# Capital Share Risk in U.S. Stock Pricing*

Martin Lettau
UC Berkeley, CEPR and NBER

Sydney C. Ludvigson
NYU and NBER

Sai Ma
NYU

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**Abstract**

Capital share risk exhibits significant explanatory power for several cross-sections of expected returns, while subsuming much or all of the explanatory power of predominant return-based factor models. For most portfolios, positive exposure to capital share risk earns a positive risk premium, commensurate with recent inequality-based asset pricing models. But in a striking and puzzling exception to this finding, the risk price is strongly negative for momentum. We show that this finding is central for understanding one key feature of the data, namely the negative correlation between value and momentum strategies, both of which earn high average returns.

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*Lettau: Haas School of Business, University of California at Berkeley, 545 Student Services Bldg. #1900, Berkeley, CA 94720-1900; E-mail: lettau@haas.berkeley.edu; Tel: (510) 643-6349, http://faculty.haas.berkeley.edu/lettau. Ludvigson: Department of Economics, New York University, 19 W. 4th Street, 6th Floor, New York, NY 10012; Email: sydney.ludvigson@nyu.edu; Tel: (212) 998-8927; www.sydneyludvigson.com. Ma: Department of Economics, New York University, 19 W. 4th Street, 6th Floor, New York, NY 10012; Email: sai.ma@nyu.edu. Ludvigson thanks the C.V. Starr Center for Applied Economics at NYU for financial support. We are grateful to Federico Belo, John Y. Campbell, Kent Daniel, Lars Lochstoer, Hanno Lustig, 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

Academic studies on the empirical determinants of expected return premia have often focused on anomalies in isolation. For example, factor pricing models typically stipulate separate return-based factors for value and momentum. An ostensive reason for this approach is that portfolio strategies such as value and momentum are difficult to explain in a unified way, especially since both strategies earn high average returns yet are negatively correlated (Asness, Moskowitz, and Pedersen (2013)). This paper extends the empirical literature in several ways. First, we show that a single macroeconomic factor based on lower frequency fluctuations in capital share growth is priced in the cross-sections of a range of portfolios and asset classes that constitute previously documented anomalies, including value and momentum. Second, we show that while most portfolio anomalies exhibit a positive exposure to capital share growth and are themselves positively correlated with value, momentum has a theoretically puzzling negative exposure and is negatively correlated with most other anomalies. Third, we show that a quantitatively large part of the negative correlation between value and momentum in U.S. data is captured by opposite signed exposure to capital share risk. Fourth, because the momentum trading strategy exhibits such strong negative exposure to a priced factor that in almost all other cases commands a positive risk premium, the momentum portfolio appears massively undervalued, something we refer to as the "momentum undervalue puzzle."

Why capital share risk? Contemporary asset pricing theory remains in search of an empirically relevant stochastic discount factor (SDF) linked to the marginal utility of investors. A mainstay of the literature assumes that assets are priced as if there were a representative agent, leading to an SDF based on the marginal rate of substitution over average household consumption. This model is especially convenient from an empirical perspective, since average household consumption is readily observed in aggregate data. Unfortunately, there are reasons to question the relevance of a model based on average household consumption for the pricing of risky assets. Wealth is highly concentrated at the top. 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] Thus a *wealth-weighted* stock market participation rate is much lower than 50%, equal to 20% in 2013. Moreover, unlike the average household, the wealthiest households earn a relatively small fraction of income from labor compensation, implying that income from the ownership of firms or financial investments, i.e., capital income, finances much more of their consumption.[2] In U.S. data, the share of national income accruing to capital explains a large fraction of variation in the income shares of the wealthiest households and is strongly positively correlated with those shares, as we document below.

These observations suggest a different approach to explaining return premia on risky assets. Recent inequality-based asset pricing models imply that the capital share of aggregate income 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 earn the vast majority of income from wages rather than investments (e.g., Greenwald, Lettau, and Ludvigson (2014), GLL). In these models, capital owners are the marginal investors in risky assets and their consumption is directly linked to the capital share. If workers own no risky asset shares, as in GLL, the 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. This will remain approximately true even if workers own a small fraction of the corporate sector, so long as wealth remains heavily concentrated in the hands of a few shareholders who finance most of their consumption from capital rather than labor income.[3]

[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.

[3] These simple expressions rule out risk-sharing in the form of risk-free borrowing and lending between workers and shareholders. However, fluctuations in the capital share will be a source of systematic risk for

With this theoretical motivation as backdrop, this paper explores empirically whether the capital share is a priced risk factor for explaining cross-sections of expected returns. We find that exposure to lower frequency (e.g., 8-12 quarters) fluctuations in capital share growth captures large fractions of the cross-sectional variation in expected returns on several types of equity portfolios and asset classes. The explanatory power is especially strong for equity portfolios sorted on the basis of size/book-market and momentum, but capital share risk also exhibits explanatory power for cross-sections of expected returns on other equity portfolios and assets classes, such as equity portfolios sorted on the basis of reversal and size/investment, and non-equity portfolios of corporate bonds, sovereign bonds, options, and credit default swaps.

For most portfolio strategies and asset classes, we find that positive exposure to capital share risk earns a positive risk premium with risk prices of similar magnitude across portfolio groups, commensurate with the hypothesis that wealthy stockholders are marginal investors in several asset markets. But in a puzzle for asset pricing theory, there is a striking exception to this finding: exposure to capital share risk has a negative (and strongly statistically significant) risk price when explaining cross-sections of expected returns on portfolios formed on the basis of momentum, or recent past return performance.[4] With such strong negative exposure where most portfolios exhibit positive exposure, the winner portfolio and especially the winner-minus-loser portfolio appear massively undervalued, a finding referred to above as the "momentum undervalue" puzzle.

Although puzzling, this finding turns out to be central for understanding one key feature of the data, namely the negative correlation between value and momentum strategies. We find that a quantitatively large part of the negative correlation in U.S. data is driven by opposite signed exposure of value and momentum to capital share risk. This opposite signed exposure is displayed in Figure 1 (discussed further below), which plots average quarterly returns on size/book-market portfolios (left scale) and momentum portfolios (right scale),

capital owners even with borrowing and lending as long as there is imperfect risk-sharing across these groups.

[4] As we discuss below, this is also true for portfolios sorted on the basis of return on equity, but the effect is less strong.

against estimated capital share betas for exposures over a horizon of $H = 8$ quarters. This result helps explain why (as we show below) an empirical model with a single capital share risk factor explains larger fractions of cross-sections of expected returns sorted on the basis of size/book-market or momentum than do return-based models that rely on separate priced factors for value and momentum. Such models counterfactually imply that the rewards to value and momentum are earned entirely from covariance of their *un*correlated components with the separate priced factors, while our results imply instead that the negatively correlated component is strongly priced. To the best of our knowledge, this evidence is the first to show that the negative correlation between these two strategies plays a role in their outsized rewards.

The momentum undervalue puzzle is not unique to capital share risk. We show that the returns to value and momentum strategies exhibit opposite signed exposure to the first two principal components of a large cross-section of equity portfolio returns. Moreover, most of the anomalies we study are positively correlated with value and negatively correlated with momentum. Likewise, we find strong opposite signed exposure to a measure of the banking sector's equity-capital ratio as constructed by He, Kelly, and Manela (2016) (HKM), a variable the authors have recently shown possesses significant explanatory power for cross sections of expected returns on many asset classes, though for the equity class HKM focus on size/book-market portfolios. We confirm their main findings and add to them by showing that this measure of the equity-capital ratio for the intermediary sector has a positive risk price for explaining most anomalies, but a negative and strongly statistically significant risk price when explaining portfolios formed on the basis of momentum, as is the case for capital share risk. Indeed, the signs (and often the relative magnitudes) of the risk prices on capital share growth exposure and on the intermediary sector's aggregate capital ratio exposure are identical across many asset classes: the majority are positive, with the strong exception of momentum and equity portfolios sorted on the basis of return-on-equity (where the effect is less strong than for momentum in both cases). Interestingly, accounting for capital share risk often eliminates the explanatory power of the banking equity-capital factor, as well as the broker-dealer leverage factor studied by Adrian, Etula, and Muir (2014) (AEM). This makes some sense when one considers the similar motivations behind inequality- and intermediary-based asset pricing theories, where the latter is predicated on the idea that intermediaries are owned by "sophisticated" or "expert" investors that differ from the majority of households who comprise most of aggregate consumption. It is reasonable to expect considerable overlap between the owners of intermediaries and wealthy capital owners.

In the last part of the paper we provide additional evidence from household-level data that sharpens the puzzle. First, we show that growth in the income share accruing to 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 $C_t$ 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 at best. Of course, some income share variation between these groups is likely to be idiosyncratic and capable of being diversified away. We therefore form an estimate of the component of income share variation that represents systematic risk as the fitted values from a projection of each group's income share on the aggregate capital share. Finally, we form a proxy for the consumption of a representative investor of each group as the product of aggregate consumption times the group's fitted income share and ask whether the growth in this variable is priced. Restricting the risk prices to be positive, we find that the variable for rich stockowners explains return premia on size/book-market portfolios and has some explanatory power for reversal and size/investment portfolios. The puzzling exception is again momentum, which is priced as if the non-rich were the marginal investors for that portfolio strategy.

What might explain these findings? One possible resolution of the momentum undervalue puzzle is to simply revert to explaining the data with a complete markets SDF that specifies separate priced factors for value and momentum, as has been long-standing practice (e.g., Fama and French (1996), Asness, Moskowitz, and Pedersen (2013)). There are however several limitations with this approach to explaining the data. First, the very assumption that the rewards to value and momentum are earned entirely from covariance of their uncorrelated components with separate priced factors is contradicted by the empirical evidence of this paper showing strong opposite signed exposure of value and momentum returns to capital share growth and to other priced factors. Second, the empirical value and momentum factors commonly used to explain the size/book-market and momentum premia do not work that well. An empirical model with capital share growth as the single priced source of macroeconomic risk explains a larger fraction of the cross-sectional variation in expected returns on size/book-market or momentum portfolios than do popular return-based models that rely on separate priced factors for value and momentum, notably the Fama-French three-factor model for pricing size/book-market portfolios (Fama and French (1993)), and the Fama and French (1996) four-factor model that augments the three factor model to include a momentum factor due to Carhart (1997). Moreover, the risk prices for these return-based factors are either significantly attenuated or completely driven out of the pricing regressions by opposite signed exposure to capital share risk, while the individual value and momentum return-based factors have little ability to explain both sets of portfolios even if the signs of their risk prices are left unrestricted. Third, under complete markets and a single SDF with separate priced factors, the efficient portfolio is a value/momentum combination that has a Sharpe ratio greater than 1.5, requiring an SDF that is three times as volatile as that which can price the market and almost twice as volatile as what would be required to price the value and momentum strategies separately. Whether an SDF with such an enormous implicit risk aversion is a reasonable model of behavior is an open question, but the persistence of such high Sharpe ratios in the face of risk-tolerant hedge funds operating across the value and momentum dimensions seems at the least suggestive of limits to arbitrage and market incompleteness. In the conclusion, we briefly discuss some behaviorally motivated stories that might partly account for the findings presented here, but a clearer understanding of these empirical results and their linkage to capital share variation is a important topic for future research.

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.

Our investigation is related to a classic older literature emphasizing the importance for stock pricing of limited stock market participation and heterogeneity (Mankiw (1986), Mankiw and Zeldes (1991), Constantinides and Duffie (1996), Vissing-Jorgensen (2002), Ait-Sahalia, Parker, and Yogo (2004), Guvenen (2009), and Malloy, Moskowitz, and Vissing-Jorgensen (2009)). In contrast to this literature, our paper builds on a growing body of theoretical and empirical work that considers the role of shocks that redistribute resources between shareholders and workers as a source of priced risk when there is imperfect insurance between the two groups. In this literature, labor compensation is a charge to claimants on the firm and is therefore a systematic risk factor for aggregate stock and bond markets (Danthine and Donaldson (2002); Favilukis and Lin (2013a, 2013b, 2015), GLL, Marfe (2016)). The maintained assumption in this literature is that shareholders are risk averse and command a premium for engaging in risky assets exposed to systematic capital share risk. The findings here are also 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 are more likely to 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)).

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 describes our data. A complete 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:Q1 to 2013:Q4 before loosing observations to computing long horizon relations as described below.

We use return data available from Kenneth French's Dartmouth website on 25 size/book-market sorted portfolios (size/BM), 10 momentum portfolios (MOM), 10 long-run reversal portfolios (REV), and 25 size/investment portfolios (size/INV), where the latter span 1963:Q3 to 2013:Q4.[5] We also investigate equity returns on 10 portfolios sorted on the basis of return on equity (ROE or earnings relative to book-value), as constructed in Hou, Xue, and Zhang (2015) spanning 1967:Q1-2013:Q4. Finally, we 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.[6]

We denote the *labor share* of national income as $LS$, and the *capital share* as $KS \equiv 1-LS$. 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 all very similar if we use the BLS nonfinancial labor share measure. There are well known difficulties with accurately measuring the labor share. Perhaps 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

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

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

for the labor share within the corporate sector that are similar to those for sectors that include sole proprietors, such as the BLS nonfarm measure (which makes specific assumptions on how proprietors' income is proportioned). Indirect taxes and subsidies can also create a wedge between the labor share and the capital share, but Gomme and Rupert (2004) find that these do not vary much over time, so that movements in the labor share are still strongly (inversely) correlated with movements in the capital share. Thus the main difficulties with measuring the labor share pertain to getting the *level* of the labor share right. Our results rely instead on *changes* in the labor share, and we maintain the hypothesis that they are informative about opposite signed changes in the capital share. Figure 2 plots the rolling eight-quarter log difference in the capital share over time, and shows that 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 this question, we make use of two household-level datasets that provide information on wealth and income inequality. The first is the triennial survey data from the survey of consumer finances (SCF), the best source of micro-level data on household-level assets and liabilities for the United States. The SCF also provides information on income and on whether the household owns stocks directly or indirectly.[7] 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

[7] The empirical literature on limited stock market participation and heterogeneity has instead relied on the Consumer Expenditure Survey (CEX). As a measure of assets and liabilities, it is considered far less reliable than the SCF. CEX answers to asset questions are often missing for more than half of the sample and much of the survey is top-coded. In addition, wealthy households are known to exhibit 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)).

