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ABSTRACT

Value and momentum strategies earn persistently large return premia yet are negatively correlated. Why? We find that the negative correlation is largely attributable to opposite signed exposure of value and momentum to long-horizon growth in the capital share of income, which explains up to 85% of the variation in returns on size-book/market portfolios and up to 95% of momentum returns, while outperforming popular return-based factor models. Opposite signed exposure of value and momentum to capital share risk coincides with opposite signed exposure to the income shares of stockholders in the top 10 versus bottom 90 percent of the stock-wealth distribution.

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1 Introduction

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. But a large number of real-world frictions, individual-specific risks, informational asymmetries, and/or possible behavioral factors could in theory lead to departures from the conditions under which such a pricing kernel is an appropriate measure of systematic risk. These departures represent potentially important sources of heterogeneity that may lead some households to own no stocks and to differences within stockholding households as to which stocks are held.

One place where heterogeneity is clearly evident is in the distribution of stock market wealth. Many households own no equity at all, but even among those who do, most own very little. Although almost 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. If shareholders located in different percentiles of the wealth distribution have heterogeneous incomes, information, beliefs, or preferences, they may pursue different investment strategies, thereby creating an additional layer of heterogeneity important for the pricing of stocks. A central question that to-date has no definitive empirical answer is how quantitatively important such heterogeneity might be for explaining key patterns in U.S. stock pricing, such as the persistently large return premia on well known portfolio strategies like value and momentum.

The desire to jointly explain momentum and value premia within a single empirical model is an important objective of finance research. This objective presents a special challenge for asset pricing theories because both strategies produce high average returns yet are negatively correlated (Asness, Moskowitz, and Pedersen (2013)). As a consequence, the empirical models

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

that have so far worked best to explain the data rely on separate priced factors for momentum and value (Fama and French (1996), Asness, Moskowitz, and Pedersen (2013), Hou, Xue, and Zhang (2015)). But this approach creates a new puzzle, since it is unclear what economic model of investor utility would imply separate risk factors for different high return strategies. The essential unanswered question is, why are the two strategies negatively correlated?

The empirical model we study implies that a quantitatively large part of the negative correlation in U.S. data is driven by opposite signed exposure to low frequency capital share risk. This key finding 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) against estimated capital share betas for exposures over a horizon of $H = 8$ quarters. Because of this strong opposite signed exposure, models with capital share risk can simultaneously explain economically large magnitudes of the return premia on momentum and size-book/market portfolios without requiring separate factors to do so. Moreover, a single capital share risk factor eliminates the explanatory power of the separate return-based factors long used to explain value and momentum premia in U.S. data. These findings run contrary to theories in which the rewards to value and momentum are earned entirely from covariance of their *un*correlated components with separate priced factors. Indeed, our results imply 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 an important role in their outsized rewards.

Of course, the findings presented here raise their own questions. Why is the capital share an important risk factor, and why are value and momentum premia inversely exposed to it? Evidence suggests that factors share movements are strongly related to the long-run performance of the aggregate stock market. Lettau and Ludvigson (2013) (LL) and Greenwald, Lettau, and Ludvigson (2014) (GLL) estimate an important role for a persistent factors-share shock that shifts labor income without moving aggregate consumption. Given that consumption is financed out of labor and capital income, such a shock must eventually move capital income opposite to labor income. This paper turns to the cross-section of equity returns and considers the implications of such capital share risk for shareholders located at different points in the wealth distribution.

We argue that shareholders located in different percentiles of the stock wealth distribution are likely to have marginal utilities that vary inversely with the capital share. We call these inversely related components *systematic* heterogeneity.[2] To see why, observe that, because wealth is so concentrated, most working-age households (including most shareholders) have relatively small amounts of capital income and finance most of their consumption out of labor earnings. Fixing aggregate consumption, these shareholders are, on average, likely to realize higher consumption from an increase in the labor share. By contrast, the wealthiest households earn large amounts of income from investments and are likely to realize lower consumption from an increase in the labor share (conversely higher consumption from an increase in the capital share). Consistent with this, we find that an increase in the national capital share is *positively* correlated with the income share of the top 10% of stockholders in the SCF, while it is strongly *negatively* correlated with the income share of stockholders in the bottom 90%. Opposite signed exposure of value and momentum to the capital share is therefore synonymous with opposite signed exposure to the income shares of these two groups of stockholders.

To investigate whether risks associated with the capital share are empirically related to equity premia in cross sections of stock returns, we proceed in three steps.

First, we investigate a model of the SDF in which the systematic cash flow risk over which investors derive utility depends directly on the capital share. This *capital share SDF* is derived from a power utility function over "capital consumption," defined to equal aggregate (average across households) consumption C_t, times the capital share raised to a power χ. The standard Lucas-Breeden (Lucas (1978) and Breeden (1979)) representative agent consumption capital asset pricing model (CCAPM) is a special case when $\chi = 0$. When non-zero, the sign of

[2] Systematic heterogeneity may be contrasted conceptually with the more commonly modeled idiosyncratic heterogeneity generated from i.i.d. shocks.

χ governs the sign of an asset's exposure to capital share risk. In an approximate linearized version of this SDF there are two risk factors: aggregate consumption growth and capital share growth, and the sign on the price of capital share risk is governed by the sign of χ. Since a risky asset is defined to be one that is negatively correlated with marginal utility growth (positively correlated with consumption growth), estimates of χ should be *positive* when this model is confronted with cross-sections of returns priced "as if" the marginal investor were a representative of the top 10 percent of the wealth distribution who is likely to realize *higher* consumption from an increase in the capital share, and *negative* when estimated on cross-sections priced as if the marginal investor were a representative of the bottom 90 percent who is likely to realize *lower* consumption. Observe that if the standard representative agent specification were a good description of the data, $\chi = 0$ and the share of national income accruing to capital should not be priced positively or negatively. More generally, if there in fact exists a single SDF for pricing all asset classes, estimates of χ should not differ by asset class.

Second, we pay close attention to the horizon over which movements in the capital share may matter for return premia, with special focus on lower frequency fluctuations. Evidence in LL and GLL indicates the presence of a slow moving factors-share shock that affects the aggregate stock market over long horizons. These low frequency shocks can nevertheless have large effects on *un*conditional expected return premia measured over short horizons. In order to isolate potentially important low 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. These lower frequency risk exposures can then be related to cross-sections of *short*-horizon average return premia.

The third step in our investigation is to explicitly relate movements in the aggregate capital share to movements in the income shares of households located in different percentiles of the stock wealth distribution. In analogy to the capital share SDF, we study *percentile*-

specific SDF proxies relevant for households located in different percentiles of the stock wealth distribution. These are based on the marginal rate of substitution from a power utility function over aggregate consumption times a share θ_t^i, where θ_t^i equals the ith percentile's share of national income raised to a power $\chi^i \geq 0$. Because observations on income shares across the wealth distribution are available less frequently and over a shorter time period than are capital share data, we use a regression along with quarterly observations on the capital share to generate a longer time-series of income share "mimicking factors" that are used to construct values for θ_t^i and proxies for percentile-specific SDFs.

Our main findings are summarized as follows. First, we show that opposite signed exposure of value and momentum to capital share risk explains a large fraction of the negative covariance between these strategies and that long-horizon capital share growth is strongly priced in their cross-sections, especially as we isolate lower frequency exposures over horizons H from 8 to 12 quarters. Specifications using the capital share SDF explain up to 85% of the variation in average quarterly returns on size-book/market sorted portfolios and up to 95% of the variation on momentum portfolios. The estimations strongly favor positive values for χ when pricing size-book/market portfolios, and negative values when pricing momentum portfolios, indicating the presence of opposite signed exposure of value and momentum to capital share risk. Similarly, the risk prices for capital share exposure in linearized models are strongly positive when pricing size-book/market portfolios, but strongly negative when pricing momentum portfolios. We also consider portfolios sorted on long-run reversal and find that models with capital share risk explain up to 90% of the quarterly return premia on these portfolios with χ is strongly positive, as for size-book/market portfolios. Thus, contrarian strategies such as value and reversal are found to be positively exposed to capital share risk, while return-chasing strategies such as momentum are negatively exposed.

Next we estimate SDF models on these portfolios using the percentile-specific SDF proxies. When we allow the SDF to be a weighted average of the top 10 and the bottom 90th percentiles' marginal rate of substitution (MRS), the estimations overwhelmingly place virtually all the weight on the top 10% for pricing size-book/market portfolios (and long-run reversal portfolios), while they put the vast majority of weight on the bottom 90% for pricing momentum portfolios. This result is inconsistent with models in which heterogeneous agents invest in the same assets. In such a model, the marginal rate of substitution of any household long in the priced assets, or any weighted average of these, would be a valid SDF that could explain these return premia.

The SDFs we study depend both on aggregate consumption growth and on growth in the capital share. To distinguish their roles, we estimate expected return-beta representations using approximate linear SDFs where these two variables are separate priced risk factors. Doing so, we confirm the findings of a growing literature showing that exposure to lower frequency aggregate consumption growth has greater explanatory power for cross-sections of average returns than do models based on short-run exposure. But we find that these lower frequency components of aggregate consumption growth are simply proxying for lower frequency capital share risk that appears to be the true driver of return premia. Capital share risk exposure explains a much larger fraction of every set of test portfolios we study and long-horizon consumption betas lose their explanatory power once the corresponding long-horizon capital share beta is included.

We compare the performance of the long-horizon capital share betas for explaining value and momentum portfolios with several other models: the Fama-French three-factor model for pricing size-book/market portfolios (Fama and French (1993)), the Fama and French (1996) four-factor model that augments the three factor model to include a momentum factor due to Carhart (1997), and the intermediary-based SDF model of Adrian, Etula, and Muir (2014) which uses the single leverage factor $LevFac_t$ for pricing both sets of returns. Models with low frequency fluctuations in the capital share as the single source of aggregate risk generate lower pricing errors than these other models and explain a larger fraction of the variation in average returns on both sets of portfolios. In a horse race where the capital share beta is included alongside betas for these other factors, the latter exhibit significantly reduced risk prices and loose their statistical significance while the capital share beta remains strongly significant. Moreover, a model with exposure only to long horizon capital share risk produces a very small pricing error for the challenging "micro cap" growth portfolio that Fama and French (2015) find is most troublesome for their newer five factor model. Finally, we find that models with capital share risk contain much of the same information for size-book/market and momentum portfolios contained in the four factor q-model of (Hou, Xue, and Zhang (2014)) and (Hou, Xue, and Zhang (2015)), and also explain sizable fractions of the variation in portfolio returns sorted on the basis of size and operating profitability, and size and investment.

The evidence presented here poses a challenge for theory. This can be understood by restating what the findings mean in terms of hypothetical marginal investors. Assets characterized by heterogeneity along the value, growth, and long-run reversal dimensions appear to be priced *"as if"* the marginal investor in these strategies were a representative of the top 10% of the wealth distribution, one whose consumption growth is likely to be positively related to capital share growth. Assets characterized by heterogeneity along the near-term past return dimension are priced *as if* the marginal investor were a representative of the bottom 90% of the wealth distribution, with consumption growth negatively related to capital share growth. This could be described as a "quasi-market segmentation," as distinct from a segmentation across asset classes, in which different stockholders hold different portfolios of the same stocks. This description is a restatement of the results, rather than an explicit model of microeconomic investment behavior. Whether shareholders located in different percentiles of the wealth distribution do in fact have a central tendency to pursue different investment strategies remains an open question. Our data do not furnish direct evidence on the specific investment strategies taken by individual households located at different places in the wealth distribution, or an empirical explanation for why they might differ (the conclusion discusses some simple stories). Providing this type of direct evidence requires both an extensive micro-level study that is beyond the scope of this paper and, more crucially, far more detailed information on individual households' investments and returns over time than what is currently publicly available for

U.S. investors. (However, a burgeoning literature on retail investment using richer datasets from other countries provides some evidence, which we discuss below.) In what follows, we pursue an empirical approach that allows the data to be described as if there could be two different SDFs, with opposite-signed exposure to capital share risk, without taking a stand on whether this representation closely corresponds to actual microeconomic behavior. The conclusion discusses a number of alternative interpretations of our findings.

The rest of this paper is organized as follows. The next section discusses related literature not discussed above. Section 3 discusses data and preliminary analyses. Section 4 describes the econometric models to be estimated and Section 5 discusses the results of these estimations. Section 6 concludes.

2 Related Literature

Partial evidence on the portfolio decisions of different investors can be found in a growing literature on retail investing that studies style tilts. U.S. datasets on individual investment behavior are not rich enough to provide a complete picture of a household's investment decisions over time. One approach is to study trades from proprietary brokerage service account data. But brokerage service accounts from a single service provider may not be representative of the entire portfolio of an investor, if that investor has multiple accounts, or untracked mutual fund, IRA, or 401K investments. Accounts from a single brokerage service dealer are also unlikely to contain representative samples of U.S. investors as a whole. There are a very small number of other developed countries, however, for which the available data offer a more comprehensive picture of investors' wealth over time. Grinblatt and Keloharju (2000) use a dataset for Finland that records the holdings and transactions of the universe of participants in the markets for Finnish stocks. Over a two-year period from December 1994 to December 1996, they find that "sophisticated" investors (defined as institutional investors or wealthy households) pursue momentum strategies and achieve superior performance compared to less sophisticated investors that are more likely to exhibit contrarian behavior. One possible caveat with these findings is that the time frame is limited to a two-year period when much could have changed in the 20 years since this time, as both value and momentum became increasingly popularized investment strategies.

Using more recent data, Betermier, Calvet, and Sodini (2014) examine a similarly comprehensive Swedish dataset and find different results, namely that the value tilt is strongly increasing in both financial and real estate wealth. But the annual frequency of these data makes it difficult to consider higher-frequency trading patterns such as momentum. Campbell, Ramadorai, and Ranish (2014) study a higher frequency dataset from India that has information on both trades and holdings. They find that the log of account value correlates negatively with value and positively with momentum tilts. An important feature of these findings is that India is an emerging market economy whose investor and capitalization rates have grown quickly in recent years, suggesting that investors are less experienced than those in developed economies with mature markets. They are also much less wealthy, as indicated by the small average account sizes in these data. Thus the Indian households studied by Campbell, Ramadorai, and Ranish (2014) are arguably more comparable to those in the bottom 90% of the U.S. wealth distribution rather than the top 10%. If new investors with low wealth are, for whatever reason, more likely to tilt toward momentum, it is reasonable to expect that they increasingly do so over a range as stockholdings increase from zero. What is clear from each of these studies is that there is measurable heterogeneity in portfolio decisions that varies with investor wealth and age.

Trend-following is a phenomenon that is likely to be closely related to active momentum tilting, since both involve investing in the most popular stocks that have recently appreciated. 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. By contrast, value tilting requires a contrarian view, and Betermier, Calvet, and Sodini (2014) find that value tilting investors are not only wealthier, they are older than non-value-tilting investors.

These patterns are consistent with the evidence of this paper because investors in the top 10% of the SCF stock wealth distribution are substantially older than those in the bottom 90%. In 2013, the median age of a stockholder in the bottom 90% was 50 while it was 61 for the top 10%.

Our findings are related to an older literature that finds evidence supportive of the hypothesis that households behave "as if" they had access to different investment opportunity sets. Barberis and Shleifer (2003) consider investors with preferences for specific styles for explaining several empirical anomalies related to asset classes. Campbell (2006) suggests that some households voluntarily limit the set of assets they trade to avoid making mistakes. Pavlova and Rigobon (2008) study a model where style arises because of portfolio constraints. Chien, Cole, and Lustig (2011) argue for heterogeneous investor trading technologies to explain the skewness and kurtosis of the wealth distribution. Vayanos and Vila (2009) explain the term structure via the interaction of investor clienteles with preferences for specific maturities and risk-averse arbitrageurs.

We build on a previous 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, we consider the possibility that investors may differ in systematic ways, rather than in (only) idiosyncratic ways. These factors create an additional layer of heterogeneity that could be important for the pricing of stocks. Just as we cannot expect the marginal rates of substitution of non-stockholders to explain stock returns, there is no reason to expect the marginal rates of substitution of a subset of shareholders to price cross-sections of stocks they don't invest in.

Kogan, Papanikolaou, and Stoffman (2002) study a production-based asset pricing model with limited stock market participation that is consistent with our finding that value stocks are more highly correlated with capital share risk and earn a premium over growth stocks for this reason. The model is silent on the implications for momentum strategies, however.

It should be emphasized that our findings run contrary to production-based theories in which the rewards to value and momentum are earned entirely from covariance of their *un*correlated components with separate priced factors. Thus our findings cannot, for example, be explained by production-based asset pricing theories in which value and momentum premia are explained by their covariances with separate technology shocks, as in Li (2012).

