Capital Share Risk in U.S. Asset Pricing*

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First draft: June 5, 2014
This draft: July 31, 2017

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 capital owners, who finance consumption primarily out of asset ownership, and workers, who finance consumption primarily out of wages and salaries.

JEL: G11, G12, E25. Keywords: value premium, capital share, labor share, inequality

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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 that are 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 assumes 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 view, 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 aggregate data.

Unfortunately, there are reasons to question a model in which average household consumption is an appropriate source of systematic risk for the pricing of risky financial securities. Wealth is highly concentrated at the top and limited stock 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 *wealth-weighted* stock market participation 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 from 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 stylized 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 wealthy asset owners, not the average household, are the marginal investors in risky assets and their consumption is directly linked to the capital share. 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 exactly 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 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.

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

[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.

With this theoretical motivation as backdrop, this paper explores whether capital share growth is a priced risk factor for explaining cross-sections of expected returns. We find that exposure to short-to-medium frequency (e.g., 4-8 quarters) fluctuations in capital share growth helps explain the cross-section of expected returns on a wide range of equity characteristics portfolios as well as other asset classes. For the equity portfolio strategies 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. In addition, pooled estimations of the many different stock portfolios jointly and one that combines the stock portfolios with the portfolios of other asset classes also find that capital share risk has substantial explanatory power for expected returns. In principle, these findings could be perfectly 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 little 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 additional result 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 the intermediary-based empirical models of Adrian, Etula, and Muir (2014) (AEM) and He, Kelly, and Manela (2016) (HKM), both of which have found recent success in explaining cross-sections of expected returns. 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 most of aggregate consumption. It is reasonable to expect that sophisticated and expert investors often coincide with wealthy asset owners and should face similar if not identical sources of systematic risk. Indeed, we find that capital share growth exposure contains some information for the pricing of risk 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, so that the estimated risk prices for intermediary factors are either significantly attenuated or driven out of the pricing regressions entirely by the estimated exposures to capital share risk.

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., top 10% of the stock wealth distribution) is sufficiently strongly negatively correlated with that of non-rich stockowners (e.g., bottom 90%), that growth in the *product* of these shares with aggregate consumption is also strongly negatively correlated. This implies that the inversely related component operating through income shares outweighs the common component operating through aggregate consumption, suggesting that risk-sharing between the two groups is imperfect. 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, hence not priced. 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 and ask whether the growth in this variable is priced. We find that estimated exposures to this variable for top stockowners 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)). As we argue here, evidence that wealth is highly concentrated and that those at the top earn much larger fractions of income from owning assets than those at the bottom implies that the relevant limited participation dimension is not shareholders versus non-shareholders, but rather rich versus non-rich asset owners. From this perspective, growth in the capital share of aggregate income is likely to be a more important source of systematic risk than the average consumption over all households who own any amount, however small, of equity. Our work also ties into a growing body of theoretical and empirical work 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 growing body of evidence that the returns to human capital are negatively correlated with those to stock market wealth and/or that good times in the stock market may be relatively poor times for workers (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 (2014)).

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]

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

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 1 plots the rolling eight-quarter log difference in the capital share over time. This variable is volatile throughout our sample.

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

to us.

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] We define a stockholder in the SZ data as any individual who reports having non-zero income

[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 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.

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 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

[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.

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 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

[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.

common and idiosyncratic components. Figure 2 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 $i = top$ 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

Our main analysis is based on Generalized Method of Moments (GMM Hansen (1982)) estimation of SDF models with familiar Euler equations taking the form

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

or equivalently

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

where M_{t+1} is a candidate SDF and R_{t+1}^e is a gross excess return on an asset held by the investor with marginal rate of substitution M.

[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 $\widehat{\frac{Y_t^i}{Y_t}}$.

Throughout the paper, we denote the gross one-period return on asset j from the end of $t-1$ to the end of t as $R_{j,t}$, and denote the gross risk-free rate $R_{f,t}$. We use the three month Treasury bill (T-bill) rate to proxy for a risk-free rate, although in the estimations below we allow for an additional zero-beta rate parameter in case the true risk-free rate is not well proxied by the T-bill. The gross excess return is denoted $R^e_{j,t} \equiv R_{j,t} - R_{f,t}$.

The empirical investigation is guided by recent inequality-based asset pricing models discussed above with imperfect risk-sharing between workers and shareholders. In GLL for example, the representative shareholder who owns the entire corporate sector will have consumption exactly equal to $C_t \cdot KS_t$, and this investor has marginal utility that varies with the growth in this variable. Our baseline investigations focus on the capital share component of this product and ask whether growth in KS_t is a priced risk factor over various horizons H. That is we consider an approximate linearized SDF with the growth rates of the capital share as the single systematic risk factor:

$$M_{t+H,t} \approx b_0 + b_2 \left(\frac{KS_{t+H}}{KS_t} \right). \tag{3}$$

In principle, $M_{t+H,t}$ depends on the growth rate of aggregate consumption as well as the capital share, and the linearized SDF could be approximated with both $\frac{KS_{t+H}}{KS_t}$ and $\frac{C_{t+H}}{C_t}$ included as separate priced risk factors. In practice however, as we report in the Appendix (Table A1), with just one exception (options), capital share risk exposure explains a much larger fraction of the test portfolios we study and long-horizon consumption exposures are unimportant for explaining the cross-sections of expected returns we investigate once exposure to capital share risk are accounted for. This is partly because aggregate consumption growth is far less volatile than capital share growth and therefore, as shown above, the growth rate of $C_t \cdot KS_t$ is dominated by variation in capital share growth. Of course, if risk-sharing were perfect, capital share growth should not be priced at all and *only* growth in aggregate consumption should be priced once the betas for both variables are included. But this is not what we find as reported in the online Appendix. The results are therefore strongly supportive of a model with limited participation and imperfect risk-sharing between workers and shareholders. Our main empirical specification therefore focuses on the single factor capital share SDF given in (3).