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.[8] 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.[9] We define a stockholder in the SZ data as any individual who reports having non-zero income from dividends and/or realized capital gains. Note that this classification of stockholder fits the description of "direct" stockowner, but unlike the SCF, there is no way to account for indirect holdings in e.g., tax-deferred accounts. The annual data we employ span the period 1963-2012. We refer to these data as the "SZ data".

Finally, for some analyses in this paper we use aggregate consumption data. Aggregate consumption is measured as real, per capita expenditures on nondurables and services, excluding shoes and clothing from the BLS.

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

[9]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.

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.[10] 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 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. To compute the wealth-weighted rate, we divide 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. This shows that steady increases stock market ownership rates do not necessarily correspond to quantitatively meaningful changes

[10] 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.

in stock market ownership patterns. This evidence underscores 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 $KS_t$.[11] 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

[11] 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.

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 common and idiosyncratic components. Figure 3 provides one piece of evidence on how these components might 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.[12] 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. This shows that 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 and is suggestive of imperfect risk-sharing between the two groups.

We now turn to how movements in the capital share are related to value and momentum returns. In doing so, we pay close attention to the horizon over which movements in the

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

capital share may matter for return premia, with special focus on lower frequency fluctuations. Evidence in GLL indicates the presence of a slow moving factors-share shock that affects the aggregate stock market over long horizons. In order to isolate potentially important lower frequency components in capital share risk, we follow the approach of Bandi, Perron, Tamoni, and Tebaldi (2014) and Bandi and Tamoni (2014) and estimate covariances between *long*-horizon returns $R_{t+H,t}$ and *long*-horizon risk factors.

Table 3 presents a variety of empirical statistics for value and momentum strategies. We define the return on the value strategy as the return on a long-short position designed to exploit the maximal spread in returns on the size/book-market portfolios. This turns out to be the return on a strategy that goes long in the small stock value portfolio S1B5 and short in the small stock growth portfolio S1B1, i.e., $\widetilde{R}_{V,t+H,t} \equiv R_{S1B5,t+H,t} - R_{S1B1,t+H,t}$. The return on the momentum strategy is taken to be the return on a long-short position designed to exploit the maximal spread in returns on the momentum portfolios that goes long in the extreme winner portfolio (M10) and short in the extreme loser (M1), i.e., $\widetilde{R}_{M,t+H,t} \equiv R_{M10,t+H,t} - R_{M1,t+H,t}$. Panel A of Table 3 shows the correlation between the two strategies, for different quarterly horizons $H$, along with annualized statistics for the returns on these strategies. The results confirm the negative correlation reported in Asness, Moskowitz, and Pedersen (2013) who consider a larger set of countries, a different sample period, and a similar but not identical definition of value and momentum strategies. We find in this sample that the negative correlation is relatively weak at short horizons but becomes increasingly more negative as the horizon increases from 1 to 12 quarters. The next columns show the high annualized mean returns and Sharpe ratios on these strategies that have been a long-standing challenge for asset pricing theories to explain. Because of the negative correlation between the strategies, an optimal portfolio of the two has an even higher Sharpe ratio, with values that exceed 1 for $H \geq 8$ (right-most column). Annualized return premia and Sharp ratios rise with the horizon $H$.

Panel B of Table 3 shows results from regressions of the value and momentum strategies on capital share growth, again for different quarterly horizons $H$. This panel shows that capital share risk is strongly positively related to value strategy returns, and strongly negatively related to momentum strategy returns, with both sets of slope coefficients and $t$-statistics rising with the horizon. Moreover, the adjusted $\overline{R}^2$ statistics increase with the horizon $H$ in tandem with the increasingly negative correlation between the two strategies shown in panel A. Movements in capital share growth explain 25% of the variation in both strategies when $H = 12$. Given that financial returns are almost surely subject to common shocks that shift the willingness of investors to bear risk independently from the capital share, we find this to be surprisingly large.[13]

The three right-most columns of panel B give the results of a covariance decomposition for $\widetilde{R}_{V,t+H,t}$ and $\widetilde{R}_{M,t+H,t}$. The third column shows the fraction of the (negative) covariance between $\widetilde{R}_{V,t+H,t}$ and $\widetilde{R}_{M,t+H,t}$ that is captured by opposite-signed exposure to capital share risk, at various horizons. The fourth column shows the fraction of the negative covariance explained by the component orthogonal to capital share risk. The last column shows the correlation between the orthogonal components. The contribution of capital share risk exposure to this negative covariance rises sharply with the horizon over which exposures are measured and over which return premia increase. For return horizons of 16 quarters, opposite signed exposure to capital share risk explains 71% of the negative covariance between the returns on these strategies.

Statistics in Table 3 were presented for the value strategy in the size quintile that delivers the maximal historic average return premium, which corresponds to the small(est) stock value spread. For completeness, the Appendix presents the same statistics for value strategies corresponding to the other size quintiles. The returns to these value strategies are considerably

[13] GLL present evidence of independent shocks to risk tolerance that dominate return fluctuations over shorter horizons. Even in this model, where an independent factors-share shock plays the *largest* role in the large unconditional equity premium, risk aversion shocks create short-run noise so that $R^2$ from time-series regressions of market returns on capital share growth are small over horizons reported above, although they increase with $H$.

attenuated for portfolios of stocks in the 4th and 5th (largest) size quintiles, indicating that the value premium itself is largely a small-to-medium stock phenomenon. But for the intermediate size quintiles, where the value premium remains sizable, opposite signed exposure to capital share risk explains an even larger fraction of the negative covariance between value and momentum strategies. For the second and third size quintiles, opposite signed exposure of value and momentum strategies to capital share risk explains 98% and 89% of the negative covariation between the strategies at $H = 16$, respectively, and 92% and 61% at $H = 12$.

Table 4, Panel A, shows the correlation matrix for the high-minus-low return strategies on all equity portfolio groups we examine for $H = 8$ period returns. Value strategy returns $\widetilde{R}_{V,t+8,t}$ are negatively correlated with strategies based on momentum $\widetilde{R}_{M,t+8,t}$ and operating profitability $\widetilde{R}_{ROE,t+8,t}$, but positively correlated with strategies based on reversal $\widetilde{R}_{REV,t+8,t}$ and size/investment $\widetilde{R}_{INV,t+8,t}$. Momentum strategy returns are negatively correlated with strategies based on reversal and size/investment, but positively correlated with strategies based on operating profitability.

Panel B of Table 4 shows the correlation of each of these returns with the first two principal components of the returns on all portfolios combined, i.e., the 25 size/BM portfolios, the 10 MOM, the 10 REV, the 25 size/INV and the 10 ROE taken together. The three strategy returns that are positively correlated with capital share growth are those for value, reversal, and size/investment ($\widetilde{R}_V, \widetilde{R}_{REV}$, and $\widetilde{R}_{INV}$) and these all exhibit a *positive* correlation with the first two principal components, which in turn are both positively correlated with capital share growth. By contrast, the two strategy returns that are negatively correlated with capital share growth are those for momentum and return-on-equity ($\widetilde{R}_M, \widetilde{R}_{ROE}$) and these both exhibit a *negative* correlation with the first two principal components. Note that the principal components capture orthogonal sources of common variation in the returns and are therefore ad-hoc pricing factors for explaining cross-sectional variation in the expected returns on these portfolios. The opposite-signed correlation of value and momentum strategies with these common factors is inconsistent with a pricing model in which the rewards to these strategies are earned entirely from covariance of their uncorrelated components with separate priced factors. Instead, the results suggest that that the negatively correlated component is priced and plays a role in their high average returns. We now investigate this more formally using capital share risk as an empirical pricing factor.

# 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

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

or equivalently

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

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

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. Thus our first set of investigations asks 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), capital share risk exposure explains a much larger fraction of every set of 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. This is partly because consumption growth is far less volatile than capital share growth. For this reason, our main empirical specification is the single factor capital share SDF given in (3). 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. The findings of this paper are therefore strongly supportive of a model with imperfect risk-sharing between workers and shareholders.

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 $R^e_{j,t+1}$, previous evidence suggests that the covariance risk generated by capital share fluctuations is operative at longer horizons. Yet as emphasized by Bandi, Perron, Tamoni, and Tebaldi (2014) and Bandi and Tamoni (2014), important lower frequency relations can be masked in short-horizon data by higher frequency "noise" that may matter less for unconditional risk premia. Thus in order to identify possibly important low 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 $\frac{KS_{t+H}}{KS_t}$.[14] These lower frequency risk exposures could still have large effects on *un*conditional return premia measured over shorter horizons. We therefore investigate

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

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

whether the longer 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 $\lambda_0$ (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 $\lambda_{KS}$ is the capital share risk price parameter to be estimated. "Hats" in (5) denote estimated parameters from the time-series regression. In theory, 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 so that the standard errors of $\lambda_{KS}$ are corrected for the estimation of $\beta_{j,KS,H}$ in (4). A Newey-West (Newey and West (1987)) estimator is used to obtain serial correlation and heteroskedasticity robust standard errors. 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

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and the gross $H$-period excess return

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

alongside the capital share betas. For example, we estimate

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

when we include the Fama-French three-factor-model betas. Analogous specifications are estimated controlling for the Fama-French four-factor-model betas that adds the momentum factor beta, or controlling for the betas of the intermediary-based models, 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. For these estimations we use the more commonly employed Fama-MacBeth procedure (Fama and MacBeth (1973)). 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 asset pricing block of moments as a measure of how well the model explains the cross-section of quarterly returns.[15] Bootstrapped confidence intervals for the $\overline{R}^2$ are reported for the main specification tests. Also reported are the root-mean-squared pricing errors (RMSE) as a fraction of the root-

[15] This measure is defined as

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

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

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 $\widehat{R}_j^e = \widehat{\lambda}_0 + \widehat{\beta}_j'\widehat{\lambda}$.

# 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 five equity portfolio groups. This is followed by subsections reporting results that control for the betas of empirical pricing factors from other models, tests on non-equity asset classes, 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 Appendix provides a detailed description of the bootstrap procedure.

## 4.1 Baseline Capital Share Specifications

Table 5 reports results from estimating the cross-sectional regressions (5) on five distinct groups of equity portfolios: size/BM, REV, size/INV, MOM, and ROE. The table reports the estimated capital share factor risk prices $\widehat{\lambda}_{KS}$ with confidence intervals in square brackets. Panels A, B, and C report results for size/BM, REV and size/INV portfolios, respectively. In each of these cross-sections, the risk price for capital share growth is positive and strongly statistically significant, 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, with long horizon capital share betas explaining more than short horizon betas. For $H = 8$ and $H = 12$, the cross-sectional $\overline{R}^2$ statistics are 79% and 74%, respectively, for size/BM, compared to 50% for $H = 4$. For $H = 8$, the cross-sectional $\overline{R}^2$ statistics are 86% for REV and 62% for size/INV. More importantly, the $\overline{R}^2$ statistics remain sizable for all three portfolio groups even after taking into sampling uncertainty and small sample biases. Also reported in the table are the 95% bootstrap confidence intervals for the cross-sectional (adjusted) $\overline{R}^2$statistics, which show tight ranges around high values. For $H = 8$, the 95% confidence intervals are $[69\%, 90\%]$, $[80\%, 98\%]$, and $[54\%, 87\%]$ for size/BM, REV, and size/INV, respectively.

Panels D and E of Table 5 report statistics from the cross-sectional regressions (5) using momentum and ROE. Panel D, reporting results for MOM, shows, as previewed above, that the risk price for exposure to capital share risk is now *negative* and strongly statistically significant, and that this negative exposure to capital share risk explains 93% of the cross-sectional variation in returns for $H = 8$ and 85% for $H = 12$. The 95% bootstrapped confidence intervals for the cross-sectional $\overline{R}^2$are $[71\%, 98\%]$ for $H = 8$ and $[75\%, 90\%]$ for $H = 12$. The results for ROE portfolios, reported in Panel E, show that capital share risk is also priced with a negative value for $\widehat{\lambda}_{KS}$. However, the return premia on these portfolios are better explained over shorter e.g., $H = 4$ horizons than over longer horizons where the $\overline{R}^2$ is 68% with a 95% confidence interval of $[0.53, 0.96]$. For $H = 8$ the $\overline{R}^2$ is 0.46 but the bootstrapped confidence interval for the $\overline{R}^2$ statistic is much wider, equal to $[9\%, 96\%]$. For $H = 12$ the confidence interval includes negative values, suggesting that capital share exposure is not statistically reliably priced at these longer horizons.

Panels F and G of Table 5 report statistics from the cross-sectional regressions (5) on all portfolios together in the metagroup of portfolios comprised of all those that have the same sign for the estimated capital share risk price $\lambda_{KS}$. Panel F reports the results for the "all positive" metagroup (size/BM, REV, size/INV), while Panel G reports results for the "all negative" metagroup (MOM, ROE). We first note that the risk prices estimated from the all positive metagroup are about the same magnitude as those estimated on the individual portfolio groups (i.e., on size/BM, REV, size/INV separately), and similarly for the all negative metagroup. To give a sense of which portfolio groups are most mispriced, Panels H and I show the $RMSE_i/RMSR_i$ for each group $i$ computed from the all positive and all negative metagroup estimations. The pricing errors of size/BM, REV and size/INV are all very similar as a fraction of the mean squared expected returns on those each group. For the all negative group, we see that the pricing errors of momentum portfolios are much smaller than those for ROE, as long as $H = 8$ or $H = 12$.