Part of our results have a flavor similar to those of Malloy, Moskowitz, and Vissing-Jorgensen (2009). These authors show that, for shareholders as a whole, low-frequency exposure to shareholder consumption growth explains the cross-section of average returns on size-book/market portfolios better than low frequency exposure to aggregate consumption growth. Their study does not investigate momentum returns. We add to their insights by showing that low frequency exposure to capital share risk (an important determinant of inequality *between* shareholders) drives out long horizon aggregate consumption for explaining both sets of portfolio return premia, and in doing so helps to explain why value and momentum strategies are negatively correlated.

Finally, our paper is related to a growing body of theoretical and empirical work that considers the role of labor compensation as a systematic risk factor for aggregate stock and bond markets (Danthine and Donaldson (2002); Favilukis and Lin (2013a, 2013b, 2015), GLL, Marfe (2016)), and to a literature that finds evidence that the returns to human capital are negatively correlated with those to stock market wealth (Lustig and Van Nieuwerburgh (2008); Lettau and Ludvigson (2009); Chen, Favilukis, and Ludvigson (2014)), LL, GLL). Collectively, these studies point to a significant role for factors share movements in driving aggregate financial returns. But because these models all presume a representative shareholder, any investment strategy earning a positive risk premium must be exposed (with the same sign) to the representative shareholder's marginal utility. As a consequence, this type of framework is silent about why value and momentum strategies are negatively correlated, and cannot explain why they would exhibit strong opposite signed exposure to low frequency fluctuations in the capital share, as documented here.

3 Data and Preliminary Analysis

This section describes our data. A complete description of the data and our sources is provided in the 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, 10 momentum portfolios, and 10 long-run reversal portfolios.[3] Aggregate consumption is measured as real, per capita expenditures on nondurables and services, excluding shoes and clothing from the Bureau of Labor Statistics (BLS).

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 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 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. These findings suggest that the main difficulties with measuring the labor share primarily pertain to getting the *level* right. Our results rely on *changes* in the labor share, and we maintain the hypothesis that they are

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

likely to be informative about opposite signed changes in the capital share. For brevity, we refer to $KS_t = 1 - LS_t$, where LS_t is the BLS nonfarm labor share, as the *capital share* and study changes in this measure as it relates to U.S. stock returns.

Our empirical analysis is based on the growth 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.

We investigate how movements in the capital share relate to movements in the income shares of households in different percentiles of the stock wealth distribution using 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. The empirical literature on limited stock market participation and heterogeneity has instead relied on the Consumer Expenditure Survey (CEX). This survey has the advantage over the SCF of asking directly about consumer expenditures. It also has a limited panel element. On the other hand, as a measure of assets and liabilities, it is considered far less reliable than the SCF and is unlikely to adequately measure the assets, income, *or* consumption of the wealthiest shareholders.[4] Since our analysis considers heterogeneity related to the skewness of the wealth distribution, we require the best available information on assets. The SCF is uniquely 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. The 2013 survey is based on 6015 households. We start our analysis with the 1989 survey and use the survey weights to combine the two samples in every year.[5]

[4]The CEX surveys households in five consecutive quarters but asks about assets and liabilities only in the fifth quarter. CEX answers to asset questions are often missing for more than half of the sample and much of the survey is top-coded because the CEX gives the option of answering questions on asset holdings by reporting either a top-coded range or a value. 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)).

[5]There are two earlier surveys, but the survey in 1986 is a condensed reinterview of respondents in the 1983

We begin with a preliminary analysis of data from the SCF on the distribution of wealth and earnings. Panel A of Table 1 shows the distribution of stock wealth across households, conditional on the household owning a positive amount of corporate equity, either directly or indirectly. Stock wealth is highly concentrated. The top 5% owns 61% of the stock market and the top 10% owns 74%. The top 1% owns 33%. Wealth is more concentrated when we consider the entire population, rather than just those households who own stocks. Panel B shows that, among all households, the top 5% of the stock wealth distribution owns 75% of the stock market in 2013, while the top 10% owns 88%.

Panel C of Table 1 reports the "raw" stock market participation rate, 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 in stock market ownership patterns.

Table 2 shows the relation between income shares of households located in different percentiles of the stock wealth distribution and changes in the national capital share. Income Y_t^i (from all sources, including wages, investment income and other) for percentile group i is

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survey.

divided by aggregate income for the SCF population, Y_t, and regressed on $(1 - LS_t)$ using the triennial data from the SCF.[6] The left panel of the table reports regression results for all households, and 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 42% of the variation in the income shares of the top group, and about the same fraction for the bottom group. This is especially impressive given that some of the variation in income shares is invariably attributable to survey measurement error that would create volatility in the estimated residual. The right panel shows that the results are qualitatively similar conditioning on the shareholder population. Income shares of stockowners in the top 10% are increasing in the capital share, while those of stockowners in the bottom 90% are decreasing. The estimated relationships are similar, but the fractions explained are smaller and closer to 30% for these groups. This is not surprising because focusing on just shareholders masks a potentially large part of gains to the wealthiest from a decline in the labor share that arises from the ability to pay all workers (including nonshareholders) less, while households in the bottom group who own stocks are at least partly protected from such a decline simply by owning stocks. The estimates in the right panel are less precise, (although this is not true for the subgroup in the 90-94.99 percentile), as expected since the sample excluding non-stockholding households is much smaller. It is notable, however, that the estimated coefficients on the capital share are not dissimilar across the two panels for the top 10 and bottom 90 percentile groups.

[6] Observations are available quarterly for LS_t so we use the average of the quarterly observations on $(1 - LS_t)$ over the year corresponding to the year for which the income share observation in the SCF is available.

To assess how the consumption growth rates of these two groups of shareholders might be related, we examine the growth in aggregate consumption times the observed income share of each group. Ideally, we would multiply aggregate consumption times the consumption share of each group. Since we do not observe consumption of individual households in the SCF, we use income shares in their place. While income shares do not equate with consumption shares, the two are very likely to be positively correlated.[7] Figure 3 provides evidence suggestive of a negative correlation between the consumption growth rates (and therefore marginal utility growth rates) of shareholders in the top 10 and bottom 90th percentiles of the stock wealth distribution. The top panel plots annual observations on the gross *growth* rate of $C_t \frac{Y_t^i}{Y_t}$ for the years available from the triennial SCF data, 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 SCF 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 owning stocks. 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 (in the right panel) along with quarterly observations on the capital share to generate a longer time-series of income share "mimicking factors" that extends over the larger and higher frequency sample for which data on LS_t are available. Both panels of the figure display a clear negative comovement between these group-level consumption growth proxies. The common component in this variable, accounted for by aggregate consumption growth, is more than offset by the negatively correlated component driven by capital share growth. Using the triennial data, the correlation is -0.75. In the quarterly data, it is -0.64. We view this evidence as suggestive of a negative correlation between the marginal utilities of these two groups of shareholders.[8]

[7] As discussed, other household surveys, such as the CEX, provide limited information over time on consumption, but they are subject to a large amount of measurement error, especially for the wealthy who have significantly higher non-response rates.

[8] The common component could be relatively more important for individual consumption growth if con-

We now turn to how movements in the capital share are related to value and momentum returns. Table 3 presents a variety of empirical statistics for value and momentum strategies. The return on the value strategy is the return on a long-short position designed to exploit the maximal spread in returns on the size-book/market portfolios. This is 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., $R_{V,t+H,t} \equiv R_{S1B5,t+H,t} - R_{S1B1,t+H,t}$. 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 M10 and short in M1, i.e., $R_{M,t+H,t} \equiv R_{M10,t+H,t} - R_{M1,t+H,t}$. 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. We 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, a portfolio of the two has an even higher Sharpe ratio (right-most column). Return premia and Sharp ratios rise with the horizon.

Panel B of Table 3 shows results from regressions of 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

sumption shares are less volatile than income shares. In the estimation of percentile-specific SDFs below, we directly allow for this possibility by specifying consumption of percentile i to equal $C_t \left(\frac{Y_t^i}{Y_t}\right)^{\chi^i}$, where consumption shares can be smoother than income shares if $0 < \chi^i < 1$. But we find that a value of $\chi^i = 1$ fits the data well when explaining return premia on all the portfolios we explore, suggesting little or no consumption smoothing, an outcome that would be optimal if factors share shocks are close to permanent, as they appear to be in the data. We discuss this below.

related to momentum strategy returns. 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 the capital share 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.[9] The three right-most columns of panel B give the results of a covariance decomposition for $R_{V,t+H,t}$ and $R_{M,t+H,t}$. The third column shows the fraction of the (negative) covariance between $R_{V,t+H,t}$ and $R_{M,t+H,t}$ that is explained 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 70% of the negative covariance between the returns on these strategies.

Panel C of Table 3 shows the correlation matrix for strategies on all portfolios we examine for $H = 8$ period returns. Several of these portfolios are discussed below in the section that covers other test assets. Value strategy returns are negatively correlated with strategies based on momentum and operating profitability, but positively correlated with strategies based on reversal and investment. Momentum strategy returns are negatively correlated with strategies based on reversal and investment, but positively correlated with strategies based on operating profitability.

Statistics in Table 3 were presented for the value strategy in the size quintile that delivers

[9]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 labor share growth are small over horizons reported above, although they increase with H.

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 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. For the intermediate quintiles, a pattern similar to that exhibited by the smallest stock value strategy emerges. One difference is that opposite signed exposure to capital share risk explains an even larger fraction of the negative covariance between the 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 $H = 12$.

4 Econometric Models

Our main analysis is based on nonlinear Generalized Method of Moments (GMM Hansen (1982)) estimation of cash flow models that are power utility functions over a measure of systematic cash flow risk. These models imply 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. We explore econometric specifications of M_{t+1} that are based on a power utility function over an empirical proxy for some an investor's consumption, as described below.

Two comments are in order. First, the estimation allows for the possibility that different "average," or representative, investors may choose different investment strategies, but we don't model the portfolio decision itself. Thus the approach does not presume that portfolio decisions are made in a fully rational way. They could, for example, be subject to various forms of imperfectly rational inattention or other biases. This empirical approach does assume that, conditional on these choices, a representative investor behaves in at least a boundedly rational way to maximize utility, thereby motivating a general specification like (1), which we assume holds for any asset with gross excess return R^e_{t+1} that the investor engages in. Second, we view the power utility specification as an approximation that is likely to be an imperfect description of investor preferences and thus the SDF an incomplete model of risk. For this reason our application makes use of statistics such as the Hansen-Jaganathan distance (Hansen and Jagannathan (1997)) that explicitly recognizes model misspecification.

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

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

and the gross H-period excess return

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

Our approach has three steps. First, we investigate a model of the SDF in which the systematic cash flow risk over which investors derive utility depends directly on the capital share. In this model, the cash flow "capital consumption" C^k_t is equal to aggregate (average across households) consumption, C_t, times the capital share raised to a power χ: $C^k_t \equiv C_t (1 - LS_t)^{\chi}$. The capital share SDF is based on a standard power utility function over C^k_t, i.e., $M^k_{t+1} = \delta \left(\frac{C^k_{t+1}}{C^k_t} \right)^{-\gamma}$, where δ and γ are both nonnegative and represent a subjective time-discount factor and a relative risk aversion parameter, respectively. We investigate more general long-horizon (H-period) versions of the SDF, as discussed below:

$$M_{t+H,t}^{k} = \delta^{H}\left[\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left(\frac{1-LS_{t+H}}{1-LS_t}\right)^{-\gamma\chi}\right]. \tag{3}$$

When $H = 1$, $M_{t+H,t}^{k} = M_{t+1}^{k}$. The Lucas-Breeden (Lucas (1978) and Breeden (1979)) representative agent consumption capital asset pricing model (CCAPM) is a special case when $\chi = 0$. In GLL, shareholder consumption is a special case with $\chi = 1$.

Note that, *fixing* C_{t+H}/C_t, capital consumption growth C_{t+H}^{k}/C_t^{k} is either an increasing or decreasing function of the growth in the capital share $(1 - LS_{t+H}) / (1 - LS_t)$, depending on the sign of χ. Since a risky asset is defined to be one that is positively correlated with C_{t+H}^{k}/C_t^{k} (negatively correlated with $M_{t+H,t}^{k}$), estimates of χ from Euler equations pricing cross sections of stock returns should be *positive* when those stocks are priced "as if" the marginal investor were a representative of the top 10% of the stock wealth distribution who realizes higher consumption growth from an increase in capital share growth, and *negative* when those stocks are priced "as if" the marginal investor were a representative of the bottom 90% likely to realize lower consumption growth from an increase in capital share growth.

The capital share SDF depends both on consumption growth and on growth in the capital share. To distinguish their roles, we also estimate approximate linearized versions of the SDF, where the growth rates of aggregate consumption and the capital share are separate risk factors:

$$M_{t+H,t}^{k,lin} \approx b_0 + b_1\left(\frac{C_{t+H}}{C_t}\right) + b_2\left(\frac{KS_{t+H}}{KS_t}\right). \tag{4}$$

Although this is only an approximation of the true nonlinear SDF, the *sign* of b_2 is determined by the sign of χ and this in turn determines the sign of the risk price for exposure to capital share fluctuations in expected return beta representations. Observe that if the representative agent specification were a good description of the data, the share of national income accruing to capital should not be priced (positively or negatively) once a pricing kernel based on aggregate consumption is introduced. The standard representative agent consumption CAPM (CCAPM) of Lucas (1978) and Breeden (1979) is again a special case when $\chi = 0$ implies $b_2 = 0$. More generally, if there exists a single SDF for pricing all asset classes, estimates of χ and/or b_2 should not differ in sign by asset class.

The second step in our analysis requires us to pay close attention to the horizon over which movements in the capital share may matter for stock returns, with special focus on lower frequency fluctuations. 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 $R^e_{j,t+1}$, estimating *this* relation may not reveal all the true covariance risk that determine return premia. This is likely to be the case when the SDF is subject to multiple shocks operating at different frequencies where some of the important drivers of this risk are slow-moving shocks that operate at lower frequencies. As emphasized by Bandi, Perron, Tamoni, and Tebaldi (2014) and Bandi and Tamoni (2014), important low frequency relations can be masked in short-horizon data by higher frequency "noise" that may matter less for unconditional expected returns. GLL report evidence of a slow moving factors-share shock that plays a large role in aggregate stock market fluctuations over long horizons but not over short horizons. These slow moving, low frequency shocks can nevertheless have large effects on the long-run level of the stock market and on *un*conditional return premia measured over shorter horizons. In order to identify possibly important low frequency components in capital share risk exposure, we follow the approach of Bandi and Tamoni (2014) and measure covariances between *long*-horizon (multi-quarter) returns $R_{t+H,t}$ and risk factors $\frac{C_{t+H}}{C_t}$ and $\frac{KS_{t+H}}{KS_t}$, or more generally between $R_{t+H,t}$ and the long-horizon SDFs $M^k_{t+H,t}$, and relate them to *short*-horizon (one quarter) average returns $E\left(R_{t+1}\right)$.[10]

The third step in our analysis is to explicitly relate movements in the aggregate capital share to movements in the income shares of households located in different percentiles of the stock wealth distribution. In analogy to the capital consumption SDF, we suppose that the

[10] Although we focus on cross-sections of quarterly return premia, results (available on request) show that the long-horizon covariances between $M^k_{t+H,t}$ and $R_{j,t+H,t}$ we study perform equally well in explaining cross-sections of H-period returns.

consumption of shareholders in the ith percentile of the stock wealth distribution is a fraction θ_t^i of aggregate consumption, where θ_t^i is a non-negative function of the ith percentile's income share, Y^i/Y. Thus consumption of percentile i is modeled as $C_t^i \equiv C_t \theta_t^i$ with $\theta_t^i = \left(\frac{Y_t^i}{Y_t}\right)^{\chi^i}$ and $\chi^i \geq 0$. This last inequality restriction is made on theoretical grounds. Standard utility-theoretic axioms (i.e., nonsatiation) imply that an individual's consumption growth, expressed as a fraction of aggregate consumption growth, should be a nondecreasing function of her share of aggregate income growth. Fixing aggregate consumption, an increase in income share is likely to correspond with an increase in the consumption share of that group. If some of the increase in income shares is saved, so that income shares are less volatile than consumption shares, $0 < \chi^i < 1$. If today's increase signals further increases tomorrow, we could observe $\chi^i > 1$.[11] But there is no reason to expect $\chi^i < 0$. This parameter can be estimated, as described below.

Since observations on income shares are available from the SCF only on a triennial basis, we relate income shares to capital shares using the regression output of Table 2 and use estimated intercepts $\widehat{\varsigma}_0^i$ and slope coefficients $\widehat{\varsigma}_1^i$ from these regressions for shareholders (right panel) along with quarterly observations on the capital share to generate a longer time-series $\widehat{Y_t^i/Y_t} = \widehat{\varsigma}_0^i + \widehat{\varsigma}_1^i\left(KS_t\right)$ of income share "mimicking factors" that extends over the larger and higher frequency sample for which data on $KS_t = 1 - LS_t$ are available. This procedure also minimizes the potential for survey measurement error to bias the estimates, since such error would not affect the mimicking factors but instead be swept into the residual of the regression. We estimate models based on *percentile-specific* SDFs $M_{t+H,t}^i$ taking the form

$$M_{t+H,t}^i = \delta^{H,i}\left[\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{-\gamma\chi^i}\right]. \tag{5}$$

[11] If income growth is positively serially correlated, an increase today implies an even greater increase in permanent income growth. Standard models of optimizing behavior predict that consumption growth should in this case increase by more than today's increase in income growth (Campbell and Deaton (1989)).