Although (2) relates one-period average return premia $E\left(R^e_{j,t+1}\right)$ to the covariance between the one-period-ahead SDF M_{t+1} and one-period returns $R^e_{j,t+1}$, there are good econometric reasons to consider multi-period risk exposures even for explaining one-period average return premia. As emphasized by Bandi, Perron, Tamoni, and Tebaldi (2014) and Bandi and Tamoni (2014), important lower frequency risk relations can be masked in short-horizon data by higher frequency "noise" that may matter less for unconditional risk premia. For example, a long-run risk model that has both transitory and persistent shocks to consumption growth or volatility typically implies that the less volatile but more persistent shocks matter far more for risk premia than do the more volatile but transitory shocks. Yet if one considers only short-horizon exposures, the more volatile transitory shocks may mask risks created by the persistent shocks. In another example, short-run shocks to risk-tolerance or consumption growth may create high-frequency fluctuations in returns that can mask the importance of lower frequency risk exposures to capital share variation. (This occurs in the model of GLL.) Thus in order to identify possibly important lower frequency components in capital share risk exposure, we follow Bandi and Tamoni (2014) and measure covariances between *longer* horizon (multi-quarter) returns $R_{t+H,t}$ and $\frac{KS_{t+H}}{KS_t}$.[9] As they emphasize, these lower frequency risk exposures could still have large effects on *un*conditional return premia measured over shorter horizons. We therefore investigate whether the multi-quarter (e.g., $H = 4$ or 8 quar-

[9]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

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

ters) horizon exposures explain cross-sections of *short*-horizon (i.e., quarterly) unconditional return premia $E\left(R^e_{j,t+1}\right)$.

Let N denote the number of portfolio returns in the cross-sectional investigation. Exposures to capital share risk are estimated via time-series regressions, one for each asset $j = 1, 2....N$

$$R^e_{j,t+H,t} = a_{j,H} + \beta_{j,KS,H}\left(KS_{t+H}/KS_t\right) + u_{j,t+H,t}, \quad t = 1, 2...T, \tag{4}$$

where $\beta_{j,KS,H}$ measures asset j's exposure to capital share risk over H horizons. We then estimate the extent to which these exposures explain cross-sectional variation in quarterly return premia by running the cross-sectional regressions:

$$E_T\left(R^e_{j,t}\right) = \lambda_0 + \widehat{\beta}_{j,KS,H}\lambda_{KS} + \epsilon_j, \qquad j = 1, 2....N, \tag{5}$$

where 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), t represents a quarterly time period, and λ_{KS} is the capital share risk price parameter to be estimated. "Hats" in (5) denote estimated parameters from the time-series regression. This risk price should be positive when estimated against any asset market returns where wealthy capital owners, whose consumption varies positively with the capital share, are marginal investors. Equations (4) and (5) are estimated jointly in one GMM system and all standard errors are computed using a block bootstrap procedure described below. The Appendix provides estimation details.

We 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,

$$E\left(R^e_{j,t}\right) = \lambda_0 + \widehat{\beta}_{j,KS,H}\lambda_{KS} + \widehat{\beta}_{j,MKT}\lambda_{MKT} + \widehat{\beta}_{j,SMB}\lambda_{SMB} + \widehat{\beta}_{j,HML}\lambda_{HML} + \epsilon_{j,t} \tag{6}$$

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.

In the final empirical analysis of the paper, we explicitly connect the capital share to fluctuations in the income shares of rich and non-rich stockowners using the SZ household-level data and ask whether a proxy for the consumption of wealthy stockholders is priced. 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.[10] Bootstrapped confidence intervals for the $\overline{R}^2$ are reported. Also reported are the root-mean-squared pricing errors (RMSE) as a fraction of the root-mean-squared return (RMSR) on the portfolios being priced, i.e.,

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

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

[10] This measure is defined as

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

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.

4 Results

This section presents empirical results. The next subsection presents our main results on whether capital share risk is priced 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 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 detailed description of the bootstrap procedure.

4.1 Baseline Capital Share Specifications

Panels A-E of Table 3 report results from estimating the cross-sectional regressions (5) 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 $\widehat{\lambda}_{KS}$ 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.

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. The 95% bootstrap confidence intervals for the cross-sectional (adjusted) $\overline{R}^2$statistics generally show tight ranges around high values. For $H = 8$, the 95% confidence intervals are $[75\%, 94\%]$, $[81\%, 98\%]$, $[55\%, 88\%]$, and $[70\%, 92\%]$ for size/BM, REV, size/INV and size/OP, respectively. Moreover, across the different portfolio group estimations, the risk price estimates are similar, as are the relatively small intercepts (the intercept values reported in the table are multiplied by 100). This is reflected in the finding that the pooled estimation on the many different equity portfolios combined retains substantial explanatory power with an $\overline{R}^2$ equal to 0.74% and tight confidence intervals around this number. Moreover, the risk price estimate from the pooled "all equity" group 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.

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 $H = 4$, and tight confidence intervals around this number. 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 3 and Figure 4 give a visual impression of these results. Figure 3 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 3 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 bondsare 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.

4.2 Controlling for Other Pricing Factors

In this section we consider whether the explanatory power of capital share risk merely proxying for exposure to other risk factors. To address this question we include estimated betas from several alternative factor models. 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 shows 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.

4.3 Pricing Factors Based On Household-Level Data

In the final empirical analysis of the paper, we explicitly connect capital share variation to fluctuations in the micro-level income shares of rich and non-rich stockowners using the SZ household-level data. The SZ household-level income and wealth data are used because they are high quality and detailed and, as discussed above, reliable household-level consumption data are unavailable for the wealthy. We therefore construct a proxy for the consumption growth of rich stockowners using the SZ data.

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 7.

Table 7 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. Positive exposure to capital share risk earns a significant, positive risk premium with estimated risk prices of similar magnitude across portfolio groups. 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 are an important source of systematic risk.

A striking aspect of these findings it that a single *macro*economic factor 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 that are 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. 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.

