Capital Share Risk and Shareholder Heterogeneity in U.S. Stock Pricing*

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Abstract

Value and momentum strategies earn persistently large return premia yet are negatively correlated. Why? We show that a quantitatively large fraction of the negative correlation is explained by strong opposite signed exposure of value and momentum portfolios to a single aggregate risk factor based on low frequency fluctuations in the capital share. Moreover, this negatively correlated component is priced. 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 and the pricing errors on both sets of portfolios are lower than those of the Fama-French three- and four-factor models, the intermediary SDF model of Adrian, Etula, and Muir (2014), and models based on low frequency exposure to aggregate consumption risk. None of the betas for these factors survive in a horse race where a long-horizon capital share beta is included. We show that capital share fluctuations generate a strong negative correlation between the income shares of stockholders in the top 10 and bottom 90 percent of the stock wealth distribution, implying that size/book-market portfolios are priced as if the marginal investor were a representative of the top 10 percent of the stock wealth distribution, while momentum portfolios are priced as if the representative investor were from the bottom 90 percent.

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

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 a long-standing 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 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

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

(2013)). 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 (top panel) and momentum portfolios (bottom panel) 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. From the perspective of canonical asset pricing theories, this finding presents its own puzzle. Why is the capital share an important risk factor, and why are value and momentum premia inversely exposed to it?

Factors share movements have been found to be 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

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

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%. This implies that an increase in the capital share is itself very unevenly distributed, with all the gains going to the top 10% at the expense of the bottom 90%. Opposite signed exposure of value and momentum to the capital share is really a phenomenon of opposite signed exposure to the income shares of these two groups of stockholders.

To assess the likely behavior of the consumption growth rates of these two groups of shareholders, we examine the growth in aggregate consumption times the income share of each group and find them to be strongly negatively related.[3] The positively correlated component in their consumption growth rates, accounted for by aggregate consumption, is more than offset by the negatively correlated component driven by the capital share. These findings suggest that the marginal utility growth of these two groups of shareholders is negatively correlated. Since assets that earn a positive risk premium are *defined* to be those that are negatively correlated with an investor's marginal utility growth (positively correlated with consumption growth), the results imply that size/book-market and momentum portfolio returns are priced *as if* there were two different representative stockholders who have segmented themselves along the value and momentum dimension. One of these invests in value and growth and does well out of an increase in the capital share, and one invests in momentum and does poorly out of an increase in the capital share.

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.

[3] Ideally we would examine the growth in aggregate consumption times *consumption* shares, but reliable measures of consumption across the wealth distribution (especially for the wealthy) do not exist. We discuss this further below.

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 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 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.

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. The focus on lower frequencies is motivated by evidence in LL and GLL indicating the presence of a slow moving factors-share shock that affects the aggregate stock market over long horizons. These slow moving, 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 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 fluctuations in the capital share are strongly priced, 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. 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. The estimations strongly favor positive values for χ when pricing size-book/market portfolios and long-run reversal 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 and long-run reversal portfolios, but strongly negative when pricing momentum portfolios.

Given our evidence on how the capital share varies with income shares, these findings suggest that any marginal utility-linked explanation for the large, negatively correlated return premia on these strategies must imply that a representative value investor is more akin to a stockholder in the top 10% of the stock wealth distribution, while a representative momentum investor is more akin to a stockholder in the bottom 90%. Estimations based on the percentile-specific SDFs are consistent with this hypothesis. When we allow the SDF to be a weighted average of the top 10 and the bottom 90th percentiles' SDFs, 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 a world 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.[4] 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.

Finally, 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-French four-factor model for pricing momentum portfolios (Fama and French (1996)), 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

[4]See for example Bansal, Dittmar, and Kiku (2009), Hansen, Heaton, and Li (2008), Dew-Becker and Giglio (2013), and Bandi and Tamoni (2014). These models all implicitly or explicitly explain short-run returns with covariances between long-horizon aggregate consumption growth and either short or long-horizon returns or dividend growth. Parker and Julliard (2004) study a slightly different model in which short-run returns are driven by covariances between short-run returns and *future* consumption growth, motivated by a sluggish adjustment story for consumption. We discuss this paper further below.

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.

The evidence presented here can be restated in terms of hypothetical marginal investors. Assets characterized by heterogeneity along the value, growth, and long-run reversal dimensions appear priced as if the marginal investor in these asset classes 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 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 representative investors, 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 caveat with these findings is that the time frame is limited to a two-year period and much could have changed in the 20 years since this time, as both value and momentum became increasingly popularized investment strategies. For example, in the U.S. sample studied here, the returns on momentum strategies exceed those of value strategies in the first two-thirds of the sample, but they have not earned superior returns in the last third (covering approximately 20 years), when the annualized return on the momentum strategy was 8.76%, compared to 10.4% for the small-stock value strategy. In Sharpe ratio units, the contrast in the last third of our sample is even starker: the momentum strategy had an annualized Sharpe ratio of just 0.27 in this subsample, compared to 0.50 for the small-stock value strategy.

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. This dataset sidesteps some of the problems with U.S. brokerage service account data because they are able to observe direct equity holdings of a single household over time for a large number of stock market participants whose trades are tracked by India's largest securities depository. 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%, more akin to a U.S. investor who is a recent first-time stockowner with little initial wealth for whom investing is a relatively new experience. 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 hypothesis and 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%.

We build on a previous literature emphasizing the importance for stock pricing of limited stock market participation and heterogeneity (Mankiw (1986), Constantinides and Duffie

(1996), Mankiw and Zeldes (1991), Vissing-Jorgensen (2002), Ait-Sahalia, Parker, and Yogo (2004), Guvenen (2009), and Malloy, Moskowitz, and Vissing-Jorgensen (2009)). The form of heterogeneity and limited participation considered in this paper is, differently from this literature, specifically concerned with shareholders located in different percentiles of the wealth distribution who have opposite signed exposure to capital share risk and who, due to heterogeneous risks, information, beliefs, or preferences, may pursue different investment strategies. 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. In their model, innovation reduces the market value of older vintages of capital trading on the stockmarket. This benefits workers but hurts existing shareholders, thereby reducing the capital share. But innovation reduces the returns to value stocks more than growth stocks, because the latter derive most of their value from the present value of future growth opportunities rather than older vintages. The model is silent on the implications for momentum strategies, however.

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.

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). 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.

We view our findings as indirectly related to the intermediary-based asset pricing literature. The time-varying balance sheet capacity of intermediaries that drives risk premia in these models is fundamentally determined by the households that supply them with capital and so must ultimately be linked back to their marginal utilities. In this sense, our findings are complementary to and consistent with the implicit interpretation in Adrian, Etula, and Muir (2014) of $LevFac_t$ as a summary risk factor that proxies for the marginal utilities of diverse investors who are all likely to trade through intermediaries. Although $LevFac_t$ does not work as well as existing multi-factor models for pricing both momentum and value stocks separately, we find that $LevFac_t$ has some ability to explain both strategies because it picks up at least part of the opposite signed capital share exposure we document here. Additional results (not reported) show that the betas for $LevFac_t$ are positively cross-sectionally correlated with the capital share betas for size-book/market portfolios, but negatively correlated for momentum portfolios. More work is needed to understand the precise linkages between intermediary balance sheets and the marginal utilities of shareholders.

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.[5] 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 $1 - LS$. 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 of 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. In short, 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 likely to be informative about opposite signed changes in the capital share. For brevity, we refer to $1 - LS_t$, 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.

Figure 2 plots the capital share over our sample. Over the last 20 years, this variable has become quite volatile, and is at a post-war high at the sample's end. Our empirical analysis is based on the growth in the capital share, rather than the level. The bottom panel plots the rolling eight-quarter log difference in the capital share over time, and shows that this variable is volatile throughout our sample.

In constructing the percentile-based SDFs, we use triennial survey data from the SCF,

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

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. As a measure of assets and liabilities though, it is considered far less reliable than the SCF and is unlikely to adequately measure the assets, income, *or* consumption of the wealthiest shareholders.[6] 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.[7]

We begin with a preliminary analysis of data from the SCF on the distribution of wealth and earnings. The top panel 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. The bottom panel 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%.

Table 2 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

[6] 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.

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

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 tables 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 3 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 divided by aggregate income for the SCF population, Y_t, and regressed on $(1 - LS_t)$ using the triennial data from the SCF.[8] 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 the top 10% and strongly *negatively* related to the income share of the bottom 90% of the stock wealth distribution. Indeed, this single variable explains 43% 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

[8] 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.

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.

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. Ideally, we would directly measure the consumption growth rates of each group by multiplying aggregate consumption times the consumption share of each group. But we do not have observations on the consumption shares of individual households from the SCF. 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. Because the SCF is better suited for measuring the income and assets of the wealthy, we use income shares from the SCF in place of unobserved consumption shares. While income shares do not equate with consumption shares, the two are almost certainly positively correlated. The top panel plots annual observations on the growth in $C_t \frac{Y_t^i}{Y_t}$ for the years available from the triennial SCF data. C_t is aggregate consumption for the corresponding year, measured from the National Income and Product Accounts, as detailed in the appendix. The income ratio $\frac{Y_t^i}{Y_t}$ 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 3 eliminating all households who are not stockholders. Specifically, $\widehat{\frac{Y_t^i}{Y_t}}$ is constructed using the estimated intercepts $\widehat{\alpha}^i$ and slope coefficients $\widehat{\beta}^i$ 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 positively correlated component in their consumption growth rates, accounted for by aggregate consumption, is more than offset by the negatively correlated component driven by the capital share.[9] Using the triennial data, the correlation is -0.75. In the quarterly data, it is -0.64. We view this evidence as strongly suggestive of a negative correlation between the marginal utilities of these two groups of shareholders.