4.1 Nonlinear GMM Estimation

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

$$g_T(b) = E_T \begin{bmatrix} \mathbf{R}_t^e - \alpha \mathbf{1}_N + \frac{\left(M_{t+H,t}^k - \mu_H\right)\mathbf{R}_{t+H,t}^e}{\mu_H} \\ M_{t+H,t}^k - \mu_H \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ 0 \end{bmatrix} \tag{6}$$

where E_T denotes the sample mean in a sample with T time series observations, $\mathbf{R}_t^e = \left[R_{1,t}^e ... R_{N,t}^e\right]'$denotes an $N \times 1$ vector of excess returns, and the parameters to be estimated are $\mathbf{b} \equiv (\mu_H, \gamma, \chi, \alpha)'$.[12] The first N moments are the empirical counterparts to (2), with two differences. First, the parameter α (the same in each return equation) is included to account for a "zero beta" rate if there is no true risk-free rate and quarterly T-bills are not an accurate measure of the zero beta rate.

The second difference is that the equations to be estimated specify models in which *long*-horizon H-period empirical covariances between excess returns $\mathbf{R}_{t+H,t}^e$ and the SDF $M_{t+H,t}^k$ are used to explain *short*-horizon (quarterly) average return premia $E_T(\mathbf{R}_t^e)$. This implements the approach that was the subject of prior discussion regarding low frequency risk exposures. We estimate models of the form (6) for different values of H.[13]

The equations above are estimated using a weighting matrix consisting of an identity matrix for the first N moments, and a very large fixed weight on the last moment used to estimate μ_H. By equally weighting the N Euler equation moments, we insure that the model is forced to explain spreads in the original test assets, and not spreads in reweighted portfolios of these.[14] This is crucial for our analysis, since we seek to understand the large spreads on size-book/market and momentum strategies, not on other portfolios. However, it is important

[12] The parameter δ is poorly identified in systems using excess returns in Euler equations so we set it to $\delta = (0.95)^{1/4}$.

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

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

to estimate the mean of the stochastic discount factor accurately. Since the SDF is less volatile than stock returns, this requires placing a large (fixed) weight on the last moment.

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

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

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

GMM estimations for the percentile SDFs are conducted in the same way, replacing $M_{t+H,t}^k$ with $M_{t+H,t}^i$ but imposing the restriction $\widehat{\chi}^i \geq 0$. We also consider weighted averages of the percentile SDFs as an SDF. These are denoted $M_{t+H,t}^{\omega^i}$, where

$$M_{t+H,t}^{\omega^{\cdot}} \equiv \sum_{i \in G} \omega^i M_{t+H,t}^i, \tag{7}$$

where $0 \leq \omega^i \leq 1$ is the endogenous weight (to be estimated) that is placed on the ith percentile's marginal rate of substitution (5). We estimate the weight ω^i that best explains the return premia on value and momentum portfolios.

4.2 Linear Expected Return-Beta Estimation

To assess the distinct roles of aggregate consumption and capital share risk, we investigate models with approximate linearized versions of the SDF (4) where the growth rates of aggregate consumption and the capital share are separate risk factors. A time-series regression is used to estimate betas for each factor by running one regression for each asset $j = 1, 2....N$

$$R_{j,t+H,t}^e = a_{j,H} + \beta_{j,C,H}\left(C_{t+H}/C_t\right) + \beta_{j,KS,H}\left(KS_{t+H}/KS_t\right) + u_{j,t+H,t} \quad t = 1, 2...T,$$

where $\beta_{j,C,H}$ measures exposure to aggregate consumption growth over H horizons and $\beta_{j,KS,H}$ measures exposure to capital share risk over H horizons. To estimate the role of the separate exposures $\widehat{\beta}_{i,C,H}$ and $\widehat{\beta}_{i,KS,H}$, we run a cross-sectional regression of average returns on betas:

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

where t represents a quarterly time period, λ_k is the price of risk for factor k. We also estimate models using either $\widehat{\beta}_{j,KS,H}$ or $\widehat{\beta}_{j,C,H}$ as the single explanatory variable.

The above regressions are implemented in one step using a GMM system estimation, thereby simultaneously correcting standard errors for first-stage estimation of the βs, as well as cross-sectional and serial correlation of the time-series errors terms. A Newey-West (Newey and West (1987)) estimator is used to obtain serial correlation and heteroskedasticity robust standard errors. The Appendix provides additional details on this estimation.

Our final expected return-beta estimations run horse races with other models by including different betas in the cross-sectional regression, e.g.,

$$E\left(R^e_{j,t}\right) = \lambda_0 + \widehat{\beta}_{j,KS,H}\lambda_{KS} + \widehat{\beta}_{j,MKT}\lambda_{MKT} + \widehat{\beta}_{j,SMB}\lambda_{SMB} + \widehat{\beta}_{j,HML}\lambda_{HML} + \epsilon_{j,t} \tag{9}$$

when we include the Fama-French three-factor model betas. Analogous estimations including the Fama-French four-factor model betas including the momentum factor and the intermediary-based model using the estimated beta for $LevFac_t$ are also considered and various combinations of risk exposures across models are explored. For these estimations we use the more commonly employed Fama-MacBeth procedure (Fama and MacBeth (1973)). In each case, we explain quarterly return premia (excess over the T-bill) with betas for each model that are estimated in the same way as they were in the original papers introducing those risk factors.

4.3 Additional Statistics

To assess the degree of misspecification in each model, we present two additional statistics. First, we compute a Hansen-Jagannathan (HJ) distance for each model (Hansen and Jagannathan (1997)). In no case do we choose a model's parameters to minimize the HJ distance.

Instead, they are chosen based on the estimations described above. But, as emphasized by Hansen and Jagannathan (1997), we can still use the HJ distance to compare specification error across any competing set of approximate SDFs. We also report root mean squared pricing errors (RMSE) for each model. To give a sense of the size of these errors relative to the size of the average returns being explained, we report RMSE/RMSR, where RMSR is the square root of the average squared returns on the portfolios being studied. We do not compute statistics designed to assess whether the mean pricing errors or the HJ distance of a *particular model* are exactly zero. As Hansen and Jagannathan (1997) point out, owing to the axiom that all models are approximations of reality and therefore misspecified, such tests are uninformative: any nonrejection of the null of zero specification error can only occur as a result of sampling error, not because the model truly has a zero HJ distance or RMSE. Moreover, since tests of the null of zero specification error rely on a model-specific weighting matrix, they cannot be used to compare models. The interesting question is not whether a model is misspecified, but instead, which models are least misspecified? The HJ distance and RMSE statistics are well suited to making such comparisons across models.

We also present estimates of the finite sample distribution of the cross-sectional $\overline{R}^2$ statistic for the linear models, using a bootstrap procedure. Doing so for the nonlinear estimations is prohibitively time consuming since those estimations require exhaustive searches to avoid getting stuck at a local minimum. Fortunately, the $\overline{R}^2$ statistics for the approximate linear SDF models are very similar to those of the nonlinear models, so the sampling procedure for the linear models should give a sense of the distribution in both cases.

Before presenting results, we note that the estimations above are generally not subject to the criticisms of Lewellen, Nagel, and Shanken (2010), namely that any multifactor model with three (or four) factors even weakly correlated with the three- (or four-) Fama-French factors could possibly explain returns with implausibly large risk prices and tiny spreads in betas, for several reasons. First, although our benchmark model has two factors, our main findings are driven by one of those two factors (capital share risk) and opposite signed exposure of momentum and value to this single factor, not by different multifactor models for pricing value and momentum separately that have the same number of factors as the separate Fama-French models. Second, the spreads in betas for capital share risk exposure are large (Figure 1). Moreover, the capital share betas perform better and drive out the betas for both Fama-French mutifactor models for pricing both sets of returns. Third, our benchmark capital share SDF model is an explicit nonlinear function of the primitive theoretical parameters that determine the risk prices (χ and γ) and our GMM estimation provides direct estimates of these. By and large, these estimates satisfy the theoretical restrictions of the model and are reasonable. Fourth, the appendix presents one way of sorting firms into portfolios on the basis of low frequency labor share exposure. As we explain there, the usual procedure of unconditionally using firm-level data to estimate the betas for firms' exposures to a factor, forming portfolios on the basis of these betas, and then comparing average returns across these portfolios, is inappropriate in a world where there is opposite signed exposure to a single risk factor. We use an alternative sorting procedure that explicitly conditions on characteristics using estimates from the original characteristic-sorted portfolios. Portfolios sorted according to labor share betas under these assumptions have large spreads in average returns, of the predicted sign.

5 Results

This section presents the results. We begin with estimations of the approximate linear expected return beta relations and then move on to the full nonlinear models.

5.1 Expected Return-Beta Representations

This section presents estimation results of expected return-beta representations using approximate linear SDFs where these aggregate consumption growth and capital share growth are separate priced risk factors, as in (8). Table 4, Panel A, reports the results from this estimation on size-book/market portfolios, and also includes results for estimations where only the H-period consumption growth beta $\widehat{\beta}_{j,C,H}$, or only the capital share growth beta $\widehat{\beta}_{j,KS,H}$ are used as regressors in the second-stage cross-sectional regression. Panel B reports the same set of results for the 10 momentum portfolios. In both tables, all coefficients including the constant are multiplied by 100. The last column of each panel reports a small T adjusted R^2 distribution from a bootstrap procedure.

Using size-book/market portfolios, Panel A shows that long-horizon aggregate consumption betas perform better than short-horizon betas. For $H = 8$ and $H = 12$, the R^2 statistics are 33 and 30%, respectively, compared to 6% for $H = 1$. But in each case, the capital share betas $\widehat{\beta}_{j,KS,H}$ explain a much larger fraction of the return premia (80% for $H = 8$ and 76% for $H = 12$). When both betas are included, the risk prices on the long-horizon aggregate consumption betas are driven nearly to zero and rendered statistically insignificant, while the risk price for capital share beta $\widehat{\beta}_{j,KS,H}$ remains large, positive, and different from zero statistically. The long-horizon consumption betas are strongly positively correlated cross-sectionally with the long horizon capital share betas (table in the Appendix), and so proxy for the latter's explanatory power when the capital share beta is excluded. These results suggest that it is not long-horizon aggregate consumption growth, but instead long-horizon growth in the capital share, that is the true driver of quarterly return premia. Once the latter is included, there is little left for exposure to low frequency aggregate consumption growth to explain.[15]

Panel B reports the analogous output for the momentum portfolios. The punchline is much the same as it is for size-book/market portfolios, except that, as above, the estimated risk prices for the capital share betas $\widehat{\beta}_{j,KS,H}$ are strongly negative, rather than positive. For momentum portfolios, the consumption betas explain more of the cross-sectional variation at the shortest $H = 1$ horizon than do the capital share betas, but they are surpassed in explanatory power as the horizon increases past $H = 1$. At $H = 8$, exposure to capital share

[15] In results not reported, we also find that the long-horizon capital share betas drive out various S-period ahead *future* consumption growth betas formed from regressions of quarterly returns on future consumption growth over S periods, as studied by Parker and Julliard (2004).

risk explains 93% of the variation in the return premia on these portfolios and drives out consumption risk.

The estimated size of the zero-beta rate parameter from these linear regressions is about 10 times as large as those from the nonlinear SDFs estimations reported on below, where they are in most cases small and statistically indistinguishable from zero for both sets of portfolios. This can happen if the true SDF model is the nonlinear one, because the linear representation is merely an approximation that omits higher order terms. If these higher order terms are not irrelevant for return premia and there is a common component in exposure to them across assets, the linear regression is likely to deliver an upwardly biased estimate of the zero-beta constant in the second stage regression.

The last column of each panel of Table 4 reports estimates of the finite sample distribution of the cross-sectional $\overline{R}^2$ statistics for regressions using the capital share betas as the single risk factor. The table reports the 90% confidence interval for these statistics constructed from a bootstrap procedure described in the Appendix. As is well known, finite sample distributions show fairly wide intervals, but for the horizons $H = 8, 12$ these confidence intervals have lower bounds that are close to 70% for both sets of portfolios.

A visual impression of the key result from these linear regressions is given in Figure 1, which plots observed quarterly return premia (average excess returns) on each portfolio on the y-axis against the portfolio capital share beta for exposures of $H = 8$ quarters on the x-axis. The 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.

Figure 1 illustrates several 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 smallest 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 figure shows that 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, the model 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%.

But 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 explained by opposite signed exposure to low frequency capital share risk.

To insure that the our results are not unduly influenced by the use of overlapping long-horizon return data in the first stage estimation of betas, we also conducted the same estimations above using non-overlapping long-horizon data. For a return horizon of $H = 4$, for example, there are four ways to do this: use non-overlapping data from Q1 to Q1, Q2 to Q2, Q3 to Q3, or Q4 to Q4 of each year. We estimate the long horizon capital share beta in the first stage using non-overlapping data from samples formed all four ways and take the average beta across these as an estimate of capital share risk exposure at $H = 4$. We proceed analogously for the other horizons. Estimates of the second-stage expected return beta relations using the betas estimated in this way are presented in the Appendix, table A9. The results are very similar to those using the longer sample formed from overlapping data.

5.2 Nonlinear GMM Estimation using Capital Share SDF

Table 5 presents results from estimations based on the moment conditions (6) of the nonlinear capital share SDF $M^k_{t+H,t}$. Results are presented for values of H from 4 to 16 quarters. To conserve space in the Table, we omit the $H = 1$ results but comment on them below. The left panel shows results for $\chi = 0$, which is the special case where the SDF is equal to the standard power utility CCAPM. The right panel is the more general case where χ is nonzero.

Panel A reports results for the 25 size-book/market portfolios. The left panel confirms previous findings (Brainard, Nelson, and Shapiro (1991); Bansal, Dittmar, and Kiku (2009); Hansen, Heaton, and Li (2008); Dew-Becker and Giglio (2013); Bandi and Tamoni (2014)) that lower frequency exposures to aggregate consumption growth have a greater ability to explain the cross-section of average returns on these portfolios than do short-horizon exposures. The cross-sectional R^2 statistics rise from 7% for $H = 1$ (not shown in the Table) to a peak of 36% at $H = 8$. There is a commensurate decline in the RMSE pricing errors as H increases. The right panel shows the performance of the capital share SDF with χ freely estimated. No matter what the horizon, this model has larger R^2 statistics, lower HJ distances, and lower pricing errors than the model with $\chi = 0$ that excludes the capital share. The R^2 rises from 36% for $H = 1$ (not shown) to a peak of 86% at $H = 8$ and remains high at 84% for $H = 16$. The pricing errors in this right panel are roughly half as large as those in the left panel in most cases.

The standard errors for the parameters χ and γ reported in Panel A of Table 5 are large, however, indicating that the estimation has difficulty distinguishing the separate roles of these two parameters. To understand the source of these large standard errors, recall that the SDF takes the form $M^k_{t+H,t} = \delta^H \left[\left(\frac{C_{t+H}}{C_t} \right)^{-\gamma} \left(\frac{1-LS_{t+H}}{1-LS_t} \right)^{-\gamma\chi} \right]$. If the term involving aggregate consumption growth contributed nothing but noise for explaining returns, or if it were constant, the estimation would only be able to identify the product $\chi\gamma$, but not the individual terms in this product. This is approximately what we find: long horizon consumption growth is not an important risk factor once we have controlled for long horizon capital share growth, implying that it is difficult to separately identify γ and χ, a phenomenon that shows up in the large standard errors for these parameters.

For this reason, we shall henceforth restrict χ to a central value such as $\chi = 1$ for size-book/market portfolios or $\chi = -1$ for momentum portfolios, as explained below. This allows for more precise estimates of the relative risk aversion coefficient γ. Note that imposing such a restriction can only make it harder for the model to fit the cross-section of return premia, since if the constraint binds the Euler equation errors are at least as large as the unconstrained case, while they are the same if the constraint is nonbinding. Panel B of Table 5 shows the results under the restriction $\chi = 1$. The R^2, RMSE pricing errors and HJ distances are all very similar to the unconstrained case, indicating that the restriction has little effect on the model's ability to explain return data. But the estimates of γ are now precise, and imply reasonable values that monotonically decline with H from a high of $\gamma = 30$ at $H = 1$ (not shown) to $\gamma = 1.5$ at $H = 16$. Note also that estimates of the zero-beta terms are economically small and in all but one case not statistically distinguishable from zero.