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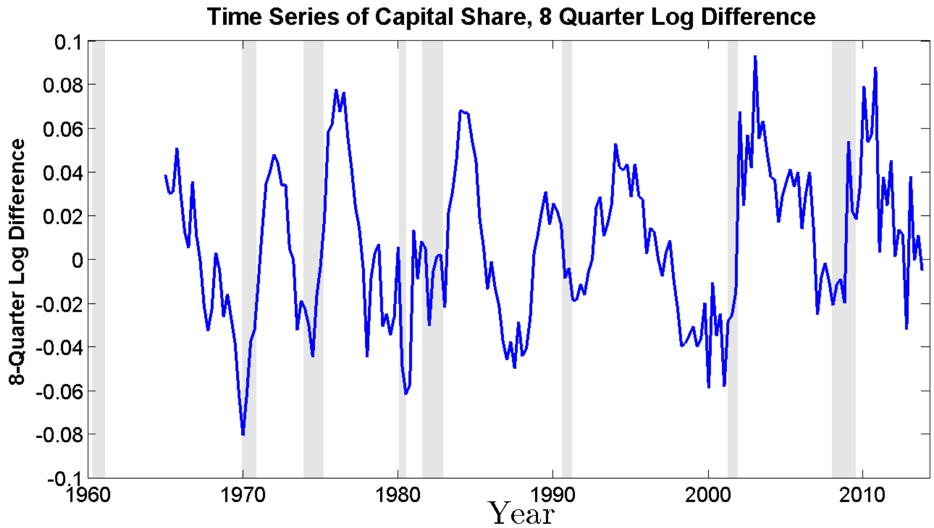

Figure 1: Capital share, 8 quarter log difference. The vertical lines correspond to the NBER recession dates. The sample spans the period 1963Q3 to 2013Q4.

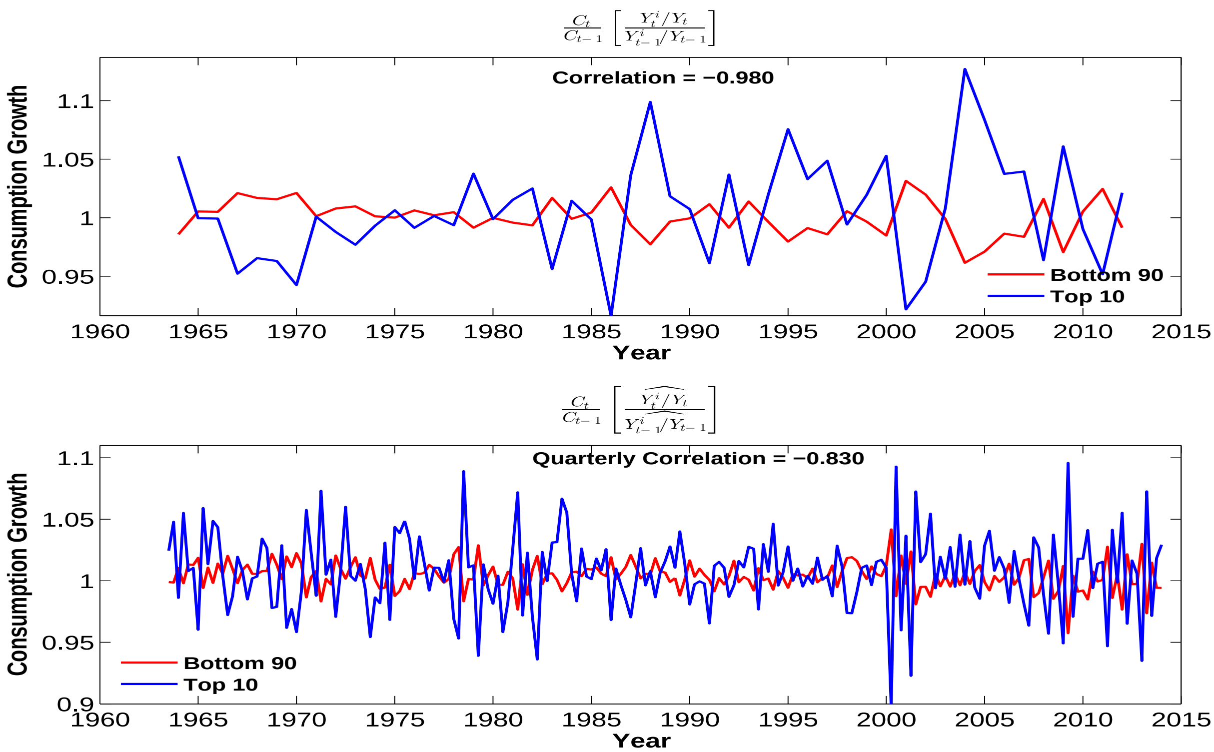

Figure 2: Growth in aggregate consumption times income share. The top panel reports annual observations on the annual value of $\frac{C_t}{C_{t-1}}\left[\frac{Y_t^i/Y_t}{Y_{t-1}^i/Y_{t-1}}\right]$ corresponding to the years for which SZ data are available. Y_t^i/Y_t is the shareholder's income share 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.