Table 4 presents a variety of empirical statistics for value and moment strategies in our U.S. dataset, and their relation to capital share growth. For this table we define the return on the value strategy as the return on a long-short position designed to exploit the maximal spread in returns on the size-book/market portfolios. This is the return on a strategy that goes long in S1B5 and short in 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. This is the return on a strategy 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 4 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

[9] These findings are consistent with other evidence. Lettau and Ludvigson (2013) find that factors share shocks that move labor income and the stock market in opposite directions are the most important source of variation in labor earnings over short to intermediate horizons including business cycle frequencies. In particular, they dominate shocks that move aggregate consumption.

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. Return premia and Sharp ratios rise with the horizon. Panel B 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 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.[10] Finally, Panel C of this table shows a covariance decomposition for $R_{V,t+H,t}$ and $R_{M,t+H,t}$. The first 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 second 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 independent 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. At a horizon of 16 quarters, opposite signed exposure to capital share risk explains 70% of the negative covariance between these strategies.

Statistics in Table 4 were presented for the value strategy in the size quintile that delivers the maximal historic average return premium, which corresponds to the small(est) stock

[10] 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. R^2 are also small because the model is nonlinear while the regressions are not. A Table in the Appendix reports results from model-based regressions for the single market return on labor share growth, using simulated data from the GLL model, and shows that R^2 found in the data are by comparison surprisingly large.

value spread. For completeness, Table 5 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 example, looking at 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 $H = 12$. As for the smallest stock value strategy, means and Sharpe ratios rise with the horizon in tandem with the increasing fractions of covariance explained by capital share risk. We turn to formal statistical tests next.

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. But this empirical approach does assumes 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. For example, GLL find evidence of a stochastic preference-type shock that affects investor's willingness to bear risk independently of consumption and factor share dynamics. The utility specification employed in the estimation of this paper ignores such preference shocks and other possible amendments to the simplest power utility function. For this reason we consider the specification an incomplete model of risk, and our application makes use of statistics such as the Hansen-Jaganathan distance (Hansen and Jagannathan (1997)) that explicitly recognize 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., $M_{t+1}^{k} = \beta \left(\frac{C_{t+1}^{k}}{C_{t}^{k}}\right)^{-\gamma}$, where β 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:

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

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 of this 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 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 consider approximate linearized versions of the SDF, where the growth rates of aggregate consumption and the capital share are separate risk factors:

$$M_{t+H,t}^{k,lin} \approx b_{0} + b_{1} \left(\frac{C_{t+H}}{C_{t}}\right) + b_{2} \left(\frac{1 - LS_{t+H}}{1 - LS_{t}}\right). \tag{4}$$

Although this is only an approximation of the true nonlinear SDF that omits higher order terms, 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. We estimate these versions of the model, in addition to the nonlinear GMM models, with explicit betas and risk prices for each factor. As above, we expect the risk price to be positive for cross-sections of assets held by wealthy households and negative for those in the bottom 90% of the stockholder wealth distribution. 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 $\chi = b_2 = 0$.

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) implies that covariances between one-period-ahead SDFs M_{t+1} and one-period returns $R^e_{j,t+1}$ are related to one-period average return premia $E\left(R^e_{j,t+1}\right)$, 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 the most 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. Factors shares in particular move more slowly over time than do many macro series and most financial return variables. 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.[11] 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 $\left(\frac{1-LS_{t+H}}{1-LS_t}\right)$, or more generally between $R_{t+H,t}$ and the long-horizon

[11] Indeed, this outcome arises in the model of GLL which is designed to match the evidence on the slow moving dynamics of factors-shares. That model produces a high unconditional (quarterly) equity premium primarily due to the slow moving factors-share shock, which has long-term consequences for dividend growth and therefore the stock price. A higher frequency risk aversion shock that governs how future dividends are discounted dominates at short-horizons and causes volatility in the *conditional* equity premium in this model, but is less quantitatively important for the *un*conditional return premium.

SDFs $M^k_{t+H,t}$, and relate them to *short*-horizon (one quarter) average returns $E(R_{t+1})$.[12]

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 consumption of shareholders in the ith percentile of the stock wealth distribution is a fraction θ^i_t of aggregate consumption, where θ^i_t is a non-negative function of the ith percentile's income share, Y^i/Y. Thus consumption of percentile i is modeled as $C^i_t \equiv C_t\theta^i_t$ with $\theta^i_t = \left(\frac{Y^i_t}{Y_t}\right)^{\chi^i}$ 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, $\chi^i < 1$. If today's increase signals further increases tomorrow, we could observe $\chi^i > 1$.[13] But there is no reason to expect $\chi^i < 0$. Under these axioms, we should be able to infer something about the growth in the ith percentile's consumption from the growth in their income shares times the growth aggregate consumption.

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 3 and use estimated intercepts $\widehat{\alpha}^i$ and slope coefficients $\widehat{\beta}^i$ from these regressions 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. 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. With the mimicking factors in hand, we estimate models

[12] 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.

[13] 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)).

based on *percentile-specific* SDFs $M^i_{t+H,t}$ taking the form

$$M^i_{t+H,t} = \beta^{H,i} \left[\left(\frac{C_{t+H}}{C_t} \right)^{-\gamma^i} \left(\frac{\widehat{Y^i_{t+H}/Y_{t+H}}}{\widehat{Y^i_t/Y_t}} \right)^{-\gamma^i \chi^i} \right], \tag{5}$$

where $\widehat{Y^i_t/Y_t} = \widehat{\alpha}^i + \widehat{\beta}^i (1 - LS_t)$. The regression parameters are reported in Table 3. The reported results below use the parameters from regressions on the data restricted to the stockholding population (right panel), but it turns out not to matter much.

4.1 Nonlinear GMM Estimation

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

$$g_T(b) = E_T \left[\begin{array}{c} \mathbf{R}^e_t - \alpha \mathbf{1}_N + \frac{\left(M^k_{t+H,t} - \mu_H\right) \mathbf{R}^e_{t+H,t}}{\mu_H} \\ M^k_{t+H,t} - \mu_H \end{array} \right] = \left[\begin{array}{c} \mathbf{0} \\ 0 \end{array} \right] \tag{6}$$

where E_T denotes the sample mean in a sample with T time series observations, $\mathbf{R}^e_t = \left[R^e_{1,t} ... R^e_{N,t}\right]'$ denotes an $N \times 1$ vector of excess returns, and the parameters to be estimated are $\mathbf{b} \equiv (\mu_H, \gamma, \alpha, \beta)'$. 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 $\mathbf{R}^e_{t+H,t}$ and the SDF $M^k_{t+H,t}$ are used to explain *short*-horizon (quarterly) average return premia $E_T(\mathbf{R}^e_t)$. 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.[14]

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

[14] 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.

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.[15] 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 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 as above, replacing $M_{t+H,t}^k$ with $M_{t+H,t}^i$ but imposing the restriction $\chi^i \geq 0$. We also consider weighted averages of the percentile SDFs as an SDF. We denote these weighted average SDFs $M_{t+H,t}^{\omega^i}$, 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 aggre-

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

gate 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 $j = 1, 2....N$

$$R^e_{j,t+H,t} = a_{j,H} + \beta_{j,C,H} \left(C_{t+H}/C_t\right) + \beta_{j,KS,H} \left(\left[1 - LS_{t+H}\right] / \left[1 - LS_t\right]\right) + u_{j,t+H,t} \quad t = 1, 2...T,$$

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. Denote the factors together as

$$\mathbf{f}_t = \left[\left(C_{t+H}/C_t\right), \left(\left[1 - LS_{t+H}\right] / \left[1 - LS_t\right]\right)\right]'$$

and let K generically denote the number of factors (two here). 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 the long-horizon capital share beta alone, i.e.,

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

or the analogous expression using the long-horizon consumption beta alone.

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. Denote the $K \times 1$ vector $\boldsymbol{\beta}_i = \left[\widehat{\beta}_{i,C,H}, \widehat{\beta}_{i,LS,H}\right]'$. The moment conditions are

$$g_T(\boldsymbol{b}) = \begin{bmatrix} E_T\left(\underbrace{\mathbf{R}^e_{t+H,t}}_{N\times 1} - \underbrace{\mathbf{a}}_{N\times 1} - \underbrace{\boldsymbol{\beta}}_{(N\times K)}\underbrace{\mathbf{f}_t}_{(K\times 1)}\right) \\ E_T\left(\left(\mathbf{R}^e_{t+H,t} - \mathbf{a} - \boldsymbol{\beta}\mathbf{f}_t\right) \otimes \mathbf{f}_t\right) \\ E_T\left(\underbrace{\mathbf{R}^e_t}_{N\times 1} - \lambda_0 - \underbrace{\boldsymbol{\beta}}_{(N\times K)}\underbrace{\boldsymbol{\lambda}}_{(K\times 1)}\right) \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \\ \mathbf{0} \end{bmatrix} \tag{10}$$

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 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.,

$$E\left(R^e_{j,t}\right) = \lambda_0 + \widehat{\beta}_{j,KS,H}\lambda_{KS} + \widehat{\beta}_{j,MKT}\lambda_{MKT} + \widehat{\beta}_{j,SMB}\lambda_{SMB} + \widehat{\beta}_{j,HML}\lambda_{HML} + \epsilon_{j,t} \qquad (11)$$

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. In short, we don't need a statistical test to tell us whether a particular model is misspecified, since we know it is. The interesting question is, 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 (under some assumptions) 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, beginning with the benchmark nonlinear models.