The finding that estimates of risk aversion γ decline with the horizon H is of interest because it is consistent with a model in which low frequency capital share fluctuations generate sizable systematic cash flow risk for investors, such that fitting return premia does not require an outsized risk aversion parameter. By contrast, when H is low, estimates of risk aversion must be higher to fit high average return premia because covariances between the SDF and returns over short horizons are unlikely to reveal important low frequency cash flow risks, thereby biasing upward estimates of risk aversion.

Panel C of Table 5 reports results of nonlinear GMM estimation of models with $M^k_{t+H,t}$ on 10 momentum portfolios. For the reasons just mentioned, the table reports results obtained when restricting $\chi = -1$, but the fit is similar when χ is freely estimated, where the important result is that χ always takes on *negative* values when freely estimated. This finding reveals the opposite signed exposure of value and momentum to capital share risk foreshadowed above. Even when restricting $\chi = -1$, Panel C shows that the capital share SDF explains 93% of the variation in momentum returns for exposures over $H = 4$ quarters, 90% for exposures over $H = 8$ quarters, and 79% for exposures over $H = 16$ quarters. Estimates of the zero-beta terms are small and not statistically distinguishable from zero in every case, while estimates of γ are small and precisely estimated when H is sufficiently large. The RMSE on these portfolios is often just 30% of that for the aggregate consumption growth CCAPM with $\chi = 0$, displayed in the left Panel C.

We now dig deeper into the possible sources of the opposite signed exposure documented above. One possibility is that shareholders located in different percentiles of the stock wealth distribution have marginal utilities that vary inversely with the capital share and differentially pursue value and momentum strategies. If households located in different percentiles of the wealth distribution make portfolio decisions in our sample such that they exhibit dissimilar central tendencies to pursue value and momentum strategies, the markets for these two strategies would be effectively segmented (on average) across the two groups of households. The next section considers this possibility with estimations using our proxies for the percentile-specific SDFs discussed above.

5.3 Nonlinear GMM Estimation of Percentile SDF Models

Table 6, reports results of nonlinear GMM estimations using an estimated weighted average of percentile SDFs $M^{\omega}_{t+H,t}$ as in (7) where we freely estimated the weights ω^i on the SDFs of different groups of shareholders. Specifically, we consider a SDF that is a weighted average of the MRS of two groups, the bottom 90% of shareholders and the top 10%. Thus $M^{\omega}_{t+H,t} = \omega^{<90} M^{<90}_{t+H,t} + (1 - \omega^{<90}) M^{\text{top10}}_{t+H,t}$ with weight $\omega^{<90}$ placed on the MRS $M^{<90}_{t+H,t}$ of the bottom 90% and $1 - \omega^{<90}$ on the MRS $M^{\text{top10}}_{t+H,t}$ of the top 10% of the stock wealth distribution. The MRS for these groups are computed according to (5). Panel A of Table 6 reports results of these estimations on size-book/market portfolios, while Panel B reports the same results for momentum portfolios. Estimates of parameter values are again imprecise whenever χ^i is freely estimated, because, as above, it is difficult to separately identify χ^i and γ when the income share component of the SDF is generating almost all of the important comovement with returns. For this reason, we restrict $\chi^i = 1$ for both groups.[16] We always restrict $\gamma \geq 0$.

Table 6 shows that the results of this estimation deliver estimates of $\omega^{<90}$ that are right on the boundary of the parameter space. On size-book/market portfolios, the top part of Panel A shows that the estimation sets $\omega^{<90} = 0$ in every case.[17] By placing effectively no weight on the MRS of the bottom 90%, this SDF performs equally well at explaining this cross-section of average returns as an SDF that based *only* on the MRS the top 10% $M^{top10\%}_{t+H,t}$(bottom part of Panel A). The SDF $M^{top10\%}_{t+H,t}$ explains over 80% of the cross-sectional variation in size-book/market returns for most horizons H; estimates of the zero-beta rate are small and not statistically distinguishable from zero, and estimates of γ are small and precisely estimated for many horizons. The RMSE is often close to 50% of that for the model based on corresponding long-horizon aggregate consumption growth exposure alone. Additional results

[16] Note that opposite signed exposure now shows up as negative correlation between the income share growth rates of different stockholder groups. Thus χ^i is expected to be positive for both sets of portfolios and stockholder groups.

[17] The Appendix Table A12 we present the results when χ^i is freely estimated and the result is nearly the same, though parameter values are far less precisely estimated due to the identification problem.

in the Appendix tables show that using the percentile-specific SDFs for the top 5% or top 1% work about as well as these.

The same estimations are performed on momentum portfolios. Table 6, Panel B (top half), reports the results for an estimated weighted average SDF, allowing the estimation to choose how much weight to place on the bottom 90% and the top 10% MRS. Now the estimation of $\omega^{<90}$ goes to the opposite boundary and is $\omega^{<90} = 1$ for all horizons, implying that the estimations seek to place all of the weight on the MRS of the *bottom* 90% of shareholders for explaining momentum portfolio returns. This SDF explains between 75 and 96% of average returns on these portfolios. The bottom half of Panel B shows that the SDF $M_{t+H,t}^{<90}$, which uses only the MRS of the bottom 90% of shareholders, explains the data just as well.

For both sets of portfolios, the restricted estimations with $\chi^i = 1$ perform almost as well in explaining the cross-section of return premia as the unrestricted estimations where χ^i is freely estimated, suggesting that $\chi^i = 1$ is plausible and that unobservable consumption shares (proxied here by income shares raised to the power χ^i) are not appreciably smoother than income shares. This is in line with evidence presented in LL and GLL indicating that factors share shocks are extremely persistent, and would therefore be difficult to smooth. Here we exploit the link between factors shares and income shares of these two groups of shareholders. If the factors share shocks are close to permanent, increases in income (for either group) resulting from these innovations would optimally translate into a one-for-one increase in consumption ($\chi^i = 1$), with no consumption smoothing.

5.4 Fama-MacBeth Regressions: Competing Models

We now report estimates of expected return beta representations using betas from several alternative factor models: 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, and the intermediary SDF model of Adrian, Etula, and Muir (2014) using their $LevFac_t$, which measures the leverage of securities broker-dealers. We estimate each model's betas in a first stage using the same procedure employed in the original papers where the model was introduced. To conserve space, we report results for capital share betas for $H = 8$ only, but the findings are similar for other horizons as long as we measure capital share exposures for horizons greater than 4 quarters. Table 7, Panel A, shows results for quarterly returns on the size-book/market portfolios, while Panel B reports results for momentum portfolios.

The results in Panel A for size-book/market portfolios show that the single aggregate risk factor based on low frequency fluctuations in the aggregate capital share generates pricing errors that are lower than both the Fama-French three-factor model and the $LevFac_t$ model. This can be seen in Panel A by noting that including the capital share risk factor greatly reduces pricing errors and increases the cross-sectional $\overline{R}^2$. Even when the beta for (KS_{t+H}/KS_t) is the only risk factor, results not reported in the table show that this specification also explains a larger fraction of the variation in average returns than do each of these models, with 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. Note that the risk prices (all multiplied by 100 in the table) for the capital share beta are two orders of magnitude smaller than that for the $LevFac_t$ beta, indicating that the capital share model explains the same spread in returns with a much larger spread in betas. As a fraction of the root mean squared average return RMSR on these portfolios, the RMSE pricing errors from all three models are small: 12% for capital share model, 13% for the Fama-French three-factor model and 16% for the $LevFac_t$ model, each of which are much smaller than those of models using long-horizon aggregate consumption betas alone, reported above. Moreover, the risk prices on the betas for the value factor HML_t and the $LevFac_t$ are strongly statistically significant when included on their own, as reported in previous work. But in a horse race where the capital share beta is included alongside betas for these other factors, the latter loose their statistical significance while the capital share beta retains its statistically significant explanatory power.

Panel B of Table 7 shows the same comparisons for momentum portfolios. The RMSE pricing errors for the capital share model are a third smaller than the Fama-French four-factor model, and 70% smaller than the $LevFac_t$ model; this results in large declines in the RMSE when the beta for (KS_{t+H}/KS_t) is added to those of these other models as a risk factor. 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 key reason that this single capital share risk factor model outperforms these models for pricing both sets of portfolios is that the risk price on the capital share beta is now negative and opposite in sign to that for the size-book/market portfolios. The absolute value of the capital share risk price is two orders of magnitude smaller than that for $LevFac_t$ and one order smaller than that for the momentum factor MoM_t, indicating that the capital share model explains the same large spread in returns with a modest risk price and a much larger spread in betas. For momentum portfolios as for size-book/market portfolios, the risk prices for the betas of the Fama-French factors and the $LevFac_t$ are strongly significant when included on their own. But when included alongside the capital share beta, they are smaller in absolute value and loose their statistical significance, while the capital share beta retains its strong explanatory power.

It is notable that measured exposure to a single macroeconomic risk factor eliminates the explanatory power of the exposures to separate, multiple return-based factors that have long been used to explain value and momentum premia. These findings reinforce the interpretation of the previous results, namely that return premia on value and momentum are not primarily earned from covariance of their uncorrelated components with separate priced factors.

As a final comparison, we consider the four return-based factors proposed by Hou, Xue, and Zhang (2014) and Hou, Xue, and Zhang (2015) that they call the q-factor model.[18] The four q factors are a market risk premium factor, MKT_t, the difference between the return on

[18] Hou, Xue, and Zhang (2014) extend the measurement of these factors to cover a longer sample starting in 1967, which we use here. We thank Lu Zhang for providing us these data.

a portfolio of small and big market equity stocks $r_{ME,t}$, the difference between the return on a portfolio of high and low investment-to-asset stocks, $r_{I/A,t}$, and the difference between the return on a portfolio of high and low return-on-equity stocks, $r_{ROE,t}$.

Table 8 reports the results of Fama-MacBeth regressions that include exposures to different combinations of the four q factors, the long-horizon capital share and consumption growth factors. Because the number of factors varies widely in these comparisons, we rank 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. For the 25 size-B/M sorted portfolios (top panel), even the root mean squared pricing error (which does not adjust for number of free factor risk prices) is lower for a model with exposure to a single long-horizon ($H = 8$) capital share risk factor than it is for the four factor q-model, as well as for a range of other alternatives that combine different risk exposures from the q-factors with those from models with capital share and/or consumption growth risk. Exposure to just capital share risk produces the lowest BIC criterion.

The bottom panel of Table 8 reports results for momentum. Hou, Xue, and Zhang (2015) report that the $r_{ROE,t}$ factor alone drives almost all of the explanatory power of the q-factor model for momentum portfolios. The second row corroborates this finding: exposure to just the $r_{ROE,t}$ factor explains a large fraction (68%) of the cross-section of average returns and is strongly statistically significant. The last row suggests that almost all of the information in the $r_{ROE,t}$ exposure is subsumed by the beta for long-horizon capital share risk. Once both are included to explain the cross-section of return premia, the beta for $r_{ROE,t}$ is driven out of the regression and its risk price cut by two-thirds. An interesting feature of these results is that the investment return factor $r_{I/A,t}$, which has a positive risk price and appears to mimic the information in capital share risk for size-B/M portfolios, has a negative risk price when estimated on momentum portfolios. But for both sets of portfolios, once capital share risk exposure is controlled for, the risk prices for $r_{I/A,t}$ exposure become small, positive and statistically insignificant. This suggests that one reason the q-factor model is successful at explaining both sets of portfolios is that it captures part of the opposite signed exposure to capital share risk that we find here explains a large fraction of the negative covariance and outsized rewards to these strategies.

Once all factors are included, the results suggest that much of the information in models with capital share risk is common to that in the q-factor model for momentum portfolios. Indeed, the regression has difficulty statistically distinguishing the independent effects; Row 5 shows that they are each rendered statistically insignificant by the inclusion of the others. Nevertheless, the lowest BIC criterion is for the model that includes these six betas, suggesting that while much of the information in the models is shared, there is some value in considering exposure to all factors. The second most preferred model according to the BIC criterion is the q-factor model with all four factors.

The finding that the q-factor model mimics much of the information in the capital share and consumption growth risk factors is of interest because the latter (unlike the return-based q-factors) are macroeconomic sources of risk that all firms in the economy are potentially exposed to. Moreover, they have immediate linkages to primitive economic shocks that appear related to movements in the aggregate stock market (GLL). Given that the capital share is a pure macroeconomic variable measured with greater error than the return-based factors, it is remarkable that its growth contains a sizable fraction of the information found in the four q factors for pricing these portfolios. The results are suggestive of a risk-based interpretation of the q-factors linked to the marginal utility growth of different investors whose consumption varies inversely with the capital share.

5.5 Other Test Assets

Here we briefly discuss estimation on other test assets. We undertook the same estimations on 10 long-run reversal portfolios.[19] Like the size-book/market portfolios, the key parameter

[19] These portfolios are formed on the basis of prior (13-60 month) returns. The highest yielding portfolio is comprised of stocks with the lowest prior returns while the lowest yielding portfolio is comprised of stocks

χ in nonlinear estimation is now estimated to be positive. With $\chi = 1$ the capital share SDF explains 88% of return premia on these portfolios when $H = 6$ and $H = 8$, 84% when $H = 10$, and 78% for exposures over $H = 12$ quarters. Estimates of the zero-beta terms are small and not statistically distinguishable from zero while estimates of γ are small and precisely estimated for most longer horizons. These results are omitted to conserve space but Table 9 shows the results for the linear expected return beta representations. Panel A shows that we find a strongly statistically significant positive risk price on long-horizon capital share growth, and adjusted R^2 of 86% for $H = 8$.

Earnings momentum has been closely related to price momentum (Novy-Marx (2015)). Table 9, panel B, shows that exposure to long-horizon capital share growth helps explain the spread in returns on portfolios sorted on the basis of return on equity (ROE, earnings relative to book-value), as constructed in Hou, Xue, and Zhang (2015), where we find a negative risk price, as appears for pricing momentum portfolios. Portfolio sorts based on book-market have been closely linked to sorts based on investment (Hou, Xue, and Zhang (2015)). Table 9, panel C, shows that long-horizon capital share risk helps explain the spread in returns on size/investment portfolios, where we find a positive risk price, as appears for pricing size/book-market portfolios. The magnitude of this explanatory power in both cases is somewhat lesser than that for the previously studied momentum and size/book-market portfolios. Finally, unreported results show capital share risk bears little relation to the spread in average returns on industry portfolios. One interpretation is that the small, statistically indistinguishable spreads in average returns on industry portfolios do not load heavily on true risk factors, which would imply a large spread in average returns. Alternatively, these portfolios may be priced by altogether different SDFs, perhaps pertaining to institutions or intermediary-based investors.

with the highest prior returns.

6 Conclusion

This paper finds that a single aggregate risk factor based on low frequency fluctuations in the growth of the capital share of national income can simultaneously explain the large excess returns on momentum and value portfolios while at the same time explaining why the two investment strategies are negatively correlated. The results imply that the negative correlation is in large part the result of opposite signed exposure to capital share risk. Models with capital share risk explain up to 85% of the variation in average returns on size-book/market portfolios and up to 95% of momentum returns. 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.

Our analysis is motivated by the idea that high wealth inequality is likely to mean that households located in different percentiles of the stock wealth distribution have marginal utilities that very inversely with the national capital share. Consistent with this, we show that income shares of the top 10% of the stock wealth distribution are strongly positively correlated with the capital share, while those of shareholders in the bottom 90% are strongly negatively correlated. Because growth in the capital share is more volatile than aggregate consumption growth, this evidence implies that the marginal utility growth of these two groups of shareholders are likely to be inversely related. The totality of evidence can be restated in terms of hypothetical marginal investors. Assets characterized by heterogeneity along the value, growth, and long-run reversal dimensions are priced "as if" the marginal investor were a representative of the top 10% of the wealth distribution. Assets characterized by heterogeneity along the near-term past return dimension are priced "as if" the marginal investor were a representative of the bottom 90% of the wealth distribution. Estimations based on proxies for percentile-specific SDFs support this characterization.

Our results can be interpreted in several different ways. Clearly, the results are inconsistent with a frictionless market characterized by fully rational and unconstrained investors. In strictly separated asset markets, it would be possible for different SDFs to price assets if the set of investors in one market is different from the set of investors in the other market. Anecdotal evidence suggests that some investors have a preference for stocks with certain characteristics. For example, 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. Why participants in the stock market choose to focus on stocks with certain characteristics without exploiting potential gains from correlations across characteristics is unclear. Unfortunately, detailed data on individual stock ownership in the U.S. is scarce, so it is difficult to directly assess to what extent individual investors' portfolios are concentrated across different asset characteristics. Our results suggest that such "quasi-market segmentation" might be important for equilibrium prices and returns of stocks.