Figure 1 and Figure 4 give a visual impression of these results. Figure 1 focuses on size/BM and MOM 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 left scale plots these relations for the 25 size/book-market portfolios; the right scale for the 10 momentum portfolios. The solid and dotted lines show the fitted return implied by the model using the single capital share beta as a measure of risk for size/book-market and momentum portfolios, respectively. 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. Momentum portfolios are denoted $M1, ...M10$, where $M10$ has the highest return over the prior (2-12) months and $M1$ the lowest.

The key result in Figure 1 is that the estimation on size/book-market portfolios has a fitted line that slopes strongly up, while the estimation on momentum portfolios has a fitted line that slopes strongly down. The highest return size/book-market portfolio is positively correlated with growth in the capital share, while the highest return momentum portfolio is negatively correlated with growth in the capital share. Figure 1 shows graphically that the high return premia on these negatively correlated strategies is in large part captured by opposite signed exposure to low frequency capital share risk.

Figure 1 illustrates several other results. First, as mentioned, 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. Second, 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 M10, and low return S1B1 and M1 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. Third, 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. Fourth, the figure shows that the spread in betas for both sets of portfolios is large. 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. The spread in the capital share betas between M1 and M10 is 4.5 compared to a spread in returns of (negative) 3.8%.

Figure 4 shows the analogous plot for all five equity portfolios, with the left scale showing average returns for the positive risk price portfolio groups (size/BM, REV, size/INV), and the right scale showing the negative risk price portfolio groups (MOM, ROE). The solid lines correspond to the fitted return premia predicted by the model when estimated on the all positive or all negative groups. The results show that ROE1, REV1 and S1I1 are among the least well priced portfolios in the metagroups, but the micro cap S1B1 remains well priced in the all positive metagroup.

## 4.2 Controlling for Other Pricing Factors

Is 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, namely the Fama-French three-factor model using the market return $Rm_t$, $SMB_t$ and $HML_t$ as factors, the Fama-French four-factor model using these factors and the momentum factor $MoM_t$, the intermediary SDF model of AEM using their $LevFac_t$, and intermediary SDF model of HKM using their banking equity-capital ratio factor $EqFac_t$ jointly with the market return $Rm_t$, 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 in 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 6 shows results that control for the Fama-French factor betas and the $LevFac_t$ beta. To conserve space, comparisons with these models are restricted to explaining size/BM and momentum returns, since these models were originally narrowly focused on explaining these portfolio groups. 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 6 for size/book-market portfolios show that the capital share risk model generates pricing errors that are lower than both the Fama-French three-factor model and the $LevFac_t$ model. The RMSE/RMSR pricing errors are 12% for capital share model, 13% for the Fama-French three-factor model and 16% for the $LevFac_t$ model. The cross-sectional $\overline{R}^2 = 0.79$ for the capital share model, as compared to 0.73 for the Fama-French three-factor model and 0.68 for the $LevFac_t$ model. The risk price for the capital share beta is two orders of magnitude smaller than that for the $LevFac_t$ model, indicating that the capital share model explains the same spread in returns with a much larger spread in betas.

What happens when betas from these models are included along with the capital share beta in the cross-sectional regression? The results are given in rows 3 and 5 of panel A. The magnitude of the risk prices on the betas for $SMB_t$, $HML_t$ and the $LevFac_t$, are cut in half or more once the capital share beta is included. Moreover, the 95% confidence intervals are wider, especially for the betas for $SMB_t$, $HML_t$, which now include values close to zero. By contrast, the capital share beta retains most of its magnitude and strong statistical significance. The $BIC$ criterion chooses the model with both the capital share beta and $LevFac$ beta as best, followed by the model with only the capital share beta. The cross-sectional $\overline{R}^2$ statistics suggest that includes both betas explains only a small amount of additional variation in expected returns compared to what can be explained with the $KS$ beta alone.

Panel B of Table 6 shows the same comparisons for momentum portfolios. The RMSE/RMSR pricing errors for the capital share model are now a third smaller than the Fama-French four-factor model, and 70% smaller than the $LevFac_t$ model. The adjusted cross-sectional $\overline{R}^2$ statistics are 0.93, 0.75, and 0.17, for the capital share risk model, Fama-French four factor model, and *LevFac* model, respectively. The risk prices for the betas of the Fama-French factors and the $LevFac_t$ are again strongly significant when explaining momentum portfolios on their own. But when included alongside the capital share beta, their magnitudes are much smaller and the four Fama-French factors loose their statistical significance entirely, displaying wide confidence intervals that include zero, while the capital share beta retains its strong explanatory power. The 95% confidence interval for the risk price for $LevFac_t$ remains nonzero when included along side the capital share beta, but the $\overline{R}^2$ is not any higher than when only the capital share beta is included (equal to 0.93 in both cases). The magnitude of the risk price for the momentum factor $MoM_t$ is reduced almost to zero, while that for $LevFac$ is less than 30% of the size it obtains when no capital share beta is included, while $\widehat{\lambda}_{KS}$ is about the same in all regressions. The best model for pricing momentum portfolios according to the $BIC$ criterion is the capital share model by a substantial margin. These findings underscore the extent to which opposite signed exposure to capital share risk explains a much larger fraction of the cross-sectional variation in returns on the momentum portfolios than the Fama-French four-factor model that adds a separate factor to explain momentum. The source of opposite-signed risk exposure appears to be important. Neither the $HML_t$ pricing factor, which is central for explaining the value premium, nor the $MoM_t$ factor, central for explaining momentum, can explain *both* size/BM and momentum portfolios well on their own even if the signs of the risk prices of these variables are left unrestricted. (See the Appendix Table A2.)

HKM test an alternative intermediary-based asset pricing model that uses a measure of bank equity-to-assets (what they call the equity capital ratio) for bank holding companies as a pricing factor, denoted $EqFac_t$ here, along with the market return. They report that the two factors work well for explaining cross-sections on different types of portfolio expected returns, though for equity these authors report results only for size/BM portfolios. In Table 7 we now investigate all five equity portfolio groups, using betas on the $EqFac_t$ and $Rm_t$ factors alone or in combination with the capital share beta. The HKM pricing model on its own has strong explanatory power for each group of equity portfolios. Two findings are notable. First, the risk prices on $EqFac_t$ and $Rm_t$ are positive when pricing size/BM, REV, size/INV, as is the case for exposure to capital share growth, but negative when pricing momentum and ROE portfolios, again as for capital share growth. Furthermore, the risk prices on both $EqFac_t$ and $Rm_t$ are not only negative but strongly statistically significant when explaining MOM and ROE, with the model explaining 65% of the cross-sectional variation in expected returns on MOM and 69% on ROE. But the HKM model also explains 50%, 80% and 60% of the cross-sectional variation in expected returns on size/BM, REV, and size/INV portfolios, respectively, with both risk prices positive and that for $EqFac_t$ always statistically significant. These findings reinforce the conclusions from the principal components analysis above that opposite signed exposure of value and momentum to priced risk factors is not unique to capital share risk. Second, once we account for exposure to capital share risk, the magnitudes of the risk prices for the $EqFac_t$ and $Rm_t$ factors are, like that for $LevFac_t$, substantially attenuated or in this case even flip sign. On size/BM portfolios, the risk prices for $EqFac_t$ and $Rm_t$ are both significantly negative whenever the capital share beta is included, and for REV and size/INV the confidence intervals for the risk price on $EqFac_t$ are wide and include both negative and positive values. These findings show that exposure to capital share risk subsumes and drives out the information contained in exposures to intermediary-based factors for explaining several cross-sections of expected returns.

## 4.3 Other Asset Classes

Table 8 explores whether capital share risk has any explanatory power for cross-sections of expected returns on non-equity asset classes also studied by HKM: corporate bonds, sovereign bonds, options, and CDS. The risk price for the capital share beta is positive and statistically significant in each case. It explains 88% of the cross-sectional variation in expected returns on corporate bonds, 82% on options, 93% on CDS, and 36% on sovereign bonds. Separately, the risk prices for the betas of $EqFac_t$ and $Rm_t$ are positive and have strong explanatory power for each of these groups, consistent with what HKM report. But when we account for the capital share risk exposure on these assets, the risk prices for exposures to $EqFac_t$ become negative when pricing corporate bonds and CDS and statistically insignificant when pricing sovereign bonds. 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 $Rm_t$ retain independent statistical explanatory power. However, for both models, the magnitudes of the estimated risk prices when estimated on the options portfolios are substantially 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. Interestingly, 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.

We also explored two other asset classes HKM investigated, namely a panel of foreign exchange portfolios and a panel of commodity portfolios. Exposure to capital share risk has no ability to explain the expected returns on these asset classes, in contrast to the HKM factors. The cross-sectional $R^2$ statistics for the capital share exposures are close to zero for both of these portfolio groups.

## 4.4 Pricing Factors Based On Household-Level Income Data

In the final empirical analysis of the paper, we explicitly connect aggregate capital share to fluctuations in the micro-level income shares of rich and non-rich stockowners using the SZ household-level data. To motivate this exercise, first note that the consumption of a representative stockowner in the $i$th percentile of the stock wealth distribution can be tautologically expressed as $C_t\theta_t^i$, where $\theta_t^i$ is the $i$th percentile's consumption share in period $t$. We do not observe $C_t\theta_t^i$ from data because reliable observations on $\theta_t^i$ are unavailable, especially for wealthy households. We do observe income shares, $\frac{Y_{it}}{Y_t}$, and a crude estimate of the $i$th percentile's consumption could be constructed as $C_t\frac{Y_{it}}{Y_t}$. However, some of the variation in $\frac{Y_{it}}{Y_t}$ across percentile groups is still likely to be idiosyncratic, capable of being insured against and therefore not priced. But given imperfect insurance between workers and capital owners, the inequality-based literature discuss above implies that fluctuations in the aggregate capital share should be a source of non-diversifiable income risk to which all households are exposed. We therefore form an estimate of the component of income share variation for the $i$th percentile that represents systematic risk by replacing observations on $\frac{Y_{it}}{Y_t}$ with the fitted values from a projection of $\frac{Y_{it}}{Y_t}$ on $KS_t$. That is, we ask whether betas for the $H$-period growth in $C_t\widehat{\frac{Y_t^i}{Y_t}}$ are priced, where $\widehat{Y_t^i/Y_t} = \widehat{\varsigma}_0^i + \widehat{\varsigma}_1^i\,(KS_t)$ are quarterly observations on fitted income shares from the $i$th percentile. The parameters $\widehat{\varsigma}_0^i$ and $\widehat{\varsigma}_1^i$ are the estimated intercepts and slope coefficients from the regressions of income shares on the capital share reported in the right panel of Table 2 pertaining to households who are stockholders. Finally, we restrict the estimated risk-prices to be positive and focus on $i =$ *top* 10%, *bottom* 90% of the stockowner stock wealth distribution. If the fitted risk prices are negative for either group, we discard this pricing factor and no results are reported. We refer to $C_t\widehat{\frac{Y_t^i}{Y_t}}$ as a proxy for the $i$th percentiles consumption. Estimates from the cross-sectional regressions of expected returns on the five equity portfolios are given in Table 9.

Table 9 shows that this proxy for rich stockowner's consumption growth strongly explains return premia on size/book-market portfolios and has some explanatory power for reversal and size/investment portfolios. For size/BM portfolios, the $H = 8$ quarter growth in $C_t \frac{\widehat{Y_t^{>10}}}{Y_t}$ (where "$> 10$" denotes *top* 10% in the table) explains 87% of the cross-sectional variation in expected returns, with a positive and strongly statistically significant risk price. This same proxy explains 66% and 67% of the variation in expected returns on the REV and size/INV portfolios. These findings are consistent with the hypothesis that rich stockowners are marginal investors for these portfolio groups. The puzzling exception is again momentum, which is priced as if non-rich stockowners were the marginal investors for that portfolio strategy (Panel D). On momentum the $H = 8$ quarter growth in $C_t \frac{\widehat{Y_t^{<90}}}{Y_t}$ (where "$< 90$" denotes *bottom* 90% in the table) explains 90% of the cross-sectional variation in expected returns, with a positive and strongly statistically significant risk price. However, this same variable explains little of the cross-section of expected returns on ROE.

Why doesn't the growth in $C_t \frac{\widehat{Y_t^{>10}}}{Y_t}$ explain the cross-section of momentum expected returns? Because this variable is strongly *positively* correlated with the capital share, to which momentum strategies are *negatively* exposed. Thus this proxy for the consumption growth of rich stockholders cannot explain momentum premia with a positive risk price. By contrast, growth in $C_t \frac{\widehat{Y_t^{<90}}}{Y_t}$ is strongly *negatively* correlated with the capital share, implying that this proxy for the consumption growth of the non-rich stockholder group can explain momentum premia with a positive risk price. Note that this is a description of the empirical findings, rather than an explicit equilibrium model of heterogeneous investment behavior. Future work is needed to understand these results more fully.

# 5 Conclusion

This paper finds that exposure to fluctuations in the capital share of national income has substantial explanatory power for several types of equity portfolios and asset classes. For most portfolio strategies and asset classes, we find that positive exposure to capital share risk earns a positive risk premium with risk prices of similar magnitude across portfolio groups, commensurate with the hypothesis that wealthy households, whose income shares are strongly positive related to the aggregate capital share, are marginal investors in many asset markets. But in a puzzle for asset pricing theory, there is a striking exception to this finding: exposure to capital share risk has a *negative* (and strongly statistically significant) risk price when explaining cross-sections of expected returns on equity portfolios formed on the basis of momentum. These findings suggest that momentum strategies are massively undervalued vis-a-vis the non-diversifiable aggregate capital share risk to which many wealthy investors are ostensibly exposed.

As we show, however, this puzzling finding turns out to be central for understanding the negative observed correlation between value and momentum strategies, both of which earn high average returns. A quantitatively large part of the negative correlation in U.S. data is driven by opposite signed exposure of value and momentum to capital share risk. This opposite signed exposure also appears in relation to other priced factors, such as the measure of the banking sector's equity-capital ratio. To the best of our knowledge, this evidence is the first to find that the negatively correlated component between these two strategies plays an important role in their outsized rewards.