5.1 Nonlinear GMM Estimation using Capital Share SDF

Table 6 presents results from estimations based on the moment conditions (6) of the nonlinear capital share SDF $M^k_{t+H,t}$ using 25 size-book/market portfolios. Results are presented for values of H from 1 to 15 quarters. 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.

The left panel confirms a long list of previous findings (Bansal, Dittmar, and Kiku (2009); Hansen, Heaton, and Li (2008) Dew-Becker and Giglio (2013); Bandi and Tamoni (2014)) showing 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 $H = 1$ to a peak of 44% at $H = 8$ and are still 41% at $H = 15$. 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 much larger R^2 statistics, much lower HJ distances, and much lower pricing errors than the model with $\chi = 0$ that excludes the capital share. The R^2 rises from 36% for $H = 1$ to a peak of 87% at $H = 8$ and remains high at 85% for $H = 15$. 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 are large, however, indicating that the estimation has difficulty distinguishing the separate roles of these two parameters. However, this is to be expected if the capital share component of the SDF is the most important source of covariance between the SDF and returns. To understand why, recall that the SDF takes the form $M^k_{t+H,t} = \beta^H \left[\left(\frac{C_{t+H}}{C_t} \right)^{-\gamma} \left(\frac{1-LS_{t+H}}{1-LS_t} \right)^{-\gamma\chi} \right]$. 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. Since we find that long horizon consumption growth is not a very important risk factor once we have controlled for long horizon capital share growth, we can expect it to be difficult to identify γ and χ separately, a phenomenon that shows up in the large standard errors.

For this reason, we shall often abandon the attempt to separately identify the two parameters and instead restrict χ to a reasonable 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 worsen the model's ability 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. Table 7 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 indicate reasonable values that monotonically decline with H from a high of $\gamma = 30$ at $H = 1$ to $\gamma = 1.5$ at $H = 15$. Note also that estimates of the zero-beta terms are in most cases small and 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 out-sized risk aversion parameters. 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.

Table 8 turns to nonlinear GMM estimation of $M^k_{t+H,t}$ using 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 it always takes on *negative* values. This is the opposite signed exposure of value and momentum to capital share risk foreshadowed above. Even when restricting $\chi = -1$, the table shows that the capital share SDF explains 95% of the variation in momentum returns for exposures over $H = 4$ quarters, 90% for exposures over $H = 6$ quarters, and 83% for exposures over $H = 8$ quarters. As for tests on size-book/market portfolios, estimates of the zero-beta terms are small and not statistically distinguishable from zero in almost every case, while estimates of γ are small and precisely estimated when the horizon over which exposure is measured is sufficiently large. The RMSE is often just 30% of that for the aggregate consumption growth CCAPM with $\chi = 0$.

Table 9 reports results for the same estimations on 10 long-run reversal portfolios.[16] Like the size-book/market portfolios, the key parameter χ is now estimated to be positive. The table reports results restricting $\chi = 1$. The capital share SDF explains 88% of return premia on these portfolios when measuring exposures over $H = 6$ and $H = 8$ quarters, 84% for exposures over $H = 10$ quarters, and 78% for exposures over $H = 12$ quarters. As above, 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. The CCAPM with $\chi = 0$ does not explain large fractions of the return premia on these portfolios.

[16] 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 with the highest prior returns.

5.2 Expected Return-Beta Representations

We now turn to estimations 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 10 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. Table 11 reports the same set of results for the 10 momentum portfolios. In both tables, all coefficients including the constant are multiplied by 100.

First consider the results for size-book/market portfolios in Table 10. The table 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 in the cross-sectional regression, the risk prices on the 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. This happens because 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. But these results imply 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.[17]

The finding that capital share risk is more important for return premia than is consumption risk, even at longer horizons, is consistent with both theory and evidence. LL and GLL find empirically that shocks to consumption have small effects on the aggregate stock

[17] 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).

market over any horizon, while a factors share shock is increasingly important at the horizon extends. GLL explain these findings with a model that naturally implies aggregate shocks (such as total factor productivity shocks that drive aggregate consumption and benefit both workers and shareholders) have smaller effects on the equilibrium share price than those that redistribute rewards from a fixed amount of output.

Table 11 reports the same set of results for the momentum portfolios. The punchline is much the same as it is for size-book/market portfolios, except that, importantly, the estimated risk prices for the capital share betas $\widehat{\beta}_{j,KS,H}$ are strongly negative, rather than positive. Interestingly, 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 risk explains 93% of the variation in the return premia on these portfolios and drives out consumption risk.

Table 12 shows estimates of the finite sample distribution of the cross-sectional $\overline{R}^2$ statistics for the 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 $H = 8, 12$ that work best in the historical data, the intervals have lower bounds that are all close to 70% for both sets of portfolios. These findings reinforce the conclusion that the single capital share risk factor explains large fractions of the return premia on these portfolios even if we consider the lowest ranges of what is likely in our finite sample.

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, where they are in most cases small and statistically indistinguishable from zero for both sets of portfolios. If the true SDF model is the nonlinear one, the linear expected return beta 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 the 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.

A visual impression of the key result from these 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 top panel plots these relations for the 25 size-book/market portfolios; the bottom panel for the 10 momentum portfolios. The solid line shows the fitted return implied by the model using the single capital share beta as a measure of risk. Size-book/market portfolios are denoted SiBj, where $i, j = 1, 2, ..., 5$, with $i = 1$ denoting 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 returns 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 capital share model explains the small-stock growth portfolio S1B1 extremely well, something that most models (e.g., the Fama-French three-factor model) find challenging. Indeed, the average return for this portfolio is spot on the fitted line for the model-predicted average return. Third, 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. 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 top panel has a fitted line that slopes strongly up, while the bottom panel 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. 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 A8. The results are very similar to those using the longer sample formed from overlapping data, with high fractions of variation in the returns explained by these betas, strongly significant risk prices for $H \geq 4$, and opposite signed exposures of size-book/market and momentum portfolios to capital share risk.

One explanation for the opposite signed exposure documented above 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 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 13 reports results of nonlinear GMM estimations on size-book/market portfolios 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. Estimates of parameter values are again imprecise whenever χ^i is freely estimated, because, analogously to the estimations discussed 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 in the right panel, which shows the results of estimates an SDF $M^{\omega\cdot}_{t+H,t}$ where weight $\omega^{<90}$ is placed on the marginal rate of substitution (MRS) $M^{<90}_{t+H,t}$ of the bottom 90% and $1-\omega^{<90}$ on the MRS $M^{\text{top10}}_{t+H,t}$ for those in the top 10% of the stock wealth distribution. We always restrict $\gamma \geq 0$. The results of this estimation deliver estimates of $\omega^{<90}$ that are right on the boundary of the parameter space, setting $\omega^{<90} = 0$ in every case. In the Appendix Table A11 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). The estimation always chooses $\omega^{<90}$ equal to a tiny value, less than or equal to 0.001 in most cases. 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%. Additional results in the Appendix tables show that using the percentile-specific SDFs for the top 5% or top 1% work about as well as these.

Table 14 repeats the findings for the percentile SDF $M^{top10\%}_{t+H,t}$ in the right panel where $\chi^{top10\%} = 1$ and compares these to the CCAPM model with $\chi^{top10\%} = 0$. 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.

The same estimations are performed on momentum portfolios. Table 16 (right panel) 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. This estimation restricts $\chi^i = 1$. Results are only slightly different if χ^i is freely estimated (Appendix Table A12). In that case, the weight $\omega^{<90}$ assigned to the bottom 90% MRS is unity for $H \leq 6$, and it exceeds 0.76 for all greater horizons, implying that the estimations seek to place close to all of the weight on the MRS of the *bottom* 90% of shareholders for explaining momentum portfolio returns. This SDF explains between 71 and 94% of average returns on these portfolios.

Table 16 shows that the SDF $M^{<90}_{t+H,t}$ with $\chi^{<90} = 1$ (right panel) performs far better than the long-horizon CCAPM model with $\chi^{<90} = 0$ (left panel).

5.4 Fama-MacBeth Regressions: Comparisons With Other Models

The last two tables 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 17 shows results for quarterly returns on the size-book/market portfolios. 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 model 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, 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. The risk prices on the betas for the value factor HML 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.

Table 18 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. The adjusted cross-sectional $\overline{R}^2$ statistics are 0.93, 0.75, and 0.17, for the three models respectively. The key reason that this single capital share risk factor 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 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 they 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 suggest that the return based factors are not even mimicking factors for capital share risk, and that the return premia on value and momentum are not earned from covariance of their uncorrelated components with separate priced factors.