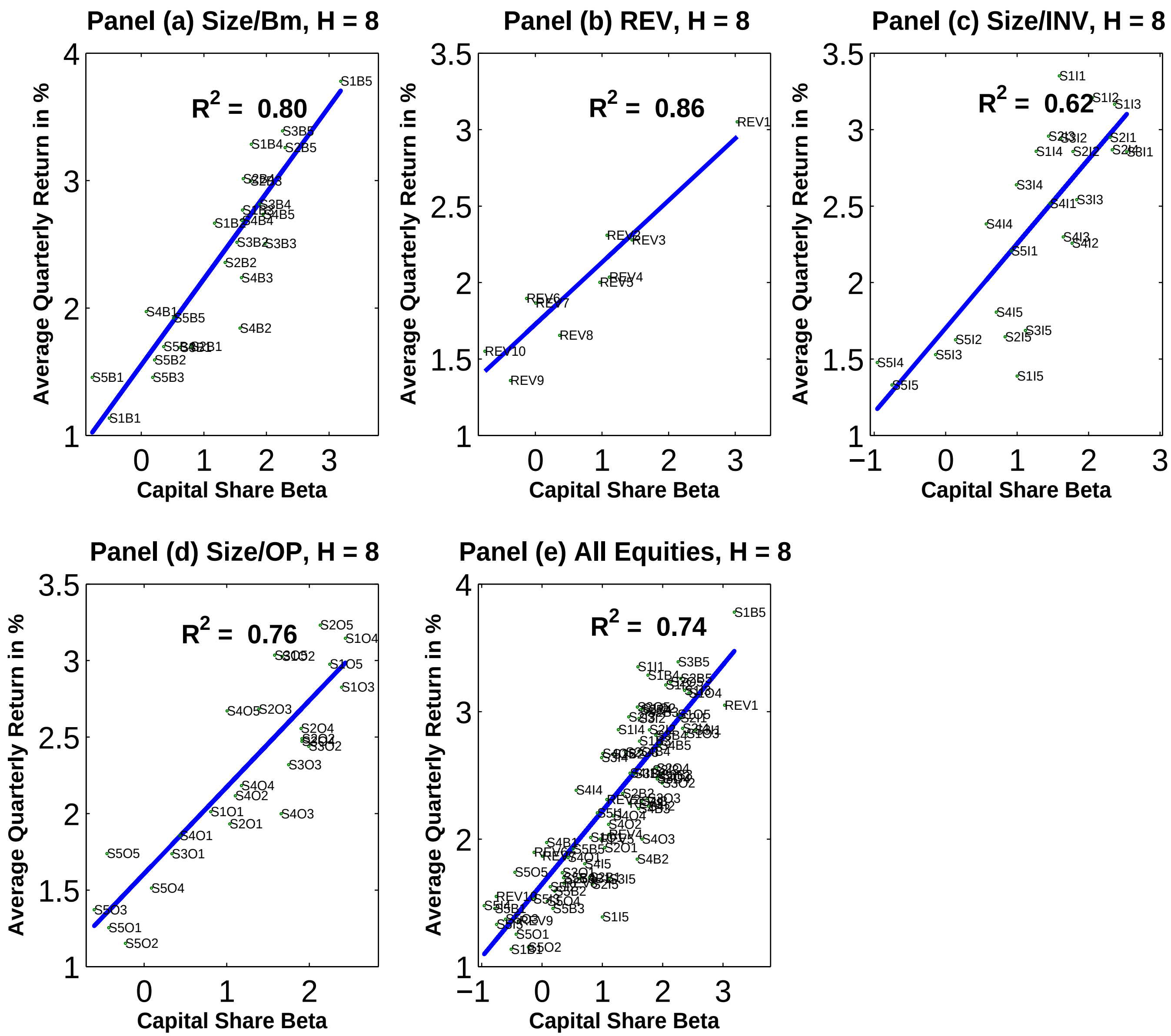

Figure 3: Capital share betas. Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using all equities (size/bm, REV, size/INV and size/OP). H indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q3 to 2013Q4.