What might explain these findings? Additional evidence using household-level income data finds that a proxy for the consumption of the richest households prices most portfolios with a positive risk price, except momentum, which is priced as if the non-rich are the marginal investors for that equity style. This could be consistent with a behavioral model of clientele effects, in which heterogenous investors have a preference for stocks with certain characteristics. Warren Buffett is known to invest only in "value"-type companies. Cookson and Niessner (2016) document that investor heterogeneity in reported investment approaches (Fundamental, Technical, Momentum, Growth, or Value) accounts for a sizable fraction of stock return volatility on earnings announcement dates. Moreover, most mutual funds follow well-defined investment styles, as exemplified by the Morningstar style box that categorizes mutual funds in a three-by-three matrix according to their focus on value/blend/growth and large/medium/small stocks. Several researchers have considered investors with preferences for specific styles for explaining empirical anomalies related to asset classes (e.g., Barberis and Shleifer (2003), Vayanos and Vila (2009)). Greenwood and Nagel (2009) find that younger mutual fund managers are more likely to engage in trend-chasing behavior in their investments than are older managers, while value tilting, which requires a contrarian view, has been found to be more common among wealthier, older investors (Betermier, Calvet, and Sodini (2014)). The results in this paper hint at the possibility that such quasi-market segmentation, in which different investors have preferences for different portfolios of the same assets, might be important for equilibrium prices and returns of stocks. Whether such a behavioral phenomenon is consistent with a sustained market equilibrium and why participants in the stock market might choose to focus on stocks with certain characteristics without exploiting potential gains from correlations across characteristics is unclear. These remain intriguing areas for future research.

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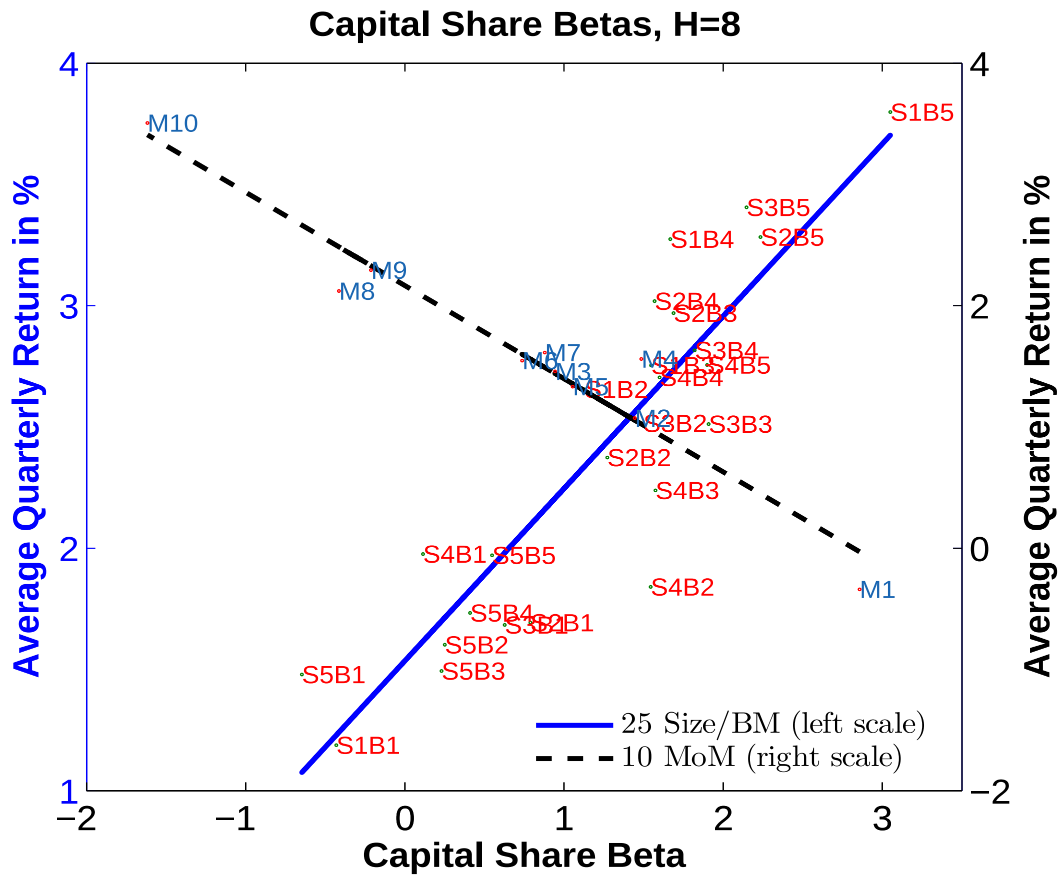


**Figure 1: Capital share betas.** Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using 25 size-book/market portfolios (Solid Blue) denoted $S_iB_j$, i,j=1,...,5 or 10 momentum portfolios (Dashed Black) denoted $M_i$. $H = 8$ indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q1 to 2013Q4.

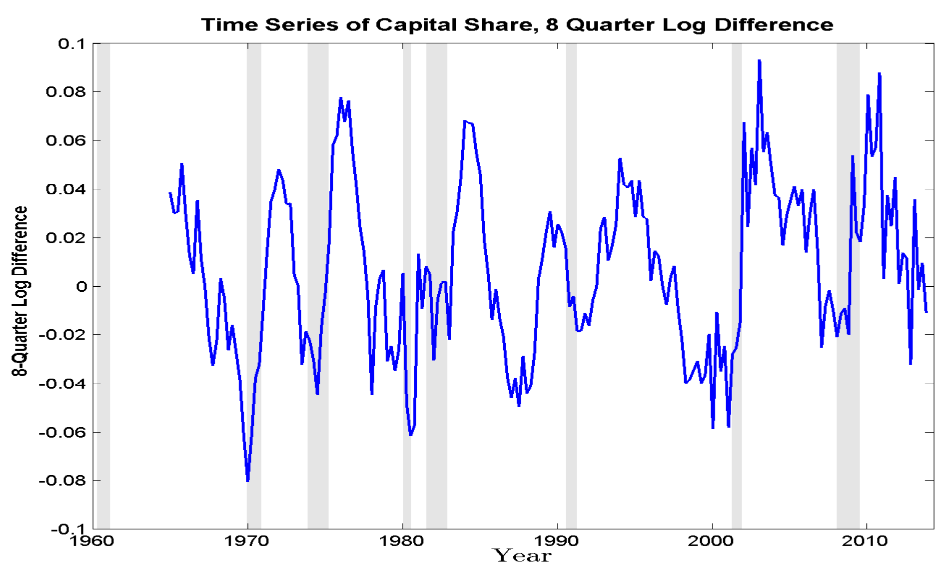


**Figure 2: Capital share, 8 quarter log difference.** The vertical lines correspond to the NBER recession dates. The sample spans the period 1963Q1 to 2013Q4.

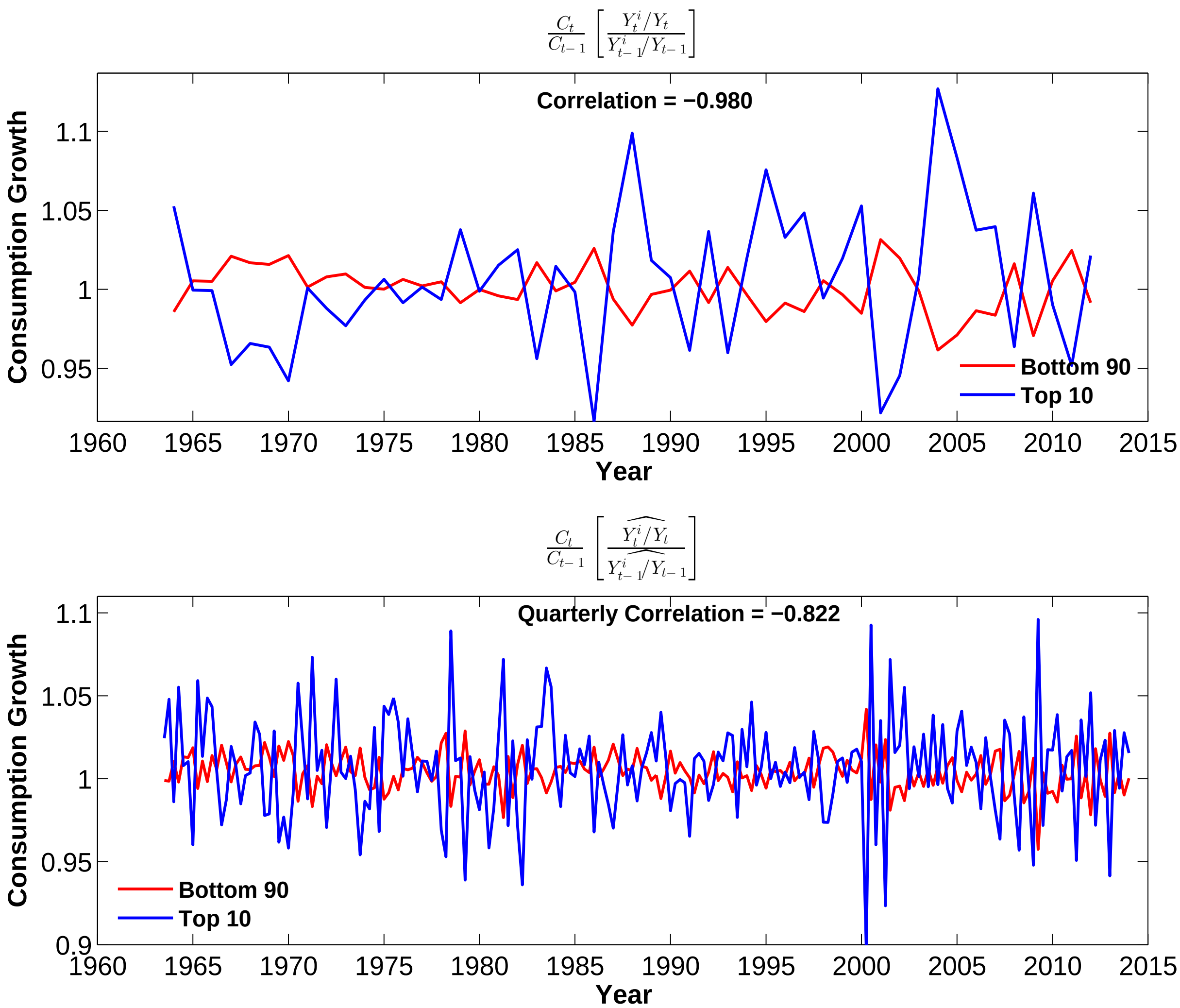


**Figure 3: Growth in aggregate consumption times income share.** The top panel reports annual observations on the annual value of $\frac{C_t}{C_{t-1}}\left[\frac{Y_t^i/Y_t}{Y_{t-1}^i/Y_{t-1}}\right]$ corresponding to the years for which SZ data are available. $Y_t^i/Y_t$ is the shareholder's income share for group $i$ calculated from the SZ. The bottom panel reports quarterly observations on quarterly values of $\frac{C_t}{C_{t-1}}\left[\frac{\widehat{Y_t^i/Y_t}}{\widehat{Y_{t-1}^i/Y_{t-1}}}\right]$ using the mimicking income share factor $\widehat{Y_t^i/Y_t} = \widehat{\alpha}^i + \widehat{\beta}^i KS_t$. The annual SZ data spans the period 1963 - 2012. The quarterly sample spans the period 1963Q1 - 2013Q4.