6 Conclusion

This paper considers the role of capital share risk for explaining return premia on cross-sections of U.S. stocks. Our empirical approach pays close attention to the low frequency nature of this potential risk exposure. We show that a single aggregate risk factor based on low frequency fluctuations in the national capital share 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.

Although capital share risk appears strongly related to value, momentum, and long-run reversal portfolio returns, unreported results show that it bears little relation to the spread in average returns on industry portfolios. This is perhaps not surprising since the small, statistically indistinguishable spreads in average returns on industry portfolios are unlikely to load on true risk factors, which would imply a large spread in average returns.

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.

This evidence can be interpreted in one of several ways. One interpretation is that the findings simply present a puzzle from the perspective of integrated capital markets and fully rational portfolio choice. By definition, this perspective provides no explanation for the findings. An alternative interpretation is that portfolio decisions regarding which asset classes to invest in may in fact differ systematically with investor wealth (and/or age, which is correlated with wealth). Note that this explanation does not rule out the possibility that some arbitrage capital operates across the value and momentum dimensions. (It also does not imply that *every* investor in a particular wealth percentile pursue the same investment strategies). It merely requires that arbitrage activity does not fully eliminate the differing central portfolio tendencies of these two segments of the stock market. This perspective offers the advantage of explaining the finding rather than leaving it as a puzzle. Its disadvantage is that the U.S. wealth data for individual investors or households are not detailed enough to either affirm or refute the hypothesis. It also 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 merely begs the question of why these premia are then so strongly related to the share of national income accruing to capital.

Regardless of which interpretation one takes, we argue that the findings presented here pose a challenge for a number 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, the negatively correlated component of value and momentum is itself strongly priced: value and momentum are inversely exposed to capital share risk, and this largely explains their negative correlation. Thus, models in which value and momentum premia are earned 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 actually 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. To the extent that more detailed micro-level datasets can be brought to bear on the questions raised by these findings, much could be learned about how, why, and by whom, return premia on diverse investment strategies are earned in U.S. equity markets. All of these themes warrant investigation in future research.

Appendix

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.[18]

TEST PORTFOLIOS

All returns of test asset portfolios used in the paper are obtained from professor French's online data library.[19] 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

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

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

months in the quarter, $m1$,...,$m3$:

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

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

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

where m denotes a month within quarter Q, and

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

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

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

The leverage factor is constructed as seasonally adjusted log changes

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

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

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

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

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

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

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

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

where

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

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

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

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

$$\mathbf{S}=\sum_{j=-\infty}^{\infty}E\left(\begin{bmatrix}\mathbf{R}^{e}_{t+H,t}-\mathbf{a}-\boldsymbol{\beta}\mathbf{f}_{t}\\ \left(\mathbf{R}^{e}_{t+H,t}-\mathbf{a}-\boldsymbol{\beta}\mathbf{f}_{t}\right)\otimes\mathbf{f}_{t}\\ \mathbf{R}^{e}_{t}-\ \lambda_{0}-\boldsymbol{\beta}\boldsymbol{\lambda}\end{bmatrix}\begin{bmatrix}\mathbf{R}^{e}_{t+H-j,t-j}-\mathbf{a}-\boldsymbol{\beta}\mathbf{f}_{t-j}\\ \left(\mathbf{R}^{e}_{t+H-j,t-j}-\mathbf{a}-\boldsymbol{\beta}\mathbf{f}_{t-j}\right)\otimes\mathbf{f}_{t-j}\\ \mathbf{R}^{e}_{t-j}-\ \lambda_{0}-\boldsymbol{\beta}\boldsymbol{\lambda}\end{bmatrix}\right).$$

Denote

$$h_{t}\left(\mathbf{b}\right)=\begin{bmatrix}\mathbf{R}^{e}_{t+H,t}-\mathbf{a}-\boldsymbol{\beta}\mathbf{f}_{t}\\ \left(\mathbf{R}^{e}_{t+H,t}-\mathbf{a}-\boldsymbol{\beta}\mathbf{f}_{t}\right)\otimes\mathbf{f}_{t}\\ \mathbf{R}^{e}_{t}-\ \lambda_{0}-\boldsymbol{\beta}\boldsymbol{\lambda}\end{bmatrix}.$$

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

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

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

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

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 A1 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 A1, 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 A1.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:

$$R_{j,t+H,t}^{e} = a_{j,H} + \beta_{j,KS,H}\left(\left[1 - LS_{t+H}\right] / \left[1 - LS_{t}\right]\right) + u_{j,t+H,t} \tag{12}$$

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 $\{\widehat{\epsilon}_j\}_j$ and historical sample estimates $\widehat{\lambda}_0$ and $\widehat{\lambda}$.

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

$$\begin{bmatrix} \widehat{u}_{j,1+H,1} & \widehat{e}_{1+H,1} \\ \widehat{u}_{j,2+H,2} & \widehat{e}_{2+H,2} \\ \vdots & \vdots \\ \widehat{u}_{j,T,T-H} & \widehat{e}_{T,T-H} \end{bmatrix} \tag{13}$$

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 $\left\{ e^{(m)}_{t+H,t} \right\}_t$ 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 $\left\{ R^{(m)}_{j,t+H,t} \right\}_t$ from new data on $\left\{ u^{(m)}_{j,t+H,t} \right\}_t$ 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 $\left\{\overline{R}^{(m)2}\right\}_m$.

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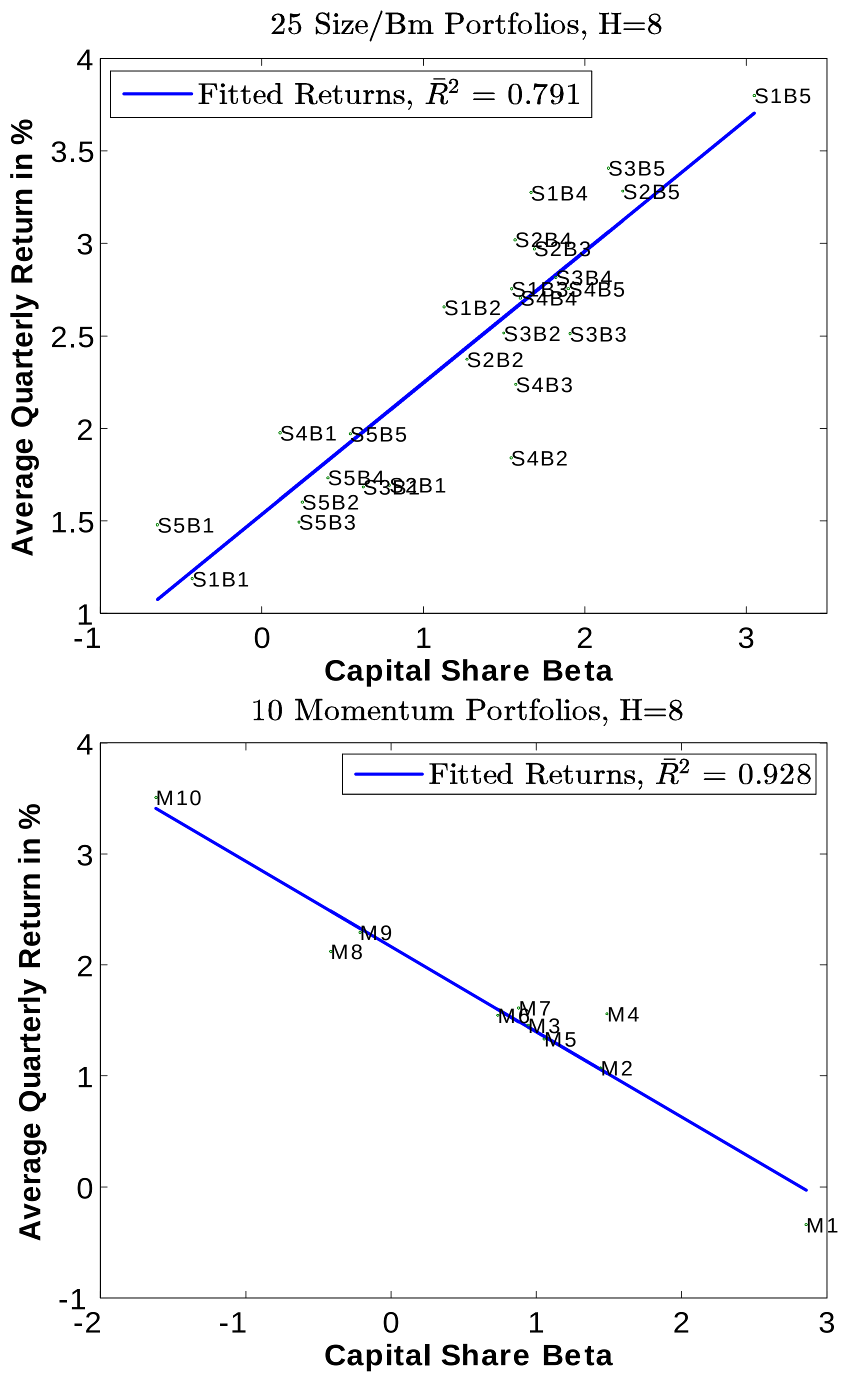

Figure 1: Capital share betas. Betas constructed from Fama-MacBeth regressions of average returns on capital share beta using 25 size-book/market portfolios (top panel) or 10 momentum portfolios (bottom panel). $\beta_{KS,H}$. $H = 8$ indicates the horizon in quarters over which capital share exposure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