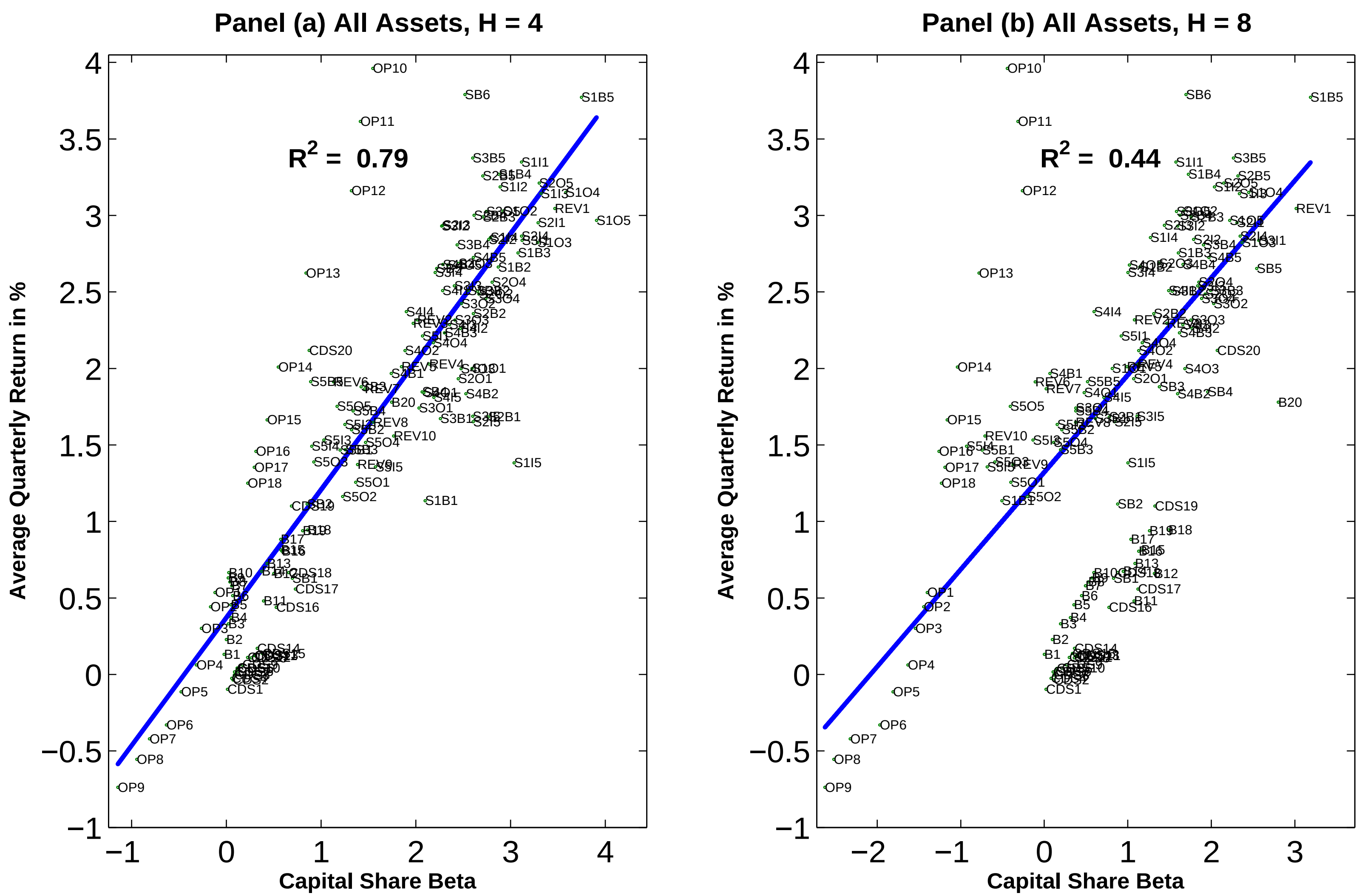

Figure 4: Capital share betas. Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using all assets (size/bm, REV, size/INV, size/OP equities plus bonds, sovereign bonds, CDS and Options). H indicates the horizon in quarters over which capital share exposure is measured. 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^{**}	-1.13^{**}	0.61	$< 90\%$	1.24^{**}	-1.27^{**}	0.49
	(23.60)	(-8.65)			(17.36)	(-6.82)	
$95-100\%$	-0.24^{**}	1.08^{**}	0.61	$95-100\%$	-0.28^{**}	1.20^{**}	0.53
	(-5.10)	(8.65)			(-4.47)	(7.34)	
$99-100\%$	-0.24^{**}	0.82^{**}	0.62	$99-100\%$	-0.27^{**}	0.93^{**}	0.59
	(-6.71)	(8.88)			(-6.16)	(8.25)	
$99.9-100\%$	-0.16^{**}	0.48^{**}	0.65	$99.9-100\%$	-0.17^{**}	0.54^{**}	0.63
	(-7.91)	(9.41)			(-7.61)	(9.13)	
$90-100\%$	-0.18^{**}	1.13^{**}	0.61	$90-100\%$	-0.24^{**}	1.27^{**}	0.49
	(-3.54)	(8.64)			(-3.32)	(6.82)	

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

$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$, Estimates of Factor Risk Prices λ

Equity Portfolios

	Panel A: **Size/BM**				Panel B: **REV**			
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	0.65	0.74	0.51	0.19	0.83	0.63	0.70	0.11
	$[0.19, 1.07]$	$[0.53, 0.96]$	$[0.40, 0.84]$		$[0.50, 1.15]$	$[0.46, 0.79]$	$[0.63, 0.96]$	
8	1.55	0.68	0.80	0.12	1.73	0.41	0.86	0.08
	$[1.42, 1.69]$	$[0.57, 0.78]$	$[0.75, 0.94]$		$[1.63, 1.83]$	$[0.33, 0.49]$	$[0.81, 0.98]$	
	Panel C: **Size/INV**				Panel D: **Size/OP**			
H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	Constant	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.92	0.61	0.39	0.19	0.60	0.70	0.78	0.12
	$[0.43, 1.35]$	$[0.40, 0.81]$	$[0.28, 0.82]$		$[0.31, 0.88]$	$[0.58, 0.82]$	$[0.74, 0.92]$	
8	1.70	0.55	0.62	0.16	1.61	0.57	0.76	0.12
	$[1.53, 1.87]$	$[0.42, 0.68]$	$[0.55, 0.88]$		$[1.48, 1.74]$	$[0.46, 0.67]$	$[0.70, 0.92]$	
	Panel E: **All Equities**				Panel F: **All Equities** $\frac{\text{RMSE}_i}{\text{RMSR}_i}$			
H	Constant	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$	Size/Bm	REV	Size/INV	Size/OP
4	0.74	0.68	0.58	0.17	0.19	0.12	0.19	0.20
	$[0.51, 0.96]$	$[0.58, 0.78]$	$[0.56, 0.79]$					
8	1.65	0.57	0.74	0.14	0.13	0.11	0.16	0.16
	$[1.57, 1.72]$	$[0.51, 0.64]$	$[0.73, 0.86]$					

Table 3 continued next page

Expected Return-Beta Regressions

$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$, Estimates of Factor Risk Prices λ

Other Asset Classes

Panel G: **Bonds**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.43	0.82	0.86	0.17
	[0.37, 0.49]	[0.73, 0.90]	[0.86, 0.98]	
8	0.23	0.57	0.89	0.15
	[0.17, 0.28]	[0.51, 0.63]	[0.88, 0.99]	

Panel H: **Sovereign Bonds**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	−0.32	1.41	0.79	0.18
	[−0.81, 0.10]	[1.17, 1.66]	[0.79, 0.99]	
8	0.16	1.18	0.32	0.33
	[−0.37, 0.94]	[0.65, 1.69]	[0.27, 0.99]	

Panel I: **Options**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.56	1.87	0.95	0.18
	[0.43, 0.72]	[1.74, 2.01]	[0.95, 0.99]	
8	3.68	1.80	0.81	0.34
	[3.15, 4.28]	[1.54, 2.06]	[0.81, 0.98]	

Panel J: **CDS**

H	Constant	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	−0.24	1.26	0.84	0.34
	[−0.33, −0.14]	[1.11, 1.42]	[0.84, 0.99]	
8	−0.16	0.77	0.94	0.20
	[−0.21, −0.11]	[0.70, 0.84]	[0.92, 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
	[0.17, 0.89]	[0.78, 1.29]	[0.70, 0.89]	
8	1.34	0.63	0.44	0.41
	[1.07, 1.39]	[0.63, 0.99]	[0.43, 0.88]	

Table 3: (cont.) **Expected return-beta regressions,equity portfolios.** Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. 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 $\text{RMSE}_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left(E_T\left(R^e_{ji}\right)\right)^2}$ where R^e_{ji} refers to the return of portfolio j in group i and RMSR_i=$\sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left(E_T\left(R^e_{ji}\right) - \widehat{R}^e_{ji}\right)}$ where $\widehat{R}^e_{ji} = \widehat{\lambda}_0 + \widehat{\beta}'_{ji}\widehat{\lambda}$. The sample spans the period 1963Q3 to 2013Q4.

Expected Return-Beta Regressions: Competing Models, Equities

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

Constant	$\frac{KS_{t+H}}{KS_t}$	$R^e_{m,t}$	SMB_t	HML_t	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
Panel A: **Size/BM**							
1.55	0.68				0.80	0.12	-283.41
[1.42, 1.69]	[0.57, 0.78]				[0.75, 0.94]		
3.63		-1.96	0.70	1.35	0.69	0.15	-268.12
[1.54, 5.75]		[-4.06, 0.07]	[0.40, 1.00]	[0.82, 1.86]	[0.54, 0.89]		
3.57	0.50	-2.04	0.22	0.24	0.84	0.10	-282.29
[2.11, 5.19]	[0.40, 0.67]	[-3.80, -0.79]	[-0.07, 0.43]	[-0.30, 0.63]	[0.81, 0.95]		
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
[1.57, 1.72]	[0.51, 0.64]				[0.73, 0.86]		
3.02		-1.28	0.67	1.37	0.68	0.15	-943.11
[1.99, 4.09]		[-2.32, -0.27]	[0.52, 0.83]	[0.98, 1.74]	[0.58, 0.80]		
2.89	0.39	-1.25	0.25	0.40	0.78	0.12	-970.29
[2.15, 3.91]	[0.32, 0.48]	[-2.40, -0.70]	[0.06, 0.38]	[-0.06, 0.70]	[0.74, 0.87]		

Table 4: Fama-MacBeth regressions of average returns on factor betas. Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. The sample spans the period 1963Q3 to 2013Q4.