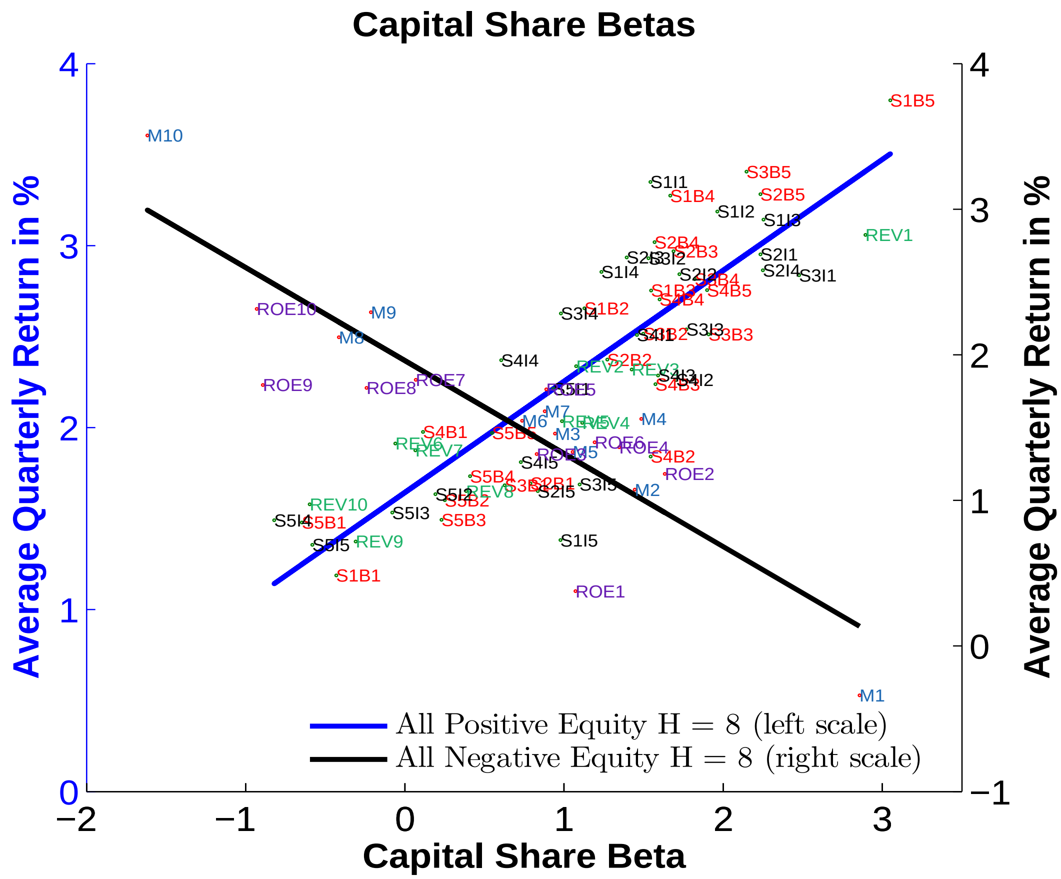


**Figure 4: Capital share betas.** Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using all positive equity portfolios (Blue) including 25 size/bm (denoted $S_iB_j$, i,j=1,...,5), 10 REV (denoted $\text{REV}_i$) and 25 size/INV (denoted $S_iI_j$, i,j=1,...,5) or all negative equity portfolios (Black) including 10 momentum (denoted $\text{M}_i$) and 10 ROE portfolios (denoted $\text{ROE}_i$). $H = 8$ indicates the horizon in quarters over which capital share exposure is measured. The sample spans the period 1963Q1 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 | $\widehat{\varsigma}_0^i$ | $\widehat{\varsigma}_1^i$ | $R^2$ |
| $< 90\%$ | 1.15** | −1.10** | 0.62 | $< 90\%$ | 1.20** | −1.24** | 0.50 |
| | (24.96) | (−8.77) | | | (18.25) | (−6.88) | |
| $95 - 100\%$ | −0.21** | 1.05** | 0.62 | $95 - 100\%$ | −0.25** | 1.18** | 0.53 |
| | (−4.92) | (8.75) | | | (−4.31) | (7.41) | |
| $99 - 100\%$ | −0.22** | 0.80** | 0.63 | $99 - 100\%$ | −0.24** | 0.91** | 0.59 |
| | (−6.63) | (8.98) | | | (−6.07) | (8.33) | |
| $99.9 - 100\%$ | −0.14** | 0.47** | 0.65 | $99.9 - 100\%$ | −0.16** | 0.53** | 0.64 |
| | (−7.89) | (9.51) | | | (−7.58) | (9.21) | |
| $90 - 100\%$ | −0.15** | 1.10** | 0.62 | $90 - 100\%$ | −0.20** | 1.24** | 0.50 |
| | (−3.23) | (8.77) | | | (−3.10) | (6.88) | |

**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.

**Small Stock Value and Momentum Strategies**

| Panel A : Annualized Statistics | | | | | | |
|---|---|---|---|---|---|---|
| $H$ | $Corr\left(\widetilde{R}^e_{V,H},\widetilde{R}^e_{M,H}\right)$ | Mean | | Sharpe Ratio | | $\max_w \frac{E\left(w\widetilde{R}^e_{V,H}+(1-w)\widetilde{R}^e_{M,H}\right)}{std\left(w\widetilde{R}^e_{V,H}+(1-w)\widetilde{R}^e_{M,H}\right)}$ |
| | | $\widetilde{R}^e_{V,H}$ | $\widetilde{R}^e_{M,H}$ | $\widetilde{R}^e_{V,H}$ | $\widetilde{R}^e_{M,H}$ | |
| 1 | −0.03 | 0.11 | 0.15 | 0.64 | 0.62 | 0.90 |
| 4 | −0.23 | 0.11 | 0.17 | 0.58 | 0.64 | 0.98 |
| 8 | −0.33 | 0.14 | 0.19 | 0.61 | 0.70 | 1.13 |
| 12 | −0.40 | 0.16 | 0.22 | 0.60 | 0.75 | 1.24 |
| 16 | −0.38 | 0.18 | 0.24 | 0.62 | 0.72 | 1.21 |

| Panel B: $\widetilde{R}^e_{i,H}=\alpha_i+\beta_{i,H}\frac{KS_{t+H}}{KS_t}+\epsilon_{i,H},\ i\in\{V,M\}$ | | | | | | | |
|---|---|---|---|---|---|---|---|
| | $\beta_{i,H}$ | | $\bar{R}^2$ | | $\frac{\beta_{M,H}\beta_{V,H}Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(\widetilde{R}^e_{M,H},\widetilde{R}^e_{V,H}\right)}$ | $\frac{Cov(\widehat{\epsilon}_{M,H},\widehat{\epsilon}_{V,H})}{Cov\left(\widetilde{R}^e_{M,H},\widetilde{R}^e_{V,H}\right)}$ | $Corr\left(\widehat{\epsilon}_{M,H},\widehat{\epsilon}_{V,H}\right)$ |
| $H$ | $\widetilde{R}^e_{V,H}$ | $\widetilde{R}^e_{M,H}$ | $\widetilde{R}^e_{V,H}$ | $\widetilde{R}^e_{M,H}$ | | | |
| 4 | 1.56** | −2.98** | 0.04 | 0.09 | 0.29 | 0.71 | −0.17 |
| | [3.09] | [−4.55] | | | | | |
| 8 | 3.48** | −4.47** | 0.16 | 0.18 | 0.52 | 0.48 | −0.19 |
| | [6.09] | [−6.66] | | | | | |
| 12 | 5.27** | −5.88** | 0.25 | 0.25 | 0.64 | 0.36 | −0.20 |
| | [8.12] | [−8.06] | | | | | |
| 16 | 6.43** | −7.68** | 0.25 | 0.28 | 0.71 | 0.29 | −0.15 |
| | [7.99] | [−8.62] | | | | | |

**Table 3: Value and momentum strategies.** The H-period return on the value strategy is $\widetilde{R}^e_{V,H}\equiv\prod_{h=1}^{H}R_{S1B5,t+h}-\prod_{h=1}^{H}R_{S1B1,t+h}$. The H-period return on the momentum strategy is $\widetilde{R}^e_{M,H}\equiv\prod_{h=1}^{H}R_{M10,t+h}-\prod_{h=1}^{H}R_{M1,t+h}$. Panel B reports regression results and the fraction of (the negative) covariance between the strategies' returns that can be explained by capital share growth exposure (forth column) and the residual component orthogonal to that (fifth column).The t-statistics is reported in square bracket. "$*$" and "$**$" indicate statistical significance at the 10% and 5% level, respectively. The sample spans the period 1963Q1 to 2013Q4.

| Panel A: Correlation Matrix between Strategies for $H = 8$, | | | | | |
|---|---|---|---|---|---|
| | $\widetilde{R}^e_{V,H}$ | $\widetilde{R}^e_{M,H}$ | $\widetilde{R}^e_{REV,H}$ | $\widetilde{R}^e_{ROE,H}$ | $\widetilde{R}^e_{INV,H}$ |
| $\widetilde{R}^e_{V,H}$ | 1 | $-0.33$ | 0.24 | $-0.08$ | 0.26 |
| $\widetilde{R}^e_{M,H}$ | | 1 | $-0.22$ | 0.34 | $-0.16$ |
| $\widetilde{R}^e_{REV,H}$ | | | 1 | $-0.46$ | 0.30 |
| $\widetilde{R}^e_{ROE,H}$ | | | | 1 | $-0.50$ |
| $\widetilde{R}^e_{INV,H}$ | | | | | 1 |

| Panel B: Correlation between Principle Components and Strategies | | | | | | |
|---|---|---|---|---|---|---|
| | $\widetilde{R}^e_{V,H}$ | $\widetilde{R}^e_{M,H}$ | $\widetilde{R}^e_{REV,H}$ | $\widetilde{R}^e_{ROE,H}$ | $\widetilde{R}^e_{INV,H}$ | $\frac{KS_{t+H}}{KS_t}$ |
| PC1 | 0.08 | $-0.15$ | 0.01 | $-0.25$ | 0.12 | 0.21 |
| PC2 | 0.28 | $-0.23$ | 0.75 | $-0.28$ | 0.25 | 0.24 |

**Table 4: Sample Statistics Portfolio Strategies.** Panel A reports the correlation matrix between strategies. $\widetilde{R}^e_{i,H} = R^{e,\text{High}}_{i,H} - R^{e,\text{Low}}_{i,H}$, where $R^{e,\text{High}}_{i,H}$ ($R^{e,\text{Low}}_{i,H}$) is the portfolio return with the highest (lowest) sample mean return for asset group $i$: V = Value strategy, M = momentum strategy, INV = Size/inv. Panel B reports the correlation between strategies and principle components. The first two principles components are computed from demeaned 8-period returns of the following portfolios: 25 Size/BM, 10 Momentum, 10 Reversal, 10 ROE and 25 Size/Investment. The unbalanced panel spans the periods 1963Q1 to 2013Q4.

**Expected Return-Beta Regressions, Equity Portfolios**

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

| | Panel A: **25 Size/BM** | | | | Panel B: **10 REV** | | | | Panel C: **25 Size/INV** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $H$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
| 4 | 0.64 | 0.79 | 0.50 | 0.19 | 0.85 | 0.65 | 0.68 | 0.12 | 0.91 | 0.64 | 0.39 | 0.20 |
| | $[0.17, 1.08]$ | $[0.56, 1.03]$ | $[0.37, 0.83]$ | | $[0.51, 1.19]$ | $[0.47, 0.83]$ | $[0.62, 0.96]$ | | $[0.42, 1.34]$ | $[0.43, 0.86]$ | $[0.28, 0.83]$ | |
| 8 | 1.54 | 0.71 | 0.79 | 0.12 | 1.71 | 0.43 | 0.86 | 0.08 | 1.67 | 0.59 | 0.62 | 0.16 |
| | $[1.39, 1.67]$ | $[0.59, 0.83]$ | $[0.69, 0.90]$ | | $[1.61, 1.81]$ | $[0.35, 0.52]$ | $[0.80, 0.98]$ | | $[1.50, 1.84]$ | $[0.45, 0.73]$ | $[0.54, 0.87]$ | |
| 12 | 1.94 | 0.49 | 0.74 | 0.13 | 1.95 | 0.35 | 0.77 | 0.10 | 2.01 | 0.44 | 0.64 | 0.15 |
| | $[1.80, 2.06]$ | $[0.40, 0.59]$ | $[0.68, 0.91]$ | | $[0.81, 2.08]$ | $[0.26, 0.45]$ | $[0.66, 0.95]$ | | $[1.87, 2.16]$ | $[0.34, 0.55]$ | $[0.54, 0.87]$ | |

| | Panel D: **10 Momentum** | | | | Panel E: **10 ROE** | | | | Panel F: **All Positive** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $H$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $R^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
| 4 | 3.52 | $-0.96$ | 0.76 | 0.23 | 2.85 | $-0.78$ | 0.66 | 0.17 | 0.78 | 0.71 | 0.51 | 0.19 |
| | $[3.04, 4.09]$ | $[-1.21, -0.68]$ | $[0.61, 0.98]$ | | $[2.43, 3.27]$ | $[-1.01, -0.54]$ | $[0.53, 0.96]$ | | $[0.71, 1.17]$ | $[0.59, 0.84]$ | $[0.42, 0.80]$ | |
| 8 | 2.17 | $-0.77$ | 0.93 | 0.13 | 1.73 | $-0.40$ | 0.46 | 0.21 | 1.64 | 0.61 | 0.73 | 0.14 |
| | $[2.02, 2.33]$ | $[-0.88, -0.66]$ | $[0.71, 0.98]$ | | $[1.49, 1.91]$ | $[-0.60, -0.18]$ | $[0.09, 0.96]$ | | $[1.54, 2.01]$ | $[0.54, 0.69]$ | $[0.72, 0.88]$ | |
| 12 | 1.65 | $-0.55$ | 0.85 | 0.18 | 1.46 | $-0.25$ | 0.34 | 0.24 | 1.98 | 0.46 | 0.73 | 0.14 |
| | $[1.44, 1.86]$ | $[-0.67, -0.42]$ | $[0.72, 0.98]$ | | $[1.19, 1.67]$ | $[-0.42, -0.07]$ | $[-0.06, 0.94]$ | | $[1.88, 3.36]$ | $[0.40, 0.51]$ | $[0.71, 0.87]$ | |

| | Panel G: **All Negative** | | | | Panel H: All Positive $\frac{\text{RMSE}_i}{\text{RMSR}_i}$ | | | | Panel I: All Negative $\frac{\text{RMSE}_i}{\text{RMSR}_i}$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $H$ | Constant | $\frac{KS_{t+H}}{KS_t}$ | $R^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | Size/Bm | REV | Size/INV | Total | Momentum | ROE | Total |
| 4 | 3.16 | $-0.86$ | 0.71 | 0.23 | 0.19 | 0.12 | 0.19 | 0.19 | 0.25 | 0.21 | 0.23 |
| | $[2.55, 3.15]$ | $[-0.98, -0.63]$ | $[0.64, 0.94]$ | | | | | | | | |
| 8 | 1.96 | $-0.64$ | 0.80 | 0.21 | 0.13 | 0.12 | 0.15 | 0.14 | 0.16 | 0.26 | 0.21 |
| | $[1.47, 2.00]$ | $[-0.72, -0.46]$ | $[0.62, 0.93]$ | | | | | | | | |
| 12 | 1.56 | $-0.45$ | 0.72 | 0.24 | 0.13 | 0.12 | 0.15 | 0.14 | 0.21 | 0.28 | 0.24 |
| | $[1.04, 1.77]$ | $[-0.53, -0.30]$ | $[0.61, 0.93]$ | | | | | | | | |

**Table 5: Expected return-beta regressions,equity portfolios.** Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. Panel H and I report 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 $\widehat{R}^e_{ji} = \widehat{\lambda}_0 + \widehat{\beta}'_{ji}\widehat{\lambda}$

