Capital Share Risk in U.S. Asset Pricing*

Martin Lettau
UC Berkeley, CEPR and NBER

Sydney C. Ludvigson
NYU and NBER

Sai Ma
NYU

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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 non-equity 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.

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*Lettau: Haas School of Business, University of California at Berkeley, 545 Student Services Bldg. #1900, Berkeley, CA 94720-1900; E-mail: lettau@haas.berkeley.edu; Tel: (510) 643-6349, http://faculty.haas.berkeley.edu/lettau. Ludvigson: Department of Economics, New York University, 19 W. 4th Street, 6th Floor, New York, NY 10012; Email: sydney.ludvigson@nyu.edu; Tel: (212) 998-8927; www.sydneyludvigson.com. Ma: Department of Economics, New York University, 19 W. 4th Street, 6th Floor, New York, NY 10012; Email: sai.ma@nyu.edu. Ludvigson thanks the C.V. Starr Center for Applied Economics at NYU for financial support. We are grateful to Federico Belo, John Y. Campbell, Kent Daniel, Lars Lochstoer, Hanno Lustig, Stefan Nagel, Dimitris Papanikolaou, and to seminar participants at Duke, USC, the Berkeley-Stanford joint seminar, the Berkeley Fun Center for Risk Management, Minnesota Macro-Asset Pricing Conference 2015, the NBER Asset Pricing meeting April 10, 2015, the Minnesota Asset Pricing Conference May 7-8, 2015, and the 2016 Finance Down Under Conference for helpful comments.

1 Introduction

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 non-equity asset classes, with positive risk price estimates of similar magnitude. These assets include equity portfolios formed from sorts on size/book-market, size/investment, size/operating profitability, long-run reversal, and non-equity 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 (the "capital share" hereafter) 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 substitution over aggregate household consumption. Under this paradigm, the division between labor and capital of aggregate consumption (or alternatively aggregate income, which finances aggregate consumption) 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 a model in which 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 still own no equity but even among those who do, most own very little. Although 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

[1] Source: 2013 Survey of Consumer Finances (SCF).

rate will 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, i.e., capital income, finances much more of their consumption.[2] Consistent with this fact, we find that the capital share explains a large fraction of variation in the income shares of the wealthiest households in micro-level data and is strongly positively correlated with those shares.

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 whenever 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, limited participation combines with limited risk-sharing to imply that fluctuations in the capital share are a source of aggregate risk. In the extreme case where workers own no risky asset shares and there is no risk-sharing, 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. Redistributive shocks that shift the share of income between labor and capital are therefore a source of systematic risk for asset owners. 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.

With this theoretical motivation as backdrop, this paper explores whether growth in the capital share is a priced risk factor for explaining cross-sections of expected asset returns. We

[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 proprietorship or farm.

find that exposure to short-to-medium frequency (e.g., 4-8 quarter) fluctuations in capital share growth have strong explanatory power for the cross-section of expected returns on a range of equity characteristics 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 characteristics 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 many different stock portfolios jointly and one that combines the stock portfolios 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 either exhibits far lower explanatory power for the cross-section of returns, and/or is not statistically important once we control for exposures to capital share growth.

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-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 completely driven 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 by 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 the majority of 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.

The last part of the paper provides 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 non-rich 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 variable helps explain 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 non-shareholder, but rather rich versus non-rich investors who differ according to whether their income is earned primarily from supplying labor or from owning assets. From this perspective, growth in the capital share of aggregate income is likely to be a more important source of systematic risk than is growth in the average consumption over all households who own any amount (however small) of equity.

Our work also ties into a growing body of literature that 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 (2013a, 2013b, 2015), Gomez (2016), GLL, Marfe (2016)). 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 those models that combine these features with limited stock market participation, 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); Chen, Favilukis, and Ludvigson (2014), Lettau and Ludvigson (2013), 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. Results (not reported) indicate 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 are particularly puzzling both for the inequality-based and the intermediary-based models, since these factors earn either a zero or strongly negative risk price when explaining cross-sections of expected momentum returns. The 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. The next section discusses data and presents some preliminary analyses. Section 3 describes the econometric models to be estimated, while Section 4 discusses the results of these estimations. Section 5 concludes.

2 Data and Preliminary Analysis

This section briefly describes our data. A more detailed description of the data and our sources is provided in the Online Appendix. Our sample is quarterly and unless otherwise noted spans the period 1963:Q3 to 2013:Q4 before loosing 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-market sorted portfolios (size/BM), 25 size/operating profitability portfolios (size/OP), 10 long-run reversal portfolios (REV), 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:Q3-1973:Q2 and 1975:Q1-2012:Q4 ("bonds"), six sovereign bond portfolios from Borri and Verdelhan (2011) spanning 1995:Q1-2011:Q1 ("sovereign bonds"), 54 S&P 500 index options portfolios sorted on moneyness and maturity from Constantinides, Jackwerth, and Savov (2013) spanning

1986:Q2-2011:Q4 ("options") and the 20 CDS portfolios constructed by HKM spanning 2001:Q2-2012:Q4.[3]

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. Results available upon request show that our findings are very similar if we use the BLS nonfinancial labor share measure.

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, i.e., 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 share and the capital share, 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

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

returns on risky assets. To address these questions, we make use of two household-level datasets 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 US 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 6015 households.

The second household level dataset uses the income-capitalization method of Saez and Zucman (2016) (SZ) that combines information from income tax returns with aggregate household balance sheet data to estimate the wealth distribution across households annually.[4] 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 US Financial Accounts. Wealth for a 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.[5]

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

[5] We follow the "mixed" method of capitalizing income from dividends and capital gains proposed by SZ. Specifically, when ranking households into wealth groups, only dividends are capitalized. Thus, if in 2000 the ratio of equities to the sum of dividend income reported on tax returns is 54, then a family's ranking in the wealth distribution is determined by taking its dividend income and multiplying by 54. By contrast, when computing the wealth and or income of each percentile group, both dividends and capital gains are capitalized. Thus, if in 2000 the ratio of equities to the sum of dividend and capital gain income reported on tax returns is 10, a household's equity wealth for that year is captured by multiplying it's dividend and

We define a stockholder in the SZ data as any individual who reports having non-zero 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 e.g., tax-deferred accounts. The annual data we employ span the period 1963-2012. We refer to these data as the "SZ data".

We note that 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 is an inferior measure of household-level assets and liabilities as compared to the SCF and SZ data, which both have 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 non-response rates in surveys such as the CEX that do not have an explicit administrative tax data component that directly targets wealthy households (Sabelhaus, Johnson, Ash, Swanson, Garner, Greenlees, and Henderson (2014)). The last section of the paper considers a way to form a proxy for the top wealth households' consumption using the income data.

Panel A of Table 1 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 shows results for stockholdings held either directly or indirectly from the SCF.[6] The right part shows the analogous results for the SZ data, corresponding to direct ownership. Panel B shows the distribution of stock wealth among all households, including non-stockowners. 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

capital gains income by 10. The purpose of this mixed method given by SZ is to smooth realized capital gains and not overstate the concentration of wealth.

[6] 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.

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 1 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 stockowning households representing $(rpr - .05)\,\%$ 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% are 46% of households, and those who hold no stocks are 51% of households. The wealth-weighted participation rate is then $5\% \cdot w^{5\%} + (rpr - 0.05)\,\% \cdot \left(1 - w^{5\%}\right) + (1 - rpr)\,\% \cdot 0$, where $w^{5\%}$ is the fraction of wealth owned by the top 5%. The table shows that the raw participation rate has steadily increased 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 stockmarket participation. The calculation shows that steady increases 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 2 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, though the results are similar using either dataset. 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.[7] The left panel of the table reports regression results for all households, while the right panel reports results for stockowners.

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 share of 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 8. 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 stockowners in the top 10% of the stock wealth distribution and strongly statistically significant, while it is negatively related to the income share of stockowners in the bottom 90%. The capital share explains 55% of the top one percent's income share, 48% of the top 10%, and 50% of the bottom 90%. This underscores the extent to which most households, even those who own some stocks, are better described

[7] 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.

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 a 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 stockowner stock wealth distribution, where C_t is aggregate consumption for the corresponding year, measured from the National Income and Product Accounts, while $\frac{Y_t^i}{Y_t}$ is computed from the SZ data for the two groups $i = \textit{top}$ 10, *bottom* 90. The bottom panel plots the same concept on quarterly data using the fitted values $\widehat{\frac{Y_t^i}{Y_t}}$ from the right-hand-panel regressions in Table 2, which is based on the subsample of households that report having income from stocks.[8] 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 stockowner 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, accounted for by 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.

3 Econometric Tests

Throughout the paper we use the superscript "o" to denote the true value of a parameter and "hats" to denote estimated values.

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

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

[8]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 a quarterly observations on fitted income shares $\widehat{\frac{Y_t^i}{Y_t}}$.

or equivalently,

$$\mathbb{E}\left(R_{jt+1}^{e}\right)=\frac{-\mathrm{Cov}\left(M_{t+1},R_{t+1}^{e}\right)}{\mathbb{E}\left(M_{t+1}\right)},\tag{2}$$

where M_{t+1} is a candidate SDF and R_{jt+1}^{e} is the excess return on an asset indexed by j held by the investor with marginal rate of substitution M_{t+1} at time $t+1$. The excess return is defined to be $R_{j,t}^{e}\equiv R_{j,t}-R_{f,t}$, 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. These features of the model follow GLL.

A simplified version of that model arises if stockholders have power utility over their own consumption, in which case the SDF for pricing risky asset claims takes the form

$$M_{t+1}=\delta\left(\frac{C_{t+1}\cdot KS_{t+1}}{C_t\cdot KS_t}\right)^{-\gamma},\tag{3}$$

where δ is a subjective time-discount factor and γ is 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.

An approximate linear factor model for this SDF takes 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 $f\equiv\left(\frac{C_{t+1}}{C_t}-1,\frac{KS_{t+1}}{KS_t}-1\right)'$ 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:

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

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).

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 $\beta_j' = \left(\beta_{jC,1}, \beta_{jKS,1}\right)'$, where β_j' are obtained from a first-stage time series regression of excess returns on factors,[9]

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

The above 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 $t+1$.[10] The gross H-period excess return on asset j from the end of t to the end of $t+H$ is denoted $R^e_{j,t+H,t}$.[11] Longer horizon risk exposures

[9]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.

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

[11]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

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

$\beta'_{jH} = \left(\beta_{jC,H}, \beta_{jKS,H}\right)'$ may be estimated from a regression of long-horizon returns on long-horizon factors, i.e.,

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

Our objective in this paper is to investigate the potential empirical relevance of one possible source of marginal utility risk in the limited participation framework with concentrated wealth, namely fluctuations in the capital share. For this purpose, the power utility SDF is an especially convenient empirical framework, but as with all models it is an approximation of reality and thus misspecified to some degree. We therefore make use of statistics for model comparison such as the Hansen-Jaganathan distance (HJ-distance, Hansen and Jagannathan (1997)) that explicitly recognize model misspecification. But we go one step further than the use of such statistics to consider a particular type of misspecification that is likely to have important implications for estimates of capital share risk exposures from regressions such as (6).

Specifically, we consider the implications of an omitted or unobserved risk factor that is negatively correlated with capital share growth on the right-hand-side of (6). In particular, evidence suggests that the risk aversion or curvature parameter γ in the power utility specification varies over time and is negatively correlated with, but less persistent than, capital share growth, which appears on the right-hand-side of (6).[12] Such a negative correlation is reminiscent of a Campbell and Cochrane (1999) style countercyclical risk aversion mechanism, in this case applied directly to capital share component of shareholder consumption

[12] GLL and Lettau and Wachter (2007) fit a model of the SDF that is the same as above except that it has a time-varying curvature γ_t parameter and a compensating factor in the subjective time-discount factor that makes the risk-free rate constant. In this case the SDF may be written

$$M_{t+1} = \exp\left[-r_f - \ln E_t \exp\left(-\gamma_t \Delta d_{t+1}\right) - \gamma_t \Delta d_{t+1}\right]$$

where d_t is log dividends. Lettau and Wachter (2007) show that γ_t must be negatively correlated with dividend growth, which depends on capital share growth in the GLL model, to fit the data. Estimates of the GLL model using the Hamilton filter to recover the latent risk aversion parameter also confirm that it is negatively correlated with but less persistent than capital share growth.

growth rather than to per capita aggregate consumption. The Online Appendix shows that a time-varying γ_t effectively appears as an additional risk factor in the approximate linear factor model of the SDF (4). If such an additional source of aggregate risk exists but an estimate of its risk exposure is omitted from (6) for any reason (e.g., because the factor is latent as in the case of risk aversion and/or difficult to measure), estimates of the included factor risk exposures will tend to be biased down as long as the omitted source of aggregate risk is negatively correlated with the included factor.

Fortunately, this bias can be mitigated under certain circumstances. In particular, if the omitted source of risk (i.e., γ_t) is less persistent than the included risk factor with which it is negatively correlated (i.e., KS_{t+1}/KS_t), estimates of *multi*-period capital share risk exposures $\widehat{\beta}_{jKS,H}$ from (7) with $H > 1$ will often be much closer to the true *one*-period exposures $\beta^o_{jKS,1}$ than are estimates of the one-period risk exposures $\widehat{\beta}_{jKS,1}$ from (6). The Online Appendix gives a specific parametric example and simulation in repeated finite samples of this phenomenon in which it is shown that a substantial downward bias $\mathbb{E}\left(\widehat{\beta}_{jKS,1}\right) << \beta^0_{jKS,1}$ in estimated one-period exposures can be significantly attenuated by estimating the longer-horizon relationships in (7), with $\mathbb{E}\left(\widehat{\beta}_{jKS,H}\right) \rightarrow \beta^0_{jKS,1}$ as H increases. In essence, this occurs because estimates of the long-horizon relationships in (7) filter out the higher frequency "noise" generated by the less persistent omitted factor γ_{t+1} that is the source of the bias in the estimated one-period exposure $\widehat{\beta}_{jKS,1}$. Under these conditions, the best way to extract the true *short*-horizon capital share beta is to run *longer*-horizon regressions. We refer the reader to the Online Appendix section on "Low Frequency Risk Exposures" for details on the example and simulation.