Expected Return-Beta Regressions: Competing Models, Equities

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

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	0.68				0.80	0.12	−283.41
[1.42, 1.69]	[0.57, 0.78]				[0.75, 0.94]		
0.89			13.91		0.66	0.16	−270.41
[0.60, 1.16]			[11.72, 16.10]		[0.65, 0.94]		
1.24	0.50		4.96		0.82	0.11	−284.67
[0.79, 1.22]	[0.40, 0.62]		[3.31, 6.74]		[0.80, 0.95]		
0.48		1.19		6.88	0.49	0.20	−258.63
[−0.99, 1.85]		[−0.00, 2.40]		[4.00, 9.85]	[0.33, 0.85]		
3.19	0.62	−1.53		−2.72	0.81	0.13	−279.07
[2.19, 4.16]	[0.51, 0.74]	[−2.35, −0.68]		[−4.94, −0.47]	[0.78, 0.94]		

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	0.41				0.86	0.08	−124.54
[1.63, 1.83]	[0.33, 0.49]				[0.81, 0.98]		
1.44			6.53		0.01	0.21	−104.63
[1.10, 1.90]			[2.99, 10.11]		[0.01, 0.94]		
1.86	0.42		−1.73		0.85	0.07	−122.80
[1.50, 1.88]	[0.30, 0.45]		[−1.99, 0.47]		[0.80, 0.98]		
0.71		1.10		4.23	0.79	0.08	−120.86
[−0.02, 1.39]		[0.43, 1.86]		[3.23, 5.53]	[0.67, 0.98]		
0.86	0.20	0.92		2.32	0.76	0.10	−116.75
[−0.10, 1.80]	[0.07, 0.32]	[0.05, 1.86]		[0.01, 4.54]	[0.65, 0.98]		

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	0.55				0.62	0.16	−272.08
[1.53, 1.87]	[0.42, 0.68]				[0.55, 0.88]		
0.59			18.06		0.52	0.16	−272.03
[0.35, 0.85]			[15.98, 20.16]		[0.44, 0.97]		
0.97	0.32		10.33		0.70	0.13	−276.07
[0.43, 0.98]	[0.17, 0.40]		[9.48, 13.25]		[0.68, 0.96]		
1.35		0.46		7.51	0.60	0.16	−269.89
[0.27, 2.37]		[−0.44, 1.35]		[5.02, 10.05]	[0.43, 0.90]		
2.28	0.30	−0.58		2.37	0.73	0.14	−277.09
[1.29, 3.25]	[0.18, 0.41]	[−1.46, 0.26]		[−0.30, 4.96]	[0.60, 0.93]		

Table 5 continued next page

Expected Return-Beta Regressions: Competing Models, Equities

$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$, Estimates of Factor Risk Prices $\lambda, H = 8$							
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
[1.48, 1.74]	[0.46, 0.67]				[0.70, 0.92]		
0.62			16.83		0.58	0.16	−272.43
[0.31, 0.89]			[14.35, 19.32]		[0.57, 0.95]		
1.42	0.50		2.69		0.76	0.12	−283.83
[1.05, 1.51]	[0.43, 0.65]		[−0.28, 3.79]		[0.70, 0.92]		
1.45		0.36		4.60	0.11	0.23	−255.09
[−0.10, 2.96]		[−1.01, 1.69]		[0.97, 8.21]	[−0.05, 0.55]		
2.47	0.43	−0.85		−0.23	0.60	0.17	−270.80
[1.31, 3.63]	[0.30, 0.56]	[−1.87, 0.19]		[−3.16, 2.76]	[0.51, 0.87]		
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
[1.57, 1.72]	[0.51, 0.64]				[0.73, 0.86]		
0.80			15.03		0.59	0.17	−927.89
[0.64, 0.96]			[13.67, 16.37]		[0.59, 0.91]		
1.24	0.43		5.70		0.77	0.13	−975.12
[0.87, 1.24]	[0.36, 0.48]		[0.08, 7.19]		[0.77, 0.89]		
1.20		0.59		5.55	0.43	0.20	−904.68
[0.53, 1.86]		[0.01, 1.17]		[4.05, 7.01]	[0.32, 0.63]		
2.54	0.41	−0.85		−0.17	0.70	0.16	−949.95
[1.95, 3.14]	[0.34, 0.48]	[−1.36, −0.34]		[−1.66, 1.31]	[0.67, 0.83]		

Table 5: (cont.) **Fama-MacBeth regressions of average returns on factor betas.** Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. The sample spans the period 1963Q3 to 2013Q4.

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

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

Constant	$\frac{KS_{t+H}}{KS_t}$	$EqFac_t$	$R^e_{m,t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$	BIC
Panel A: **Bonds**						
0.23	0.57			0.89	0.15	−262.49
[0.17, 0.28]	[0.51, 0.63]			[0.88, 0.99]		
0.41		7.56	1.43	0.82	0.19	−249.97
[0.32, 0.50]		[6.66, 8.45]	[0.67, 2.17]	[0.80, 0.98]		
0.20	0.50	−1.80	1.31	0.84	0.16	−257.26
[0.11, 0.28]	[0.42, 0.58]	[−2.56, −1.02]	[0.59, 2.01]	[0.84, 0.98]		
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	1.18			0.32	0.33	−54.91
[−0.37, 0.94]	[0.65, 1.69]			[0.27, 0.99]		
0.34		7.05	1.24	0.68	0.20	−59.45
[−0.42, 1.24]		[4.23, 10.04]	[−1.87, 4.29]	[0.43, 0.99]		
−1.33	1.11	4.07	3.44	0.74	0.15	−62.84
[−2.40, −0.36]	[0.80, 1.41]	[−0.91, 9.24]	[1.04, 5.81]	[0.83, 0.99]		
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	1.80			0.81	0.34	−178.57
[3.15, 4.28]	[1.54, 2.06]			[0.81, 0.98]		
−1.11		22.42	2.81	0.99	0.09	−222.10
[−1.71, −0.49]		[20.93, 23.97]	[2.09, 2.54]	[0.98, 0.99]		
5.36	0.73	15.08	−4.40	0.98	0.10	−221.04
[4.44, 6.27]	[0.64, 0.81]	[13.79, 16.39]	[−5.45, −3.34]	[0.98, 0.99]		
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	0.77			0.94	0.20	−263.27
[−0.21, −0.11]	[0.70, 0.84]			[0.92, 0.99]		
−0.39		11.08	1.11	0.63	0.50	−224.44
[−0.62, −0.12]		[8.55, 13.65]	[−1.16, 3.58]	[0.57, 0.97]		
−0.06	0.93	−3.17	−0.60	0.94	0.20	−256.54
[−0.18, 0.06]	[0.85, 1.00]	[−4.30, −2.03]	[−1.55, 0.35]	[0.94, 0.99]		