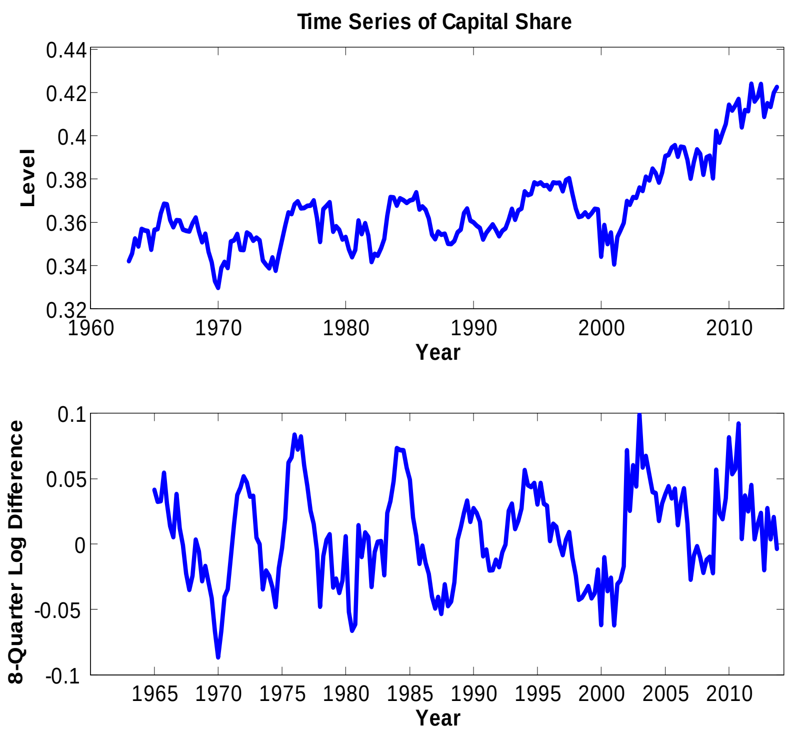

Figure 2: Capital share. The capital share is constructed by $1 - LS_t$ where LS_t is the seasonally adjusted quarterly non-farm sector labor share obtained from BLS. The top panel reports the level and the bottom panel reports the 8 quarter log difference. The sample spans the period 1963Q1 to 2013Q4.

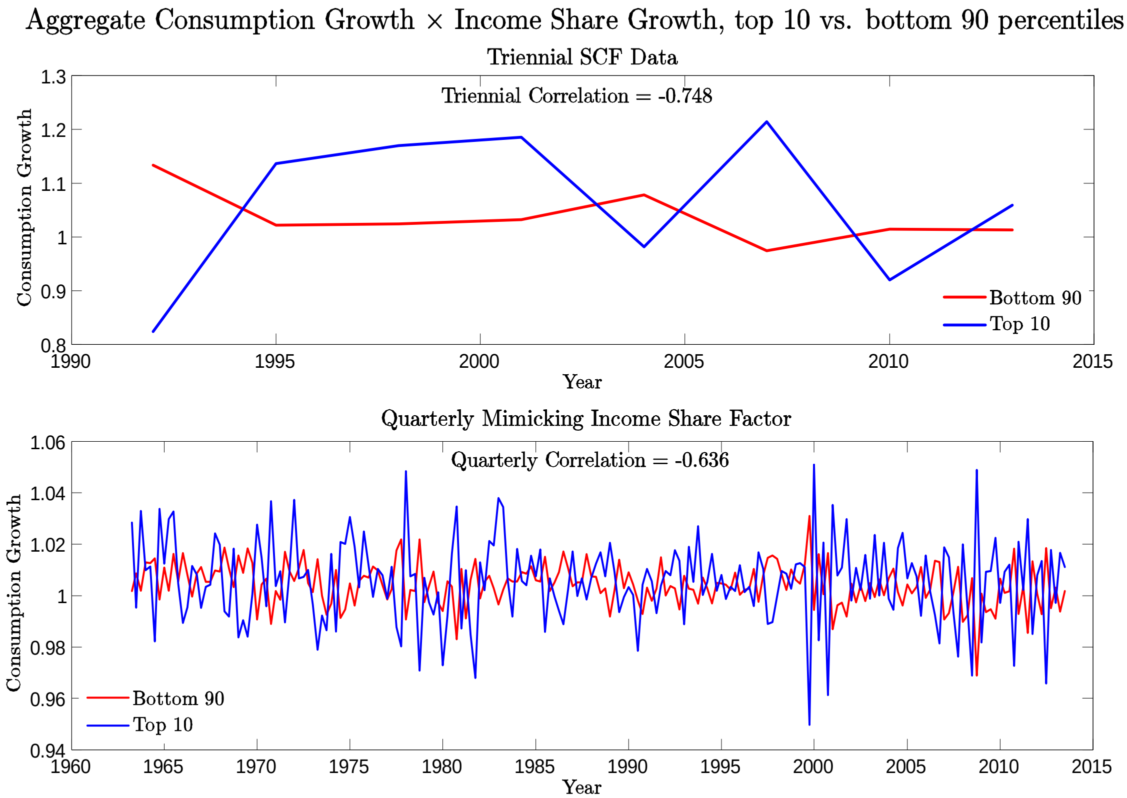

Figure 3: Growth in aggregate consumption times income share. The top panel reports triennial observations on the annual value of $\frac{C_t}{C_{t-1}}\left[\frac{Y_t^i/Y_t}{Y_{t-1}^i/Y_{t-1}}\right]$ corresponding to the years for which SCF data are available. Y_t^i/Y_t is the income share for group 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 $\widehat{Y_t^i/Y_t} = \widehat{\alpha}^i + \widehat{\beta}^i(1 - LS_t)$. The triennial data spans the period 1989 - 2013. The quarterly sample spans the period 1963Q1 - 2013Q4.

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%

B: Percent of Stock Wealth, sorted by Stock Wealth, All Households

Percentile of Stock Wealth	1989	1992	1995	1998	2001	2004	2007	2010	2013
< 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%

Stock Market Participation Rates

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

Table 1: Distribution of stock market wealth. The table reports the 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. Source: Survey of Consumer Finances.

Stock Market Participation Rates

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

Table 2: Weighted and unweighted stock market participation rates. Households with non-zero stock wealth held directly or indirectly is counted as a stockowner. The wealth-weighted participation rate is calculated as Value-weighted ownership $\equiv$ $5\% \left(w^{5\%}\right) + (rpr - \ 0.05)\% \left(1 - w^{5\%}\right) + (1 - rpr)\,\%\,(0)$ where rpr is the raw participation rate (not in percent) in the first row. $w^{5\%}$ is the proportion of stock market wealth owned by top 5% .

OLS Regression $\frac{Y_t^i}{Y_t} = \alpha^i + \beta^i (1 - LS_t)$

All Households				Stockowners			
Group	α	β	R^2	Group	α	β	R^2
$< 90\%$	**1.035**	**−0.981**	42.12	$< 90\%$	**0.977**	−0.788	29.20
	(6.26)	(−2.26)			(5.54)	(−1.70)	
$90 - 94.99\%$	0.018	0.208	29.90	$90 - 94.99\%$	−0.046	**0.358**	48.10
	(0.40)	(1.73)			(−0.86)	(2.55)	
$95 - 100\%$	−0.058	0.789	32.44	$95 - 100\%$	0.062	0.448	12.86
	(−0.36)	(1.83)			(0.37)	(1.02)	
$99 - 100\%$	−0.023	0.348	14.58	$99 - 100\%$	−0.032	0.350	13.29
	(−0.19)	(1.09)			(−0.25)	(1.04)	
$90 - 100\%$	−0.981	**0.997**	43.43	$90 - 100\%$	0.016	0.806	29.97
	(−0.25)	(2.32)			(−1.70)	(1.73)	

Table 3: Regressions of income shares on the capital share. 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. LS is the BLS non-farm labor share. Stockowner group includes households who have direct or indirect holdings of equity.