This evidence motivates us to investigate whether multi-quarter, i.e., H-period estimated risk exposures from regressions such as (7), for various H, explain cross-sections of one-period (quarterly) expected return premia $\mathbb{E}\left(R^e_{j,t+1}\right)$. Note that the point of estimating longer-horizon risk exposures in the first stage is not to ask how they affect longer-horizon expected return premia $\mathbb{E}\left(R^e_{j,t+H,t}\right)$ in the cross section.[13] The point is instead to obtain a more accurate estimate of the true one-period exposure, which can be used to explain one-period expected return premia $\mathbb{E}\left(R^e_{j,t+1,t}\right)$ in the cross-section. In the presence of the bias just described, we expect longer-horizon capital share exposures to do a better job explaining one-period expected return premia in the cross-section than do estimates of one-period exposures, a hypothesis we investigate below. For the linearized SDF model (4), this may be implemented by running time-series regressions of the form (7) to obtain $\widehat{\beta}'_{jH} = \left(\widehat{\beta}_{jC,H}, \widehat{\beta}_{jKS,H}\right)$, and then running a second-pass cross-sectional regression of the form

$$\mathbb{E}\left(R^e_{j,t}\right) = \lambda_0 + \widehat{\beta}_{j,C,H}\lambda_{C,H} + \widehat{\beta}_{j,KS,H}\lambda_{KS,H} + \epsilon_j, \qquad j = 1, 2....N, \tag{8}$$

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

For reasons discussed below, we also investigate a more parsimonious SDF model that depends only on capital share growth. In this case, 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 $\lambda_{KS,H}$:

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

In all the above equations, t represents a quarterly time period, and $\lambda_{.,H}$ are the H-period risk price parameters to be estimated. We refer to the 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 Online Appendix.

Although we maintain the linear SDF specifications as our baseline, we also undertake a GMM estimation that applies the approach just discussed to the nonlinear power utility

[13] In the parametric example of in the Online Appendix, the true short- and long-horizon risk exposures coincide, so estimated long-horizon exposures $\widehat{\beta}_{b,H}$ are less biased estimates of *both* $\beta^0_{b,H}$ and $\beta^0_{b,1}$. It follows that $\widehat{\beta}_{b,H}$ should explain cross-section of expected H-period returns as well as the cross-section of one-period returns. Results available upon request confirm that this is the case in our data.

SDF (3). The moment conditions upon which the estimation is based are in this case given by

$$\mathbb{E}\left[\begin{array}{c}\mathbf{R}_t^e - \lambda_0 \mathbf{1}_N + \frac{\left(M_{t+H,t}-\mu_H\right)\mathbf{R}^e_{t+H,t}}{\mu_H} \\ M_{t+H,t} - \mu_H\end{array}\right] = \left[\begin{array}{c}\mathbf{0}\\ 0\end{array}\right] \tag{10}$$

where

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

The equations to be estimated for the nonlinear SDF use H-period empirical covariances between excess returns $\mathbf{R}^e_{t+H,t}$ and the SDF $M_{t+H,t}$ to explain short-horizon (quarterly) average return premia $\mathbb{E}\left(\mathbf{R}_t^e\right)$. This implements the approach just discussed that uses H-period risk exposures to explain one-period expected returns in the cross-section. The details of this estimation are given in the Online Appendix and will be commented on briefly below.

In the final empirical analysis of the paper, we explicitly connect aggregate capital share fluctuations to fluctuations in the income shares of rich versus non-rich stockowners using the 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 a cross sectional $\overline{R}^2$ for the cross-sectional block of moments as a measure of how well the model explains the cross-section of quarterly returns.[14] 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

[14]This measure is defined as

$$\begin{aligned} R^2 &= 1 - \frac{Var_c\left(\mathbb{E}\left(R_j^e\right) - \widehat{R}_j^e\right)}{Var_c\left(\mathbb{E}\left(R_j^e\right)\right)} \\ \widehat{R}_j^e &= \widehat{\lambda}_0 + \underbrace{\widehat{\beta}'_{j,H}}_{1\times K}\underbrace{\widehat{\lambda}_H}_{K\times 1}, \end{aligned}$$

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

the portfolios being priced, i.e.,

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

where R_j^e refers to the excess return of portfolio j and $\widehat{R}_j^e = \widehat{\lambda}_0 + \widehat{\beta}_{j,H}'\widehat{\lambda}_H$.

4 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).

4.1 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, this is tantamount to asking whether covariances of H-period excess returns $R_{t+H,t}^e$ with the H-period linearized SDF $M_{t+H,t}$, where

$$M_{t+H,t} \equiv b_0 - b_1\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+H}}{KS_t} - 1\right), \tag{11}$$

have explanatory power for one-period expected return premia $\mathbb{E}\left(R_{j,t+1,t}^e\right)$. Although the specification (11), 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 (8) 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 is 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

$$\lambda_H = \mathbb{E}\left(M_{t+H,t}\right)^{-1} \operatorname{Cov}\left(f_H, f_H'\right) b, \tag{12}$$

where $f_H = \left(\frac{C_{t+H}}{C_t} - 1, \frac{KS_{t+H}}{KS_t} - 1\right)'$, and $b = (b_1, b_2)'$. Equation (12) 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 $\text{Cov}(f_H, f_H')$ 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 (12). The following results are reported in the Online Appendix, for $H = 4$ and $H = 8$ quarters. First, estimates of $\text{Cov}(f_H', f_H)$ show that consumption growth is much less volatile than capital share growth while the off-diagonal elements of $\text{Cov}(f_H', f_H)$ are small. As a consequence, estimates of $\lambda_{C,H}$ from (12) using data on different asset classes and equity characteristic portfolios are in most cases several times smaller than those of $\lambda_{KS,H}$ despite $b_1 = b_2$. (See Table A1. The big exception to this are the estimates using options data for $H = 8$). Note that if aggregate consumption growth were constant, $\lambda_{C,H} = 0$ no matter what the value of $b_1 = b_2$. This reasoning and 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.

This is the essence of what we find. Table A2 of the Online Appendix shows the GMM restricted parameter estimates of $b_1 = b_2$ (denoted b in the table) along with cross-sectional R^2 and $RMSE/RMSR$ for explaining quarterly expected return premia when both H-period consumption and capital share growth are included in the H-period SDF. Table A3 shows the same when b_1 is restricted to be 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 be zero. By contrast, restricting b_2 to be zero, i.e., dropping capital share growth from the linearized SDF, makes a big difference to the cross-sectional fit, which is typically far lower than the previous two cases (Table A4). This estimation is described in the Section on GMM Estimations of the Online Appendix.

Given these results, we make the more parsimonious SDF that depends only on capital share growth our baseline empirical model, i.e., $M_{t+H,t} = b_0 - b_2 \left(\frac{KS_{t+H}}{KS_t} - 1 \right)$, referred to hereafter as the *capital share* SDF. This is estimated with a univariate time-series regression to obtain $\widehat{\beta}_{j,KS,H}$ combined with the cross-sectional regression (9) 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 findings are therefore strongly supportive of a model with limited participation and imperfect risk-sharing between workers and shareholders.

The next 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 non-equity 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 Appendix provides a description of the bootstrap procedure.

4.2 A Parsimonious Capital Share SDF

Panels A-E of Table 3 report results from estimating the cross-sectional regressions (9) 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 the pooled estimation, Panel F reports the

$RMSE_i/RMSR_i$ for each group i computed from the pooled estimation on "all equity" characteristics portfolios. Panels G-J report results from estimating the cross-sectional regressions on portfolios of four non-equity asset classes: 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 column. Estimates for other horizons H are available upon request and generally show that estimated shorter horizon capital share risk exposures, e.g., $H = 1$ or $H = 2$, explain far less of the cross-sectional variation in expected quarterly returns, consistent with the specification bias discussed above.

Turning first to the equity characteristic portfolios, Table 3 shows that the risk price for capital share growth is positive and strongly statistically significant in each of these cross-sections, as indicated by the 95% 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, and 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 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, i.e., $[52\%, 91\%]$, $[68\%, 96\%]$, $[29\%, 81\%]$, 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 equity" 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 those 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 show 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 non-equity 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 characteristics portfolios, but they remain roughly in the same ballpark. This is reflected in the finding that the pooled estimation on "all assets" that 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, equal to 44%, in part because the fit for sovereign bonds is lower for this horizon.

Figure 1 and Figure 4 give a visual impression of 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 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-book/market portfolios are denoted SiBj, where $i, j = 1, 2, ..., 5$, with $i = 1$ the smallest size category and $i = 5$

the largest, while $j = 1$ denotes the lowest book-market category and $j = 5$ the largest. Analogously, size/INV portfolios are denoted SiIj, size/OP portfolios are denoted SiOj, and REV portfolios are denote REVi.

Figure 1 shows that the largest spread in returns on size/book-market portfolios is found by comparing the high and low book-market portfolios is 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 book-market) portfolios for studying the value premium in U.S. data. The betas for size/book-market portfolios line up strongly with return spreads for the smaller sized portfolios, but the model performs least well for larger stock portfolios, e.g., 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 spot 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 shows the 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 options portfolios are the least well priced in the estimations with $H = 4$ while CDS and sovereign bonds are less well priced when $H = 8$. On the other hand, 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 3 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 empirical model $M_{t+H,t} = b_0 - b_2 \left(\frac{KS_{t+H}}{KS_t} - 1 \right)$ using GMM and the restriction (12). (The GMM estimates of $\lambda_{KS,H}$ for each portfolio group are given in Table A5 of the Online 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 estimates of $\widehat{\lambda}_{KS,H} = 0.74$ and $\widehat{\lambda}_{KS,H} = 0.69$. Moreover, the GMM estimates of $\lambda_{KS,H}$ correspond to estimates of b_2 that are 10.1 and 4.9 for $H = 4$, and $H = 8$ respectively. (See Table A3 of the Online Appendix). Bearing in mind that b_2 should equal γ from the theoretical model, this demonstrates that the estimates of $\lambda_{KS,H}$ reported in Table 3 are consistent with plausible levels of risk aversion.

We close this section by briefly commenting on the results for the nonlinear SDF estimation (equations 10). These results are reported in Table A6. Several results 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 A3 of the Online Appendix.) The finding that estimates of risk aversion γ decline with the 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 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 in the linear SDF specification contain a common component across assets, thereby biasing upward the estimate of the zero-beta constant in the second stage regression.

4.3 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 alongside the capital share betas. For example, we estimate a baseline Fama-French three-factor specification taking the form,

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

and then include $\widehat{\beta}_{j,KS,H}$ as an additional regressor. Analogous specifications are estimated controlling for the intermediary-based factor exposures, i.e., 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 are estimated in the same way as in the original papers introducing those risk factors.

For size/BM we compare the model to the Fama-French 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 $H = 8$ quarter horizons. 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 $\boldsymbol{\lambda}$ chosen to minimize the pricing errors. The smaller is the BIC criterion, the more preferred is the model.

Table 4 reports results that control for the Fama-French factor betas. The first set of results forms the relevant benchmark by showing how these models perform on their own. Comparing to this benchmark, the results in Panel A of Table 4 for size/book-market portfolios show that the capital share risk model generates pricing errors that are lower than the Fama-French three-factor model. The RMSE/RMSR pricing errors are 12% for capital share model and 15% for the Fama-French three-factor model. The cross-sectional $\overline{R}^2 = 0.80$ for the capital share model, as compared to 0.69 for the Fama-French three-factor model. Panel B shows a similar comparison holds for the pooled estimation on all four types of equity characteristic portfolios.

Once the capital share beta is included alongside the betas from the Fama-French 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 for these risk prices are far wider, 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 5 compares the pricing power of the capital share model to the intermediary-based models for the four equity characteristics 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 portfolios types, however, the capital share risk model has the lowest pricing errors, lowest BIC criterion, and highest $\overline{R}^2$. Once we include the capital share beta alongside the betas for these factors we find that the risk prices for 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 once 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 that in capital share growth.

Table 6 further compares the capital share model's explanatory power for cross-sections of expected returns on the non-equity asset classes with the HKM intermediary model, which was also employed to study a broad range of non-equity classes. As shown above, the risk price for the capital share beta is positive and statistically significant in non-equity 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 alongside 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. By 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 statistical explanatory power. However, for both models, the magnitudes of the estimated risk prices when estimated on the options portfolios are somewhat larger than those estimated on other portfolios. For example, compared to the estimations on 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 options returns, the risk-price for KS growth is then about the same as it is for explaining size/BM, while that for $EqFac_t$ is still more than twice as large.

4.4 Spreads Between the Betas

Figures (1) and (4) discussed above 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 95% bootstrapped confidence interval for the spread. For comparison, we also report the same numbers for the spread in the Fama-French 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 the comparison across models, all factors are standardized to unit variance before performing the calculation.[15] The results are reported in Table 7.

Panel A of Table 7 shows 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 $H = 8$. (The spread in $H = 8$ quarter capital share betas is 0.13, versus 0.06 for 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 sets for the spreads that exclude zero. Panel B shows 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 significant.

Panels C-J of Table 7 present results for the other eight portfolio groups and may be summarized as follows.[16] There are three sets of portfolios for which the spread in capital share

[15] For this reason the units of the betas are than those in Figures (1) and (4).

[16] The numbers in Panel F for "All Equities" are itdentical to those in Panel A for the value premium

betas between the high and low average 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. 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 remaining five other portfolios groups (REV, size/OP, all equities, bonds, and CDS), the spread in capital share betas is in each case 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 magnitude identified with the capital share betas equal to 0.129, followed by 0.056 for the HML beta spread and 0.041, for the $EqFac$ beta spread. For size/OP, only the spread in the capital share betas (for both $H = 4, 8$) and the spread in 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 spread 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 is five times large in magnitude 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.

because the spread in average returns between the $S1B5$ and $S1B1$ portfolios is the largest in the All Equities category.

4.5 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 is one based on that of the average household. In the final empirical analysis of the paper, we therefore explicitly connect capital share variation to fluctuations in the micro-level income shares of rich and non-rich stockowners using the 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 and, as discussed above, reliable household-level consumption data are unavailable for the wealthy. Thus we 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 stockowner in the ith percentile of the stock wealth distribution can be tautologically expressed as $C_t\theta_t^i$, where θ_t^i is the ith 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 ith 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 non-diversifiable income risk to which investors are exposed. We therefore form an estimate of the component of income share variation for the ith 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 ith 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 2 pertaining to households who are stockholders. We refer to $C_t \widehat{\frac{Y_t^i}{Y_t}}$ as a proxy for the ith percentiles consumption. Finally, we focus on $i = top$ 10% of the stockowner stock wealth distribution. Estimates from the cross-sectional regressions of expected returns on the five equity portfolios are given in Table 8.