Of course, this interpretation leaves unanswered the question of why high and low wealth investors might segment themselves into different asset classes. One simple story is that growth in the capital share tends to be positively correlated with current and recent lagged changes in the stock market, but negatively related with labor income growth (Lettau and Ludvigson (2013)). Thus shareholders in the bottom 90% of the wealth distribution may seek to hedge risks associated with an increase in the capital share by chasing returns and flocking to stocks whose prices have appreciated most recently. On the other hand, those in the top 10%, such as corporate executives whose fortunes are highly correlated with recent stock market gains, may have compensation structures that are already "momentum-like." These shareholders may seek to hedge their compensation structures by undertaking contrarian investment strategies that go long in stocks whose prices are low or recently depreciated. Behavioral factors involving heterogeneous information or beliefs may also play a role. Older, more experienced, shareholders who occupy the top 10% of the wealth distribution could have a different perception of the risks associated with leveraged momentum investing than their younger counterparts in the bottom 90% of the distribution have. A third perspective is that the return premia on these assets have nothing to do with the marginal utility of investors. This perspective begs the question of why these premia are then so strongly related to the share of national income accruing to capital.

Regardless of the specific interpretation, we argue that the findings presented here pose a challenge for a range of asset pricing theories (including many of the modeling approaches taken by the authors of this paper in other work). First, the capital share is a strongly priced risk factor for both value and momentum and it drives out aggregate consumption growth, even at long horizons. Thus models with a single representative agent are unlikely to be correct frameworks for describing asset pricing behavior. Second, value and momentum are inversely exposed to capital share risk, and this largely explains both their negative correlation and their high average returns. Thus, models in which value and momentum premia are earned entirely from covariance of their *un*correlated components with separate priced factors are unlikely to be correct descriptions of these asset classes. Third, the capital share is inversely related to the income shares of the top 10 and bottom 90 percent of the stockholder wealth distribution, suggesting that the component of their marginal utility growth that depends on capital share growth and that prices the assets empirically is inversely related. This poses a challenge to incomplete markets models in which the marginal rate of substitution of any heterogeneous investor is a valid pricing kernel. It also poses a challenge to limited participation models in which a single wealthy shareholder is the marginal investor for all asset classes.

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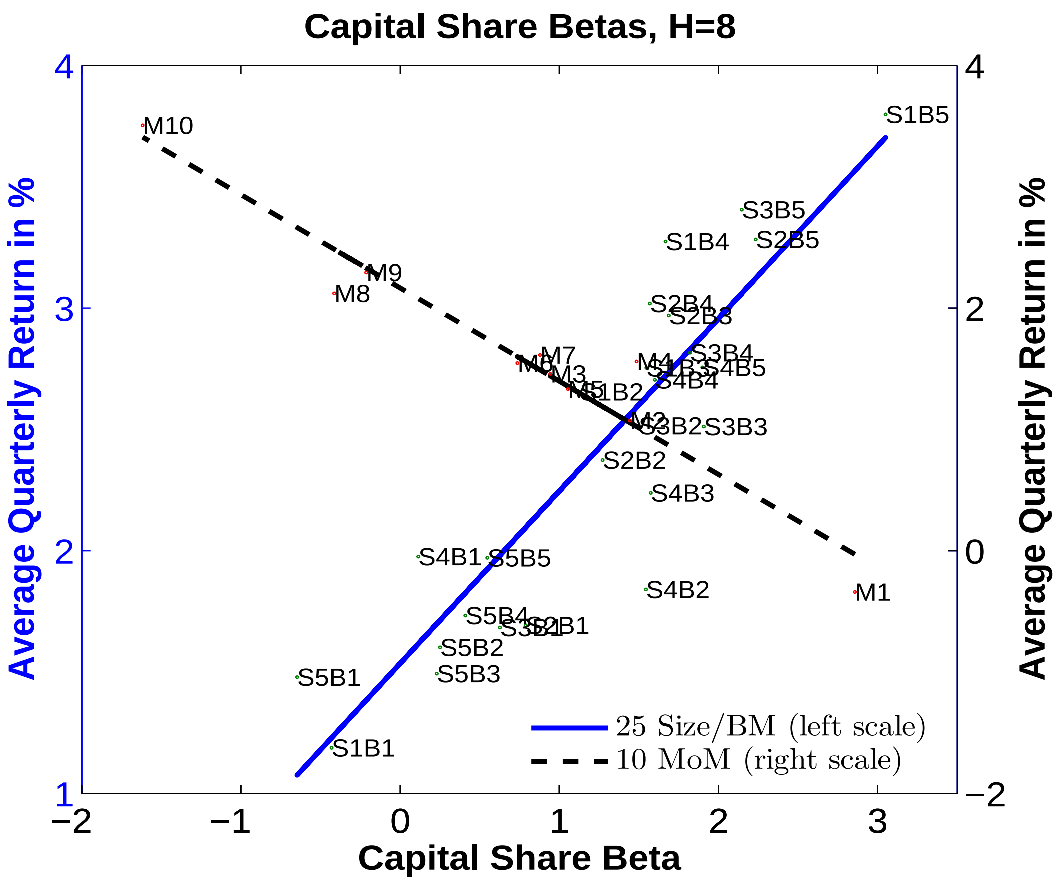

Figure 1: Capital share betas. Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using 25 size-book/market portfolios (Solid Blue) or 10 momentum portfolios (Dashed Black). $\beta_{KS,H}$. $H = 8$ indicates the horizon in quarters over which capital share exposure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

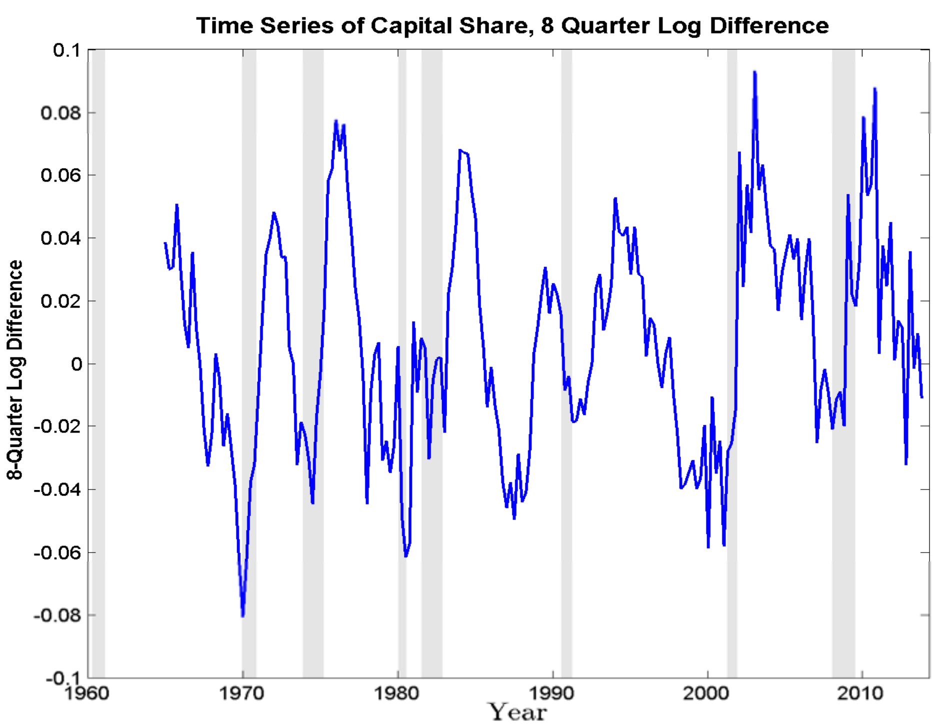

Figure 2: Capital share, 8 quarter log difference. The vertical lines correspond to the NBER recession dates. The sample spans the period 1963Q1 to 2013Q4.

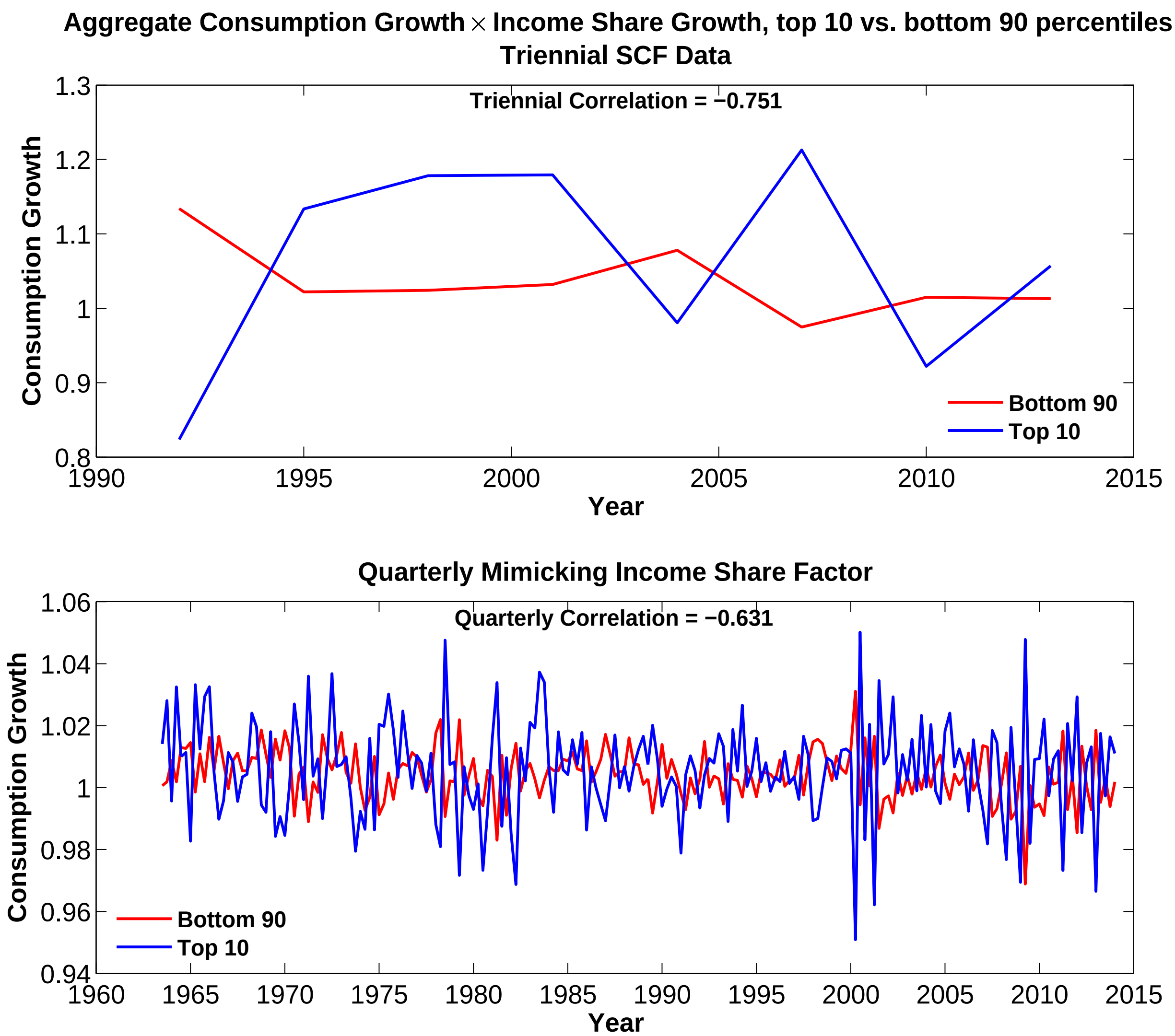

Figure 3: Growth in aggregate consumption times income share. Notes: The top panel reports triennial observations on the annual value of $\frac{C_t}{C_{t-1}}\left[\frac{Y_t^i/Y_t}{Y_{t-1}^i/Y_{t-1}}\right]$ corresponding to the years for which SCF data are available. Y_t^i/Y_t is the shareholder's income share for group i caluculated from the SCF. 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 triennial data spans the period 1989 - 2013. The quarterly sample spans the period 1963Q1 - 2013Q4.

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

Percentile of Stock Wealth	1989	1992	1995	1998	2001	2004	2007	2010	2013
< 70%	7.80%	8.53%	8.09%	9.15%	8.96%	8.86%	7.52%	7.15%	7.21%
70 – 85%	11.76%	11.27%	10.45%	10.95%	12.69%	12.08%	10.00%	10.99%	11.32%
85 – 90%	8.39%	7.73%	7.02%	6.59%	8.21%	7.88%	7.13%	7.98%	7.42%
90 – 95%	12.52%	12.66%	11.71%	11.18%	13.38%	13.33%	12.81%	13.80%	13.40%
95 – 100%	59.56%	59.92%	62.52%	62.09%	56.49%	57.95%	62.58%	60.08%	60.74%
Panel B: Percent of Stock Wealth, sorted by Stock Wealth, All Households									
< 70%	0.01%	0.23%	0.50%	1.30%	1.64%	1.35%	1.50%	1.00%	0.84%
70 – 85%	3.12%	4.54%	5.12%	7.42%	8.36%	7.41%	6.77%	6.13%	5.92%
85 – 90%	4.19%	5.18%	5.27%	6.45%	7.31%	6.70%	5.61%	6.01%	6.17%
90 – 95%	11.16%	11.74%	10.63%	11.28%	13.96%	13.26%	12.10%	12.97%	12.67%
95 – 100%	81.54%	78.37%	78.29%	73.93%	68.51%	71.21%	73.87%	73.76%	74.54%
Panel C: Stock Market Participation Rates									
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. Notes: The table reports the distribution of stock wealth across households. Panel A is conditional on the household being a stockowner, while Panel B reports the distribution across all households. Stock Wealth ownership is based on indirect and indirect holdings of public equity. Indirect holdings include annuities, trusts, mutual funds, IRA, Keogh Plan, other retirement accounts. 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% . Source: Survey of Consumer Finances.

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
$< 90\%$	**1.04**	**−0.98**	42.12	$< 90\%$	**0.98**	−0.79	29.20
	(6.26)	(−2.26)			(5.54)	(−1.70)	
$90 - 94.99\%$	0.02	0.21	29.90	$90 - 94.99\%$	−0.05	**0.36**	48.10
	(0.40)	(1.73)			(−0.86)	(2.55)	
$95 - 100\%$	−0.05	0.77	31.47	$95 - 100\%$	0.07	0.43	12.17
	(−0.32)	(1.79)			(0.41)	(0.99)	
$99 - 100\%$	−0.02	0.33	13.66	$99 - 100\%$	−0.03	0.33	12.49
	(−0.15)	(1.05)			(−0.20)	(1.00)	
$90 - 100\%$	−0.04	**0.98**	42.12	$90 - 100\%$	0.02	0.79	29.20
	(−0.21)	(2.26)			(0.13)	(1.70)	

Table 2: Regressions of income shares on the capital share. Notes: OLS t-values in parenthesis. Coefficients that are statistically significant at the 5%. level appear in bold. $\frac{Y_t^i}{Y_t}$ is the income share for group i. KS is the capital share. Stockowner group includes households who have direct or indirect holdings of equity.

Small Stock Value and Momentum Strategies

Panel A : Annualized Statistics

H	$Corr\left(R_{V,H},R_{M,H}\right)$	Mean		Sharpe Ratio		$\max_w \frac{E(wR_{V,H}+(1-w)R_{M,H})}{std(wR_{V,H}+(1-w)R_{M,H})}$
		$R_{V,t+H,t}$	$R_{M,t+H,t}$	$R_{V,t+H,t}$	$R_{M,t+H,t}$	
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: $R_{i,t+H,t}=\alpha_i+\beta_{i,H}\frac{KS_{t+H}}{KS_t}+\epsilon_{i,t+H,t},\ i\in\{V,M\}$

H	$\beta_{i,H}$		$\bar{R}^2$		$\frac{\beta_{M,H}\beta_{V,H}Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov(R_{M,H},R_{V,H})}$	$\frac{Cov(\widehat{\epsilon}_{M,H},\widehat{\epsilon}_{V,H})}{Cov(R_{M,H},R_{V,H})}$	$Corr\left(\widehat{\epsilon}_{M,H},\widehat{\epsilon}_{V,H}\right)$
	$R_{V,t+H,t}$	$R_{M,t+H,t}$	$R_{V,t+H,t}$	$R_{M,t+H,t}$			
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]					

Panel C: Correlation Matrix between Strategies for $H=8$, Post 1967Q1

	$R_{V,H}$	$R_{M,H}$	$R_{REV,H}$	$R_{ROE,H}$	R_{INV}
$R_{V,H}$	1	−0.33	0.34	−0.10	0.24
$R_{M,H}$		1	−0.26	0.34	−0.13
$R_{REV,H}$			1	−0.45	0.37
$R_{ROE,H}$				1	−0.49
R_{INV}					1

Table 3: Value and momentum strategies. Notes: Let $R_{i,t+H,t}$, i for V, M, be denoted as $R_{i,H}$. The H-period return on the value strategy is $R_{V,t+H,t}\equiv\prod_{h=1}^{H}R_{S1B5,t+h}-\prod_{h=1}^{H}R_{S1B1,t+h}$. The H-period return on the momentum strategy is $R_{M,t+H,t}\equiv\prod_{h=1}^{H}R_{M10,t+h}-\prod_{h=1}^{H}R_{M1,t+h}$. H-period long reversal strategy is $R_{\text{REV},H}=\prod_{h=1}^{H}R_{\text{REV}10,t+h}-\prod_{h=1}^{H}R_{\text{REV}1,t+h}$. H-period ROE strategy is $R_{\text{ROE},H}=\prod_{h=1}^{H}R_{\text{ROE}10,t+h}-\prod_{h=1}^{H}R_{\text{ROE}1,t+h}$. H-period investment strategy is $R_{INV,H}=\prod_{h=1}^{H}R_{S1INV1,t+h}-\prod_{h=1}^{H}R_{S1INV5,t+h}$. 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). t-statistics is reported in parenthesis. Bolded coefficients indicate statistical significance at the 5 percent level. The sample spans the period 1963Q1 to 2013Q4. Panel C reports the correlation matrix between strategies in largest common periods that all strategies are available from 1967Q1 to 2013Q4.