**Expected Return-Beta Regressions: Competing Models**

$$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$$

Estimates of Factor Risk Prices $\lambda, H = 8$

| Row # | Constant | $\frac{KS_{t+H}}{KS_t}$ | $Rm_t$ | $SMB_t$ | $HML_t$ | $MoM_t$ | $LevFac_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | $BIC$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: **25 Size/BM** | | | | | | | | | | |
| 1 | 1.54 | 0.71 | | | | | | 0.79 | 0.12 | −282.91 |
| | [1.39, 1.67] | [0.59, 0.83] | | | | | | [0.69, 0.90] | | |
| 2 | 0.90 | | | | | | 13.94 | 0.68 | 0.15 | −271.94 |
| | [0.61, 1.17] | | | | | | [11.83, 16.09] | [0.56, 0.94] | | |
| 3 | 0.97 | 0.52 | | | | | 5.51 | 0.82 | 0.11 | −284.18 |
| | [0.76, 1.18] | [0.40, 0.63] | | | | | [3.83, 7.23] | [0.79, 0.95] | | |
| 4 | 3.13 | | −1.46 | 0.69 | 1.25 | | | 0.73 | 0.13 | −271.12 |
| | [1.18, 5.01] | | [−3.31, 0.43] | [0.44, 0.95] | [0.93, 1.59] | | | [0.61, 0.90] | | |
| 5 | 3.34 | 0.50 | −2.02 | 0.29 | 0.45 | | | 0.84 | 0.10 | −282.50 |
| | [1.90.4.81] | [0.36, 0.64] | [−3.46, −0.60] | [0.06, 0.51] | [0.11, 0.79] | | | [0.80, 0.95] | | |
| Panel B**: 10 Momentum** | | | | | | | | | | |
| 6 | 2.17 | −0.77 | | | | | | 0.93 | 0.13 | −116.59 |
| | [2.02, 2.33] | [−0.88, −0.66] | | | | | | [0.71, 0.98] | | |
| 7 | 0.71 | | | | | | 13.28 | 0.17 | 0.43 | −92.18 |
| | [0.19.1.54] | | | | | | [6.17, 20.44] | [0.09, 0.98] | | |
| 8 | 1.71 | −0.76 | | | | | 3.53 | 0.93 | 0.12 | −114.69 |
| | [1.49, 1.95] | [−0.88, −0.63] | | | | | [1.38, 5.54] | [0.89, 0.99] | | |
| 9 | 7.54 | | −6.17 | 3.87 | 1.58 | 1.91 | | 0.75 | 0.19 | −101.89 |
| | [2.51, 12.53] | | [−11.43, −0.85] | [0.80, 6.97] | [−2.12, 5.31] | [1.33, 2.49] | | [0.71, 0.98] | | |
| 10 | 2.42 | −0.80 | −0.57 | 0.75 | 1.75 | 0.10 | | 0.88 | 0.12 | −108.18 |
| | [−1.47, 6.34] | [−1.05, −0.54] | [−4.71, 3.53] | [−1.55, 2.97] | [−1.02, 4.46] | [−0.69, 0.85] | | [0.87, 0.99] | | |

**Table 6: 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 1963Q1 to 2013Q4.

## Expected Return-Beta Regressions: Competing Models

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

Panel A: **25 Size/BM**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 1.54 | 0.71 | | | 0.79 | 0.12 | −282.91 |
| [1.39, 1.67] | [0.59, 0.83] | | | [0.69, 0.90] | | |
| 0.48 | | 6.88 | 1.19 | 0.49 | 0.20 | −258.63 |
| [−0.99, 1.85] | | [4.00, 9.85] | [−0.00, 2.40] | [0.33, 0.85] | | |
| 3.37 | 0.68 | −3.31 | −1.61 | 0.81 | 0.12 | −280.25 |
| [2.21, 4.16] | [0.54, 0.79] | [−5.02, −0.53] | [−2.38, −0.71] | [0.79, 0.94] | | |

Panel B: **10 REV**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 1.71 | 0.43 | | | 0.86 | 0.08 | −124.33 |
| [1.61, 1.81] | [0.35, 0.52] | | | [0.80, 0.98] | | |
| 0.71 | | 4.23 | 1.10 | 0.79 | 0.08 | −120.86 |
| [−0.02, 1.39] | | [3.23, 5.53] | [0.43, 1.86] | [0.67, 0.98] | | |
| 0.94 | 0.19 | 2.23 | 0.93 | 0.75 | 0.08 | −117.96 |
| [−0.11, 1.81] | [0.07, 0.35] | [−0.03, 4.63] | [0.04, 1.86] | [0.65, 0.98] | | |

Panel C: **25 Size/INV**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 1.67 | 0.59 | | | 0.62 | 0.16 | −272.13 |
| [1.50, 1.84] | [0.45, 0.73] | | | [0.54, 0.87] | | |
| 1.35 | | 7.51 | 0.46 | 0.60 | 0.16 | −269.89 |
| [0.27, 2.37] | | [5.02, 10.05] | [−0.44, 1.35] | [0.43, 0.90] | | |
| 2.42 | 0.32 | 2.10 | −0.62 | 0.70 | 0.13 | −276.30 |
| [1.30, 3.27] | [0.20, 0.44] | [−0.34, 4.90] | [−1.46, 0.24] | [0.61, 0.93] | | |

Panel D: **10 Momentum**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 2.17 | −0.77 | | | 0.93 | 0.13 | −116.59 |
| [3.04, 4.09] | [−1.21, −0.68] | | | [0.71, 0.98] | | |
| 4.03 | | −8.25 | −2.09 | 0.65 | 0.27 | −100.40 |
| [2.51, 5.52] | | [−11.31, −5.12] | [−3.50, −0.62] | [0.48, 0.93] | | |
| 1.81 | −0.74 | 1.85 | −0.30 | 0.92 | 0.12 | −113.78 |
| [0.95, 2.71] | [−0.87, −0.57] | [−0.62, 3.98] | [−1.25, 0.40] | [0.89, 0.99] | | |

Panel E: **10 ROE**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 1.73 | −0.40 | | | 0.46 | 0.21 | −109.09 |
| [1.49, 1.91] | [−0.60, −0.18] | | | [0.09, 0.96] | | |
| 4.33 | | −5.94 | −3.00 | 0.69 | 0.18 | −111.82 |
| [3.09, 5.42] | | [−9.38, −2.46] | [−4.00, −1.75] | [0.50, 0.95] | | |
| 3.79 | −0.30 | −0.68 | −2.34 | 0.83 | 0.12 | −116.12 |
| [2.81, 4.49] | [−0.44, −0.17] | [−3.64, 2.52] | [−3.14, −1.49] | [0.78, 0.98] | | |

Panel F: **All Positive**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 1.64 | 0.61 | | | 0.73 | 0.14 | −675.86 |
| [1.54, 2.01] | [0.54, 0.69] | | | [0.72, 0.88] | | |
| 1.08 | | 5.87 | 0.71 | 0.52 | 0.19 | −642.80 |
| [0.33, 1.82] | | [4.27, 7.42] | [0.06, 1.35] | [0.41, 0.74] | | |
| 2.66 | 0.43 | −0.44 | −0.84 | 0.70 | 0.15 | −668.71 |
| [1.84, 3.19] | [0.35, 0.51] | [−1.74, 1.62] | [−1.41, −0.23] | [0.69, 0.87] | | |

Panel G: **All Negative**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 1.96 | −0.64 | | | 0.80 | 0.21 | −218.93 |
| [2.55, 3.15] | [−0.98, −0.63] | | | [0.62, 0.93] | | |
| 4.12 | | −5.60 | −2.57 | 0.52 | 0.30 | −204.22 |
| [2.78, 5.33] | | [−8.00, −2.95] | [−3.67, −1.22] | [0.25, 0.82] | | |
| 2.83 | −0.51 | 0.13 | −1.36 | 0.80 | 0.19 | −218.36 |
| [1.92, 3.65] | [−0.64, −0.37] | [−2.02, 2.43] | [−2.24, −0.59] | [0.74, 0.95] | | |

**Table 7: 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 1963Q1 to 2013Q4.

## Expected Return-Beta Regressions: Other Asset Classes

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

Panel A: **Bonds**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 0.23 | 0.62 | | | 0.88 | 0.15 | −262.30 |
| [0.16, 0.27] | [0.57, 0.70] | | | [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 | 0.56 | −1.44 | 1.12 | 0.85 | 0.15 | −256.48 |
| [0.11, 0.28] | [0.45, 0.62] | [−2.61, −1.04] | [0.56, 1.99] | [0.78, 0.98] | | |

Panel B: **Sovereign Bonds**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 0.03 | 1.29 | | | 0.36 | 0.32 | −55.35 |
| [−0.66, 0.56] | [0.86, 1.86] | | | [0.35, 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] | | |
| −0.43 | 0.83 | 2.24 | 1.81 | 0.92 | 0.05 | −73.35 |
| [−2.37, −0.29] | [0.82, 1.49] | [−1.32, 9.23] | [0.94, 5.78] | [0.84, 0.99] | | |

Panel C: **Options**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| 3.25 | 1.71 | | | 0.82 | 0.33 | −179.67 |
| [2.87, 3.88] | [1.49, 1.97] | | | [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] | | |
| 6.39 | 0.78 | 15.47 | −5.82 | 0.98 | 0.09 | −220.14 |
| [4.56, 7.40] | [0.71, 0.88] | [13.46, 16.00] | [−5.59, −3.48] | [0.98, 0.99] | | |

Panel D: **CDS**

| Constant | $\frac{KS_{t+H}}{KS_t}$ | $EqFac_t$ | $Rm_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ | BIC |
|---|---|---|---|---|---|---|
| −0.16 | 0.74 | | | 0.93 | 0.23 | −258.74 |
| [−0.19, −0.09] | [0.67, 0.80] | | | [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] | | |
| −0.05 | 1.01 | −3.99 | −1.16 | 0.93 | 0.23 | −251.91 |
| [−0.19, 0.06] | [0.88, 1.05] | [−4.71, −2.27] | [−1.96, 0.00] | [0.93, 0.99] | | |

**Table 8: 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 1963Q1 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 $\lambda$

Panel A: **25 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 | 0.24 | 1.49 | 0.55 | 0.19 |
| | [−0.16, 0.88] | [1.08, 1.93] | [0.42, 0.88] | |
| 8 | 0.90 | 1.26 | 0.87 | 0.11 |
| | [0.83, 1.26] | [1.06, 1.42] | [0.80, 0.95] | |

Panel B: **10 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 | 0.55 | 1.23 | 0.62 | 0.12 |
| | [0.19, 1.10] | [0.84, 1.63] | [0.54, 0.95] | |
| 8 | 1.32 | 0.75 | 0.66 | 0.08 |
| | [1.30, 1.87] | [0.45, 0.82] | [0.60, 0.94] | |

Panel C: **25 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 | 0.58 | 1.19 | 0.39 | 0.19 |
| | [0.12, 1.21] | [0.79, 1.61] | [0.27, 0.83] | |
| 8 | 1.01 | 1.15 | 0.67 | 0.14 |
| | [0.94, 1.40] | [0.91, 1.39] | [0.60, 0.92] | |

Panel D: **10 Momentum**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{<90\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{<90\%}_t/Y_t}}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|
| 4 | 2.07 | 0.80 | 0.99 | 0.09 |
| | [2.01, 2.29] | [0.71, 0.86] | [0.94, 0.99] | |
| 8 | 0.93 | 0.66 | 0.90 | 0.21 |
| | [0.80, 1.42] | [0.47, 0.78] | [0.69, 0.98] | |

Panel E: **10 ROE**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{<90\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{<90\%}_t/Y_t}}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|
| 4 | 1.49* | 0.54 | 0.15 | 0.29 |
| | [1.33, 1.91] | [0.17, 0.92] | [−0.05, 0.92] | |
| 8 | 1.07 | 0.25 | 0.01 | 0.32 |
| | [0.54, 1.81] | [−0.05, 0.60] | [−0.12, 0.81] | |

Panel F: **All Positive**

| $H$ | 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 | 0.44 | 1.32 | 0.52 | 0.18 |
| | [0.39, 0.95] | [1.11, 1.59] | [0.51, 0.81] | |
| 8 | 1.05 | 1.13 | 0.77 | 0.13 |
| | [1.03, 1.54] | [1.01, 1.26] | [0.76, 0.91] | |

Panel G: **All Negative**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}\frac{\widehat{Y^{<90\%}_{t+H}/Y_{t+H}}}{\widehat{Y^{<90\%}_t/Y_t}}$ | $R^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|
| 4 | 1.79 | 0.70 | 0.73 | 0.24 |
| | [1.47, 1.84] | [0.48, 0.81] | [0.52, 0.93] | |
| 8 | 0.89 | 0.57 | 0.66 | 0.29 |
| | [0.39, 1.19] | [0.38, 0.71] | [0.42, 0.91] | |

**Table 9: Income Share and Cross Section.** Bootstrap 95% confidence intervals are reported in square brackets. All coefficients are scaled by multiple of 100. The factor is $\frac{C_t}{C_{t-1}}\left[\frac{\widehat{Y^i_t/Y_t}}{\widehat{Y^i_{t-1}/Y_{t-1}}}\right]$ using the mimicking SZ data income share factor $\widehat{Y^i_t/Y_t} = \widehat{\varsigma}^i_0 + \widehat{\varsigma}^i_1 KS_t$ for group $i$. The sample spans the period 1963Q1 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 1963Q1 to 2013Q4 with index 2009=100. The source is from Bureau of Labor Statistics.[16]

TEST PORTFOLIOS

All returns of test asset portfolios used in the paper are obtained from professor French's online data library.[17] The test portfolio includes 25 portfolios formed on Size and Book-to-Market (5 x 5), 10 Portfolios Formed on Momentum and 10 Portfolios formed on Long-Term reversal. All original returns are monthly data and we compounded them into quarterly data. The return in quarter $Q$ of year $Y$ , is the compounded monthly return over the three months in the quarter, $m1$,...,$m3$:

$$1 + R_{Q,Y} = \left(1 + \frac{R^{m1}_{Q,Y}}{100}\right)\left(1 + \frac{R^{m2}_{Q,Y}}{100}\right)\left(1 + \frac{R^{m3}_{Q1,Y}}{100}\right)$$

[16] Available at http://research.stlouisfed.org/fred2/series/PRS85006173

[17] Link: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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. We construct a quarterly MoM (momentum factor) from monthly data. The factor return in quarter $Q$ of year $Y$

$$MoM_{Q,Y} \equiv \prod_{m=1}^{3} R_{m,Q,Y}^{High} - \prod_{m=1}^{3} R_{m,Q,Y}^{Low},$$

where $m$ denotes a month within quarter $Q$, and

$$\begin{aligned} R_{m,Q,Y}^{High} &= 1/2\left(Small\ High + Big\ High\right) \\ R_{m,Q,Y}^{Low} &= 1/2\left(Small\ Low + Big\ Low\right), \end{aligned}$$

where the returns "*Small High*," etc., are constructed from data on Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ftp/6_Portfolios_ME_Prior_12_2.zip. The portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The sample spans 1963:Q1 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.[18] In this paper we use the larger sample 1963Q1 to 2013Q4. There are no negative observations on broker-dealer leverage in this sample.