Table 8 shows that the betas for this proxy for rich stockowner's consumption growth strongly explains 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 explains 84%, 69%, and 74%, respectively, of the variation in expected returns on the REV, size/INV and size/OP portfolios. These findings are consistent with the hypothesis that rich stockowners are marginal investors for these portfolio groups.

5 Conclusion

This paper finds 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 characteristics portfolios and other asset classes. These assets include equity portfolios formed from sorts on size/book-market, size/investment, size/operating profitability, long-run reversal, and non-equity 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 characteristics 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 commensurate 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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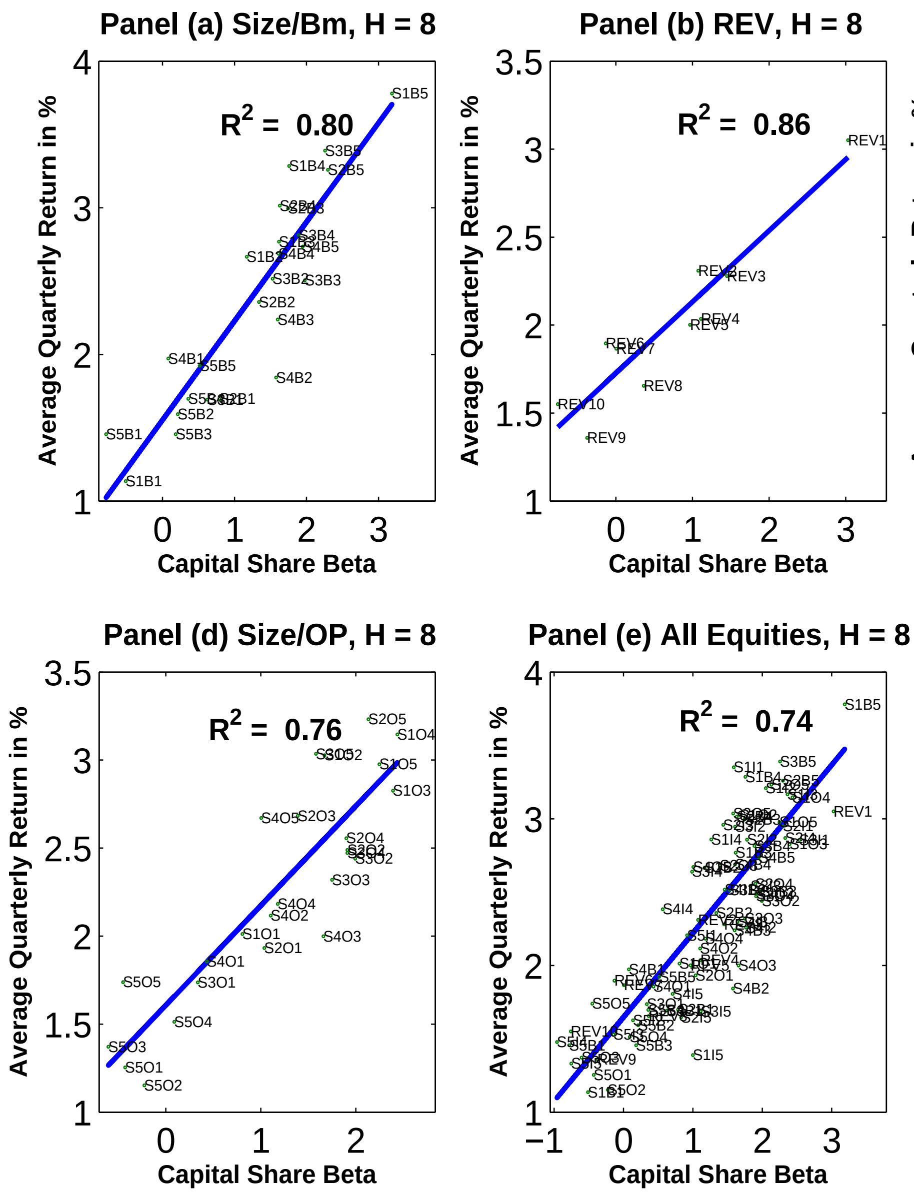

Figure 1: Capital share betas. Betas constructed from Fama-MacBeth regressions of average returns on capital share beta for different equity characteristic portfolios or using all equity portfolios together (size/bm, REV, size/INV and size/OP). H indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q3 to 2013Q4.

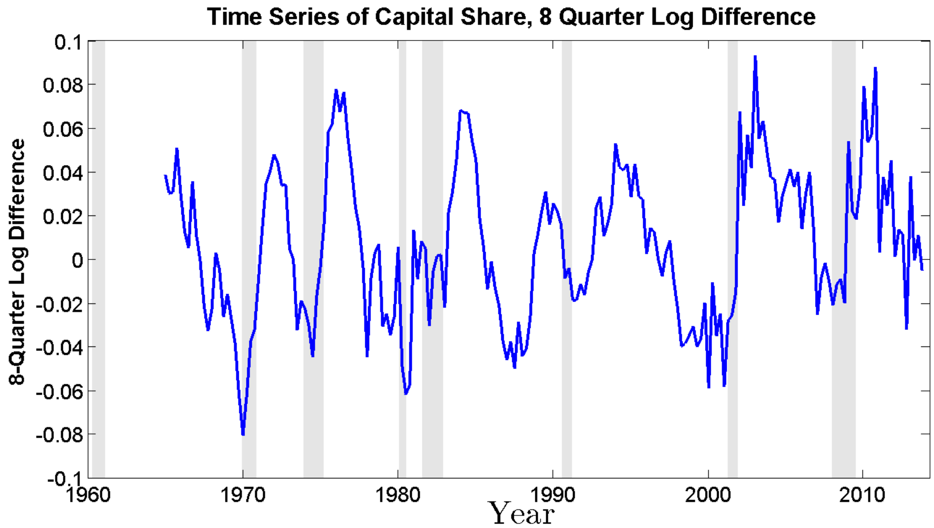

Figure 2: Capital share, 8 quarter log difference. The vertical lines correspond to the NBER recession dates. The sample spans the period 1963Q3 to 2013Q4.

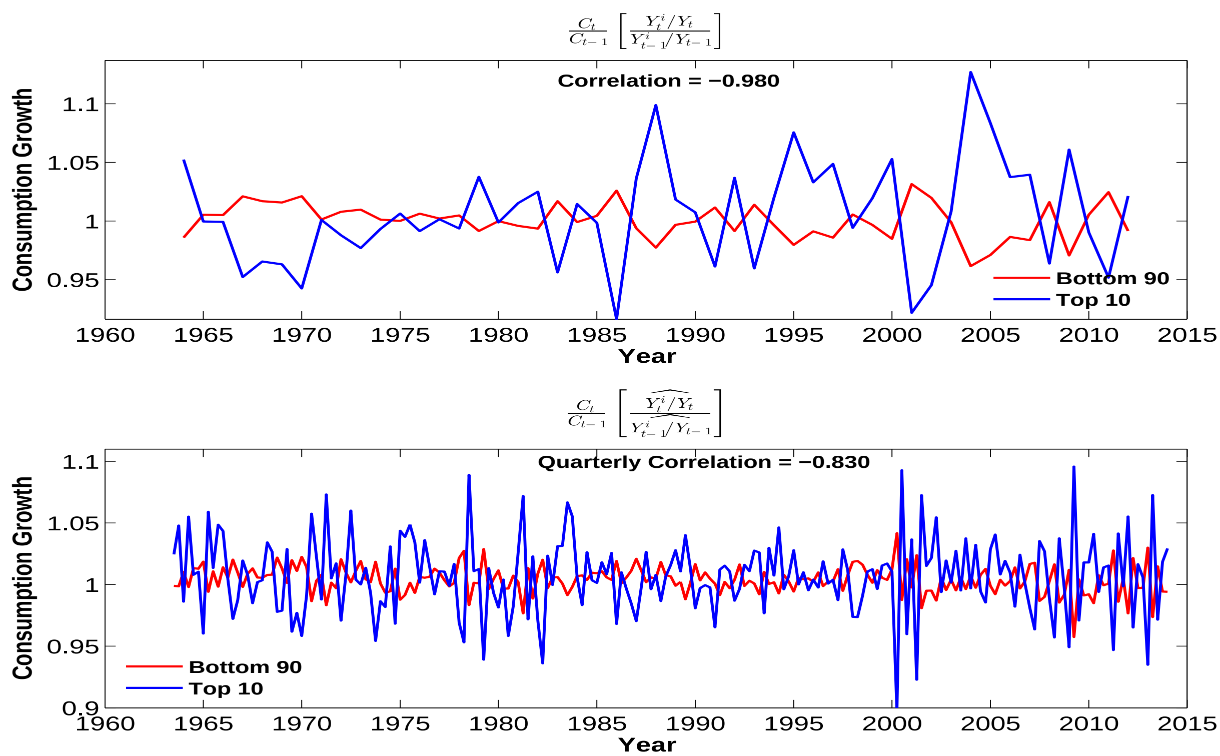

Figure 3: Growth in aggregate consumption times income share. The top panel reports annual observations on the annual value of $\frac{C_t}{C_{t-1}}\left[\frac{Y_t^i/Y_t}{Y_{t-1}^i/Y_{t-1}}\right]$ corresponding to the years for which SZ data are available. Y_t^i/Y_t is the shareholder's income share for group i calculated from the SZ. The bottom panel reports quarterly observations on quarterly values of $\frac{C_t}{C_{t-1}}\left[\frac{\widehat{Y_t^i/Y_t}}{\widehat{Y_{t-1}^i/Y_{t-1}}}\right]$ 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 - 2012. The quarterly sample spans the period 1963Q3 to 2013Q4.

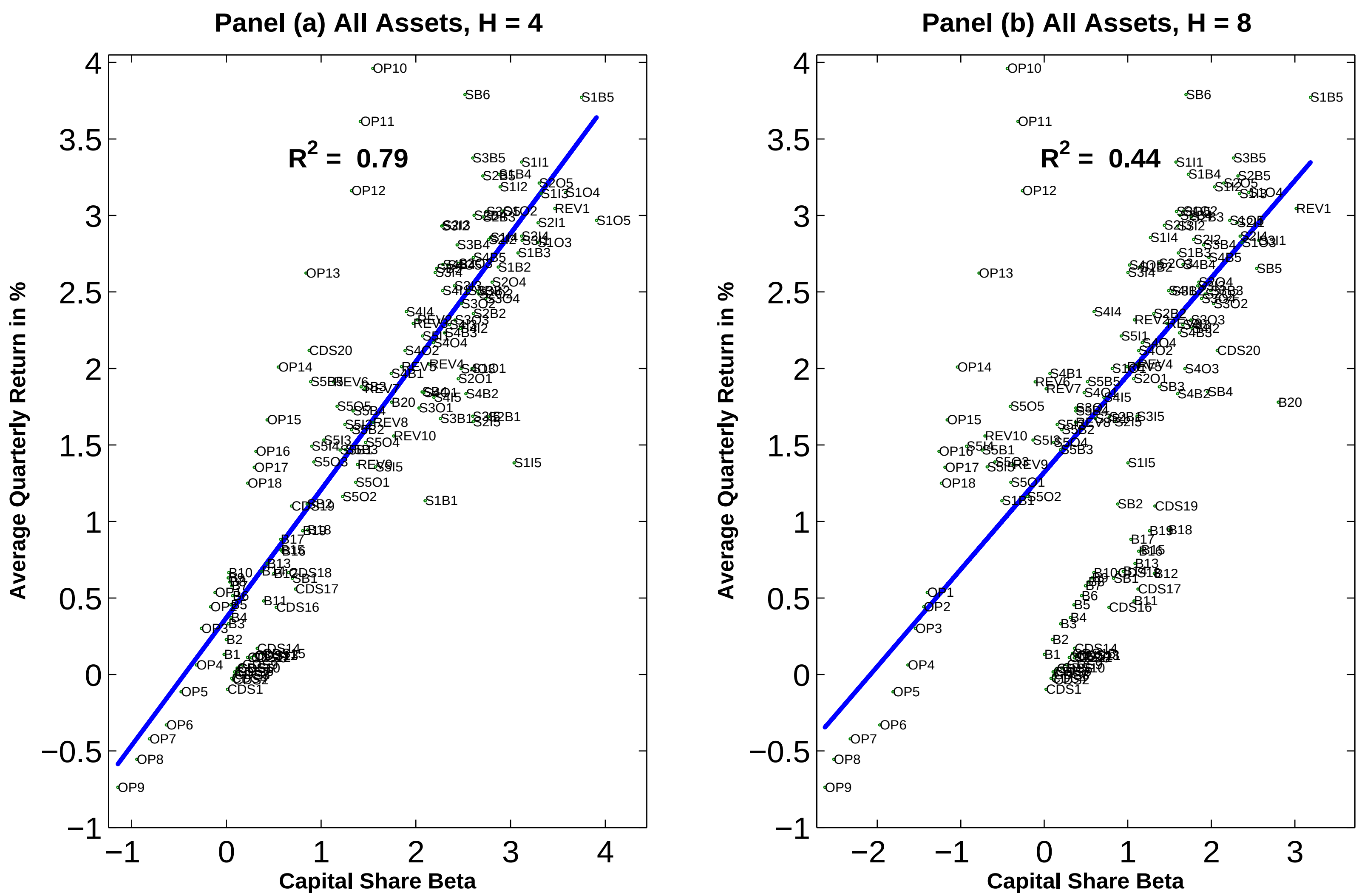

Figure 4: Capital share betas. Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using all assets (size/bm, REV, size/INV, size/OP equities plus bonds, sovereign bonds, CDS and Options). H indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q3 to 2013Q4.