Value and Momentum Strategies

A : Annualized Statistics						
H	$Corr\,(R_{V,H}, R_{M,H})$	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	−0.0254	0.1054	0.1543	0.6407	0.6192	0.9026
4	−0.2285	0.1145	0.1696	0.5771	0.6389	0.9797
8	−0.3337	0.1378	0.1899	0.6068	0.7007	1.1342
12	−0.4044	0.1574	0.2177	0.6042	0.7462	1.2401
16	−0.3833	0.1812	0.2399	0.6174	0.7232	1.2087

B: Regression of Long Horizon Strategies Returns on $\frac{1-LS_{t+H}}{1-LS_t}$						
	β_H		t-$stat$		$\bar{R}^2$	
H	$R_{V,t+H,t}$	$R_{M,t+H,t}$	$R_{V,t+H,t}$	$R_{M,t+H,t}$	$R_{V,t+H,t}$	$R_{M,t+H,t}$
4	**1.56**	**−2.98**	3.09	−4.55	0.04	0.09
8	**3.48**	**−4.47**	6.09	−6.66	0.16	0.18
12	**5.27**	**−5.88**	8.12	−8.06	0.25	0.25
16	**6.43**	**−7.68**	7.99	−8.62	0.25	0.28

C: $R_{i,t+H,t} = \alpha_i + \beta_i \left(\frac{1-LS_{t+H}}{1-LS_t}\right) + \epsilon_{i,t+H,t},\ i \in \{V, M\}$			
H	$\frac{\beta_M \beta_V Var\left(\frac{1-LS_{t+H}}{1-LS_t}\right)}{Cov(R_{M,H}, R_{V,H})}$	$\frac{Cov(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H})}{Cov(R_{M,H}, R_{V,H})}$	$Corr\,(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H})$
4	0.2901	0.7099	−0.1746
8	0.5198	0.4802	−0.1940
12	0.6362	0.3638	−0.1981
16	0.7073	0.2927	−0.1540

Table 4: Value and momentum strategies. Panel A reports annualized statistics for returns on value and momentum strategies. Panel B reports the results of regressions of these strategies on capital share growth. The long horizon 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 long-horizon return on the momentum strategy is $R_{M,t+H,t} \equiv \prod_{h=1}^{H} R_{M10,t+h} - \prod_{h=1}^{H} R_{M1,t+h}$. The first two columns of panel B reports the time series slope coefficients for each regression, β_H, t-statistics "t-$stat$,"and adjusted $\bar{R}^2$ statistic. Panel C report the fraction of (the negative) covariance between the strategies' returns that can be explained by capital share growth exposure (first column) and the residual component orthogonal to that (second column). Bolded coefficients indicate statistical significance at the 5 percent level. We abbreviate $R_{i,t+H,t}$, i included in V, M, as $R_{i,H}$. The sample spans the period 1963Q1 to 2013Q4.

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 $\frac{1-LS_{t+H}}{1-LS_t}$ $R_{i,t+H,t} = \alpha_i + \beta_i \left(\frac{1-LS_{t+H}}{1-LS_t}\right) + \epsilon_{i,t+H,t},\ i \in \{V, M\}$					
H	$\frac{\beta_M \beta_V Var\left(\frac{1-LS_{t+H}}{1-LS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$		$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$	
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 5: 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

3rd Size Quintile Value and Momentum Strategies

A : Annualized Statistics for Value and Momentum Strategies

H	$Corr\left(R_{M,H}, R_{VS3,H}\right)$	Mean		Sharpe Ratio	
		$R_{VS3,t+H}$	$R_{M,t+H}$	$R_{VS3,t+H}$	$R_{M,t+H}$
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 $\frac{1-LS_{t+H}}{1-LS_t}$

$$R_{i,t+H,t} = \alpha_i + \beta_i\left(\frac{1-LS_{t+H}}{1-LS_t}\right) + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{1-LS_{t+H}}{1-LS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 5, continued

4th Size Quintile Value and Momentum Strategies

A : Annualized Statistics for Value and Momentum Strategies					
	$Corr\left(R_{M,H}, R_{VS4,H}\right)$	Mean		Sharpe Ratio	
H		$R_{VS4,t+H}$	$R_{M,t+H}$	$R_{VS4,t+H}$	$R_{M,t+H}$
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 $\frac{1-LS_{t+H}}{1-LS_t}$

$$R_{i,t+H,t} = \alpha_i + \beta_i \left(\frac{1-LS_{t+H}}{1-LS_t}\right) + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{1-LS_{t+H}}{1-LS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 5, continued

5th Size Quintile Value and Momentum Strategies

A : Annualized Statistics for Value and Momentum Strategies

H	$Corr\left(R_{M,H}, R_{VS5,H}\right)$	Mean		Sharpe Ratio	
		$R_{VS5,t+H}$	$R_{M,t+H}$	$R_{VS5,t+H}$	$R_{M,t+H}$
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 $\frac{1-LS_{t+H}}{1-LS_t}$

$$R_{i,t+H,t} = \alpha_i + \beta_i \left(\frac{1-LS_{t+H}}{1-LS_t}\right) + \epsilon_{i,t+H,t},\ i \in \{V, M\}$$

H	$\frac{\beta_M \beta_V Var\left(\frac{1-LS_{t+H}}{1-LS_t}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$\frac{Cov\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)}{Cov\left(R_{M,H}, R_{V,H}\right)}$	$Corr\left(\widehat{\epsilon}_{M,H}, \widehat{\epsilon}_{V,H}\right)$
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 5, continued

Nonlinear GMM, Capital Share SDF, 25 Size/book-market Portfolios

	SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma$, $(\chi = 0)$						SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$						
H	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	χ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	6.9	0.010	**56.50**	0.85	0.71	0.30	36.3	0.06	27.62	1.10	0.69	0.58	0.25
		(0.010)	(52.41)					(0.010)	(84.53)	(3.80)			
4	36.7	−0.004	19.44	0.68	0.58	0.25	64.1	0.001	5.28	1.70	0.53	0.44	0.19
		(0.016)	(10.45)					(0.012)	(6.60)	(2.00)			
6	38.7	0.001	10.14	0.69	0.57	0.24	83.0	0.005	3.82	1.49	0.50	0.30	0.13
		(0.014)	(5.66)					(0.011)	(3.12)	(1.23)			
8	43.9	0.004	6.17	0.69	0.55	0.23	87.0	0.010	2.89	1.38	0.47	0.26	0.11
		(0.011)	(3.33)					(0.010)	(2.10)	(1.02)			
10	43.2	0.008	4.09	0.69	0.55	0.24	84.5	0.012	1.98	1.34	0.46	0.29	0.12
		(0.008)	(2.25)					(0.008)	(1.36)	(1.01)			
12	41.2	0.010	2.93	0.69	0.56	0.24	83.4	0.014	1.69	1.26	0.45	0.30	0.13
		(0.007)	(1.71)					(0.006)	(1.00)	(0.86)			
16	36.5	**0.014**	1.77	0.71	0.58	0.25	83.1	0.015	**1.33**	**1.22**	0.50	0.30	0.13
		(0.006)	(1.11)					(0.006)	(0.51)	(0.57)			

Table 6: Nonlinear GMM estimation of capital share SDF. 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^2 is defined as $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$.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. The SDF $M_{t+H,t}^k = \beta^H\left(\frac{C_{t+H}^k}{C_t^k}\right)^{-\gamma}$. The capital consumption is defined as $C_t^k = C_t\left(1 - LS_t\right)^\chi$. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Capital Share SDF, 25 Size/book-market Portfolios

	SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma$, $(\chi = 0)$						SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^\gamma \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$, $\chi = 1$					
H	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	6.9	0.010	**56.50**	0.85	0.71	0.30	36.3	0.005	30.50	0.79	0.58	0.25
		(0.010)	(52.41)					(0.022)	(29.61)			
4	36.7	−0.004	19.44	0.68	0.58	0.25	50.8	−0.013	**24.73**	0.74	0.51	0.22
		(0.016)	(10.45)					(0.019)	(11.09)			
6	38.7	0.001	10.14	0.69	0.57	0.24	63.8	−0.001	**8.12**	0.53	0.44	0.19
		(0.014)	(5.66)					(0.011)	(3.58)			
8	43.9	0.004	6.17	0.69	0.55	0.23	82.4	0.003	**5.23**	0.51	0.31	0.13
		(0.011)	(3.33)					(0.011)	(1.82)			
10	43.2	0.008	4.09	0.69	0.55	0.24	86.4	0.008	**3.63**	0.48	0.27	0.12
		(0.008)	(2.25)					(0.010)	(1.15)			
12	41.2	0.010	2.93	0.69	0.56	0.24	82.9	0.013	**1.98**	0.46	0.30	0.13
		(0.007)	(1.71)					(0.007)	(0.57)			
16	36.5	**0.014**	1.77	0.71	0.58	0.25	83.3	**0.015**	**1.49**	0.47	0.30	0.13
		(0.006)	(1.11)					(0.006)	(0.38)			

Table 7: Nonlinear GMM estimation of capital share SDF. 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^2 is defined as $R^2 = 1 - \frac{Var_c\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$.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. The SDF $M_{t+H,t}^k = \beta^H\left(\frac{C_{t+H}^k}{C_t^k}\right)^{-\gamma}$. The capital consumption is defined as $C_t^k = C_t\left(1 - LS_t\right)^\chi$. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Capital Share SDF, 10 Momentum Portfolio

	SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^{\gamma}$, $(\chi = 0)$						SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^{\gamma} \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$, $\chi = -1$					
H	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	15.8	−0.002	**83.56**	0.43	0.88	0.52	39.9	0.003	39.38	0.39	0.74	0.44
		(0.008)	(36.51)					(0.012)	(22.98)			
4	36.1	−0.006	18.00	0.31	0.77	0.45	94.7	0.016	9.92	0.28	0.22	0.13
		(0.014)	(9.97)					(0.011)	(5.26)			
6	35.2	−0.004	10.23	0.30	0.78	0.45	90.0	0.009	5.70	0.27	0.31	0.18
		(0.012)	(5.55)					(0.012)	(2.91)			
8	38.5	−0.003	6.98	0.29	0.76	0.44	82.8	0.006	**3.60**	0.27	0.40	0.23
		(0.011)	(3.82)					(0.010)	(1.61)			
10	41.8	−0.000	5.12	0.29	0.73	0.43	80.7	0.007	**2.48**	0.27	0.42	0.25
		(0.010)	(3.10)					(0.008)	(1.16)			
12	47.5	0.002	4.14	0.29	0.70	0.41	77.8	0.007	**1.85**	0.27	0.45	0.27
		(0.009)	(2.72)					(0.007)	(0.92)			
16	60.0	0.005	3.07	0.27	0.61	0.36	79.5	0.008	**1.32**	0.26	0.44	0.26
		(0.008)	(2.30)					(0.006)	(0.65)			