Expected Return-Beta Regressions: Size/BM and Momentum

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

	Panel A: 25 Size/book-market Portfolios					**Panel B: 10 Momentum Portfolios**				
H	Constant	C_{t+H}/C_t	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	Small T $\bar{R}^2$ dist.	Constant	C_{t+H}/C_t	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	Small T $\bar{R}^2$ dist.
1	1.53	0.26		0.06		0.39	**0.52**		0.40	
	(1.76)	(1.27)				(0.35)	(2.20)			
1	**2.24**		0.43	−0.03		**2.84**		**−2.21**	0.06	
	(4.87)		(0.71)			(4.06)		(−2.46)		
1	1.44	0.25	0.28	0.03		1.76	0.54	−2.56	0.03	
	(1.64)	(1.17)	(0.46)			(1.52)	(1.81)	(−1.82)		
4	0.77	**0.46**		0.30		0.25	**0.51**		0.52	
	(0.62)	(2.10)				(0.20)	(1.96)			
4	0.64		0.79	0.50	[36.6, 82.9]	3.52		**−0.96**	0.76	[61.3, 97.6]
	(0.63)		(1.99)			(4.21)		(−2.61)		
4	0.12	0.23	0.62	0.55		**2.27**	**0.33**	−0.77	0.96	
	(0.11)	(1.26)	(1.96)			(2.65)	(2.03)	(−1.83)		
8	1.07	**0.37**		0.33		0.41	**0.45**		0.43	
	(1.16)	(2.20)				(0.41)	(2.09)			
8	1.54		**0.71**	0.79	[68.8, 90.4]	**2.17**		**−0.77**	0.93	[70.6, 97.8]
	(1.46)		(2.89)			(3.01)		(−2.82)		
8	1.07	0.10	**0.58**	0.84		**2.07**	0.10	**−0.75**	0.92	
	(0.92)	(0.65)	(3.60)			(3.42)	(0.81)	(−2.60)		
12	**1.53**	**0.28**		0.30		**0.72**	0.41		0.42	
	(2.39)	(2.19)				(0.85)	(1.91)			
12	**1.94**		**0.49**	0.76	[67.8, 89.9]	**1.65**		**−0.55**	0.85	[75.0, 98.4]
	(2.87)		(2.91)			(3.11)		(−2.78)		
12	**1.57**	0.05	**0.39**	0.83		**1.83**	0.03	**−0.59**	0.83	
	(2.31)	(0.50)	(3.49)			(3.68)	(0.23)	(−2.66)		

Table 4: Expected return-beta regressions. Notes: Newey West t-statistics in parenthesis. Bolded coefficients indicate significance at 5 percent or better level. Small T $\bar{R}^2$ dist reports finite sample 95 percent confidence interval for $\bar{R}^2$ from the bootstrap procedure described in the Appendix. All coefficients are scaled by multiple of 100. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Capital Share SDF

Panel A: 25 Size/book-market Portfolios

	SDF: $\delta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma$, $(\chi = 0)$						SDF: $\delta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$, χ est.						
H	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	χ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$
4	−0.002	24.75	0.70	0.59	34.4	0.25	−0.007	16.88	0.49	0.58	0.47	57.7	0.20
	(0.020)	(15.24)					(0.016)	(12.95)	(0.92)				
8	0.005	6.71	0.68	0.58	35.7	0.25	0.007	3.31	1.44	0.51	0.28	85.5	0.12
	(0.011)	(3.82)					(0.011)	(2.40)	(1.02)				
12	0.011	3.10	0.70	0.58	35.5	0.25	0.013	1.69	1.40	0.47	0.30	83.3	0.13
	(0.007)	(1.89)					(0.007)	(1.04)	(0.91)				
16	**0.014**	1.77	0.71	0.58	36.6	0.25	0.015	**1.07**	**1.63**	0.50	0.29	83.9	0.13
	(0.006)	(1.11)					(0.006)	(0.47)	(0.82)				

Panel B: 25 Size/book-market Portfolios

	SDF: $\delta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma$, $(\chi = 0)$						SDF: $\delta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$, $\chi = 1$					
H	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$
4	−0.002	24.75	0.70	0.59	34.4	0.25	−0.004	**9.82**	0.55	0.48	56.4	0.21
	(0.020)	(15.24)					(0.012)	(4.51)				
8	0.005	6.71	0.68	0.58	35.7	0.25	0.005	**4.33**	0.51	0.28	84.7	0.12
	(0.011)	(3.82)					(0.011)	(1.36)				
12	0.011	3.10	0.70	0.58	35.5	0.25	0.011	**2.15**	0.48	0.30	82.4	0.13
	(0.007)	(1.89)					(0.008)	(0.61)				
16	**0.014**	1.77	0.71	0.58	36.6	0.25	**0.014**	**1.46**	0.50	0.31	81.6	0.14
	(0.006)	(1.11)					(0.006)	(0.36)				

Panel C: 10 Momentum Portfolio

	SDF: $\delta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma$, $(\chi = 0)$						SDF: $\delta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$, $\chi = -1$					
H	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$
4	−0.008	28.30	0.34	0.56	66.7	0.33	0.023	9.85	0.30	0.26	92.8	0.15
	(0.023)	(18.68)					(0.009)	(5.44)				
8	−0.004	8.64	0.30	0.67	52.5	0.39	0.010	**3.91**	0.25	0.30	90.4	0.18
	(0.013)	(4.86)					(0.010)	(1.68)				
12	0.002	4.64	0.28	0.67	51.4	0.40	0.009	**2.04**	0.27	0.42	80.9	0.25
	(0.010)	(3.08)					(0.007)	(0.95)				
16	0.005	3.07	0.27	0.61	59.8	0.36	0.008	**1.32**	0.26	0.44	79.4	0.26
	(0.008)	(2.30)					(0.006)	(0.66)				

Table 5: Nonlinear GMM estimation of capital share SDF. Notes: HJ refers to HJ distance, defined as $\sqrt{g_T\left(\widehat{b}\right)'\left(\frac{1}{T}R_t^{e\prime}R_t^e\right)^{-1}g_T\left(\widehat{b}\right)}$. Serial correlation and heteroskedasticity robust standard errors are reported in parenthesis. The cross sectional R^2 is defined as $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(E_T(R_i^e)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)\right)^2}$. RMSE is reported in quarterly percentage point. Bolded coefficients indicate significance at 5 mpercent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Weighted Average Percentile SDFs

	Panel A: 25 Size/book-market Portfolios							**Panel B: 10 Momentum Portfolios**						
	Two Groups (<90%, 90-100%), Restrict $\chi = 1$							Two Groups (<90%, 90-100%), Restrict $\chi = 1$						
H	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	$R^2\,(\%)$	$\frac{RMSE}{RMSR}$	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	$R^2\,(\%)$	$\frac{RMSE}{RMSR}$
4	-0.008	15.87	0.00	0.60	0.47	58.0	0.20	0.014	16.69	**1.00**	0.25	0.19	96.0	0.11
	(0.018)	(12.55)	(0.40)					(0.009)	(10.23)	(0.40)				
8	0.005	4.49	0.00	0.51	0.29	84.4	0.12	0.004	6.08	1.00	0.24	0.40	83.0	0.24
	(0.012)	(2.32)	(0.34)					(0.009)	(3.97)	(0.52)				
12	0.011	**2.23**	0.00	0.48	0.31	82.1	0.13	0.006	3.14	1.00	0.25	0.49	74.9	0.29
	(0.007)	(1.00)	(0.32)					(0.008)	(2.17)	(0.54)				
16	**0.014**	**1.50**	0.00	0.51	0.31	81.1	0.14	0.007	1.99	1.00	0.24	0.48	74.9	0.29
	(0.006)	(0.37)	(0.38)					(0.007)	(1.43)	(0.67)				
	Top 10% Group, Restrict $\chi^{top10\%} = 1$							Only Bottom 90%, Restrict $\chi^{<90\%} = 1$						
H	α	γ	HJ	$RMSE$	$R^2\,(\%)$	$\frac{RMSE}{RMSR}$		α	γ	HJ	$RMSE$	$R^2\,(\%)$	$\frac{RMSE}{RMSR}$	
4	-0.008	15.87	0.60	0.47	58.0	0.20		0.014	16.69	0.25	0.19	96.0	0.11	
	(0.018)	(12.55)						(0.009)	(10.23)					
8	0.005	4.49	0.51	0.29	84.4	0.12		0.004	6.08	0.24	0.40	83.0	0.24	
	(0.012)	(2.32)						(0.009)	(3.97)					
12	0.011	**2.23**	0.48	0.31	82.1	0.13		0.006	3.14	0.25	0.49	74.9	0.29	
	(0.007)	(1.00)						(0.008)	(2.17)					
16	**0.014**	**1.50**	0.51	0.31	81.1	0.14		0.007	1.99	0.24	0.48	74.9	0.29	
	(0.006)	(0.37)						(0.007)	(1.43)					

Table 6: GMM estimation of percentile SDFs. Notes: See Table 5. The percentile SDF is defined as $M^i_{t+H,t} = \beta^H \left(\frac{C_{t+H}}{C_t}\right)^{-\gamma} \left\{ \left[\left(\frac{\widehat{Y^i_{t+H}/Y_{t+H}}}{\widehat{Y^i_t/Y_t}} \right)^{\chi} \right]^{-\gamma} \right\}$

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	$LevFac_t$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
Panel A: 25 Size-book/market Portfolios										
1	0.61						**14.19**	0.68	0.39	0.17
	(0.69)						(3.54)			
	[0.46]						[2.39]			
2	0.97	**0.52**					5.51	0.82	0.28	0.12
	(1.00)	(2.79)					(1.09)			
	[0.91]	[2.54]					[0.99]			
3	**3.09**		−1.61	0.68	**1.28**			0.73	0.34	0.14
	(3.19)		(−1.39)	(1.64)	(2.94)					
	[3.02]		[−1.31]	[1.56]	[2.79]					
4	**3.34**	**0.50**	−2.02	0.29	0.45			0.84	0.25	0.10
	(3.41)	(3.53)	(−1.72)	(0.65)	(0.94)					
	[3.26]	[3.38]	[−1.65]	[0.62]	[0.90]					
Panel B: 10 Momentum Portfolios										
5	0.36						**14.29**	0.17	0.83	0.48
	(0.35)						(2.28)			
	[0.24]						[1.53]			
6	1.71	**−0.76**					3.53	0.93	0.23	0.13
	(1.74)	(−3.87)					(0.61)			
	[1.65]	[−3.68]					[0.58]			
7	**7.01**		**−5.82**	**3.52**	1.54	**2.02**		0.73	0.37	0.20
	(3.42)		(−2.51)	(2.29)	(1.19)	(3.51)				
	[2.08]		[−1.53]	[1.40]	[0.72]	[2.14]				
8	2.52	**−0.80**	−0.57	0.75	1.75	0.10		0.88	0.22	0.12
	(1.14)	(−4.36)	(−0.24)	(0.47)	(1.34)	(0.14)				
	[1.04]	[−3.96]	[−0.22]	[0.43]	[1.22]	[0.13]				

Table 7: Fama-MacBeth regressions of average returns on factor betas. Notes: See table 6. OLS t-statistics is in parentheses and Shanken corrected t-statistics in brackets. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R_i^e\right)\right)^2}$ where $\widehat{R}_i^e \equiv \widehat{\alpha} + \widehat{\beta}'\widehat{\lambda}$. The sample spans the period 1963Q1 to 2013Q4.

Expected Return-Beta Regressions: Competing Models

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

Estimates of Factor Risk Prices λ, $H = 8$

Row #	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	MKT_t	$r_{ME,t}$	$r_{I/A,t}$	$r_{ROE,t}$	$\bar{R}^2$	$RMSE$	BIC
Panel A: 25 Size-book/market Portfolios										
1	**2.69** (3.82) [3.76]					0.66 (1.79) [1.76]		0.29	0.57	−252.27
2	1.26 (1.09) [1.00]			0.02 (0.02) [0.01]	**1.10** (2.38) [2.16]	**1.02** (2.61) [2.37]	0.86 (1.42) [1.29]	0.71	0.34	−268.16
3	**3.42** (3.14) [2.80]	**0.17** (2.04) [1.81]	**0.82** (5.65) [5.02]	**−2.75** (−2.20) [−1.96]	−0.38 (−0.68) [−0.60]	−0.49 (−1.11) [−0.99]	0.35 (0.57) [0.51]	0.83	0.24	−278.30
4	**2.10** (2.15) [2.11]		**0.66** (3.85) [3.78]	−0.86 (−0.73) [−0.72]				0.82	0.28	−284.92
5	1.47 (2.52) [2.46]		**0.75** (3.34) [3.27]		−0.38 (−0.62) [−0.60]			0.80	0.29	−282.19
6	**1.54** (2.70) [2.67]		**0.57** (2.78) [2.75]			0.29 (0.69) [0.68]		0.81	0.28	−283.40
7	**1.43** (2.42) [2.36]		**0.72** (3.87) [3.78]				0.50 (0.63) [0.61]	0.79	0.30	−280.68
Panel B: 10 Momentum Portfolios										
8	**2.31** (3.84) [3.66]						**1.54** (2.87) [2.74]	0.68	0.51	−101.10
9	5.13 (1.69) [0.94]			−4.18 (−1.32) [−0.73]	**4.16** (2.57) [1.43]	**−1.44** (−2.15) [−1.20]	**2.91** (4.49) [2.51]	0.97	0.12	−122.46
10	−0.27 (−0.07) [−0.07]	0.28 (1.68) [1.60]	−0.23 (−0.90) [−0.86]	0.99 (0.27) [0.25]	−0.16 (−0.06) [−0.06]	0.15 (0.12) [0.12]	1.06 (0.83) [0.79]	0.98	0.07	−125.53
11	**2.57** (2.88) [2.81]		**−0.70** (−3.58) [−3.50]	−0.65 (−0.59) [−0.58]				0.92	0.24	−113.61
12	**2.21** (3.80) [3.74]		**−0.69** (−3.62) [−3.56]		−0.40 (−0.50) [−0.50]			0.91	0.25	−112.98
13	**2.28** (3.98) [3.87]		**−0.75** (−3.55) [−3.45]			0.35 (0.64) [0.62]		0.92	0.24	−113.99
14	**2.09** (3.61) [3.56]		**−0.61** (−2.84) [−2.79]				0.42 (0.71) [0.70]	0.92	0.23	−114.54

Table 8: Fama-MacBeth regressions of average returns on factor betas. Notes: See Table 8. BIC $= N ln\left(\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)^2\right) + N_\lambda ln N$ where N_λ is number of free factor risk prices chosen to minimize the squared pricing errors. The sample spans the period 1967Q1 to 2013Q4.