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

	SCF (indirect + direct stock holdings)				SZ (direct stock holdings)			
Percentile of Stock Wealth	1989	1998	2004	2013	1989	1998	2004	2012
$< 70\%$	7.80%	9.15%	8.86%	7.21%	23.62%	15.50%	18.93%	16.51%
$70 - 85\%$	11.76%	10.95%	12.08%	11.32%	9.56%	9.37%	7.90%	6.91%
$85 - 90\%$	8.39%	6.59%	7.88%	7.42%	5.91%	6.09%	4.97%	5.10%
$90 - 95\%$	12.52%	11.18%	13.33%	13.40%	9.86%	10.69%	8.27%	8.06%
$95 - 100\%$	59.56%	62.09%	57.95%	60.74%	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)				SZ (direct stock holdings)			
$< 70\%$	0.01%	1.30%	1.35%	0.84%	11.32%	4.95%	8.48%	6.92%
$70 - 85\%$	3.12%	7.42%	7.41%	5.92%	4.22%	3.76%	4.68%	3.77%
$85 - 90\%$	4.19%	6.45%	6.70%	6.17%	4.20%	4.25%	3.86%	3.29%
$90 - 95\%$	11.16%	11.28%	13.26%	12.67%	8.81%	9.39%	7.43%	6.71%
$95 - 100\%$	81.54%	73.93%	71.21%	74.54%	71.44%	77.65%	75.55%	79.29%

Panel C: Stock Market Participation Rates, SCF (indirect + direct stock holdings)

	1989	1992	1995	1998	2001	2004	2007	2010	2013
Raw Participation Rate	31.7%	36.9%	40.5%	49.3%	53.4%	49.7%	53.1%	49.9%	48.8%
Wealth-weighted Participation Rate	13.8%	15.8%	16.4%	19.9%	23.9%	21.7%	21.1%	20.9%	20.2%

Table 1: Distribution of stock market wealth. The table reports the percentage of the stock weath 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, IRA, Keogh Plan, other retirement accounts. Stock ownership in SZ data is based on direct stock holdings only. Panel C reports stock market participation rate. The wealth-weighted participation rate is calculated as Value-weighted ownership $\equiv 5\% \left(w^{5\%}\right) + (rpr - 0.05)\% \left(1 - w^{5\%}\right) + (1 - rpr)\,\%\,(0)$ where rpr is the raw participation rate (not in percent) in the first row. $w^{5\%}$ is the proportion of stock market wealth owned by top 5% .

OLS Regression $\frac{Y_t^i}{Y_t} = \varsigma_0^i + \varsigma_1^i KS_t + \varepsilon_t$

All Households				Stockowners			
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^{**} (23.60)	-1.13^{**} (-8.65)	0.61	$< 90\%$	1.24^{**} (17.36)	-1.27^{**} (-6.82)	0.49
$95 - 100\%$	-0.24^{**} (-5.10)	1.08^{**} (8.65)	0.61	$95 - 100\%$	-0.28^{**} (-4.47)	1.20^{**} (7.34)	0.53
$99 - 100\%$	-0.24^{**} (-6.71)	0.82^{**} (8.88)	0.62	$99 - 100\%$	-0.27^{**} (-6.16)	0.93^{**} (8.25)	0.59
$99.9 - 100\%$	-0.16^{**} (-7.91)	0.48^{**} (9.41)	0.65	$99.9 - 100\%$	-0.17^{**} (-7.61)	0.54^{**} (9.13)	0.63
$90 - 100\%$	-0.18^{**} (-3.54)	1.13^{**} (8.64)	0.61	$90 - 100\%$	-0.24^{**} (-3.32)	1.27^{**} (6.82)	0.49

Table 2: Regressions of income shares on the capital share. OLS t-values in parenthesis. 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. The sample spans the period 1963Q3 to 2013Q4.

Expected Return-Beta Regressions

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

Equity Portfolios

Panel A: **Size/BM**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.65	0.74	0.51	0.19
	[0.01, 1.23]	[0.42, 1.08]	[0.13, 0.77]	
8	1.55	0.68	0.80	0.12
	[1.39, 1.71]	[0.53, 0.83]	[0.52, 0.91]	

Panel B: **REV**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.83	0.63	0.70	0.11
	[0.35, 1.32]	[0.33, 0.92]	[0.17, 0.91]	
8	1.73	0.41	0.86	0.08
	[1.62, 1.84]	[0.30, 0.50]	[0.68, 0.96]	

Panel C: **Size/INV**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.92	0.61	0.39	0.19
	[0.20, 1.54]	[0.27, 0.96]	[0.03, 0.70]	
8	1.70	0.55	0.62	0.16
	[1.50, 1.90]	[0.37, 0.74]	[0.29, 0.81]	

Panel D: **Size/OP**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.60	0.70	0.78	0.12
	[0.26, 0.94]	[0.54, 0.87]	[0.48, 0.89]	
8	1.61	0.57	0.76	0.12
	[1.46, 1.77]	[0.45, 0.71]	[0.42, 0.90]	

Panel E: **All Equities**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.74	0.68	0.58	0.17
	[0.45, 1.01]	[0.54, 0.83]	[0.28, 0.73]	
8	1.65	0.57	0.74	0.14
	[1.56, 1.74]	[0.49, 0.66]	[0.51, 0.84]	

Panel F: **All Equities** $\frac{\text{RMSE}_i}{\text{RMSR}_i}$

H	Size/Bm	REV	Size/INV	Size/OP
4	0.19	0.12	0.19	0.20
8	0.13	0.11	0.16	0.16

Table 3 continued next page

Expected Return-Beta Regressions

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

Other Asset Classes

	Panel G: **Bonds**				Panel H: **Sovereign Bonds**			
H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.43	0.82	0.86	0.17	-0.32	1.41	0.79	0.18
	$[0.35, 0.51]$	$[0.59, 1.03]$	$[0.32, 0.96]$		$[-1.08, 0.34]$	$[0.88, 1.93]$	$[0.44, 0.99]$	
8	0.23	0.57	0.89	0.15	0.16	1.18	0.32	0.33
	$[0.13, 0.32]$	$[0.40, 0.72]$	$[0.34, 0.96]$		$[-1.00, 1.62]$	$[0.20, 2.19]$	$[0.20, 0.99]$	
	Panel I: **Options**				Panel J: **CDS**			
H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.56	1.87	0.95	0.18	-0.24	1.26	0.84	0.34
	$[0.10, 1.07]$	$[1.43, 2.35]$	$[0.32, 0.99]$		$[-0.36, -0.11]$	$[0.84, 1.71]$	$[0.17, 0.97]$	
8	3.68	1.80	0.81	0.34	-0.16	0.77	0.94	0.20
	$[1.35, 6.11]$	$[0.83, 2.76]$	$[0.01, 0.95]$		$[-0.22, -0.09]$	$[0.64, 0.89]$	$[0.68, 0.99]$	
	Panel K: **All Assets**							
H	Constant	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$				
4	0.39	0.83	0.78	0.25				
	$[-0.91, 0.63]$	$[0.71, 1.21]$	$[0.28, 0.79]$					
8	1.34	0.63	0.44	0.41				
	$[0.81, 1.72]$	$[0.63, 0.96]$	$[0.42, 0.84]$					

Table 3: (cont.) **Expected return-beta regressions.** The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrap 95% confidence intervals are reported in square brackets. Panel F reports the $\text{RMSE}_i/\text{RMSR}_i$ attributable to the group i named in the column. The pricing error is defined as $\text{RMSR}_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left(\mathbb{E}\left(R^e_{ji}\right)\right)^2}$ where R^e_{ji} refers to the return of portfolio j in group i and $\text{RMSE}_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left(\mathbb{E}\left(R^e_{ji}\right) - \widehat{R}^e_{ji}\right)}$ where $\widehat{R}^e_{ji} = \widehat{\lambda}_0 + \widehat{\beta}'_{ji,H}\widehat{\lambda_H}$. The sample spans the period 1963Q3 to 2013Q4.

Expected Return-Beta Regressions: Competing Models, Equities

$\mathbb{E}\left(R^e_{j,t}\right) = \lambda_0 + \boldsymbol{\lambda}'_H \boldsymbol{\beta}_H + \epsilon_j$, Estimates of Factor Risk Prices $\lambda_H, H = 8$							
Panel A: **Size/BM**							
Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	SMB_t	HML_t	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
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**							
Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	SMB_t	HML_t	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
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]		

Table 4: Fama-MacBeth regressions of average returns on factor betas. The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrap 95% confidence intervals are reported in square brackets. The sample spans the period 1963Q3 to 2013Q4.

Expected Return-Beta Regressions: Competing Models, Equities

$$\mathbb{E}\left(R^e_{j,t}\right) = \lambda_0 + \boldsymbol{\lambda}'_H \boldsymbol{\beta}_H + \epsilon_j, \text{ Estimates of Factor Risk Prices } \lambda_H, H = 8$$

Panel A: **Size/BM**

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

Panel B: **REV**

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

Panel C: **Size/INV**

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

Table 5 continued next page

Expected Return-Beta Regressions: Competing Models, Equities

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

Panel D: **Size/OP**

Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	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]		

Panel E: All Equities

Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	$LevFac_t$	$EqFac_t$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	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 5: (cont.) **Fama-MacBeth regressions of average returns on factor betas.** The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrap 95% confidence intervals are reported in square brackets. The sample spans the period 1963Q3 to 2013Q4.

Expected Return-Beta Regressions: Competing Models, Other Asset Classes

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

Panel A: **Bonds**

Constant	$\frac{KS_{t+H}}{KS_t}$	$EqFac_t$	$R^e_{m,t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
0.23 [0.13, 0.32]	0.57 [0.40, 0.72]			0.89 [0.34, 0.96]	0.15	−262.49
0.41 [0.28, 0.54]		7.56 [4.16, 10.94]	1.43 [−0.25, 3.06]	0.82 [0.43, 0.95]	0.19	−249.97
0.20 [0.07, 0.33]	0.50 [0.18, 0.81]	−1.80 [−5.34, 1.74]	1.31 [−0.43, 2.97]	0.84 [0.27, 0.95]	0.16	−257.26

Panel B: **Sovereign Bonds**

Constant	$\frac{KS_{t+H}}{KS_t}$	$EqFac_t$	$R^e_{m,t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
0.16 [−1.00, 1.62]	1.18 [0.20, 2.19]			0.32 [0.20, 0.99]	0.33	−54.91
0.34 [−0.58, 1.34]		7.05 [2.77, 11.50]	1.24 [−2.63, 5.37]	0.68 [0.05, 0.99]	0.20	−59.45
−1.33 [−2.73, 0.06]	1.11 [0.46, 1.73]	4.07 [−2.46, 10.49]	3.44 [0.61, 6.32]	0.74 [0.37, 0.99]	0.15	−62.84

Panel C: **Options**

Constant	$\frac{KS_{t+H}}{KS_t}$	$EqFac_t$	$R^e_{m,t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
3.68 [1.35, 6.11]	1.80 [0.83, 2.76]			0.81 [0.01, 0.95]	0.34	−178.57
−1.11 [−2.40, 0.29]		22.42 [18.62, 26.62]	2.81 [1.18, 4.34]	0.99 [0.78, 0.99]	0.09	−222.10
5.36 [2.52, 8.21]	0.73 [0.29, 1.24]	15.08 [10.62, 19.60]	−4.40 [−7.16, −1.61]	0.98 [0.75, 0.99]	0.10	−221.04

Panel D: **CDS**

Constant	$\frac{KS_{t+H}}{KS_t}$	$EqFac_t$	$R^e_{m,t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
−0.16 [−0.22, −0.09]	0.77 [0.64, 0.89]			0.94 [0.68, 0.99]	0.20	−263.27
−0.39 [−0.63, −0.12]		11.08 [6.39, 16.61]	1.11 [−2.94, 6.16]	0.63 [0.20, 0.95]	0.50	−224.44
−0.06 [−0.18, 0.06]	0.93 [0.66, 1.19]	−3.17 [−6.61, 0.28]	−0.60 [−2.68, 1.46]	0.94 [0.71, 0.99]	0.20	−256.54

Table 6: Expected return-beta regressions. The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrap 95% confidence intervals are reported in square brackets. The sample spans the period 1970Q1 to 2012Q4.

Beta Spread – All Factors Standardized Unit Variance

	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
	$[-0.00, 0.06]$	$[0.06, 0.15]$	$[0.00, 0.03]$	$[0.02, 0.06]$	$[-0.03, -0.01]$	$[0.04, 0.07]$

Table 7 continued next page

Beta Spread – All Factors Standardized Unit Variance

Other Asset Classes						
	Panel G: **Bonds**					
	KS($H=4$)	KS($H=8$)	$LevFac$	$EqFac$	SMB	HML
$\beta^{\text{High}} - \beta^{\text{Low}}$	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
	$[0.00, 0.05]$	$[0.03, 0.09]$	$[-0.03, -0.00]$	$[-0.00, 0.03]$	$[-0.01, 0.02]$	$[-0.01, 0.02]$

Table 7: (cont.) **Beta spread.** The 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) adn size dimension (size spread) where e.g., S1B5 denotes the highest return portfolio along the value dimension, which is the portfolio is the smallest size category and largest book-market category. Bootstrap 95% confidence intervals are reported in square brackets.