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

To extend the sample to 1963Q1 to 2013Q4 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 1968Q1 to 2009Q4, with the exception of a few observations in the 1970s, a 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.

STOCK PRICE, RETURN, DIVIDENDS

The stock price is measured using the Center for Research on Securities Pricing (CRSP) value-weighted stock market index covering stocks on the NASDAQ, AMEX, and NYSE. The data are monthly. The stock market price is the price of a portfolio that does not reinvest dividends. The CRSP dataset consists of $vwretx(t) = (P_t/P_{t-1}) - 1$, the return on a portfolio that doesn't pay dividends, and $vwretd_t = (P_t + D_t)/P_t - 1$, the return on a portfolio that does pay dividends. The stock price index we use is the price $P_t^x$ of a portfolio that does not reinvest dividends, which can be computed iteratively as

$$P_{t+1}^x = P_t^x \left(1 + vwretx_{t+1}\right),$$

where $P_0^x = 1$. Dividends on this portfolio that does not reinvest are computed as

$$D_t = P_{t-1}^x \left(vwretd_t - vwretx_t\right).$$

The above give monthly returns, dividends and prices. The annual log return is the sum of the 12 monthly log returns over the year. We create annual log dividend growth rates by summing the log differences over the 12 months in the year: $d_{t+12} - d_t = d_{t+12} - d_{t+11} + d_{t+11} - d_{t+10} + \cdots + d_{t+1} - d_t$. The annual log price-dividend ratio is created by summing dividends in levels over the year to obtain an annual dividend in levels, $D_t^A$, where $t$ denotes a year hear. The annual observation on $P_t^x$ is taken to be the last monthly price observation of the year, $P_t^{Ax}$. The annual log price-dividend ratio is $\ln\left(P_t^{Ax}/D_t^A\right)$.

SCF HOUSEHOLD STOCK MARKET WEALTH

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

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

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

SCF HOUSEHOLD INCOME

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

Federal Reserve System from 1989-2013. All the income is adjusted relative to 2013 dollars. Throughout the paper, we define the labor income as

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

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

Similarly, we define the capital income

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

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

The other income is defined as

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

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

## 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 $\lambda_0$ and $\boldsymbol{\lambda}$, we choose parameters $\boldsymbol{b}$ to set the following linear combination of moments to zero

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

where

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

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

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

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

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

where

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

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

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

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

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

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

Denote

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

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

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

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

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

## Labor Share Beta Spread

A procedure sometimes employed in empirical work that studies a new factor is to use firm-level stock data from CRSP to estimate the betas for firms' exposures to the factor and then to sort stocks into portfolios on the basis of these betas. The objective is to then look at spreads in average returns across portfolios sorted on the basis of beta. Note that this procedure treats each firm equally and does not condition on any firm-level characteristics. Importantly, this procedure will *not* work when there is opposite signed exposure of different classes of firms to the same factor, as here. Sorting firms into labor (or capital) share beta categories without first conditioning on characteristics, specifically on their size and book/market ratios, and then separately their (2-12 month) prior returns, will result in a mix of firms that belong to these different groups. If there is opposite signed exposure to a single risk factor, the spread in betas can be expected to be small or nonexistent since high average return firms with one set of characteristics (e.g., high 2-12 month prior returns) will have betas of one sign, while high average return firms with another set of characteristics (e.g., the smallest stocks with the highest book/market ratios) will have betas of the opposite sign, and vice versa for the low average return firms of these respective characteristic-conditional groups. In short, the common procedure of unconditionally sorting all firms into beta portfolios to investigate the spread in returns on these portfolios is predicated on the assumption that the a single factor should produce the same signed exposure of *all* firms to that factor. But this view of the world is inconsistent with a fundamental aspect of the data, in which portfolios of two different types of firms earn high average returns but are negatively correlated.

A separate reason that this procedure is inappropriate for our application is that it does not work well for long-horizon exposures, even if we condition on characteristics. The labor share beta using all available data for each firm is based on a time-series regression of long horizon gross excess returns on the long horizon labor share

$$R^e_{j,t+H,t} = a + \beta_{j,LS,H} \left( LS_{t+H}/LS_t \right) + u_{j,t} \ .$$

This requires firms in the sample to be alive at least $H$ quarters, but substantially more than this to have degrees of freedom left to run a regression. However, for $H = 8, 10, 12$ quarters, there are far fewer firms left that survive long enough. This creates an important survivorship bias and high degree of noise in estimated betas as estimations are conducted over relatively short samples for which a few individual firms are alive.

The bottom line: firms have to be placed into portfolios that condition on characteristics in order to find spreads in average returns on portfolios of firms sorted by the beta. If there is opposite signed exposure of different types of stocks to a single risk factor, the usual unconditional procedure should lead to no spread in average returns on beta-sorted portfolios. In addition, using actual firm-level data is impractical for assessing long-horizon exposures due to survivorship bias and estimation error.

As an alternative to this procedure, we proceed as follows. We assign each firm that is included in computation of the Fama-French 25 size/book-market portfolios in a given size category the labor share beta of the book/market portfolio of which it is a part. Under this assumption, we can use labor share betas estimated on size/book-market portfolios to infer spreads in returns on portfolios of individual stocks sorted on the basis of labor share beta: firms in a given size category sorted into portfolios on the basis of labor share beta will have the labor share beta and average returns of the size/book-market portfolio to which they belong. For example, the labor share beta for firms in the smallest size category and lowest book-market group will have the same labor share beta and average return as the S1B1 size/book-market portfolio. Panel C of Table A4 shows how the labor share betas are assigned to firms that exist in different size and book-to-market categories. Note that because we study labor share betas here, the signs of the risk exposures are the opposite of those for capital share betas.

With average returns on portfolios sorted on basis of $LS$ beta from Panel C of Table A4, we compute average returns on the $LS$ beta portfolio in a given size category for $m = 1, .., 5$ groups formed on the basis $LS$ beta from lowest $LS$ beta group $(m = 1)$ to highest $LS$ beta group $(m = 5)$ and construct the spread in average returns

$$E\left(R_{st}^{(5-1)}\right) = E\left(R_{st}^{(1)}\right) - E\left(R_{st}^{(5)}\right),$$

where $s = 1, ...5$ size categories, and where $E\left(R_{st}^{(m)}\right)$ is the average return on the labor share beta portfolio with the $m$th highest beta, in size category $s$. Note that for betas formed on labor share, as opposed to capital share, the highest labor share beta groups have the lowest average returns. The OLS $t$-*statistic* for the null hypothesis that the spread in returns across $LS$ beta portfolios is zero is computed from a regression of spread $E\left(R_{st}^{(5-1)}\right)$ on a constant. The results are presented in Panel B of Table A4.They show that firms sorted on the basis of labor share betas in each size category have the right sign and exhibit large spreads.

## 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 $\lambda_0$ and $\lambda$ 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 $m$th 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 $\left\{e_{t+H,t}^{(m)}\right\}_t$ thereby generating an $m$th 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 $\left\{R_{j,t+H,t}^{(m)}\right\}_t$ from new data on $\left\{u_{j,t+H,t}^{(m)}\right\}_t$ 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 $m$th observation $\beta_{j,KS,H}^{(m)}$ from regression of $\left\{R_{j,t+H,t}^{e(m)}\right\}_t$ on $\left\{\left(\frac{KS_{t+H}}{KS_t}\right)^{(m)}\right\}_t$ and a constant.

6. We obtain an $m$th bootstrap sample $\left\{\epsilon_j^{(m)}\right\}_j$ by sampling the fitted errors $\left\{\widehat{\epsilon}_j\right\}_j$ 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 $\left\{E\left(R_{j,t}^{e(m)}\right)\right\}_j$ from new data on $\left\{\epsilon_j^{(m)}\right\}_j$ and $\left\{\beta_{j,KS,H}^{(m)}\right\}_j$ and the sample estimates $\widehat{\lambda}_0$ and $\widehat{\lambda}$.

7. We form the $m$th estimates $\lambda_0^{(m)}$ and $\lambda^{(m)}$ by regressing $\left\{E\left(R_{j,t}^{e(m)}\right)\right\}_j$ on the $m$th observation $\left\{\beta_{j,KS,H}^{(m)}\right\}_j$ and a constant. We store the $m$th sample cross-sectional $\overline{R}^2$, $\overline{R}^{(m)2}$ along with the $m$th values of $\lambda_0^{(m)}$ 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 $m$th bootstrap.

2. Obtain an $m$th 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 $\left\{\widehat{\epsilon}_j\right\}_j$ 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 $\lambda_{HS}$

3. Form the $m$th 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 $m$th observation $\left\{\beta_{j,KS,H}^{(m)}, \beta_{j,f,H}^{(m)}\right\}_j$ and a constant. We store the $m$th 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 $\lambda$

Panel A: **25 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 | 0.13 | 0.23 | 0.62** | 0.56 | 0.18 |
| | (0.11) | (1.33) | (1.96) | | |
| 8 | 1.07 | 0.10 | 0.58** | 0.84 | 0.10 |
| | (1.07) | (0.73) | (3.25) | | |
| 12 | 1.57** | 0.05 | 0.39** | 0.83 | 0.11 |
| | (2.31) | (0.51) | (3.15) | | |

Panel B: **10 REV**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}$ | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|---|
| 4 | 2.13* | −0.52 | 0.75 | 0.79 | 0.09 |
| | (1.81) | (−1.02) | (1.19) | | |
| 8 | 2.05** | −0.17 | 0.47 | 0.85 | 0.07 |
| | (3.46) | (−0.65) | (1.40) | | |
| 12 | 2.21** | −0.19 | 0.41 | 0.74 | 0.10 |
| | (2.27) | (−0.64) | (1.30) | | |

Panel C: **25 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 | 0.67 | 0.09 | 0.58** | 0.38 | 0.19 |
| | (0.65) | (0.52) | (1.96) | | |
| 8 | 1.07 | 0.11 | 0.53** | 0.68 | 0.14 |
| | (1.03) | (0.57) | (2.28) | | |
| 12 | 1.42** | 0.10 | 0.38* | 0.76 | 0.12 |
| | (1.96) | (0.76) | (1.87) | | |

Panel D: **10 Momentum**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}$ | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|---|
| 4 | 2.27** | 0.33** | −0.77 | 0.96 | 0.09 |
| | (2.55) | (2.04) | (−1.33) | | |
| 8 | 2.07** | 0.10 | −0.75** | 0.92 | 0.12 |
| | (2.81) | (0.70) | (−2.27) | | |
| 12 | 1.83** | 0.03 | −0.59** | 0.83 | 0.18 |
| | (2.99) | (0.23) | (−2.57) | | |

Panel E: **10 ROE**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}$ | $\frac{KS_{t+H}}{KS_t}$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|---|
| 4 | 3.50** | −0.24 | −0.56 | 0.79 | 0.13 |
| | (3.57) | (−1.17) | (−1.48) | | |
| 8 | 2.82** | −0.28 | −0.28 | 0.75 | 0.14 |
| | (3.69) | (−1.34) | (−1.21) | | |
| 12 | 2.47** | −0.30 | −0.23 | 0.58 | 0.18 |
| | (3.36) | (−1.58) | (−1.40) | | |

Panel F: **All Positive**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}$ | $\frac{KS_{t+H}}{KS_t}$ | $R^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|---|
| 4 | 0.44 | 0.15 | 0.61** | 0.54 | 0.18 |
| | (0.43) | (1.24) | (2.15) | | |
| 8 | 1.13 | 0.12 | 0.52** | 0.79 | 0.12 |
| | (1.20) | (0.82) | (2.83) | | |
| 12 | 1.57** | 0.07 | 0.36** | 0.80 | 0.12 |
| | (2.26) | (0.67) | (2.53) | | |

Panel G: **All Negative**

| $H$ | Constant | $\frac{C_{t+H}}{C_t}$ | $\frac{KS_{t+H}}{KS_t}$ | $R^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|---|
| 4 | 2.77** | 0.13 | −0.82* | 0.74 | 0.20 |
| | (3.61) | (0.98) | (−1.68) | | |
| 8 | 2.03** | 0.05 | −0.64** | 0.78 | 0.20 |
| | (2.87) | (0.39) | (−2.51) | | |
| 12 | 1.77** | 0.01 | −0.47** | 0.72 | 0.24 |
| | (2.94) | (0.06) | (−2.85) | | |

**Table A1: Expected return-beta regressions.** Heteroskedasticity and serial correlation corrected $t$-statistics in parenthesis. All coefficients are scaled by multiple of 100. "∗" and "∗ ∗" indicate statistical significance at the 10% and 5% level, respectively. The sample spans the period 1963Q1 to 2013Q4.