Table 6: Expected return-beta regressions. Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. The sample spans the period 1970Q1 to 2012Q4.

Expected Return-Beta Regressions Using Top Income Shares

$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$, Estimates of Factor Risk Prices λ

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
	$[-0.14, 0.87]$	$[1.05, 1.88]$	$[0.42, 0.86]$	
8	1.11	1.24	0.85	0.11
	$[0.95, 1.27]$	$[1.07, 1.41]$	$[0.81, 0.95]$	

Panel B: **REV**

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	0.65	1.25	0.66	0.12
	$[0.21, 1.08]$	$[0.87, 1.63]$	$[0.55, 0.96]$	
8	1.46	0.82	0.84	0.08
	$[1.33, 1.59]$	$[0.64, 0.99]$	$[0.76, 0.97]$	

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
	$[0.12, 1.22]$	$[0.79, 1.64]$	$[0.28, 0.84]$	
8	1.22	1.15	0.69	0.14
	$[0.98, 1.43]$	$[0.90, 1.40]$	$[0.59, 0.92]$	

Panel D: **Size/OP**

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	0.34	1.41	0.71	0.13
	$[-0.05, 0.74]$	$[1.12, 1.69]$	$[0.65, .89]$	
8	1.13	1.18	0.74	0.13
	$[0.93, 1.34]$	$[0.96, 1.41]$	$[0.68, 0.91]$	

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
	$[0.37, 0.87]$	$[1.18, 1.57]$	$[0.56, 0.80]$	
8	1.43	1.16	0.78	0.12
	$[1.34, 1.52]$	$[1.04, 1.27]$	$[0.76, 0.88]$	

Table 7: Top Income Shares and the Cross Section. Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. The factor is $\frac{C_t}{C_{t-1}}\left[\frac{\widehat{Y^{>10\%}_t/Y_t}}{\widehat{Y^{>10\%}_{t-1}/Y_{t-1}}}\right]$ using the mimicking SZ data income share factor $\widehat{Y^{>10\%}_t}/Y_t = \widehat{\varsigma}^{>10\%}_0 + \widehat{\varsigma}^{>10\%}_1 KS_t$ 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, $m1,...,m3$:

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

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.[11] 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

[11] 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

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

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.

GMM Estimation Detail

Denote the factors together as

$$\mathbf{f}_t = \left[\left(C_{t+H}/C_t \right), \left(KS_{t+H}/KS_t \right) \right]'$$

and let K generically denote the number of factors (two here). Denote the $K \times 1$ vector $\boldsymbol{\beta}_i = \left[\widehat{\beta}_{i,C,H}, \widehat{\beta}_{i,LS,H} \right]'$. The moment conditions for the expected return-beta representations are

$$g_T(\boldsymbol{b}) = \begin{bmatrix} E_T\left(\underbrace{\mathbf{R}_{t+H,t}^{e}}_{N\times 1} - \underbrace{\mathbf{a}}_{N\times 1} - \underbrace{\boldsymbol{\beta}}_{(N\times K)} \underbrace{\mathbf{f}_t}_{(K\times 1)} \right) \\ E_T\left(\left(\mathbf{R}_{t+H,t}^{e} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t \right) \otimes \mathbf{f}_t \right) \\ E_T\left(\underbrace{\mathbf{R}_{t}^{e}}_{N\times 1} - \lambda_0 - \underbrace{\boldsymbol{\beta}}_{(N\times K)} \underbrace{\boldsymbol{\lambda}}_{(K\times 1)} \right) \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \tag{A1}$$

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

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

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

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

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

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

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

Denote

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

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

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

To get standard errors for the factor risk price estimates, λ, we use Hansen's formula for the sampling distribution of the parameter estimates

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

Controlling for Aggregate Consumption Risk

Appendix Table A1 reports estimations on all portfolio groups where we controll for betas for aggregate consumption growth and capital share growth simultaneously. If risk-sharing were perfect, alternatively, if the representative agent consumption model were valid, capital share growth should not be priced at all once the betas for both variables are included. But this is not what we find. As Table A1 shows, with just one exception (options), capital share risk exposure explains a much larger fraction of the test portfolios we study and long-horizon consumption exposures are unimportant for explain the cross-sections of expected returns we investigate once exposure to capital share risk are accounted for. For all portfolios besides options, a comparison of $\overline{R}^2$ statistics in Table A1 with the benchmark results of the main text shows that adding betas for consumption growth does little to increase the explanatory power for the cross-section. For most portfolios, the risk price for consumption growth exposures is not different from zero according to the confidence interval, and for five of the portfolio groups the point estimate is negative. The one exception is options, where consumption risk has strong explanatory power and the risk price for capital share growth flips sign.

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:

$$R^e_{j,t+H,t} = a_{j,H} + \beta_{j,KS,H} \left([KS_{t+H}] \, / \, [KS_t] \right) + u_{j,t+H,t} \tag{A2}$$

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:

$$\begin{bmatrix} \widehat{u}_{j,1+H,1} & \widehat{e}_{1+H,1} \\ \widehat{u}_{j,2+H,2} & \widehat{e}_{2+H,2} \\ \vdots & \vdots \\ \widehat{u}_{j,T,T-H} & \widehat{e}_{T,T-H} \end{bmatrix} \tag{A3}$$

The mth bootstrap sample $\left\{ u^{(m)}_{j,t+H,t}, e^{(m)}_{t+H,t} \right\}$ 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 $\left\{\overline{R}^{(m)2}, \lambda_0^{(m)}, \lambda^{(m)}\right\}_m$.