Expected Return-Beta Regressions Using Top Income Shares

$$\mathbb{E}\left(R^e_{j,t}\right) = \lambda_0 + \boldsymbol{\lambda}'_H \boldsymbol{\beta}_H + \epsilon_j, \text{ Estimates of Factor Risk Prices } \lambda_H$$

Panel A: **Size/BM**

H	Constant	$\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{>10\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{>10\%}_t/Y_t}}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.39	1.47	0.55	0.18
	$[-0.31, 1.05]$	$[0.89, 2.05]$	$[0.16, 0.81]$	
8	1.11	1.24	0.85	0.11
	$[0.91, 1.30]$	$[1.01, 1.47]$	$[0.64, 0.93]$	

Panel B: **REV**

Constant	$\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{>10\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{>10\%}_t/Y_t}}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
0.65	1.25	0.66	0.12
$[0.07, 1.23]$	$[0.64, 1.84]$	$[0.19, 0.91]$	
1.46	0.82	0.84	0.08
$[1.32, 1.61]$	$[0.61, 1.02]$	$[0.68, 0.96]$	

Panel C: **Size/INV**

H	Constant	$\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{>10\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{>10\%}_t/Y_t}}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.70	1.21	0.42	0.19
	$[-0.10, 1.44]$	$[0.58, 1.85]$	$[0.05, 0.75]$	
8	1.22	1.15	0.69	0.14
	$[0.93, 1.48]$	$[0.82, 1.49]$	$[0.36, 0.88]$	

Panel D: **Size/OP**

Constant	$\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{>10\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{>10\%}_t/Y_t}}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
0.34	1.41	0.71	0.13
$[-0.11, 0.82]$	$[1.01, 1.78]$	$[0.38, 0.87]$	
1.13	1.18	0.74	0.13
$[0.88, 1.38]$	$[0.86, 1.50]$	$[0.39, 0.89]$	

Panel E: **All Equities**

H	Constant	$\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{>10\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{>10\%}_t/Y_t}}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.63	1.37	0.59	0.17
	$[0.33, 0.93]$	$[1.10, 1.65]$	$[0.31, 0.77]$	
8	1.43	1.16	0.78	0.12
	$[1.32, 1.53]$	$[1.01, 1.31]$	$[0.57, 0.87]$	

Table 8: Top Income Shares and the Cross Section. The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. Bootstrap 95% confidence intervals are reported in square brackets. The factor is $\frac{C_t}{C_{t-1}}\left[\frac{\widehat{Y_t^{>10\%}/Y_t}}{\widehat{Y_{t-1}^{>10\%}/Y_{t-1}}}\right]$ 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 shareholder wealth distribution. The sample spans the period 1963Q3 to 2013Q4.

Appendix: For Online Publication

Data Description

CONSUMPTION

Consumption is measured as expenditures on nondurables and services, excluding shoes and clothing. The quarterly data are seasonally adjusted at annual rates, in billions of chain-weighted 2005 dollars. The components are chain-weighted together, and this series is scaled up so that the sample mean matches the sample mean of total personal consumption expenditures. Our source is the U.S. Department of Commerce, Bureau of Economic Analysis.

LABOR SHARE

We use nonfarm business sector labor share throughout the paper. For nonfarm business sector, the methodology is summarized in Gomme and Rupert (2004). Labor share is measured as labor compensation divided by value added. The labor compensation is defined as Compensation of Employees - Government Wages and Salaries- Compensation of Employees of Nonprofit Institutions - Private Compensation (Households) - Farm Compensation of Employees - Housing Compensation of Employees - Imputed Labor Compensation of Self-Employed. The value added is defined as Compensation of Employees + Corporate Profits + Rental Income + Net Interest Income + Proprietors' Income + Indirect Taxes Less Subsidies + Depreciation. The quarterly, seasonally adjusted data spans from 1963:Q3 to 2013:Q4 with index 2009=100. The source is from Bureau of Labor Statistics. The labor share index is available at http://research.stlouisfed.org/fred2/series/PRS85006173 and the quarterly LS level can be found from the dataset at https://www.bls.gov/lpc/special_requests/msp_dataset.zip.

QUARTERLY RETURNS

The return in quarter Q of year Y, denoted $R_{Q,Y}$, is the compounded monthly return over the three months in the quarter, $m1,...,m3$:

$$1 + R_{Q,Y} = \left(1 + \frac{R_{Q,Y}^{m1}}{100}\right)\left(1 + \frac{R_{Q,Y}^{m2}}{100}\right)\left(1 + \frac{R_{Q,Y}^{m3}}{100}\right)$$

As test portfolios, we use the excess return constructed by subtracting the quarterly 3-month Treasury bill rate from the above. The sample spans from 1963Q1 to 2013Q4.

FAMA FRENCH PRICING FACTORS

We obtain quarterly Fama French pricing factor HML, SMB, Rm, and risk free rates from professor French's online data library http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/F-F_Benchmark_Factors_Quarterly.zip. The sample spans 1963:Q3 to 2013:Q4.

LEVERAGE FACTOR

The broker-dealer leverage factor $LevFac$ is constructed as follows. Broker-dealer (BD) leverage is defined as

$$Leverage_t^{BD} = \frac{\text{Total Financial Assets}_t^{BD}}{\text{Total Financial Assets}_t^{BD} - \text{ Total Liabilities}_t^{BD}}$$

The leverage factor is constructed as seasonally adjusted log changes

$$LevFac_t = \left[\Delta \log \left(Leverage_t^{BD}\right)\right]^{SA}.$$

This variable is available from Tyler Muir's website over the sample used in Adrian, Etula, and Muir (2014), which is 1968:Q1-2009:Q4.[17] In this paper we use the larger sample 1963:Q3 to 2013:Q4. There are no negative observations on broker-dealer leverage in this sample. To extend the sample to 1963:Q3 to 2013:Q4 we use the original data on the total financial asset and liability of brokers and dealers data from flow of funds, Table L.128 available at http://www.federalreserve.gov/apps/fof/DisplayTable.aspx?t=l.128. Adrian, Etula, and Muir (2014) seasonally adjust $\Delta \log \left(Leverage_t^{BD}\right)$ by computing an expanding window regression of $\Delta \log \left(Leverage_t^{BD}\right)$ on dummies for three of the four quarters in the year at each date using the data up to that date. The initial series 1968Q1 uses data from previous 10 quarters in their sample and samples expand by recursively adding one observation on the end. Thus, the residual from this regression over the first subsample window 1965:Q3-1968:Q1 is taken as the observation for $LevFac_{68:Q1}$. An observation is added to the end and the process is repeated to obtain $LevFac_{68:Q2}$, and so on. We follow the same procedure (starting with the same initial window 1965:Q3-1968:Q1) to extend the sample forward to 2013Q4. To extend backwards to 1963:Q1, we take data on $\Delta \log \left(Leverage_t^{BD}\right)$ from 1963:Q1 to 1967:Q4 and regress on dummies for three of four quarters and take the residuals of this regression as the observations on $LevFac_t$ for t =1963:Q1-1967:Q4. Using this procedure, we exactly reproduce the series available on Tyler Muir's website for the overlapping subsample 1968:Q1 to 2009:Q4, with the exception of a few observations in the 1970s, a

[17] Link: http://faculty.som.yale.edu/tylermuir/LEVERAGEFACTORDATA_001.txt

discrepancy we can't explain. To make the observations we use identical for the overlapping sample, we simply replace these few observations with the ones available on Tyler Muir's website.

SCF HOUSEHOLD STOCK MARKET WEALTH

We obtain the stock market wealth data from the triennial Survey of Consumer Finance (SCF) conducted by Board of Governors of the Federal Reserve System from 1989-2013. Stock Wealth includes both direct and indirect holdings of public stock. Stock wealth for each household is calculated according to the construction in SCF, which is the sum of following items: 1. directly-held stock. 2. stock mutual funds: full value if described as stock mutual fund, 1/2 value of combination mutual funds. 3. IRAs/Keoghs invested in stock: full value if mostly invested in stock, 1/2 value if split between stocks/bonds or stocks/money market, 1/3 value if split between. 4. other managed assets w/equity interest (annuities, trusts, MIAs): full value if mostly invested in stock, 1/2 value if split between stocks/MFs & bonds/CDs, or "mixed/diversified," 1/3 value if "other" stocks/bonds/money market. 5. thrift-type retirement accounts invested in stock full value if mostly invested in stock, 1/2 value if split between stocks and interest earning assets. 6. savings accounts classified as 529 or other accounts that may be invested in stocks.

Households with a non-zero/non-missing stock wealth by any of the above are counted as a stockowner. All stock wealth values are in real terms adjusted to 2013 dollars.

All summary statistics (mean, median, participation rate, etc) are computed using SCF weights. In particular, in the original data, in order to minimize the measurement error, each household has five imputations. We follow the exact method suggested in SCF website by computing the desired statistic separately for each implicate using the sample weight (X42001). The final point estimate is given by the average of the estimates for the five implicates.

SCF HOUSEHOLD INCOME

The total income is defined as the sum of three components. $Y_t^i = Y_{i,t}^L + Y_{i,t}^c + Y_{i,t}^o$. The mimicking factors for the income shares is computed by taking the fitted values $\widehat{Y_t^i/Y_t}$ from regressions of Y_t^i/Y_t on $(1 - LS_t)$ to obtain quarterly observations extending over the larger sample for which data on LS_t are available. We obtain the household income data from the triennial Survey of Consumer Finance (SCF) conducted by Board of Governors of the Federal Reserve System from 1989-2013. All the income is adjusted relative to 2013 dollars.

Throughout the paper, we define the labor income as

$$Y_{i,t}^{L} \equiv wage_{i,t} + LS_t \times se_{i,t}$$

where $wage_{i,t}$ is the labor wage at time t and $se_{i,t}$ is the income from self-employment at time t, and LS_t is the labor share at time t

Similarly, we define the capital income

$$Y_{i,t}^{c} \equiv se_{i,t} + int_{i,t} + \text{div}_{i,t} + cg_{i,t} + pension_{i,t}$$

where $int_{i,t}$ is the taxable and tax-exempt interest, div is the dividends, cg is the realized capital gains and $pensiYon_{i,t}$ is the pensions and withdrawals from retirement accounts.

The other income is defined as

$$Y_{i,t}^{o} \equiv gov_{i,t} + ss_{i,t} + alm_{i,t} + others_{i,t}$$

where $gov_{i,t}$ is the food stamps and other related support programs provided by government, $ss_{i,t}$ is the social security, $alm_{i,t}$ is the alimony and other support payments, $others_{i,t}$ is the miscellaneous sources of income for all members of the primary economic unit in the household.

A Stylized Model of Asset Owners and Workers

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

$$D_t = Y_t - w_t N_t$$

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

$$w_t N_t = \alpha_t Y_t => D_t = (1 - \alpha_t) Y_t. \tag{A1}$$

We rule out short sales in the risky asset:

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

Asset owners can trade with one another in a one-period bond with price at time t denoted q_t. The real quantity of bonds are denoted B_{t+1}, where $B_{t+1} < 0$ represents a borrowing position. The bond is in zero-net supply among asset owners. Asset owners could also have idiosyncratic investment income ζ_t^i. The gross financial assets of investor i at time t is defined

$$A_t^i \equiv \theta_t^i (V_t + D_t) + B_t^i.$$

The budget constraint for the ith investor is

$$\begin{aligned} C_t^i + B_{t+1}^i q_t + \theta_{t+1}^i V_t &= A_t^i + \zeta_t^i \\ &= \theta_t^i (V_t + D_t) + B_t^i + \zeta_t^i, \end{aligned} \tag{A2}$$

where C_t^i denotes the consumption of investor i.

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

$$C^w = \alpha_t Y_t. \tag{A3}$$

Equity market clearing requires

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

Bond market clearing requires

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

Aggregating (A2) and (A3) and imposing market clearing and (A1) implies that aggregate (worker plus shareholder) consumption, C_t, is equal to total output Y_t. Aggregating over the budget constraint of the shareholders shows that their consumption is equal to the capital share times C_t:

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

A representative shareholder who owns the entire corporate sector will therefore have consumption equal to $C_t \cdot KS_t$. This reasoning goes through as an approximation if workers own a small fraction of the corporate sector even if there is some risk-sharing in the form of risk-free borrowing and lending between workers and shareholders, as long as any risk-sharing across these groups is imperfect.

Low Frequency Risk Exposures

This Section provides a parametric example of conditions underwhich *longer* horizon (e.g., multi-quarter) risk exposures more acurately measure the true *short* horizon (e.g., one-quarter) exposure in finite samples. We start with the SDF

$$M_t = \delta \left(\frac{C_t^s}{C_{t-1}^s} \right)^{-\gamma_t},$$

or

$$\log M_t = \log(\delta) - \gamma_t \Delta \ln C_t^s,$$

where C_t^s stands for shareholder consumption. We suppose that the preference parameter γ_t varies over time. A first-order Taylor expansion around $\bar{\gamma}$ and $\Delta \ln C_t^s = g$ implies

$$\gamma_t \Delta \ln C_t^s \approx \bar{\gamma} g + \Delta \ln C_t^s (\gamma_t - \bar{\gamma}) + \gamma_t (\Delta \ln C_t^s - g).$$

It follows that

$$\begin{aligned} \log M_t &\approx \log(\delta) - \{\bar{\gamma} g + \Delta \ln C_t^s (\gamma_t - \bar{\gamma}) + \gamma_t (\Delta \ln C_t^s - g)\} \\ &= \log(\delta) - \{\bar{\gamma} g + \gamma_t \Delta \ln C_t^s - \bar{\gamma} \Delta \ln C_t^s \gamma_t + \gamma_t \Delta \ln C_t^s - \gamma_t g\} \\ &= \log(\delta) - \bar{\gamma} g - 2\gamma_t \Delta \ln C_t^s + \bar{\gamma} \Delta \ln C_t^s + \gamma_t g \end{aligned}$$

With $\gamma_t \Delta \ln C_t^s = \log(\delta) - \log M_t$, we have

$$\begin{aligned} \log M_t &= \log(\delta) - \bar{\gamma} g - 2(\log(\delta) - \log m_t) + \bar{\gamma} \Delta \ln C_t^s + \gamma_t g \\ &= [\bar{\gamma} g + \log(\delta)] - \bar{\gamma} \Delta \ln C_t^s - g\gamma_t \\ &\approx [\bar{\gamma} g + \log(\delta)] - \bar{\gamma} \left(\frac{C_t^s}{C_{t-1}^s} - 1 \right) - g\gamma_t \end{aligned}$$

Finally, using the approximation $\log M_t \approx M_t - 1$, we have

$$M_t \approx [1 + \bar{\gamma} g + \log(\delta)] - \bar{\gamma} \left(\frac{C_t^s}{C_{t-1}^s} - 1 \right) - g\gamma_t$$

which takes the form

$$M_t = b_0 - b_1 \left(\frac{C_t^s}{C_{t-1}^s} - 1 \right) - b_2 \gamma_t.$$

This is an approximately linear two factor model with factors given by $\frac{C_t^s}{C_{t-1}^s} - 1$ and the latent risk aversion variable γ_t.