Table 8: Nonlinear GMM estimation of capital share SDF. 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^2 is defined as $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e) - \widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^k - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$.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. The SDF $M_{t+H,t}^k = \beta^H \left(\frac{C_{t+H}^k}{C_t^k}\right)^{-\gamma}$. The capital consumption is defined as $C_t^k = C_t\left(1 - LS_t\right)^{\chi}$. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Capital Share SDF, Long-run Reversal Portfolios

	SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^{\gamma}$, $(\chi = 0)$						SDF: $\beta^H \left(\frac{C_{t+H}}{C_t}\right)^{\gamma} \left(\frac{KS_{t+H}}{KS_t}\right)^{\gamma\chi}$, $\chi = 1$					
H	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	12.6	0.010	45.08	0.22	0.45	0.24	26.4	0.012	13.54	0.21	0.42	0.22
		(0.009)	(55.60)					(0.007)	(14.45)			
4	9.9	0.005	12.63	0.24	0.46	0.24	74.0	0.004	6.12	0.23	0.25	0.13
		(0.014)	(12.50)					(0.012)	(3.44)			
6	5.2	0.008	6.01	0.23	0.47	0.25	88.0	0.008	3.79	0.20	0.17	0.09
		(0.010)	(5.44)					(0.010)	(2.08)			
8	14.3	0.002	6.85	0.30	0.45	0.24	88.4	0.012	2.72	0.19	0.17	0.09
		(0.014)	(5.18)					(0.009)	(1.51)			
10	24.1	−0.000	6.60	0.36	0.42	0.22	84.8	0.013	**1.99**	0.21	0.19	0.10
		(0.016)	(5.26)					(0.008)	(1.04)			
12	18.9	0.002	5.04	0.36	0.44	0.23	78.0	**0.015**	**1.69**	0.23	0.23	0.12
		(0.014)	(4.18)					(0.007)	(0.83)			
16	4.7	0.011	2.17	0.28	0.47	0.25	52.5	**0.016**	**1.17**	0.27	0.32	0.17
		(0.008)	(2.13)					(0.007)	(0.59)			

Table 9: Nonlinear GMM estimation of capital share SDF. 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^2 is defined as $R^2 = 1 - \frac{Var_c\left(E_T\left(R_i^e\right)-\widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^k-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$.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. The SDF $M_{t+H,t}^k = \beta^H\left(\frac{C_{t+H}^k}{C_t^k}\right)^{-\gamma}$. The capital consumption is defined as $C_t^k = C_t\left(1-LS_t\right)^{\chi}$. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Linear Expected Return-Beta Regressions

$$E_T\left(R^e_{i,t}\right) = \boldsymbol{\lambda}_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$$

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

H	Constant	C_{t+H}/C_t	$\frac{1-LS_{t+H}}{1-LS_t}$	$\bar{R}^2$	H	Constant	C_{t+H}/C_t	$\frac{1-LS_{t+H}}{1-LS_t}$	$\bar{R}^2$
1	1.53	0.26		0.06	8	1.07	**0.37**		0.33
	(1.76)	(1.27)				(1.16)	(2.20)		
1	**2.24**		0.43	−0.03	8	1.54		**0.71**	0.79
	(4.87)		(0.71)			(1.46)		(2.89)	
1	1.44	0.25	0.28	0.03	8	1.07	0.10	**0.58**	0.84
	(1.64)	(1.17)	(0.46)			(0.92)	(0.65)	(3.60)	
4	0.77	**0.46**		0.30	12	**1.53**	**0.28**		0.30
	(0.62)	(2.10)				(2.39)	(2.19)		
4	0.64		0.79	0.50	12	**1.94**		**0.49**	0.76
	(0.63)		(1.99)			(2.87)		(2.91)	
4	0.12	0.23	0.62	0.55	12	**1.57**	0.05	**0.39**	0.83
	(0.11)	(1.26)	(1.96)			(2.31)	(0.50)	(3.49)	
6	0.91	**0.42**		0.30	16	**1.68**	**0.22**		0.40
	(0.82)	(2.07)				(3.14)	(2.20)		
6	1.04		**0.79**	0.75	16	**2.15**		**0.40**	0.75
	(0.90)		(2.48)			(3.69)		(2.66)	
6	0.67	0.11	**0.67**	0.78	16	**1.80**	0.01	**0.30**	0.83
	(0.55)	(0.72)	(2.71)			(3.20)	(0.16)	(3.09)	

Table 10: Expected return-beta regressions with separately priced consumption and capital share factors. Estimates from GMM using 25 size-book/market portfolios are reported for each specification. Newey West t-statistics in parenthesis. Bolded coefficients indicate significance at 5 percent or better level. $\bar{R}^2$ is adjusted R^2 statistic, corrected for the number of regressors. All Coefficients are scaled by multiple of 100. The sample spans the period 1963Q1 to 2013Q4..

Linear Expected Return-Beta Regressions

$$E_T\left(R^e_{i,t}\right) = \boldsymbol{\lambda}_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$$

Estimates of Factor Risk Prices λ, 10 Momentum Portfolios

H	Constant	C_{t+H}/C_t	$\frac{1-LS_{t+H}}{1-LS_t}$	$\bar{R}^2$	H	Constant	C_{t+H}/C_t	$\frac{1-LS_{t+H}}{1-LS_t}$	$\bar{R}^2$
1	0.39	**0.52**		0.40	8	0.41	**0.45**		0.43
	(0.35)	(2.20)				(0.41)	(2.09)		
1	**2.84**		**−2.21**	0.06	8	**2.17**		**−0.77**	0.93
	(4.06)		(−2.46)			(3.01)		(−2.82)	
1	1.76	0.54	−2.56	0.03	8	**2.07**	0.10	**−0.75**	0.92
	(1.52)	(1.81)	(−1.82)			(3.42)	(0.81)	(−2.60)	
4	0.25	**0.51**		0.52	12	**0.72**	0.41		0.42
	(0.20)	(1.96)				(0.85)	(1.91)		
4	3.52		**−0.96**	0.76	12	**1.65**		**−0.55**	0.85
	(4.21)		(−2.61)			(3.11)		(−2.78)	
4	**2.27**	**0.33**	−0.77	0.96	12	**1.83**	0.03	**−0.59**	0.83
	(2.65)	(2.03)	(−1.83)			(3.68)	(0.23)	(−2.66)	
6	0.32	**0.48**		0.42	16	0.81	0.39		0.50
	(0.29)	(2.03)				(1.06)	(1.85)		
6	**2.83**		**−0.92**	0.91	16	**1.37**		**−0.42**	0.83
	(3.32)		(−2.52)			(2.48)		(−2.67)	
6	**2.20**	0.21	**−0.82**	0.95	16	**1.56**	0.05	**−0.46**	0.82
	(3.30)	(1.69)	(−2.15)			(2.68)	(0.49)	(−2.61)	

Table 11: Expected return-beta regressions with separately priced consumption and capital share factors. Estimates from GMM using 10 momentum portfolios are reported for each specification. Newey West t-statistics in parenthesis. Bolded coefficients indicate significance at 5 percent or better level. $\bar{R}^2$ is adjusted R^2 statistic, corrected for the number of regressors. All Coefficients are scaled by multiple of 100. The sample spans the period 1963Q1 to 2013Q4..

Finite Sample Cross-Sectional $\overline{R}^2$ Distribution

$\overline{R}^2$ from $E_T\left(R^e_{j,t}\right) = \boldsymbol{\lambda}_0 + \boldsymbol{\lambda}'\boldsymbol{\beta}_{j,KS,H} + \epsilon_j$		
95% Confidence Interval of $\bar{R}^2$		
H	25 Size/book-market	10 Momentum Portfolios
4	$[36.6, 82.9]$	$[61.3, 97.6]$
8	$[68.8, 90.4]$	$[70.6, 97.8]$
12	$[67.8, 89.9]$	$[75.0, 98.4]$
16	$[65.2, 89.3]$	$[69.8, 97.0]$

Table 12: Finite sample distribution of cross-sectional $\bar{R}^2$ statistic. The table reports finite sample 95 percent confidence interval for $\bar{R}^2$ from the bootstrap procedure described in the Appendix.. The historical sample spans the period 1963Q1 to 2013Q4.