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 $\beta_{j,KS,H}^{(m)}$ and $\beta_{j,f,H}^{(m)}$ for the mth bootstrap.

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

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

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 $\left\{E\left(R_{j,t}^{e(m)}\right)\right\}_j$ from new data on $\left\{\epsilon_j^{(m)}\right\}_j$ and $\left\{\beta_{j,KS,H}^{(m)}, \beta_{j,f,H}^{(m)}\right\}_j$ and the sample estimates $\widehat{\lambda}_0$, $\widehat{\lambda}_{KS}$ and λ_{HS}

3. Form the mth estimates $\lambda_0^{(m)}$ and $\lambda^{(m)} = \left(\lambda_{KS}^{(m)}, \lambda_f^{(m)}\right)$ by regressing $\left\{E\left(R_{j,t}^{e(m)}\right)\right\}_j$ on the mth observation $\left\{\beta_{j,KS,H}^{(m)}, \beta_{j,f,H}^{(m)}\right\}_j$ 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 $\left\{\overline{R}^{(m)2}, \lambda_{KS}^{(m)}, \lambda_f^{(m)}\right\}_m$.

Appendix Tables and Figures

Expected Return-Beta Regressions

$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$, Estimates of Factor Risk Prices λ

Equity Portfolios

Panel A: **Size/BM**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.21 $[-0.50, 0.88]$	0.20 $[0.06, 0.35]$	0.59 $[0.38, 0.81]$	0.54 $[0.39, 0.87]$	0.18
8	1.09 $[0.73, 1.44]$	0.09 $[0.01, 0.16]$	0.56 $[0.46, 0.65]$	0.85 $[0.81, 0.95]$	0.10

Panel B: **REV**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	2.07 $[1.54, 2.59]$	-0.52 $[-0.62, -0.42]$	0.77 $[0.61, 0.88]$	0.81 $[0.80, 0.99]$	0.08
8	2.12 $[1.71, 2.50]$	-0.19 $[-0.29, -0.10]$	0.45 $[0.37, 0.53]$	0.86 $[0.84, 0.99]$	0.07

Panel C: **Size/INV**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.68 $[-0.14, 1.46]$	0.09 $[-0.05, 0.23]$	0.55 $[0.34, 0.77]$	0.38 $[0.25, 0.83]$	0.19
8	1.10 $[0.57, 1.59]$	0.11 $[0.01, 0.21]$	0.50 $[0.38, 0.62]$	0.68 $[0.56, 0.92]$	0.14

Panel D: **Size/OP**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.97 $[0.49, 1.46]$	-0.12 $[-0.20, -0.04]$	0.70 $[0.58, 0.82]$	0.80 $[0.77, 0.93]$	0.11
8	1.44 $[1.01, 1.87]$	-0.02 $[-0.10, 0.06]$	0.57 $[0.46, 0.67]$	0.76 $[0.71, 0.92]$	0.12

Panel E: **All Equities**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.63 $[0.26, 1.00]$	0.02 $[-0.04, 0.09]$	0.66 $[0.56, 0.76]$	0.57 $[0.54, 0.78]$	0.17
8	1.25 $[1.02, 1.47]$	0.06 $[0.01, 0.10]$	0.52 $[0.47, 0.58]$	0.77 $[0.75, 0.88]$	0.12

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	0.11	0.12	0.14	0.15

Other Asset Classes

Panel G: **Bonds**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	0.44 $[0.30, 0.58]$	-0.08 $[-0.13, -0.03]$	0.85 $[0.76, 0.94]$	0.86 $[0.80, 0.98]$	0.16
8	0.24 $[0.10, 0.36]$	-0.11 $[-0.15, -0.07]$	0.59 $[0.53, 0.65]$	0.88 $[0.88, 0.99]$	0.15

Panel H: **Sovereign Bonds**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	-0.28 $[-0.70, 0.07]$	-0.16 $[-0.22, 0.09]$	1.23 $[1.09, 1.38]$	0.92 $[0.92, 0.99]$	0.10
8	-0.11 $[-0.70, 0.43]$	-0.06 $[-0.17, 0.04]$	1.01 $[0.78, 1.26]$	0.83 $[0.81, 0.99]$	0.14

Panel I: **Options**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	-3.18 $[-3.41, -2.96]$	0.99 $[0.95, 1.03]$	-0.46 $[-0.53, -0.39]$	0.99 $[0.98, 0.99]$	0.08
8	-2.32 $[-2.43, -2.20]$	0.64 $[0.62, 0.65]$	-0.05 $[-0.08, -0.02]$	0.99 $[0.99, 0.99]$	0.04

Panel J: **CDS**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$\frac{\text{RMSE}}{\text{RMSR}}$
4	-0.08 $[-0.17, 0.02]$	-0.35 $[-0.38, -0.32]$	1.15 $[1.05, 1.25]$	0.93 $[0.93, 0.98]$	0.22
8	-0.08 $[-0.16, 0.00]$	-0.19 $[-0.22, -0.16]$	0.75 $[0.69, 0.81]$	0.95 $[0.95, 0.99]$	0.18

Panel K: **All Assets**

H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	R^2	$\frac{\text{RMSE}}{\text{RMSR}}$
4	-0.07 $[-0.75, 0.55]$	0.12 $[-0.26, 0.40]$	0.80 $[0.70, 1.32]$	0.97 $[0.72, 0.98]$	0.21
8	0.18 $[-0.62, 1.73]$	0.30 $[-0.18, 0.36]$	0.53 $[0.43, 0.98]$	0.82 $[0.68, 0.88]$	0.23

Table A1: Expected return-beta regressions,equity portfolios. Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. 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 $\text{RMSE}_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left(E_T\left(R^e_{ji}\right)\right)^2}$ where R^e_{ji} refers to the return of portfolio j in group i and $\text{RMSR}_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left(E_T\left(R^e_{ji}\right) - \widehat{R}^e_{ji}\right)}$ where $\widehat{R}^e_{ji} = \widehat{\lambda}_0 + \widehat{\beta}'_{ji}\widehat{\lambda}$. The sample spans the period 1963Q3 to 2013Q4.