Let stockholder consumption be $C_t^s = C_t KS_t$, where C_t is aggregate (shareholder plus worker) consumption. Aggregate consumption growth is very stable compared to capital share growth in our sample. For the sake of illustration in this appendix, we assume it is constant. Then KS_t is the only source of variation in stockholder consumption growth and the two factors are now the latent γ_t and KS_t. We denote the true value of the parameters with superscript "o". Suppose the data generating processes (DGPs) of gross returns $R_{j,t+1}$ and $\Delta \ln KS_{t+1}$ are given by

$$\begin{aligned} R_{j,t+1} &= \exp\left(\beta_\gamma^o \gamma_{t+1} + \beta_{KS,1}^o \Delta \ln KS_{t+1} + u_{j,t+1}\right) \\ &= 1 + \beta_\gamma^o \gamma_{t+1} + \beta_{KS,1}^o \frac{KS_{t+1}}{KS_t} + \zeta_{j,t+1} \ + \mathcal{O}\left(x^2\right) \\ \left(\frac{KS_{t+1}}{KS_t} - \mu_{KS}^o\right) &= \rho_{KS}^o \left(\frac{KS_t}{KS_{t-1}} - \mu_{KS}^o\right) + \varepsilon_{KS,t+1} \\ \gamma_{t+1} &= \rho_\gamma^o \gamma_t + \varepsilon_{\gamma,t+1} \end{aligned}$$

where the second line uses the approximation $\ln(1+x) \approx x$, $\zeta_{j,t+1}$ is an idiosyncratic shock, and $\mathcal{O}\left(x^2\right)$ represents higher-order terms ignored by a first-order approximation. Under this DGP for returns, long-horizon returns $R_{j,t+H,t} = \prod_{k=1}^H R_{j,t+k}$ take the form

$$\begin{aligned} R_{j,t+H,t} &= \exp\left(\beta_\gamma^0 \sum_{k=1}^H \gamma_{t+k} + \beta_{KS,1}^o \sum_{k=1}^H \Delta \ln KS_{t+k} + \sum_{k=1}^H \zeta_{j,t+k}\right) \\ &= 1 + \beta_\gamma^o \sum_{k=1}^H \gamma_{t+k} + \beta_{KS,1}^o \frac{KS_{t+H}}{KS_t} + \zeta_{j,t+H,t} \ + \mathcal{O}_H\left(x^2\right). \end{aligned}$$

The true one-period exposure $\beta_{KS,1}^o$ coincides with the true H-period exposure $\beta_{KS,H}^o$.

We let $\zeta_{j,t+1}$ be drawn from Normal distribution $N(0,1)$ and $(\varepsilon_{KS,t+1}, \varepsilon_{\gamma,t+1})$ be jointly drawn from a bivariate Normal distribution, i.e,

$$\begin{aligned} \zeta_{j,t} &\sim N(0,1) \\ (\varepsilon_{\gamma,t}, \varepsilon_{KS,t})' &\sim N(\bar{\mu}, \Sigma) \end{aligned}$$

where

$$\begin{aligned} \bar{\mu} &= \left(\mu_\gamma, 0\right)' \\ \Sigma &= \begin{bmatrix} \sigma_\gamma^2 & \sigma_{\gamma KS} \\ \sigma_{\gamma KS} & \sigma_{KS}^2 \end{bmatrix} \end{aligned}$$

Suppose γ_t is omitted from the econometrician's set of risk factors for any reason (e.g., because its latent and difficult to measure or due to misspecification), so that capital share risk exposures are estimated using the univariate regressions

$$R_{j,t+H,t} = a + \beta_{KS,H} \frac{KS_{t+H,t}}{KS_t} + u_{j,t+1},$$

for various $H = 1, 2, ...,$ where H represents the horizon over which returns and capital share growth are measured and $R_{j,t+H,t}$ denotes the gross return from the end of t to the end of $t + H$. We now consider a parameteric example intended to be illustrative of the conditions under which longer horizon risk exposures more accurately measure true risk exposures even at short horizons. The parametrization is given in the table below.

Parameters

β_γ	β_{KS}	ρ_{KS}	ρ_γ	σ_γ	σ_{KS}	μ_γ	μ_{KS}	$\sigma_{\gamma KS}$
0.1	0.1	0.95	0.5	0.9	0.27	1.7	1.3	-0.1

The key aspects of this parametrization are that $\sigma_{\gamma KS} < 0$ and $\rho_\gamma < \rho_{KS}$. That is, the omitted factor γ_t is negatively correlated with the included factor $\frac{KS_{t+H,t}}{KS_t}$ but less persistent than the included factor. These parameter choices are roughly in line with evidence in updated work by Greenwald, Lettau, and Ludvigson (2014) that estimates the model above along with the latent risk aversion parameter using the Hamilton filter. Because γ_t is an omitted factor, $\widehat{\beta}_{KS,H}$ will be biased down compared to the true $\beta^0_{KS,1}$, but more so for H small. The results for a sample size of $T = 202$ as in our data are below. The estimated betas are reported as averages over $N = 10,000$ samples for $\widehat{\beta}_{KS,H}$

Average Estimated $\widehat{\beta}_{KS,H}$, with $N = 10,000$ Samples

H	1	4	8	12	16	True
$\rho_\gamma = 0.5$	0.0393	0.0521	0.0614	0.0851	0.0935	0.1000

The long-horizon estimated exposures $\widehat{\beta}_{KS,H}$ for $H = 8$ or 12 are a better estimates of both the true one-period capital share exposure $\beta^0_{KS,1}$ as well as the true H-period exposure, which coincides with the one-period exposure. Under these conditions, the multi-quarter exposure $\widehat{\beta}_{KS,H}$ provides a better estimate in finite samples of the true one-period exposure. The reason is that the long-horizon regressions attenuate the bias in short–horizon betas created by omitting the less persistent but more volatile γ_t. This factor is a source of noise at in the short-horizon regressions but is largely dissipated in the long-horizon relationships.

GMM Estimations

Nonlinear SDF Estimation Estimates of the benchmark nonlinear models are based on the following $N+1$ moment conditions

$$g_T(b) = \mathbb{E}_T \begin{bmatrix} \mathbf{R}_t^e - \lambda_0 \mathbf{1}_N + \frac{(M_{t+H,t}-\mu_H)\mathbf{R}_{t+H,t}^e}{\mu_H} \\ M_{t+H,t} - \mu_H \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ 0 \end{bmatrix} \tag{A4}$$

where $\mathbb{E}_T$ denotes the sample mean in a sample with T time series observations, $\mathbf{R}_t^e = \left[R_{1,t}^e ... R_{N,t}^e\right]'$denotes an $N \times 1$ vector of excess returns, and the parameters to be estimated are $\mathbf{b} \equiv (\mu_H, \gamma, \lambda_0, \beta)'$. The first N moments are the empirical counterparts to $\mathbb{E}\left(R_{jt+1}^e\right) = \frac{-\text{Cov}\left(M_{t+1}, R_{t+1}^e\right)}{\mathbb{E}(M_{t+1})}$, with two differences. First, 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 and quarterly T-bills are not an accurate measure of the zero beta rate. Second, the equations to be estimated specify models in which *long*-horizon H-period empirical covariances between excess returns $\mathbf{R}_{t+H,t}^e$ and the SDF $M_{t+H,t}^k$ are used to explain *short*-horizon (quarterly) average return premia $\mathbb{E}(\mathbf{R}_t^e)$. This implements the approach that is discussed in the text regarding low frequency risk exposures. We estimate models of the form (A4) for different values of H.[18]

The equations above are estimated using a weighting matrix consisting of an identity matrix for the first N moments, and a very large fixed weight on the last moment used to estimate μ_H. By equally weighting the N Euler equation moments, we insure that the model is forced to explain spreads in the original test assets, and not spreads in reweighted portfolios of these.[19] This is crucial for our analysis, since we seek to understand the large

[18]This approach and underlying model are different than that taken by Parker and Julliard (2004), which studies covariances between short-horizon returns and *future* consumption growth over longer horizons. We don't pursue this approach here because such covariances are unlikely to capture low frequency components in the stock return-capital share relationship, which requires relating *long*-horizon returns to long-horizon SDFs.

[19]See Cochrane (2005) for a discussion of this issue.

spreads on size-book/market and momentum strategies, not on other portfolios. However, it is important to estimate the mean of the stochastic discount factor accurately. Since the SDF is less volatile than stock returns, this requires placing a large (fixed) weight on the last moment.

For these estimations, we report a cross sectional R^2 for the asset pricing block of moments as a measure of how well the model explains the cross-section of quarterly returns. This measure is defined as

$$\begin{aligned} R^2 &= 1 - \frac{Var_c\left(\mathbb{E}_T\left(R_j^e\right) - \widehat{R}_j^e\right)}{Var_c\left(\mathbb{E}_T\left(R_i^e\right)\right)} \\ \widehat{R}_j^e &= \widehat{\lambda}_0 + \frac{\mathbb{E}_T\left[\left(\widehat{M}_{t+H,t}^k - \widehat{\mu}_H\right) R_{j,t+H,t}^e\right]}{\widehat{\mu}_H}, \end{aligned}$$

where Var_c denotes cross-sectional variance and $\widehat{R}_j^e$ is the average return premium predicted by the model for asset j, and "hats" denote estimated parameters.

Linear SDF Estimation The nonlinear SDF is

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

We take a linear approximation of the above as follows. Taking logs, we have

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

Using $\ln(1+x) \approx x$, we have

$$\begin{aligned} M_{t+H,t} - 1 &\approx \ln\left(M_{t+H,t}\right) = \ln\left(\delta^H\right) - \gamma \ln\left(\frac{C_{t+H}}{C_t}\right) - \gamma \ln\left(\frac{KS_{t+H}}{KS_t}\right) \\ &\approx \ln\left(\delta^H\right) - \gamma\left(\frac{C_{t+H}}{C_t} - 1\right) - \gamma\left(\frac{KS_{t+H}}{KS_t} - 1\right) \end{aligned}$$

Or,

$$\begin{aligned} M_{t+H,t} &\approx \underbrace{\left[1 + \ln\left(\delta^H\right)\right]}_{b_0} - b_1\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+H}}{KS_t} - 1\right) \\ b_1 &= b_2 = \gamma. \end{aligned}$$

We use the above linearized $M_{t+H,t}$ in GMM moment conditions (A4). However, since we are using excess return data, b_0 and therefore the mean of the SDF μ_H cannot be identified in the linear SDF specification. Thus we calibrate $\delta = (0.95)^{\frac{1}{4}}$, which pins down both b_0 and $\mu_H \equiv \mathbb{E}\left(M_{t+H,t}\right) = b_0 - b_1 \mathbb{E}\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2 \mathbb{E}\left(\frac{KS_{t+H}}{KS_t} - 1\right)$. We estimate three cases, (i) $b_1 = b_2 = \gamma$ (ii) $b_1 = 0$, $b_2 = \gamma$ (iii) $b_1 = \gamma$, $b_2 = 0$ using the moment conditions

$$g_T(b) = \mathbb{E}_T \begin{bmatrix} \mathbf{R}_t^e - \lambda_0 \mathbf{1}_N + \frac{\left(M_{t+H,t} - \mu_H\right)\mathbf{R}_{t+H,t}^e}{\mathbb{E}\left(M_{t+H,t}\right)} \\ \left(\frac{C_{t+H}}{C_t} - 1\right) - \mu_{c,H} \\ \left(\frac{KS_{t+H}}{KS_t} - 1\right) - \mu_{KS,H} \\ \left(\frac{C_{t+H}}{C_t} - 1\right)\left(\frac{KS_{t+H}}{KS_t} - 1\right) - \sigma_{C,KS} \\ \left(\frac{C_{t+H}}{C_t} - 1\right)^2 - \sigma_c^2 \\ \left(\frac{KS_{t+H}}{KS_t} - 1\right)^2 - \sigma_{KS}^2 \end{bmatrix} = \mathbf{0}.$$

The first block of moment conditions estimate the Euler equations, while the remaining blocks estimate the parameter elements of the covariance matrix of factors. The factor risk prices λ_H can be derived from

$$\begin{aligned} \mathbb{E}\left(R_t^e\right) &= \lambda_0 - \frac{\left(M_{t+H,t} - \mu_H\right)\mathbf{R}_{t+H,t}^e}{\mu_H} \\ &= \lambda_0 + \frac{\operatorname{Cov}\left(\mathbf{R}_{t+H,t}^e, f_H'\right) b}{\mu_H} \\ &= \lambda_0 + \frac{\operatorname{Cov}\left(\mathbf{R}_{t+H,t}^e, f_H'\right)\operatorname{Cov}\left(f_H, f_H'\right)^{-1}\operatorname{Cov}\left(f_H, f_H'\right) b}{\mu_H} \\ &= \lambda_0 + \frac{\beta_H \operatorname{Cov}\left(f_H, f_H'\right) b}{\mu_H}, \end{aligned}$$

where $\mu_H = \mathbb{E}\left(M_{t+H,t}\right)$. It follows that

$$\lambda_H = \frac{\operatorname{Cov}\left(f_H, f_H'\right) b}{\mu_H}.$$

The estimated $\mathrm{Cov}(f_H, f_H')$ is

$\mathrm{Cov}(f_H', f_H),\ f_H = \left(\frac{C_{t+H}}{C_{t-1}} - 1, \frac{KS_{t+H}}{KS_{t-1}} - 1\right)$		
all units are in multiple of 1000		
$H = 4$	0.1968	−0.0164
	−0.0164	0.6709
$H = 8$	0.5736	−0.1405
	−0.1405	1.2184

Table A2 shows the cross-sectional explanatory power for quarterly expected returns of the model with the restriction $b_1 = b_2$ imposed. Table A1 shows that the estimates of $\lambda_{C,H}$ are often several times smaller than those of $\lambda_{KS,H}$ despite $b_1 = b_2$. From the estimates of $\mathrm{Cov}(f_H', f_H)$, we see the off-diagonal elements are small, implying that the correlation between the factors is low (equal to -0.04 for $H = 4$ and -0.17 for $H = 8$). With these estimates, an empirical model that eliminates the eliminates consumption growth from the SDF altogether is likely to perform about as well as one that includes it. Table A3 shows that this is what is found: little is lost in terms of cross-sectional R^2 or pricing errors by estimating a model with b_1 constrained to be zero, compared to the case where $b_1 = b_2$ in Table A2. By contrast, dropping capital share growth from the SDF makes a big difference to the cross-section fit, as shown in A4.