**Expected Return-Beta Regressions: Competing Models**

$$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$$

Estimates of Factor Risk Prices $\lambda, H = 8$

| Row # | Constant | $\frac{KS_{t+H}}{KS_t}$ | $HML_t$ | $MoM_t$ | $\bar{R}^2$ | $\frac{\text{RMSE}}{\text{RMSR}}$ |
|---|---|---|---|---|---|---|
| **Panel A: 25 Size/BM** | | | | | | |
| 1 | $1.54^{**}$ | $0.71^{**}$ | | | 0.79 | 0.12 |
| | (2.14) | (4.37) | | | | |
| 2 | $2.70^{**}$ | | $1.03^{**}$ | | 0.37 | 0.21 |
| | (1.05) | | (2.33) | | | |
| 3 | 0.93 | | | $-3.48^{**}$ | 0.27 | 0.23 |
| | (1.60) | | | (−2.11) | | |
| **Panel B: 10 Momentum** | | | | | | |
| 6 | $2.17^{**}$ | $-0.77^{**}$ | | | 0.93 | 0.13 |
| | (3.54) | (−3.86) | | | | |
| 7 | 0.81 | | $-1.90^{**}$ | | 0.04 | 0.46 |
| | (1.25) | | (−2.17) | | | |
| 8 | $2.41^{**}$ | | | $1.83^{**}$ | 0.79 | 0.21 |
| | (4.10) | | | (3.26) | | |

**Table A2: Expected return-beta regressions.** Heteroskedasticity and serial correlation corrected $t$-statistics in parenthesis. All coefficients are scaled by multiple of 100. "$*$" and "$**$" indicate statistical significance at the 10% and 5% level, respectively. The sample spans the period 1963Q1 to 2013Q4.

**2nd Size Quintile Value and Momentum Strategies**

A : Annualized Statistics for Value and Momentum Strategies

| $H$ | $Corr\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS2,H}\right)$ | Mean | | Sharpe Ratio | |
|---|---|---|---|---|---|
| | | $\widetilde{R}^e_{VS2,H}$ | $\widetilde{R}^e_{M,H}$ | $\widetilde{R}^e_{VS2,H}$ | $\widetilde{R}^e_{M,H}$ |
| 1 | −0.0536 | 0.0630 | 0.1543 | 0.3749 | 0.6192 |
| 4 | −0.1004 | 0.0675 | 0.1696 | 0.3628 | 0.6389 |
| 8 | −0.1474 | 0.0806 | 0.1899 | 0.3991 | 0.7007 |
| 12 | −0.1224 | 0.0946 | 0.2177 | 0.4375 | 0.7462 |

B: Regression of strategies on $\frac{KS_{t+H}}{KS_t}$

$$\widetilde{R}^e_{i,H} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,H},\ i \in \{VS2, M\}$$

| $H$ | $\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS2,H}\right)}$ | $\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS2,H}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS2,H}\right)}$ | $Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS2,H}\right)$ |
|---|---|---|---|
| 4 | −0.0604 | 1.0604 | −0.0597 |
| 8 | 0.8070 | 0.1930 | −0.0220 |
| 12 | 0.9164 | 0.0836 | −0.0149 |
| 16 | 0.9790 | 0.0210 | −0.0031 |

C: Portfolio $\omega \widetilde{R}^e_{VS2,H} + (1-\omega)\widetilde{R}^e_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega \widetilde{R}^e_{VS2,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}{std\left(\omega \widetilde{R}^e_{VS2,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}$

| $H$ | $\omega$ | Mean | Sharpe Ratio |
|---|---|---|---|
| 4 | 0.4625 | 0.1224 | 0.7525 |
| 8 | 0.4598 | 0.1396 | 0.8448 |
| 12 | 0.4769 | 0.1590 | 0.9291 |

**Table A3: Larger size value and momentum strategies.** Table spans four pages. Panel A of each reports the annualized statistics of returns on value and momentum strategies. The long horizon return on the value strategy is $\widetilde{R}^e_{V,H} \equiv \prod_{h=1}^{H} R_{SkB5,t+h} - \prod_{h=1}^{H} R_{SkB1,t+h}$ where $k = 2, 3, 4, 5$. The long-horizon return on the momentum strategy is $\widetilde{R}^e_{M,H} \equiv \prod_{h=1}^{H} R_{M10,t+h} - \prod_{h=1}^{H} R_{M1,t+h}$. Panel B uses regressions of strategies on capital share growth to compute a covariance decomposition. The first two columns of Panel B reports the fraction of (the negative) covariance between the strategies that can be explained by capital share growth exposures (first column), and the component orthogonal to capital share growth (second column), Panel C report the portfolio of two strategies that maximize the annualized sharpe ratio. We abbreviate $\widetilde{R}_{i,t+H,t}$, $i$ included in $V$, $M$, as $\widetilde{R}^e_{i,H}$. The sample spans the period 1963Q1 to 2013Q4. Table continues on the next three pages.

**3rd Size Quintile Value and Momentum Strategies**

A : Annualized Statistics for Value and Momentum Strategies

| $H$ | $Corr\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS3,H}\right)$ | Mean $\widetilde{R}^e_{VS3,H}$ | Mean $\widetilde{R}^e_{M,H}$ | Sharpe Ratio $\widetilde{R}^e_{VS3,H}$ | Sharpe Ratio $\widetilde{R}^e_{M,H}$ |
|---|---|---|---|---|---|
| 1 | −0.1321 | 0.0681 | 0.1543 | 0.4030 | 0.6192 |
| 4 | −0.1593 | 0.0753 | 0.1696 | 0.4043 | 0.6389 |
| 8 | −0.2417 | 0.0887 | 0.1899 | 0.4330 | 0.7007 |
| 12 | −0.1898 | 0.1012 | 0.2177 | 0.5057 | 0.7462 |

B: Regression of strategies on $\frac{KS_{t+H}}{KS_t}$

$$\widetilde{R}^e_{i,H} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,H},\ i \in \{VS3, M\}$$

| $H$ | $\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS3,H}\right)}$ | $\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS3,H}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS3,H}\right)}$ | $Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS3,H}\right)$ |
|---|---|---|---|
| 4 | 0.0956 | 0.9044 | −0.1258 |
| 8 | 0.5613 | 0.4397 | −0.0795 |
| 12 | 0.6059 | 0.3941 | −0.1163 |
| 16 | 0.8850 | 0.1150 | −0.0275 |

C: Portfolio $\omega \widetilde{R}^e_{VS3,H} + (1-\omega)\widetilde{R}^e_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega \widetilde{R}^e_{VS3,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}{std\left(\omega \widetilde{R}^e_{VS3,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}$

| $H$ | $\omega$ | Mean | Sharpe Ratio |
|---|---|---|---|
| 4 | 0.5015 | 0.1223 | 0.8070 |
| 8 | 0.4835 | 0.1409 | 0.8918 |
| 12 | 0.5354 | 0.1553 | 1.0279 |

**Table A3, continued**

**4th Size Quintile Value and Momentum Strategies**

| A : Annualized Statistics for Value and Momentum Strategies | | | | | |
|---|---|---|---|---|---|
| | $Corr\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS4,H}\right)$ | Mean | | Sharpe Ratio | |
| $H$ | | $\widetilde{R}^e_{VS4,H}$ | $\widetilde{R}^e_{M,H}$ | $\widetilde{R}^e_{VS4,H}$ | $\widetilde{R}^e_{M,H}$ |
| 1 | $-0.2095$ | 0.0303 | 0.1543 | 0.1856 | 0.6192 |
| 4 | $-0.1877$ | 0.0328 | 0.1696 | 0.1717 | 0.6389 |
| 8 | $-0.2310$ | 0.0365 | 0.1899 | 0.1832 | 0.7007 |
| 12 | $-0.1657$ | 0.0411 | 0.2177 | 0.2066 | 0.7462 |

B: Regression of strategies on $\frac{KS_{t+H}}{KS_t}$

$$\widetilde{R}^e_{i,H} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,H},\ i \in \{VS4, M\}$$

| $H$ | $\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS4,H}\right)}$ | $\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS4,H}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS4,H}\right)}$ | $Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS4,H}\right)$ |
|---|---|---|---|
| 4 | 0.1638 | 0.8362 | $-0.1863$ |
| 8 | 0.5249 | 0.4751 | $-0.1021$ |
| 12 | 0.6633 | 0.3367 | $-0.0951$ |
| 16 | 0.7691 | 0.2309 | $-0.0470$ |

C: Portfolio $\omega \widetilde{R}^e_{VS4,H} + (1-\omega)\widetilde{R}^e_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega \widetilde{R}^e_{VS4,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}{std\left(\omega \widetilde{R}^e_{VS4,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}$

| $H$ | $\omega$ | Mean | Sharpe Ratio |
|---|---|---|---|
| 4 | 0.3864 | 0.1167 | 0.7111 |
| 8 | 0.3677 | 0.1335 | 0.7705 |
| 12 | 0.4115 | 0.1451 | 0.8417 |

**Table A3, continued**

**5th Size Quintile Value and Momentum Strategies**

| A : Annualized Statistics for Value and Momentum Strategies | | | | | |
|---|---|---|---|---|---|
| | $Corr\left(R_{M,H}, R_{VS5,H}\right)$ | Mean | | Sharpe Ratio | |
| $H$ | | $R_{VS5,t+H}$ | $R_{M,t+H}$ | $R_{VS5,t+H}$ | $R_{M,t+H}$ |
| 1 | −0.1941 | 0.0179 | 0.1543 | 0.1249 | 0.6192 |
| 4 | −0.2290 | 0.0202 | 0.1696 | 0.1226 | 0.6389 |
| 8 | −0.2963 | 0.0209 | 0.1899 | 0.1156 | 0.7007 |
| 12 | −0.3037 | 0.0222 | 0.2177 | 0.1110 | 0.7462 |

B: Regression of strategies on $\frac{KS_{t+H}}{KS_t}$

$$\widetilde{R}^e_{i,H} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,H},\ i \in \{VS5, M\}$$

| $H$ | $\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS5,H}\right)}$ | $\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS5,H}\right)}{Cov\left(\widetilde{R}^e_{M,H}, \widetilde{R}^e_{VS5,H}\right)}$ | $Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{VS5,H}\right)$ |
|---|---|---|---|
| 4 | −0.0808 | 1.0808 | −0.2221 |
| 8 | 0.3170 | 0.6830 | −0.1784 |
| 12 | 0.4031 | 0.5969 | −0.2133 |
| 16 | 0.4793 | 0.5207 | −0.1971 |

C: Portfolio $\omega \widetilde{R}^e_{VS5,H} + (1-\omega)\widetilde{R}^e_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega \widetilde{R}^e_{VS5,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}{std\left(\omega \widetilde{R}^e_{VS5,H} + (1-\omega)\widetilde{R}^e_{M,H}\right)}$

| $H$ | $\omega$ | Mean | Sharpe Ratio |
|---|---|---|---|
| 4 | 0.3745 | 0.1137 | 0.6866 |
| 8 | 0.3630 | 0.1286 | 0.7559 |
| 12 | 0.3837 | 0.1427 | 0.8232 |

**Table A3, continued**

**Average Excess Returns Spread, $H = 8$**

| Panel A: Average Excess Returns Sorted by Size (Row) and BM (Column) | | | | | | |
|---|---|---|---|---|---|---|
| | 1(*low*) | 2 | 3 | 4 | 5 (*high*) | 5 − 1<br>t (5 − 1) |
| 1(*small*) | 1.19 | 2.66 | 2.75 | 3.27 | 3.80 | 2.61<br>(4.53) |
| 2 | 1.69 | 2.37 | 2.97 | 3.02 | 3.28 | 1.59<br>(2.70) |
| 3 | 1.68 | 2.52 | 2.51 | 3.92 | 3.41 | 1.72<br>(2.91) |
| 4 | 1.98 | 1.84 | 2.24 | 2.70 | 2.76 | 0.78<br>(1.36) |
| 5 (*big*) | 1.48 | 1.60 | 1.49 | 1.73 | 1.97 | 0.49<br>(0.98) |
| 5 − 1 | 0.29 | −1.05 | −1.26 | −1.54 | −1.83 | |
| t (5 − 1) | (0.37) | (−1.59) | (−2.09) | (−2.83) | (−2.95) | |

| Panel B: Average Excess Returns Sorted by Size (Row) and LS Beta (Column) | | | | | | |
|---|---|---|---|---|---|---|
| | 1(*low*) | 2 | 3 | 4 | 5 (*high*) | 5 − 1<br>t (5 − 1) |
| 1(*small*) | 3.80 | 3.27 | 2.75 | 2.66 | 1.19 | −2.61<br>(−4.53) |
| 2 | 3.28 | 2.97 | 3.02 | 2.37 | 1.69 | −1.59<br>(−2.70) |
| 3 | 3.41 | 2.51 | 3.92 | 2.52 | 1.68 | −1.72<br>(−2.91) |
| 4 | 2.76 | 2.70 | 2.24 | 1.84 | 1.98 | −0.78<br>(−1.36) |
| 5 (*big*) | 1.97 | 1.73 | 1.49 | 1.60 | 1.48 | −0.49<br>(−0.98) |
| 5 − 1 | −1.83 | −1.54 | −1.26 | −1.05 | 0.29 | |
| t (5 − 1) | (−2.95) | (−2.83) | (−2.09) | (−1.59) | (0.37) | |

| Panel C: Labor Share Betas Sorted by Size (Row) and BM (Column) | | | | | |
|---|---|---|---|---|---|
| | 1(*low*) | 2 | 3 | 4 | 5 (*high*) |
| 1(*small*) | 0.78 | −1.94 | −2.63 | −2.74 | −5.27 |
| 2 | −1.48 | −2.21 | −2.95 | −2.61 | −3.81 |
| 3 | −1.16 | −2.61 | −3.30 | −3.15 | −3.74 |
| 4 | −0.27 | −2.66 | −2.69 | −2.70 | −3.22 |
| 5 (*big*) | 1.19 | −0.34 | −0.36 | −0.56 | −0.85 |

**Table A4:** Equally weighted portfolio excess returns are reported in quarterly percentage point. Labor share betas are estimated using long horizon regression of long horizon quarterly returns on long horizon Labor Share Growth. 5-1 stands for the difference between returns in corresponding group 5 and 1. The sample spans the period 1963Q1 to 2013Q4