Expected Return-Beta Regressions: Alternative Portfolios

$E_T\left(R^e_{i,t}\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$, Estimates of Factor Risk Prices λ												
	Panel A: 10 Portfolios on REV				**Panel B: 10 Portfolios on ROE**				**Panel C: 25 Size/Investment Portfolios**			
H	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$
4	0.85		**0.65**	0.68	**2.85**		**−0.78**	0.66	0.91		**0.64**	0.39
	(1.34)		(2.01)		(4.49)		(−2.45)		(1.55)		(2.28)	
	[1.30]		[1.96]		(4.32)		(−2.36)		[1.51]		[2.22]	
4	**2.13**	−0.52	**0.75**	0.79	**3.50**	−0.24	**−0.56**	0.79	0.67	0.09	**0.58**	0.38
	(3.01)	(−1.55)	(2.09)		(4.89)	(−1.69)	(−2.16)		(0.97)	(0.75)	(2.47)	
	[2.74]	[−1.41]	[1.90]		[4.71]	[−1.62]	[−2.08]		[0.95]	[0.74]	[2.41]	
6	**1.38**		**0.52**	0.86	**2.14**		**−0.57**	0.52	**1.29**		**0.62**	0.56
	(2.35)		(2.12)		(3.47)		(−2.41)		(2.11)		(2.99)	
	[2.32]		[2.09]		[3.42]		[−2.38]		[2.08]		[2.94]	
6	**2.06**	−0.27	**0.55**	0.88	**3.05**	−0.25	**−0.40**	0.78	0.92	0.08	**0.58**	0.57
	(3.10)	(−1.13)	(2.12)		(4.93)	(−1.80)	(−2.01)		(1.43)	(0.69)	(3.26)	
	[3.03]	[−1.11]	[2.07]		[4.84]	[−1.77]	[−1.97]		[1.41]	[0.67]	[3.21]	
8	**1.71**		**0.43**	0.86	**1.73**		**−0.40**	0.46	**1.67**		**0.59**	0.62
	(2.90)		(2.14)		(2.56)		(−2.37)		(2.53)		(3.66)	
	[2.88]		[2.13]		[2.55]		[−2.36]		[2.50]		[3.62]	
8	**2.05**	−0.17	**0.47**	0.85	**2.82**	**−0.28**	**−0.28**	0.75	1.07	0.11	**0.53**	0.68
	(3.21)	(−0.78)	(2.09)		(4.81)	(−1.94)	(−1.98)		(1.73)	(0.96)	(3.93)	
	[3.18]	[−0.77]	[2.07]		[4.75]	[−1.91]	[−1.95]		[1.70]	[0.95]	[3.88]	

Table 9: Expected return-beta regressions. Notes: See table 8. 25 size/investment portfolios are from Professor Kenneth French's online database and span the sample 1963Q3 to 2013Q4. 10 portfolios on long reversal (REV) are from Professor Kenneth French's online database and span the sample 1963Q1 to 2013Q4. 10 portfolios sorted on ROE are from Hou, Xue and Zhang (2014) and span the sample 1967Q1 to 2013Q4.

Appendix: For Online Publication

Data Description

CONSUMPTION

Consumption is measured as either total personal consumption expenditure or expenditure 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.[20]

TEST PORTFOLIOS

All returns of test asset portfolios used in the paper are obtained from professor French's online data library.[21] 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, $m1$,...,$m3$:

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

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

[21] 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.[22] In this paper we use the larger sample 1963Q1 to 2013Q4. There are no negative observations on broker-dealer leverage in this sample.

[22] 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 λ_0 and $\boldsymbol{\lambda}$, we choose parameters $\boldsymbol{b}$ to set the following linear combination of moments to zero

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

where

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

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

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

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

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

where

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

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

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

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, λ, we use Hansen's formula for the sampling distribution of the parameter estimates

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

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 A2 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 A2, 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 mth 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 A2.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:

$$R^e_{j,t+H,t} = a_{j,H} + \beta_{j,KS,H} \left([1 - LS_{t+H}] / [1 - LS_t] \right) + u_{j,t+H,t} \tag{A2}$$

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:

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

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

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

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

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

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

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

Next we recursively generate new data series for $\frac{1-LS_{t+H}}{1-LS_t}$ by combining the initial value of $\frac{1-LS_{1+H}}{1-LS_1}$ 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 mth bootstrap sample on capital share growth $\left\{\left(\frac{1-LS_{t+H}}{1-LS_t}\right)^{(m)}\right\}_t$. 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 $\left\{\left(\frac{1-LS_{t+H}}{1-LS_t}\right)^{(m)}\right\}_t$ and the sample estimates $\widehat{a}_{j,H}$ and $\widehat{\beta}_{j,KS,H}$.

5. We generate mth observation $\beta_{j,KS,H}^{(m)}$ from regression of $\left\{R_{j,t+H,t}^{e(m)}\right\}_t$ on $\left\{\left(\frac{1-LS_{t+H}}{1-LS_t}\right)^{(m)}\right\}_t$ and a constant.

6. We obtain an mth bootstrap sample $\left\{\epsilon_j^{(m)}\right\}_j$ by sampling the fitted errors $\{\widehat{\epsilon}_j\}_j$ randomly with replacement and laying them end-to-end in the order sampled until a new sample of observations of length N equal to the historical cross-sectional sample is obtained. We then generate new samples of observations on quarterly average excess returns $\left\{E\left(R_{j,t}^{e(m)}\right)\right\}_j$ 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 mth estimates $\lambda_0^{(m)}$ and $\lambda^{(m)}$ by regressing $\left\{E\left(R_{j,t}^{e(m)}\right)\right\}_j$ on the mth observation $\left\{\beta_{j,KS,H}^{(m)}\right\}_j$ and a constant. We store the mth sample cross-sectional $\overline{R}^2$, $\overline{R}^{(m)2}$.

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

Appendix Tables

2nd Size Quintile Value and Momentum Strategies

A : Annualized Statistics for Value and Momentum Strategies					
	$Corr\left(R_{M,H}, R_{VS2,H}\right)$	Mean		Sharpe Ratio	
H		$R_{VS2,t+H}$	$R_{M,t+H}$	$R_{VS2,t+H}$	$R_{M,t+H}$
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 $\frac{KS_{t+H}}{KS_t}$

$$R_{i,t+H,t} = a_i + \beta_i \left(\frac{KS_{t+H}}{KS_t}\right) + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 $\omega R_{VS2,H} + (1-\omega) R_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega R_{VS2,H} + (1-\omega) R_{M,H}\right)}{std\left(\omega R_{VS2,H} + (1-\omega) R_{M,H}\right)}$

H	ω	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 A1: 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 $R_{V,t+H,t} \equiv \prod_{h=1}^{H} R_{SiB5,t+h} - \prod_{h=1}^{H} R_{SiB1,t+h}$ where $i = 2, 3, 4, 5.$. This is abbreviated $R_{V,H}$ in each table corresponding to different size quintiles. The long-horizon return on the momentum strategy is $R_{M,t+H,t} \equiv \prod_{h=1}^{H} R_{M10,t+h} - \prod_{h=1}^{H} R_{M1,t+h}$. This is abbreviated $R_{M,H}$. 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 $R_{i,t+H,t}$, i included in V, M, as $R_{i,H}$. 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					
	$Corr\left(R_{M,H}, R_{VS3,H}\right)$	Mean		Sharpe Ratio	
H		$R_{VS3,t+H}$	$R_{M,t+H}$	$R_{VS3,t+H}$	$R_{M,t+H}$
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 $\frac{KS_{t+H}}{KS_t}$

$$R_{i,t+H,t} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 $\omega R_{VS3,H} + (1-\omega) R_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega R_{VS3,H} + (1-\omega) R_{M,H}\right)}{std\left(\omega R_{VS3,H} + (1-\omega) R_{M,H}\right)}$

H	ω	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 A1, continued

4th Size Quintile Value and Momentum Strategies

A : Annualized Statistics for Value and Momentum Strategies

H	$Corr\left(R_{M,H}, R_{VS4,H}\right)$	Mean		Sharpe Ratio	
		$R_{VS4,t+H}$	$R_{M,t+H}$	$R_{VS4,t+H}$	$R_{M,t+H}$
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 $\frac{KS_{t+H}}{KS_t}$

$$R_{i,t+H,t} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 $\omega R_{VS4,H} + (1-\omega) R_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega R_{VS4,H} + (1-\omega) R_{M,H}\right)}{std\left(\omega R_{VS4,H} + (1-\omega) R_{M,H}\right)}$

H	ω	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 A1, 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 $\frac{KS_{t+H}}{KS_t}$

$$R_{i,t+H,t} = a_i + \beta_i \frac{KS_{t+H}}{KS_t} + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{KS_{t+H}}{KS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 $\omega R_{VS5,H} + (1-\omega) R_{M,H}$ that maximizes Sharpe Ratio $\frac{E\left(\omega R_{VS5,H} + (1-\omega) R_{M,H}\right)}{std\left(\omega R_{VS5,H} + (1-\omega) R_{M,H}\right)}$

H	ω	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 A1, 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*)	$5-1$ $t(5-1)$
1(*small*)	1.19	2.66	2.75	3.27	3.80	2.61 (4.53)
2	1.69	2.37	2.97	3.02	3.28	1.59 (2.70)
3	1.68	2.52	2.51	3.92	3.41	1.72 (2.91)
4	1.98	1.84	2.24	2.70	2.76	0.78 (1.36)
5 (*big*)	1.48	1.60	1.49	1.73	1.97	0.49 (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*)	$5-1$ $t(5-1)$
1(*small*)	3.80	3.27	2.75	2.66	1.19	−2.61 (−4.53)
2	3.28	2.97	3.02	2.37	1.69	−1.59 (−2.70)
3	3.41	2.51	3.92	2.52	1.68	−1.72 (−2.91)
4	2.76	2.70	2.24	1.84	1.98	−0.78 (−1.36)
5 (*big*)	1.97	1.73	1.49	1.60	1.48	−0.49 (−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 A2: 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

Non linear GMM, Gross Excess Return, 25 Size/book-market Portfolios

	Aggregate Consumption ($\chi = 0$)						Top 1%, Unrestricted χ					
H	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	χ	HJ	$RMSE$	R^2 (%)
1	−0.001	**89.89**	0.61	0.7	8.4	0.30	0.001	81.21	0.43	0.38	3.3	22.4
	(0.013)	(42.40)					(0.011)	(55.66)	(0.28)			
4	−0.004	19.56	0.30	0.6	31.6	0.26	−0.002	9.69	0.57	0.22	2.5	52.3
	(0.017)	(11.08)					(0.011)	(6.55)	(0.52)			
6	0.001	10.18	0.21	0.6	34.8	0.25	−0.007	9.94	0.39	0.20	2.0	69.3
	(0.014)	(5.87)					(0.016)	(5.17)	(0.28)			
8	0.004	6.25	0.16	0.6	39.9	0.25	0.005	4.88	0.55	0.13	1.5	82.8
	(0.011)	(3.44)					(0.010)	(2.30)	(0.28)			
10	0.008	4.16	0.13	0.6	41.1	0.24	0.011	2.44	0.82	0.10	1.5	83.5
	(0.009)	(2.31)					(0.008)	(1.42)	(0.51)			
12	0.011	2.97	0.11	0.6	39.4	0.24	0.012	2.26	0.62	0.10	1.6	81.4
	(0.007)	(1.73)					(0.006)	(1.04)	(0.34)			
15	**0.013**	1.96	0.10	0.6	38.9	0.25	0.018	0.71	2.17	0.09	1.5	83.3
	(0.006)	(1.19)					(0.006)	(0.62)	(1.90)			

Table A3: HJ refers to HJ distance, defined as $\sqrt{g_T\left(\widehat{b}\right)'\left(\frac{1}{T}R_t^{e\prime}R_t^e\right)^{-1}g_T\left(\widehat{b}\right)}$. Standard error in parenthesis. GMM uses an identity matrix except that the weight on the last moment is large. Covariance matrices are calculated using Newey West procedure with lags $H+1$. The cross sectional R square is defined as $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^{\omega_i} - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and RMSR$=\sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)\right)^2}$. RMSE is reported in quarterly percentage point. The percentile SDF $M_{t+H,t}^i = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi^i}\right]^{-\gamma}\right\}$, where $\widehat{Y_t^i/Y_t}$ is the fitted value of regression of i's group stock owner income share Y_t^i/Y_t on the capital share (KS_t). The right panel restricts to 99%-100% stock wealth holders. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Non linear GMM, Gross Excess Return, 25 Size/book-market Portfolios

	Aggregate Consumption ($\chi = 0$)						Top 5%, Unrestricted χ					
H	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	χ	HJ	$RMSE$	R^2 (%)
1	−0.001	**89.89**	0.61	0.7	8.4	0.30	0.002	66.27	0.73	0.54	3.4	16.7
	(0.013)	(42.40)					(0.009)	(43.84)	(0.69)			
4	−0.004	19.56	0.30	0.6	31.6	0.26	−0.003	11.57	0.84	0.23	2.5	51.7
	(0.017)	(11.08)					(0.012)	(7.35)	(0.81)			
6	0.001	10.18	0.21	0.6	34.8	0.25	0.006	3.43	2.40	0.16	1.7	79.0
	(0.014)	(5.87)					(0.011)	(3.30)	(2.26)			
8	0.004	6.25	0.16	0.6	39.9	0.25	0.010	2.71	2.21	0.16	1.4	86.0
	(0.011)	(3.44)					(0.010)	(2.30)	(1.83)			
10	0.008	4.16	0.13	0.6	41.1	0.24	0.012	2.13	1.82	0.12	1.5	84.0
	(0.009)	(2.31)					(0.008)	(1.44)	(1.29)			
12	0.011	2.97	0.11	0.6	39.4	0.24	0.015	1.49	2.15	0.10	1.5	83.3
	(0.007)	(1.73)					(0.006)	(1.06)	(1.63)			
15	**0.013**	1.96	0.10	0.6	38.9	0.25	0.019	0.63	4.57	0.09	1.5	82.4
	(0.006)	(1.19)					(0.006)	(0.63)	(4.67)			

Table A4: HJ refers to HJ distance, defined as $\sqrt{g_T\left(\widehat{b}\right)'\left(\frac{1}{T}R_t^{e\prime}R_t^e\right)^{-1}g_T\left(\widehat{b}\right)}$. Standard error in parenthesis. GMM uses an identity matrix except that the weight on the last moment is large. Covariance matrices are calculated using Newey West procedure with lags $H+1$. The cross sectional R square is defined as $R^2 = 1-\frac{Var_c\left(E_T(R_i^e)-\widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha}+\frac{E_T\left[\left(M_{t+H,t}^{\omega_i}-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)-\widehat{R}_i^e\right)^2}$ and RMSR$=\sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)\right)^2}$. RMSE is reported in quarterly percentage point. The percentile SDF $M_{t+H,t}^i = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi^i}\right]^{-\gamma}\right\}$, where $\widehat{Y_t^i/Y_t}$ is the fitted value of regression of i's group stock owner income share Y_t^i/Y_t on the capital share (KS_t). The right panel restricts to 95%-100% stock wealth holders. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Non linear GMM, Gross Excess Return, Long Reversal Portfolio

	Aggregate Consumption ($\chi = 0$)						Top 5%, Unrestricted χ					
H	α	γ	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	χ	HJ	$RMSE$	R^2 (%)
1	0.012	33.63	0.21	0.5	6.6	0.25	0.011	22.42	1.04	0.21	1.3	23.3
	(0.013)	(42.75)					(0.011)	(88.03)	(5.80)			
4	0.011	7.31	0.19	0.5	3.2	0.25	0.005	5.26	1.75	0.11	0.8	70.7
	(0.017)	(9.23)					(0.008)	(10.66)	(4.44)			
6	0.014	2.75	0.17	0.5	1.0	0.25	0.010	2.56	2.18	0.07	0.5	89.0
	(0.014)	(5.72)					(0.008)	(4.61)	(4.65)			
8	0.008	4.67	0.17	0.5	5.6	0.25	0.014	1.82	2.21	0.05	0.5	90.1
	(0.011)	(4.10)					(0.007)	(2.87)	(4.09)			
10	0.003	**5.77**	0.19	0.4	15.2	0.23	0.018	0.08	39.62	0.05	0.6	87.2
	(0.009)	(2.87)					(0.007)	(2.36)	(120.2)			
12	0.003	**5.15**	0.19	0.4	19.4	0.23	0.016	1.10	2.22	0.04	0.7	81.3
	(0.007)	(1.73)					(0.007)	(1.86)	(4.38)			
15	0.009	**2.69**	0.06	0.5	7.2	0.24	0.012	4.98	0.28	0.08	1.3	33.4
	(0.005)	(1.19)					(0.012)	(3.47)	(0.49)			

Table A5: HJ refers to HJ distance, defined as $\sqrt{g_T\left(\widehat{b}\right)'\left(\frac{1}{T}R_t^{e\prime}R_t^e\right)^{-1}g_T\left(\widehat{b}\right)}$. Standard error in parenthesis. GMM uses an identity matrix except that the weight on the last moment is large. Covariance matrices are calculated using Newey West procedure with lags $H+1$. The cross sectional R square is defined as $R^2 = 1-\frac{Var_c\left(E_T(R_i^e)-\widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha}+\frac{E_T\left[\left(M_{t+H,t}^{\omega_i}-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)-\widehat{R}_i^e\right)^2}$ and RMSR$=\sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)\right)^2}$. RMSE is reported in quarterly percentage point. The percentile SDF $M_{t+H,t}^i = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi^i}\right]^{-\gamma}\right\}$, where $\widehat{Y_t^i/Y_t}$ is the fitted value of regression of i's group stock owner income share Y_t^i/Y_t on the capital share (KS_t). The right panel restricts to 95%-100% stock wealth holders. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Linear Two Pass Regression, Log Excess Returns

$$E_T\left(r_{i,t}^e\right) + \frac{1}{2}Var\left(r_{i,t}^e\right) = \lambda_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + u_i$$

Estimates of Factor Risk Prices λ, 25 Size/book-market Portfolios

H	Constant	$\Delta c_{t+H,t}$	$\Delta \log\left(KS_{t+H,t}\right)$	$\bar{R}^2$	H	Constant	$\Delta c_{t+H,t}$	$\Delta \log\left(KS_{t+H,t}\right)$	$\bar{R}^2$
1	1.52	0.24		0.05	12	**1.66**	0.29		0.15
	(1.79)	(1.17)				(2.15)	(1.47)		
1	2.39		−0.08	−0.04	12	**1.83**		**0.74**	0.71
	(5.23)		(−0.18)			(2.40)		(2.39)	
1	1.56	0.24	−0.09	0.01	12	1.44	0.05	**0.63**	0.68
	(1.90)	(1.19)	(−0.14)			(1.82)	(0.47)	(2.71)	
4	1.01			0.12	16	**1.88**	0.25		0.15
	(0.82)	(0.82)				(2.80)	(1.52)		
4	0.91		0.74	0.34	16	**2.13**		**0.65**	0.67
	(0.96)		(1.53)			(3.59)		(2.48)	
4	0.21	0.23	0.65	0.37	16	**1.81**	−0.01	**0.53**	0.75
	(0.16)	(0.99)	(1.52)			(3.03)	(−0.09)	(2.53)	
8	1.30	0.32		0.12	20	**2.08**	0.22		0.13
	(1.29)	(1.38)				(3.09)	(1.57)		
8	1.40		**0.89**	0.72	20	**2.19**		**0.61**	0.51
	(1.22)		(2.18)			(3.22)		(2.31)	
8	0.83	0.10	**0.79**	0.76	20	**1.91**	−0.03	**0.49**	0.67
	(0.58)	(0.65)	(2.42)			(2.85)	(−0.29)	(2.10)	

Table A6: Estimates from GMM are reported for each specification. Newey West *t-stats* in parenthesis corrected with lag 20. Bolded indicate significance at 5 percent or better level. $\bar{R}^2$ is adjusted R^2 statistics, corrected for the number of regressors. A Jensen corrected term is included in the estimation. All Coefficients are scaled by multiple of 100. The sample spans the period 1963Q1 to 2013Q4.