Two Pass Regression GMM Estimation Denote a generic vector of K factors for any model as $\mathbf{f}_t$ (where K could be one, as in the capital share SDF). This appendix gives the general approach to our estimation of factor risk prices using two pass (time series and cross-sectional) regressions for any linear factor model.

The moment conditions for the expected return-beta representations are

$$g_T(\boldsymbol{b}) = \begin{bmatrix} \mathbb{E}\left(\underbrace{\mathbf{R}^e_{t+H,t}}_{N\times 1} - \underbrace{\mathbf{a}}_{N\times 1} - \underbrace{\boldsymbol{\beta}}_{(N\times K)}\underbrace{\mathbf{f}_t}_{(K\times 1)}\right) \\ \mathbb{E}\left(\left(\mathbf{R}^e_{t+H,t} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t\right) \otimes \mathbf{f}_t\right) \\ \mathbb{E}\left(\underbrace{\mathbf{R}^e_t}_{N\times 1} - \lambda_0 - \underbrace{\boldsymbol{\beta}}_{(N\times K)}\underbrace{\boldsymbol{\lambda}}_{(K\times 1)}\right) \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \tag{A5}$$

where $\mathbf{a} = [a_1 ... a_N]'$ and $\boldsymbol{\beta} = [\boldsymbol{\beta}_1 ... \boldsymbol{\beta}_N]'$, with parameter vector $\boldsymbol{b}' = [\mathbf{a}, \boldsymbol{\beta}, \lambda_0, \boldsymbol{\lambda}]'$. To obtain OLS time-series estimates of $\mathbf{a}$ and $\boldsymbol{\beta}$ and OLS cross sectional estimates of λ_0 and $\boldsymbol{\lambda}$, we choose parameters $\boldsymbol{b}$ to set the following linear combination of moments to zero

$$\boldsymbol{a}_T g_T(\boldsymbol{b}) = 0,$$

where

$$\boldsymbol{a}_T = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{0} & [\mathbf{1}_N, \boldsymbol{\beta}]' \end{bmatrix}.$$

The point estimates from GMM are identical to those from Fama MacBeth regressions. To see this, in order to do OLS cross sectional regression of $E(R_{i,t})$ on $\boldsymbol{\beta}$, recall that the first order necessary condition for minimizing the sum of squared residual is

$$\begin{aligned} \widetilde{\beta}\left(E(R_{i,t}) - \widetilde{\beta}[\lambda_0, \boldsymbol{\lambda}]\right) &= 0 \Longrightarrow \\ [\lambda_0, \boldsymbol{\lambda}] &= \left(\widetilde{\beta}'\widetilde{\beta}\right)^{-1} \widetilde{\beta} E(R_{i,t}) \end{aligned}$$

where $\widetilde{\boldsymbol{\beta}} = [\mathbf{1}_N, \boldsymbol{\beta}]$ to account for the intercept. If we multiply the first moment conditions with the identity matrix and the last moment condition with $(K+1) \times N$ vector $\widetilde{\boldsymbol{\beta}}'$, we will then have OLS time-series estimates of $\mathbf{a}$ and $\boldsymbol{\beta}$ and OLS cross sectional estimates of λ. To estimate the parameter vector $\mathbf{b}$, we set

$$\boldsymbol{a}_T g_T(\mathbf{b}) = 0$$

where

$$\underbrace{\boldsymbol{a}_T}_{\#Params \times \#Moments} = \begin{bmatrix} \underbrace{\mathbf{I}_{(K+1)N}}_{(K+1)N \times (K+1)N} & \underbrace{\mathbf{0}}_{(K+1)N \times N} \\ \underbrace{\mathbf{0}}_{(K+1) \times (K+1)N} & \underbrace{[\mathbf{1}_N, \boldsymbol{\beta}]'}_{(K+1) \times N} \end{bmatrix}$$

In order to use Hansen's formulas for standard errors, we compute the $\mathbf{d}$ matrix of derivatives

$$\underbrace{\mathbf{d}}_{(K+2)N\times[(K+1)N+K+1]} = \frac{\partial g_T}{\partial \mathbf{b}'}$$

$$= \begin{bmatrix} \underbrace{-\mathbf{I}_N}_{N\times N} & \underbrace{-\mathbf{I}_N\otimes\mathbb{E}(f_1) \quad \cdots \quad -\mathbf{I}_N\otimes\mathbb{E}(f_K)}_{N\times KN} & \underbrace{\mathbf{0}}_{N\times(K+1)} \\ \underbrace{\begin{matrix} -\mathbf{I}_N\otimes\mathbb{E}(f_1) \\ \vdots \\ -\mathbf{I}_N\otimes\mathbb{E}(f_K) \end{matrix}}_{KN\times N} & \underbrace{\begin{matrix} -\mathbf{I}_N\otimes\mathbb{E}(f_1^2) & \cdots & -\mathbf{I}_N\otimes\mathbb{E}(f_K f_1) \\ \vdots & \ddots & \vdots \\ -\mathbf{I}_N\otimes\mathbb{E}(f_1 f_K) & \cdots & -\mathbf{I}_N\otimes\mathbb{E}(f_K^2) \end{matrix}}_{KN\times KN} & \underbrace{\mathbf{0}}_{KN\times(K+1)} \\ \underbrace{\mathbf{0}}_{N\times N} & \underbrace{-\mathbf{I}_N\otimes\lambda_1' \quad \cdots \quad -\mathbf{I}_N\otimes\lambda_K'}_{N\times KN} & -\underbrace{[\mathbf{1}_N,\boldsymbol{\beta}]}_{N\times(K+1)} \end{bmatrix}$$

We also need $\mathbf{S}$ matrix, the spectral density matrix at frequency zero of the moment conditions

$$\mathbf{S} = \sum_{j=-\infty}^{\infty} E\left(\begin{bmatrix} \mathbf{R}^e_{t+H,t} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t \\ \left(\mathbf{R}^e_{t+H,t} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t\right)\otimes\mathbf{f}_t \\ \mathbf{R}^e_t - \ \lambda_0 - \boldsymbol{\beta\lambda} \end{bmatrix} \begin{bmatrix} \mathbf{R}^e_{t+H-j,t-j} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_{t-j} \\ \left(\mathbf{R}^e_{t+H-j,t-j} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_{t-j}\right)\otimes\mathbf{f}_{t-j} \\ \mathbf{R}^e_{t-j} - \ \lambda_0 - \boldsymbol{\beta\lambda} \end{bmatrix} \right).$$

Denote

$$h_t(\mathbf{b}) = \begin{bmatrix} \mathbf{R}^e_{t+H,t} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t \\ \left(\mathbf{R}^e_{t+H,t} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t\right)\otimes\mathbf{f}_t \\ \mathbf{R}^e_t - \ \lambda_0 - \boldsymbol{\beta\lambda} \end{bmatrix}.$$

We employ a Newey west correction to the standard errors with lag L by using the estimate

$$\mathbf{S}_T = \sum_{j=-L}^{L} \left(\frac{L-|j|}{L}\right) \frac{1}{T} \sum_{t=1}^{T} h_t\left(\widehat{\mathbf{b}}\right) h_{t-j}\left(\widehat{\mathbf{b}}\right)'$$

Asymptotic standard errors for the factor risk price estimates, λ, can beobtained using Hansen's formula for the sampling distribution of the parameter estimates

$$\underbrace{Var\left(\widehat{\mathbf{b}}\right)}_{[(K+1)N+K+1]\times[(K+1)N+K+1]} = \frac{1}{T}\left(\boldsymbol{a}_T\mathbf{d}\right)^{-1} \boldsymbol{a}_T\mathbf{S}_T\boldsymbol{a}_T'\left(\boldsymbol{a}_T\mathbf{d}\right)\prime^{-1}.$$

Bootstrap Procedure

This section describes the bootstrap procedure for assessing the small sample distribution of cross-sectional R^2 statistics. The bootstrap consists of the following steps.

1. For each test asset j, we estimate the time-series regressions on historical data for each H period exposure we study:

$$R^e_{j,t+H,t} = a_{j,H} + \beta_{j,KS,H}\left([KS_{t+H}]\,/\,[KS_t]\right) + u_{j,t+H,t} \tag{A6}$$

We obtain the full-sample estimates of the parameters of $a_{j,H}$ and $\beta_{j,KS,H}$, which we denote $\widehat{a}_{j,H}$ and $\widehat{\beta}_{j,KS,H}$.

2. We estimate an AR(1) model for capital share growth also on historical data:

$$\frac{KS_{t+H}}{KS_t} = a_{KG,H} + \rho_H\left(\frac{KS_{t+H-1}}{KS_{t-1}}\right) + e_{t+H,t}.$$

3. We estimate λ_0 and λ using historical data from cross-sectional regressions

$$E\left(R^e_{j,t}\right) = \lambda_0 + \lambda\widehat{\beta}_{j,KS,H} + \epsilon_j$$

where $R^e_{j,t}$ is the quarterly excess return. From this regression we obtain the cross sectional fitted errors $\{\widehat{\epsilon}_j\}_j$ and historical sample estimates $\widehat{\lambda}_0$ and $\widehat{\lambda}$.

4. For each test asset j, we draw randomly with replacement from blocks of the fitted residuals from the above time-series regressions:

$$\begin{bmatrix} \widehat{u}_{1,1+H,1} & \cdots & \widehat{u}_{N,1+H,1} & \widehat{e}_{1+H,1} \\ \widehat{u}_{1,2+H,2} & & \widehat{u}_{N,2+H,2} & \widehat{e}_{2+H,2} \\ \vdots & & \vdots & \vdots \\ \widehat{u}_{1,T,T-H} & \cdots & \widehat{u}_{N,T,T-H} & \widehat{e}_{T,T-H} \end{bmatrix} \tag{A7}$$

The mth bootstrap sample $\left\{ u^{(m)}_{1,t+H,t}, ..., \widehat{u}^{(m)}_{N,T,T-H}, e^{(m)}_{t+H,t}\right\}_{t=1}^{H}$ is obtained by sampling blocks of the raw data randomly with replacement and laying them end-to-end in the order sampled until a new sample of observations of length equal to the historical dataset is obtained. To choose the block length, we follow the recommendation of Hall, Horowitz, and Jing (1995) who show that the asymptotically optimal block length for estimating a symmetrical distribution function is $l \propto T^{1/5}$; also see Horowitz (2003).

Next we recursively generate new data series for $\frac{KS_{t+H}}{KS_t}$ by combining the initial value of $\frac{KS_{1+H}}{K_1}$ in our sample along with the estimates from historical data $\widehat{a}_{KG,H}$, $\widehat{\rho}_H$ and the new sequence of errors $\left\{e^{(m)}_{t+H,t}\right\}_t$ thereby generating an mth bootstrap sample on capital share growth $\left\{\left(\frac{KS_{t+H}}{KS_t}\right)^{(m)}\right\}_t$. We then generate new samples of observations on long-horizon returns $\left\{R^{(m)}_{j,t+H,t}\right\}_t$ from new data on $\left\{u^{(m)}_{j,t+H,t}\right\}_t$ and $\left\{\left(\frac{KS_{t+H}}{KS_t}\right)^{(m)}\right\}_t$ and the sample estimates $\widehat{a}_{j,H}$ and $\widehat{\beta}_{j,KS,H}$.

5. We generate mth observation $\beta^{(m)}_{j,KS,H}$ from regression of $\left\{R^{e(m)}_{j,t+H,t}\right\}_t$ on $\left\{\left(\frac{KS_{t+H}}{KS_t}\right)^{(m)}\right\}_t$ and a constant.

6. We obtain an mth bootstrap sample $\left\{\epsilon^{(m)}_j\right\}_j$ by sampling the fitted errors $\{\widehat{\epsilon}_j\}_j$ randomly with replacement and laying them end-to-end in the order sampled until a new sample of observations of length N equal to the historical cross-sectional sample is obtained. We then generate new samples of observations on quarterly average excess returns $\left\{E\left(R^{e(m)}_{j,t}\right)\right\}_j$ from new data on $\left\{\epsilon^{(m)}_j\right\}_j$ and $\left\{\beta^{(m)}_{j,KS,H}\right\}_j$ and the sample estimates $\widehat{\lambda}_0$ and $\widehat{\lambda}$.

7. We form the mth estimates $\lambda^{(m)}_0$ and $\lambda^{(m)}$ by regressing $\left\{E\left(R^{e(m)}_{j,t}\right)\right\}_j$ on the mth observation $\left\{\beta^{(m)}_{j,KS,H}\right\}_j$ and a constant. We store the mth sample cross-sectional $\overline{R}^2$, $\overline{R}^{(m)2}$ along with the mth values of $\lambda^{(m)}_0$ and $\lambda^{(m)}$.

8. We repeat steps 4-7 10,000 times, and report the 95% confidence intervals for $\left\{\overline{R}^{(m)2}, \lambda^{(m)}_0, \lambda^{(m)}\right\}_m$.

Procedure Controlling for Other Pricing Factors The bootstrap for cross-sectional regressions in which we control for other pricing factors is modified as follows.

1. Follow steps 1-5 separately for KS and the additional pricing factor(s) f and generate $\beta^{(m)}_{j,KS,H}$ and $\beta^{(m)}_{j,f,H}$ for the mth bootstrap.

2. Obtain an mth bootstrap sample $\left\{\epsilon^{(m)}_j\right\}_j$ from the cross-sectional regression

$$E\left(R^e_{j,t}\right) = \lambda_0 + \lambda_{KS}\widehat{\beta}_{j,KS,H} + \lambda_{HS}\beta_{j,f,H} + \epsilon_j.$$

As before, sample the fitted errors $\{\widehat{\epsilon}_j\}_j$ randomly with replacement, laying them end-to-end in the order sampled until a new sample of observations of length N equal to the historical cross-sectional sample is obtained. Generate new samples of observations on quarterly average excess returns $\left\{E\left(R^{e(m)}_{j,t}\right)\right\}_j$ from new data on $\left\{\epsilon^{(m)}_j\right\}_j$ and $\left\{\beta^{(m)}_{j,KS,H}, \beta^{(m)}_{j,f,H}\right\}_j$ and the sample estimates $\widehat{\lambda}_0$, $\widehat{\lambda}_{KS}$ and λ_{HS}

3. Form the mth estimates $\lambda^{(m)}_0$ and $\lambda^{(m)} = \left(\lambda^{(m)}_{KS}, \lambda^{(m)}_f\right)$ by regressing $\left\{E\left(R^{e(m)}_{j,t}\right)\right\}_j$

on the mth observation $\left\{\beta^{(m)}_{j,KS,H}, \beta^{(m)}_{j,f,H}\right\}_j$ and a constant. We store the mth sample cross-sectional $\overline{R}^2$, $\overline{R}^{(m)2}$.

