} + \widehat{\varsigma}_1^{>10\%} KS_t$ for the top 10% of the shareholder wealth distribution. The sample spans the period 1963Q3 to 2013Q4.

$\mathbb{E}(R^e_{j,t}) = \lambda_0 + \lambda'_H \beta_H + \epsilon_j$, Estimates of Factor Risk Prices λ_H

Equity Portfolios

	Panel A: Size/BM		Panel B: REV		Panel C: Size/INV	
H	4	8	4	8	4	8
Constant	0.39	1.11	0.65	1.46	0.70	1.22
	[−0.31, 1.05]	[0.91, 1.30]	[0.07, 1.23]	[1.32, 1.61]	[−0.10, 1.44]	[0.93, 1.48]
$\frac{C_{t+H}}{C_t} \frac{\widehat{Y_{t+H}^{>10\%}/Y_{t+H}}}{\widehat{Y_t^{>10\%}/Y_t}}$	1.47	1.24	1.25	0.82	1.21	1.15
	[0.89, 2.05]	[1.01, 1.47]	[0.64, 1.84]	[0.61, 1.02]	[0.58, 1.85]	[0.82, 1.49]
$\bar{R}^2$	0.55	0.85	0.66	0.84	0.42	0.69
	[0.16, 0.81]	[0.64, 0.93]	[0.19, 0.91]	[0.68, 0.96]	[0.05, 0.75]	[0.36, 0.88]
$\frac{RMSE}{RMSR}$	0.18	0.11	0.12	0.08	0.19	0.14

	Panel D: Size/OP		Panel E: All Equities	
H	4	8	4	8
Constant	0.34	1.13	0.63	1.43
	[−0.11, 0.82]	[0.88, 1.38]	[0.33, 0.93]	[1.32, 1.53]
$\frac{C_{t+H}}{C_t} \frac{\widehat{Y_{t+H}^{>10\%}/Y_{t+H}}}{\widehat{Y_t^{>10\%}/Y_t}}$	1.41	1.18	1.37	1.16
	[1.01, 1.78]	[0.86, 1.50]	[1.10, 1.65]	[1.01, 1.31]
$\bar{R}^2$	0.71	0.74	0.59	0.78
	[0.38, 0.87]	[0.39, 0.89]	[0.31, 0.77]	[0.57, 0.87]
$\frac{RMSE}{RMSR}$	0.13	0.13	0.17	0.12

owner stock wealth distribution. Estimates from the cross-sectional regressions of expected returns on the five equity portfolios are given in Table VIII.

Table VIII shows that the betas of this proxy for rich stockowners' consumption growth strongly explain return premia on all equity portfolios. For size/BM portfolios, the $H = 8$ quarter growth in $C_t \widehat{\frac{Y_t^{>10}}{Y_t}}$ (where "> 10" denotes *top* 10% in the table) explains 85% of the cross-sectional variation in expected returns, with a positive and strongly statistically significant risk price. It further explains 84%, 69%, and 74% of the variation in expected returns on the REV, size/INV, and size/OP portfolios, respectively. These findings are consistent with the hypothesis that rich stock owners are marginal investors for these portfolio groups.

IV. Conclusion

In this paper, we find that exposure to a single macroeconomic variable, namely, fluctuations in the growth of the capital share of national income, has substantial explanatory power for expected returns across a range of equity characteristic portfolios and other asset classes. These assets include equity portfolios formed from sorts on size/book-to-market, size/investment, size/operating profitability, long-run reversal, and nonequity asset classes such as corporate bonds, sovereign bonds, credit default swaps, and options. Positive exposure to capital share risk earns a significant positive risk premium with estimated risk prices of similar magnitude across portfolio groups. The information contained in capital share exposures subsumes the information contained in the financial factors SMB and HML for pricing equity characteristic portfolios as well as previously successful empirical factors that use intermediaries' balance sheet data. A proxy for the consumption growth of the top 10% of the stock wealth distribution using household-level income and wealth data exhibits similar substantial explanatory power for the equity characteristic portfolios. These findings are consistent with the hypothesis that wealthy households, whose income shares are strongly positively related to the capital share, are marginal investors in many asset markets and that redistributive shocks that shift the allocation of rewards between workers and asset owners are an important source of systematic risk.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.