Percent of Total Income Y, sorted by Stock Wealth, Stock Owner

Percentile of Stock Wealth	1989	1992	1995	1998	2001	2004	2007	2010	2013
< 70%	46.70%	49.24%	48.57%	48.02%	43.33%	44.80%	41.09%	42.40%	41.32%
70 – 85%	15.40%	17.04%	17.32%	14.88%	15.90%	16.01%	15.34%	15.60%	16.29%
85 – 90%	5.32%	7.74%	6.09%	6.17%	6.92%	7.43%	6.90%	7.53%	6.95%
90 – 95%	8.15%	6.90%	8.80%	9.92%	8.65%	8.45%	9.08%	11.27%	9.70%
95 – 100%	24.45%	19.02%	19.34%	20.83%	25.26%	23.38%	27.70%	23.27%	25.81%
					Top 5 Percentile				
95 – 96%	3.90%	2.63%	1.55%	2.59%	2.71%	2.27%	2.59%	2.77%	2.15%
96 – 97%	2.35%	2.98%	2.37%	2.07%	2.52%	2.55%	2.74%	3.64%	2.95%
97 – 98%	2.42%	2.94%	2.37%	3.40%	4.54%	3.22%	3.93%	4.10%	3.56%
98 – 99%	4.23%	4.24%	3.93%	4.82%	5.08%	4.26%	5.41%	4.33%	4.44%
99 – 100%	11.53%	6.29%	9.08%	7.99%	10.38%	11.08%	13.05%	8.40%	12.75%
(Total)	24.45%	19.02%	19.34%	20.83%	25.26%	23.38%	27.70%	23.27%	25.81%

Table A7: Source from Survey of Consumer Finances 1989-2013. Stock Wealth include both direct and indirect holdings of public stock. Indirect holdings include annuities, trusts, mutual funds, IRA, Keogh Plan, other retirement accounts.

Cross Sectional Correlation Between Betas

H	25 Size-Book/Market	10 Long Reversal
	Panel B: $corr\left(\widehat{\beta}_{j,C,H}, \widehat{\beta}_{j,KS,H}\right)$	
1	0.11	0.69
2	0.54	0.63
4	0.52	0.37
8	0.65	0.72
12	0.73	0.89
16	0.82	0.91

Table A8: The beta $\beta' s$ are estimated from time series regression of long horizon excess returns of each test portfolios with horizon H on both long horizon consumption and labor shares. Labor shares are using non-farm sector. $\beta_{\Delta c} = \frac{Cov\left(r^e_{i,t+H,t}, \ln C_{t+H} - \ln C_t\right)}{Var(\ln C_{t+H} - \ln C_t)}$, $\beta_{\Delta \log(KS)} = \frac{Cov\left(r^e_{i,t+H,t}, \ln \frac{KS_{t+H}}{KS_t}\right)}{Var\left(\ln \frac{KS_{t+H}}{KS_t}\right)}$. Sample spans the period 1963Q1 to 2013Q3

Linear Expected Return-Beta Regressions

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

Estimates of Factor Risk Prices λ, Non-overlapping Samples

	25 Size/Book-Market Portfolio					10 Momentum Portfolio				
H	λ_0	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$	λ_0	$\frac{KS_{t+H}}{KS_t}$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
1	**2.24**	0.43	−0.03	0.68	0.27	**2.84**	**−2.21**	0.06	0.84	0.45
	(4.87)	(0.71)				(4.06)	(−2.46)			
4	0.72	**0.72**	0.47	0.49	0.20	**3.53**	**−0.92**	0.74	0.44	0.24
	(1.29)	(2.93)				(5.73)	(−3.24)			
6	1.07	**0.74**	0.75	0.34	0.14	**2.77**	**−0.87**	0.91	0.26	0.14
	(1.72)	(3.95)				(4.74)	(−3.60)			
8	**1.69**	**0.69**	0.77	0.32	0.13	**2.03**	**−0.76**	0.94	0.22	0.12
	(2.40)	(4.45)				(3.20)	(−3.91)			
12	**2.10**	**0.45**	0.81	0.29	0.12	**1.35**	**−0.58**	0.87	0.32	0.17
	(2.94)	(4.31)				(2.01)	(−4.17)			
16	**2.22**	**0.34**	0.81	0.29	0.12	0.93	**−0.50**	0.83	0.36	0.19
	(3.12)	(4.41)				(1.31)	(−4.39)			

Table A9: Fama-MacBeth regressions of average returns on factor betas. Fama-MacBeth t-statistics in parenthesis. Bolded coefficients indicate statistical significance at 5 percent or better level. All coefficients have been scaled by 100. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R^e_i\right) - \widehat{R}^e_i\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R^e_i\right)\right)^2}$ where $\widehat{R}^e_i \equiv \widehat{\alpha} + \widehat{\beta}'\widehat{\lambda}$. The non overlapping sample spans the period 1963Q1 to 2013Q4.

Explaining Quarterly Excess Returns on 25 Size-Book/Market Portfolios

LH Consumption and Labor Share Betas for H =8

Estimates of Factor Risk Prices λ, 25 Size-book/market Portfolios								
Constant	$\frac{C_{t+H}}{C_t}$	$\frac{KS_{t+H}}{KS_t}$	$Rm_{t+H,t}$	$SMB_{t+H,t}$	$HML_{t+H,t}$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
1.54		**0.71**				0.79	0.31	0.12
(2.18)		(4.45)						
[2.14]		[4.37]						
1.07	0.10	**0.58**				0.84	0.26	0.10
(1.50)	(1.06)	(4.37)						
[1.47]	[1.05]	[4.31]						
2.24					−0.44	−0.04	0.70	0.30
(3.84)					(−0.06)			
[3.84]					[−0.06]			
1.27		**0.73**			1.24	0.79	0.31	0.13
(2.34)		(4.38)			(0.17)			
[2.29]		(4.29)			[0.17]			
0.60			**−37.98**	−2.74	−10.29	0.33	0.53	0.23
(0.78)			(−3.36)	(−0.34)	(−1.38)			
[0.41]			[−1.77]	[−0.18]	[−0.72]			
0.29		**0.72**	−8.77	−11.95	1.58	0.79	0.29	0.13
(0.39)		(5.20)	(−0.82)	(−1.64)	(0.24)			
[0.33]		[4.36]	[−0.69]	[−1.38]	[0.20]			
−0.07	0.17	**0.69**	−2.64	−13.60	2.41	0.84	0.25	0.11
(−0.08)	(1.80)	(5.22)	(−0.24)	(−1.93)	(0.37)			
[−0.07]	[1.50]	[4.32]	[−0.20]	[−1.61]	[0.31]			

Table A10: Fama-MacBeth regressions of average returns on factor betas. Fama-MacBeth t-statistics in parenthesis and Shanken (1992) Corrected t-statistics in brackets. Bolded coefficients indicate statistical significance at 5 percent or better level. All coefficients have been scaled by 100. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_T\left(R_i^e\right)\right)^2}$ where $\widehat{R}_i^e \equiv \widehat{\alpha} + \widehat{\beta}'\widehat{\lambda}$. Rm, SMB, HML are three Fama French factors for pricing size - book/market portfolios. The long horizon Fama French factors $Rm_{t+H,t} = \prod_{h=1}^{H} Rm_{t+h}$, where Rm is market gross return. The long horizon SMB and HML are constructed using 2×3 size-book/market portfolios according to the formula in professor French's data library. $SMB_{t+H,t} = \prod_{h=1}^{H} R_{t+h}^{small} - \prod_{h=1}^{H} R_{t+h}^{big}$ where $R^{small} = \frac{1}{3}\left(R_{S1B1} + R_{S2B1} + R_{S3B1}\right)$ and $R^{big} = \frac{1}{3}\left(R_{S1B2} + R_{S2B2} + R_{S3B2}\right)$. $HML_{t+H,t} = \prod_{h=1}^{H} R_{t+h}^{\text{Value}} - \prod_{h=1}^{H} R_{t+h}^{\text{Growth}}$ where $R^{\text{Value}} = \frac{1}{2}\left(R_{S3B1} + R_{S3B2}\right)$ and $R^{\text{Value}} = \frac{1}{2}\left(R_{S1B1} + R_{S1B2}\right)$. The sample spans the period 1963Q1 to 2013Q4.

Estimation of Labor Share Beta using Simulation Data

Gross LH market returns $R^M_{t+H,t}$ regressed on $\frac{LS_{t+H}}{LS_t}$						
H	1	4	8	10	12	16
$\beta^M_{LS,H}$	-0.47	-0.53	-0.62	-0.67	-0.70	-0.75
$t\left(\beta^M_{LS,H}\right)$	-10.40	-13.35	-16.50	-17.81	-18.97	-20.46
$\bar{R}^2$	0.011	0.017	0.026	0.031	0.035	0.040

Table A11: OLS estimation of coefficient, OLS t-stats, and adjusted R-sq reported. Simulated Data from Greenwald, Lettau and Ludvigson (2013) spans 10,000 quarters

Nonlinear GMM, Weighted Average Percentile SDFs, 25 Size/book-market Portfolios

	Top 10% Group, Unconstrained GMM							Two Groups (<90%, 90-100%)						
H	α	γ	$\chi^{top\ 10\%}$	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$
1	0.005	29.94	1.08	0.69	0.58	36.4	0.25	0.005	30.13	0.001	0.69	0.58	36.4	0.25
	(0.011)	(84.35)	(3.48)					(0.012)	(106.91)	(0.90)				
4	0.001	5.28	1.80	0.53	0.44	64.1	0.19	0.000	6.02	0.001	0.53	0.44	64.1	0.19
	(0.012)	(6.60)	(2.11)					(0.014)	(5.85)	(2.29)				
6	0.005	3.82	1.58	0.50	0.30	82.9	0.13	0.005	3.66	0.002	0.50	0.30	82.9	0.13
	(0.011)	(3.12)	(1.30)					(0.011)	(3.13)	(2.75)				
8	0.010	2.89	1.46	0.47	0.26	87.0	0.11	0.010	2.89	0.001	0.47	0.26	87.0	0.11
	(0.010)	(2.10)	(1.08)					(0.012)	(2.20)	(5.30)				
10	0.012	1.98	1.42	0.46	0.29	84.5	0.12	0.012	1.98	0.004	0.46	0.29	84.5	0.12
	(0.008)	(1.36)	(1.06)					(0.008)	(1.28)	(10.65)				
12	**0.014**	1.69	1.33	0.45	0.30	83.4	0.13	**0.014**	1.69	0.005	0.45	0.30	83.4	0.13
	(0.006)	(1.00)	(0.90)					(0.006)	(0.90)	(9.98)				
16	**0.016**	**1.07**	**1.72**	0.50	0.29	83.8	0.13	**0.015**	1.21	0.001	0.50	0.29	83.6	0.13
	(0.006)	(0.47)	(0.86)					(0.005)	(1.55)	(11.38)				

Table A12: GMM estimation of percentile SDFs. HJ refers to HJ distance, defined as $\sqrt{g_T\left(\widehat{b}\right)'\left(\frac{1}{T}R_t^{e\prime}R_t^e\right)^{-1}g_T\left(\widehat{b}\right)}$. Standard error in parenthesis. GMM uses an identity matrix except that the weight on the last moment is large. Covariance matrices are calculated using Newey West procedure with lags $H+1$. The cross sectional R square is defined as $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^{\omega_i} - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)^2}$ and $RMSR = \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)\right)^2}$. RMSE is reported in quarterly percentage point. The weighted average SDF $M_{t+H,t}^{\omega_i} = \omega^{<90\%}M_{t+H,t}^{<90\%} + \left(1-\omega^{<90\%}\right)M_{t+H,t}^{>90\%}$. The percentile SDF $M_{t+H,t}^i = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi^i}\right]^{-\gamma}\right\}$, where $\widehat{Y_t^i/Y}_t$ is the fitted value of regression of i's group stock owner income share Y_t^i/Y_t on the capital share (KS_t). Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Weighted Average Percentile SDFs, 10 Momentum Portfolios

	Bottom 90% Group, Unconstrained GMM							Two Groups (<90%, 90-100%)						
H	α	γ	$\chi^{<90\%}$	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	R^2 (%)	$\frac{RMSE}{RMSR}$
1	−0.001	62.83	1.14	0.34	0.74	40.2	0.43	−0.000	67.10	**1.000**	0.34	0.74	40.2	0.43
	(0.008)	(54.91)	(1.31)					(0.011)	(61.40)	(0.14)				
4	**0.016**	9.77	2.31	0.27	0.21	95.4	0.12	0.016	9.76	0.999	0.27	0.21	95.4	0.12
	(0.008)	(8.19)	(2.58)					(0.018)	(8.65)	(0.84)				
6	**0.016**	2.43	6.63	0.29	0.23	94.1	0.14	0.016	2.41	1.000	0.29	0.23	94.1	0.14
	(0.007)	(4.72)	(14.77)					(0.015)	(4.84)	(0.92)				
8	**0.014**	0.24	49.15	0.33	0.30	90.4	0.17	−0.005	2.96	**0.757**	0.33	0.23	94.5	0.13
	(0.007)	(2.93)	(61.2)					(0.019)	(3.62)	(0.07)				
10	0.013	0.07	121.25	0.33	0.32	88.7	0.19	0.008	2.16	**0.775**	0.33	0.28	91.5	0.16
	(0.006)	(2.05)	(364.4)					(0.012)	(3.71)	(0.07)				
12	0.011	0.04	174.30	0.33	0.36	86.2	0.21	0.009	1.72	**0.756**	0.33	0.23	94.1	0.14
	(0.006)	(1.68)	(799.8)					(0.010)	(2.29)	(0.07)				
16	0.011	0.03	199.72	0.34	0.35	87.1	0.20	0.010	1.64	**0.724**	0.26	0.20	95.6	0.12
	(0.006)	(1.39)	(1525.7)					(0.007)	(1.70)	(0.082)				

Table A13: GMM estimation of percentile SDFs. HJ refers to HJ distance, defined as $\sqrt{g_T\left(\widehat{b}\right)'\left(\frac{1}{T}R_t^{e\prime}R_t^e\right)^{-1}g_T\left(\widehat{b}\right)}$. Standard error in parenthesis. GMM uses an identity matrix except that the weight on the last moment is large. Covariance matrices are calculated using Newey West procedure with lags $H+1$. The cross sectional R square is defined as $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e)-\widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^{\omega_i}-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. The pricing error is defined as RMSE $= \sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)-\widehat{R}_i^e\right)^2}$ and RMSR$=\sqrt{\frac{1}{N}\sum_{i=1}^N\left(E_T\left(R_i^e\right)\right)^2}$. RMSE is reported in quarterly percentage point. The weighted average SDF $M_{t+H,t}^{\omega_i} = \omega^{<90\%}M_{t+H,t}^{<90\%} + \left(1-\omega^{<90\%}\right)M_{t+H,t}^{>90\%}$. The percentile SDF $M_{t+H,t}^i = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi^i}\right]^{-\gamma}\right\}$, where $\widehat{Y_t^i/Y_t}$ is the fitted value of regression of i's group stock owner income share Y_t^i/Y_t on the capital share (KS_t). The right panel restricts to 0%-90% stock wealth holders. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.