4. We repeat steps 1-3 10,000 times, and report the 95% confidence interval of $\left\{\overline{R}^{(m)2}, \lambda^{(m)}_{KS}, \lambda^{(m)}_{f}\right\}_m$.

Appendix Tables and Figures

GMM, Linear SDF with $f'_H = \left(\frac{C_{t+H}}{C_t}, \frac{KS_{t+H}}{KS_t}\right)$

$\lambda_H = -\mathbb{E}\left(M_{t+H,t}\right)^{-1}\text{Cov}(f'_H, f_H)\, b$, $b = [b_1, b_2]'$, $b_1 = b_2$

Equity Portfolios

	Panel A: **Size/BM**		Panel B: **REV**		Panel C: **Size/INV**	
H	$\lambda_{C,H}$	$\lambda_{KS,H}$	$\lambda_{C,H}$	$\lambda_{KS,H}$	$\lambda_{C,H}$	$\lambda_{KS,H}$
4	0.17**	0.61**	0.15*	0.53	0.14*	0.49*
	(2.22)	(2.35)	(1.82)	(1.79)	(1.68)	(1.76)
8	0.15**	0.53**	0.12*	0.30	0.18*	0.44*
	(2.81)	(2.97)	(1.69)	(1.59)	(1.77)	(1.92)

	Panel D: **Size/OP**		Panel E: **All Equities**	
H	$\lambda_{C,H}$	$\lambda_{KS,H}$	$\lambda_{C,H}$	$\lambda_{KS,H}$
4	0.16*	0.57*	0.15*	0.55**
	(1.72)	(1.84)	(1.93)	(2.02)
8	0.18	0.45	0.17**	0.43**
	(1.36)	(1.50)	(2.01)	(2.19)

Other Asset Classes

	Panel F: **Bonds**		Panel G: **Sovereign Bonds**		Panel H: **Options**	
H	$\lambda_{C,H}$	$\lambda_{KS,H}$	$\lambda_{C,H}$	$\lambda_{KS,H}$	$\lambda_{C,H}$	$\lambda_{KS,H}$
4	0.13*	0.56*	0.04	0.92	0.11	1.01**
	(1.95)	(1.74)	(0.34)	(1.18)	(1.03)	(2.25)
8	0.11*	0.31	0.07	0.52	1.17	0.71*
	(1.72)	(1.52)	(0.81)	(1.07)	(1.31)	(1.81)

	Panel I: **CDS**	
H	$\lambda_{C,H}$	$\lambda_{KS,H}$
4	0.19	0.78
	(1.46)	(1.24)
8	0.34*	0.59*
	(1.74)	(1.75)

Table A1: GMM estimation of linear capital share SDF. The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. The estimated b is from GMM estimation imposing $b_1 = b_2$. Serial correlation and heteroskedasticity robust t-stats are reported in parenthesis. $**$ and $*$ indicate significance at 5 and 10 percent or better level, respectively. The sample spans the period 1963Q3 to 2013Q4.

GMM, Linear SDF with $f'_H = \left(\frac{C_{t+H}}{C_t}, \frac{KS_{t+H}}{KS_t}\right)$

SDF: $M_{t+H,t} = b_0 - b_1\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+H}}{KS_t} - 1\right)$, $b_1 = b_2 = b$

Equity Portfolios

	Panel A: **Size/BM**			Panel B: **REV**			Panel C: **Size/INV**		
H	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	7.38**	0.56	0.20	6.57**	0.64	0.14	6.16**	0.41	0.21
	(2.69)			(2.09)			(1.97)		
8	3.21**	0.83	0.12	2.24*	0.83	0.09	3.14**	0.69	0.15
	(3.84)			(1.83)			(2.42)		

	Panel D: **Size/OP**			Panel E: **All Equities**		
H	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	6.95**	0.59	0.17	6.74**	0.53	0.19
	(2.09)			(2.29)		
8	3.17*	0.62	0.17	3.04**	0.73	0.15
	(1.91)			(2.74)		

Other Asset Classes

	Panel F: **Bonds**			Panel G: **Sovereign Bonds**			Panel H: **Options**		
H	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	7.82**	0.76	0.23	13.37*	0.85	0.18	15.90**	0.97	0.14
	(2.06)			(1.80)			(3.84)		
8	2.52	0.69	0.26	4.11	0.84	0.17	5.99**	0.96	0.15
	(1.64)			(1.43)			(2.99)		

	Panel I: **CDS**		
H	b	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	12.22*	0.33	0.75
	(1.74)		
8	5.32**	0.52	0.63
	(2.14)		

Table A2: GMM estimation of linear capital share SDF. Serial correlation and heteroskedasticity robust t-stats are reported in parenthesis. The cross sectional R^2 is defined as $R^2 = 1 - \frac{Var_c\left(\mathbb{E}(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(\mathbb{E}\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{\mathbb{E}\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(\mathbb{E}\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^N\left(\mathbb{E}\left(R_i^e\right)\right)^2}$. $**$ and $*$ indicate significance at 5 and 10 percent or better level, respectively. The sample spans the period 1963Q3 to 2013Q4.

GMM, Linear SDF with $f'_H = \left(\frac{KS_{t+H}}{KS_t}\right)$

SDF: $M_{t+H,t} = b_0 - b_1\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+H}}{KS_t} - 1\right)$, $b_1 = 0$

Equity Portfolios

	Panel A: **Size/BM**			Panel B: **REV**			Panel C: **Size/INV**		
H	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	10.10**	0.51	0.21	8.48*	0.74	0.12	8.15	0.40	0.21
	(1.99)			(1.82)			(1.62)		
8	4.90**	0.81	0.13	2.65	0.88	0.08	3.94*	0.62	0.17
	(2.96)			(1.59)			(1.86)		
	Panel D: **Size/OP**			Panel E: **All Equities**					
H	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$			
4	9.47*	0.77	0.13	9.15*	0.56	0.19			
	(1.89)			(1.89)					
8	4.17	0.77	0.13	4.12**	0.73	0.15			
	(1.53)			(2.05)					

Other Asset Classes

	Panel F: **Bonds**			Panel G: **Sovereign Bonds**			Panel H: **Options**		
H	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	12.32*	0.88	0.17	19.41	0.86	0.17	29.16**	0.95	0.18
	(1.81)			(1.46)			(2.74)		
8	4.03*	0.86	0.17	5.59*	0.58	0.27	12.04**	0.81	0.35
	(1.86)			(1.78)			(2.11)		
	Panel I: **CDS**								
H	b_2	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$						
4	18.62*	0.82	0.38						
	(1.92)								
8	7.15**	0.94	0.23						
	(2.53)								

Table A3: GMM estimation of linear capital share SDF. Serial correlation and heteroskedasticity robust t-stats are reported in parenthesis. The cross sectional R^2 is defined as $R^2 = 1 - \frac{Var_c\left(\mathbb{E}(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(\mathbb{E}\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{\mathbb{E}\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N \left(\mathbb{E}\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^N \left(\mathbb{E}\left(R_i^e\right)\right)^2}$. $**$ and $*$ indicate significance at 5 and 10 percent or better level, respectively. The sample spans the period 1963Q3 to 2013Q4.

GMM, Linear SDF with $f'_H = \left(\frac{C_{t+H}}{C_t}\right)$

SDF: $M_{t+H,t} = b_0 - b_1\left(\frac{C_{t+H}}{C_t} - 1\right) - b_2\left(\frac{KS_{t+H}}{KS_t} - 1\right)$, $b_2 = 0$

Equity Portfolios

	Panel A: **Size/BM**			Panel B: **REV**			Panel C: **Size/INV**		
H	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	15.11**	0.30	0.25	−4.70	0.00	0.23	10.46*	0.13	0.25
	(2.66)			(−0.35)			(1.92)		
8	4.53**	0.33	0.25	2.19	0.01	0.22	2.93	0.11	0.26
	(2.21)			(0.88)			(1.47)		

	Panel D: **Size/OP**			Panel E: **All Equities**		
H	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	−8.87	0.06	0.26	7.95	0.07	0.27
	(−0.66)			(1.64)		
8	−1.41	0.02	0.28	2.69*	0.10	0.27
	(−0.49)			(1.69)		

Other Asset Classes

	Panel F: **Bonds**			Panel G: **Sovereign Bonds**			Panel H: **Options**		
H		R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	10.52	0.17	0.43	7.04	0.05	0.44	34.40**	0.99	0.09
	(1.25)			(0.69)			(2.48)		
8	2.09	0.07	0.45	2.69	0.20	0.37	10.73*	0.99	0.08
	(0.92)			(0.78)			(1.91)		

	Panel I: **CDS**		
H	b_1	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	−47.05	0.45	0.68
	(−0.89)		
8	−10.38	0.28	0.76
	(−1.48)		

Table A4: GMM estimation of linear capital share SDF. Serial correlation and heteroskedasticity robust t-stats are reported in parenthesis. The cross sectional R^2 is defined as $R^2 = 1 - \frac{Var_c\left(\mathbb{E}(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(\mathbb{E}(R_i^e)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{\mathbb{E}\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\mathbb{E}\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\mathbb{E}\left(R_i^e\right)\right)^2}$. $**$ and $*$ indicate significance at 5 and 10 percent or better level, respectively. The sample spans the period 1963Q3 to 2013Q4.

GMM, Capital Share SDF

$\boldsymbol{\lambda}_H = -\mathbb{E}\left(M_{t+H,t}\right)^{-1} \mathbf{Cov}\left(\mathbf{f}_H, \mathbf{f}'_H\right) \mathbf{b}$, $\mathbf{b} = [b_1, b_2]'$, $b_1 = 0$			
Equity Portfolios			
	Panel A: **Size/BM**	Panel B: **REV**	Panel C: **Size/INV**
H	$\lambda_{KS,H}$	$\lambda_{KS,H}$	$\lambda_{KS,H}$
4	0.74**	0.62*	0.59
	(2.00)	(1.77)	(1.61)
8	0.69**	0.37	0.55*
	(2.82)	(1.52)	(1.82)
	Panel D: **Size/OP**	Panel E: **All Equities**	
H	$\lambda_{KS,H}$	$\lambda_{KS,H}$	
4	0.69*	0.67*	
	(1.90)	(1.90)	
8	0.58	0.57**	
	(1.51)	(2.00)	
Other Asset Classes			
	Panel F: **Bonds**	Panel G: **Sovereign Bonds**	Panel H: **Options**
H	$\lambda_{KS,H}$	$\lambda_{KS,H}$	$\lambda_{KS,H}$
4	0.81*	1.50	1.87**
	(1.87)	(1.36)	(2.41)
8	0.54*	0.99*	1.72*
	(1.95)	(1.95)	(1.66)
	Panel I: **CDS**		
H	$\lambda_{KS,H}$		
4	1.24*		
	(1.81)		
8	0.83**		
	(2.93)		

Table A5: GMM estimation of linear capital share SDF. The table reports estimates of risk prices λ_H. All estimates are multiplied by 100. The estimated b is from GMM estimation imposing $b_1 = 0$. Serial correlation and heteroskedasticity robust t-stats are reported in parenthesis. $**$ and $*$ indicate significance at 5 and 10 percent or better level, respectively. The sample spans the period 1963Q3 to 2013Q4.

GMM, Nonlinear SDF with $f'_H = \left(\frac{C_{t+H}}{C_t}, \frac{KS_{t+H}}{KS_t}\right)$

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

Equity Portfolios

	Panel A: **Size/BM**				Panel B: **REV**				Panel C: **Size/INV**			
H	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$
4	−0.07	10.41**	0.56	0.20	0.42	8.14	0.57	0.15	0.42	8.13	0.40	0.21
	(−0.07)	(2.19)			(0.36)	(1.54)			(0.39)	(1.54)		
8	0.66	4.46**	0.84	0.12	1.14	2.93	0.84	0.09	0.67	4.54**	0.71	0.15
	(0.64)	(3.27)			(1.30)	(1.59)			(0.70)	(2.18)		

	Panel D: **Size/OP**				Panel E: **All Equities**			
H	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$
4	−0.13	10.16*	0.63	0.16	0.14	9.28*	0.53	0.19
	(−0.12)	(1.73)			(0.14)	(1.85)		
8	0.63	4.48	0.62	0.17	0.75	4.23**	0.74	0.15
	(0.63)	(1.49)			(0.82)	(2.46)		

Other Asset Classes

	Panel F: **Bonds**				Panel G: **Sovereign Bonds**				Panel H: **Options**			
H	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$
4	0.38	9.31*	0.76	0.23	0.20	16.41	0.88	0.16	−1.56	23.70**	0.96	0.17
	(1.63)	(1.75)			(0.27)	(1.49)			(−1.46)	(2.30)		
8	0.25	3.10	0.68	0.26	0.41	5.45	0.83	0.17	−0.29	9.02**	0.96	0.16
	(1.20)	(1.48)			(0.75)	(1.18)			(−0.23)	(2.15)		

	Panel I: **CDS**			
H	λ_0	γ	R^2	$\frac{RMSE}{RMSR}$
4	−0.18**	14.34	0.30	0.76
	(−2.48)	(1.27)		
8	−0.30**	7.44	0.49	0.64
	(−3.70)	(1.59)		

Table A6: Nonlinear GMM estimation of capital share SDF. Notes: Serial correlation and heteroskedasticity robust t-stats are reported in parenthesis. The cross sectional R^2 is defined as $R^2 = 1 - \frac{Var_c\left(\mathbb{E}(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(\mathbb{E}(R_i^e)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{\mathbb{E}\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N \left(\mathbb{E}\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^N \left(\mathbb{E}\left(R_i^e\right)\right)^2}$. ** and * indicate significance at 5 and 10 percent or better level, respectively. λ_0 is reported in unit of 100. The sample spans the period 1963Q3 to 2013Q4.