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

	Two Groups (<90%, 90-100%), Restrict $\chi = 1$						
H	R^2 (%)	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	36.3	0.008	32.41	0.000	0.69	0.58	0.25
		(0.023)	(31.48)	(0.67)			
4	63.6	0.001	**8.46**	0.000	0.53	0.44	0.19
		(0.011)	(3.72)	(0.53)			
6	82.2	0.002	**5.44**	0.000	0.50	0.30	0.13
		(0.011)	(1.89)	(0.34)			
8	86.2	0.007	**3.77**	0.000	0.47	0.26	0.11
		(0.010)	(1.20)	(0.34)			
10	83.8	0.010	**2.53**	0.000	0.46	0.29	0.12
		(0.008)	(0.73)	(0.34)			
12	82.7	0.013	**2.05**	0.000	0.45	0.30	0.13
		(0.007)	(0.59)	(0.32)			
16	81.1	**0.014**	**1.50**	0.000	0.50	0.29	0.13
		(0.006)	(0.37)	(0.38)			

Table 13: 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 $R^2 = 1 - \frac{Var_c\left(E_T\left(R_i^e\right) - \widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^{\omega} - \widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. 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 $M_{t+H,t}^{\omega} = \omega^{<90\%}M_{t+H,t}^{<90\%} + \left(1-\omega^{<90\%}\right)M_{t+H,t}^{>90\%}$. The percentile SDF $M_{t+H,t}^i = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi}\right]^{-\gamma}\right\}$, 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 $(1-LS_t)$. In computation, we restrict ω to be between zero and one. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Percentile SDF, 25 Size/book-market Portfolios

	Aggregate Consumption ($\chi^{top10\%} = 0$)						Top 10% Group, Restrict $\chi^{top10\%} = 1$					
H	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	6.9	0.010	**56.50**	0.85	0.71	0.30	36.3	0.008	32.41	0.50	0.58	0.25
		(0.010)	(52.41)					(0.023)	(31.48)			
4	36.7	−0.004	19.44	0.68	0.58	0.25	63.6	0.001	**8.46**	0.53	0.44	0.19
		(0.016)	(10.45)					(0.011)	(3.72)			
6	38.7	0.001	10.14	0.69	0.57	0.24	82.2	0.002	**5.44**	0.51	0.31	0.13
		(0.014)	(5.66)					(0.011)	(1.89)			
8	43.9	0.004	6.17	0.69	0.55	0.23	86.2	0.007	**3.77**	0.48	0.27	0.12
		(0.011)	(3.33)					(0.010)	(1.20)			
10	43.2	0.008	4.09	0.69	0.55	0.24	83.8	0.010	**2.53**	0.47	0.29	0.13
		(0.008)	(2.25)					(0.008)	(0.73)			
12	41.2	0.010	2.93	0.69	0.56	0.24	82.7	0.013	**2.05**	0.46	0.30	0.13
		(0.007)	(1.71)					(0.007)	(0.59)			
16	36.5	**0.014**	1.77	0.71	0.58	0.25	81.1	**0.014**	**1.50**	0.51	0.31	0.14
		(0.006)	(1.11)					(0.006)	(0.37)			

Table 14: 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 $\widehat{R}_i^e = \widehat{\alpha}+\frac{E_T\left[\left(M_{t+H,t}^i-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. 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 $(1-LS_t)$. The right panel restricts to 90%-100% stock wealth holders. 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

	Two Groups (<90%, 90-100%), Restrict $\chi = 1$						
H	R^2 (%)	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	40.2	-0.000	**66.09**	**1.000**	0.33	0.74	0.44
		(0.008)	(32.84)	(0.05)			
4	88.8	0.005	16.02	**1.000**	0.26	0.32	0.19
		(0.016)	(9.12)	(0.40)			
6	79.8	0.002	**8.81**	**1.000**	0.26	0.43	0.25
		(0.013)	(4.47)	(0.49)			
8	72.8	0.001	**5.50**	1.000	0.26	0.50	0.29
		(0.011)	(2.63)	(0.52)			
10	72.1	0.003	**3.81**	**1.000**	0.25	0.51	0.30
		(0.009)	(1.91)	(0.48)			
12	71.2	0.004	2.85	1.000	0.25	0.52	0.30
		(0.008)	(1.52)	(0.54)			
16	74.9	0.007	1.99	1.000	0.24	0.48	0.29
		(0.007)	(1.43)	(0.67)			

Table 15: 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 $\widehat{R}_i^e = \widehat{\alpha} + \frac{E_T\left[\left(M_{t+H,t}^{\omega}-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. 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 $M_{t+H,t}^{\omega} = \omega^{<90\%}M_{t+H,t}^{<90\%} + \left(1-\omega^{<90\%}\right)M_{t+H,t}^{>90\%}$. The percentile SDF $M_{t+H,t}^{i} = \beta^H\left(\frac{C_{t+H}}{C_t}\right)^{-\gamma}\left\{\left[\left(\frac{\widehat{Y_{t+H}^i/Y_{t+H}}}{\widehat{Y_t^i/Y_t}}\right)^{\chi}\right]^{-\gamma}\right\}$, 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 $(1-LS_t)$. In computation, we restrict ω to be between zero and one. Bolded indicate significance at 5 percent or better level. The sample spans the period 1963Q1 to 2013Q4.

Nonlinear GMM, Percentile SDF, 10 Momentum Portfolios

	Aggregate Consumption ($\chi^{<90\%}=0$)						Only Bottom 90%, Restrict $\chi^{<90\%}=1$					
H	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	15.8	−0.002	**83.56**	0.43	0.88	0.52	40.2	−0.000	**66.09**	0.33	0.74	0.44
		(0.008)	(36.51)					(0.008)	(32.84)			
4	36.1	−0.006	18.00	0.31	0.77	0.45	88.8	0.005	16.02	0.26	0.32	0.19
		(0.014)	(9.97)					(0.016)	(9.12)			
6	35.2	−0.004	10.23	0.30	0.78	0.45	79.8	0.002	**8.81**	0.26	0.43	0.25
		(0.012)	(5.55)					(0.013)	(4.47)			
8	38.5	−0.003	6.98	0.29	0.76	0.44	72.8	0.001	**5.50**	0.26	0.50	0.29
		(0.011)	(3.82)					(0.011)	(2.63)			
10	41.8	−0.000	5.12	0.29	0.73	0.43	72.1	0.003	**3.81**	0.25	0.51	0.30
		(0.010)	(3.10)					(0.009)	(1.91)			
12	47.5	0.002	4.14	0.29	0.70	0.41	71.2	0.004	2.85	0.25	0.52	0.30
		(0.009)	(2.72)					(0.008)	(1.52)			
16	60.0	0.005	3.07	0.27	0.61	0.36	74.9	0.007	1.99	0.24	0.48	0.29
		(0.008)	(2.30)					(0.006)	(1.16)			

Table 16: 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 $R^2=1-\frac{Var_c\left(E_T\left(R_i^e\right)-\widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, where the fitted value $\widehat{R}_i^e=\widehat{\alpha}+\frac{E_T\left[\left(M_{t+H,t}^i-\widehat{\mu}\right)\mathbf{R}_{t+H,t}^e\right]}{\widehat{\mu}}$. 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 $(1-LS_t)$. 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.

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	$\frac{C_{t+H}}{C_t}$	$\frac{1-LS_{t+H}}{1-LS_t}$	Rm_t	SMB_t	HML_t	$LevFac_t$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
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]							
0.61						**14.19**	0.68	0.39	0.17
(0.69)						(3.54)			
[0.46]						[2.39]			
0.97		**0.52**				5.51	0.82	0.28	0.12
(1.00)		(2.79)				(1.09)			
[0.91]		[2.54]				[0.99]			
2.53					**1.06**		0.38	0.54	0.22
(3.59)					(2.33)				
[3.53]					[2.29]				
1.46		**0.67**			0.18		0.79	0.31	0.12
(2.72)		(3.04)			(0.29)				
[2.67]		[3.00]			[0.29]				
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]				
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]				

Table 17: 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. $LevFac$ is the leverage factor from Adrian, Etula, and Muir (2014). The sample spans the period 1963Q1 to 2013Q4.

Explaining Quarterly Excess Returns on 10 Momentum Portfolios

LH Consumption and Labor Share Betas for H =8

Estimates of Factor Risk Prices λ, 10 Momentum											
Constant	$\frac{C_{t+H}}{C_t}$	$\frac{1-LS_{t+H}}{1-LS_t}$	Rm_t	SMB_t	HML_t	MoM_t	$LevFac_t$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
2.17		**−0.77**						0.93	0.23	0.13
(3.54)		(−3.86)								
[3.47]		[−3.78]								
2.07	0.10	**−0.75**						0.92	0.23	0.12
(3.91)	(0.78)	(−2.92)								
[3.83]	[0.77]	[−2.87]								
0.36							**14.29**	0.17	0.83	0.48
(0.35)							(2.28)			
[0.24]							[1.53]			
1.71		**−0.76**					3.53	0.93	0.23	0.13
(1.74)		(−3.87)					(0.61)			
[1.65]		[−3.68]					[0.58]			
2.24						**1.91**		0.79	0.42	0.22
(3.70)						(3.31)				
[3.59]						[3.21]				
2.05		**−0.70**				0.29		0.91	0.25	0.13
(3.52)		(−3.50)				(0.37)				
[3.46]		[−3.44]				[0.36]				
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]				
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 18: Fama-MacBeth regressions of average returns on factor betas. Fama-MacBeth t-statistics in parenthesis and Shanken Corrected t-statistics in bracket. 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 and MoM are Fama French factors for pricing momentum. $LevFac$ is the leverage factor from Adrian, Etula, and Muir (2014). The sample spans the period 1963Q1 to 2013Q4.

Appendix Tables

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 A1: 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	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	χ	HJ	$RMSE$
1	8.4	−0.001	**89.89**	0.61	0.7	0.30	22.4	0.001	81.21	0.43	0.38	3.3
		(0.013)	(42.40)					(0.011)	(55.66)	(0.28)		
4	31.6	−0.004	19.56	0.30	0.6	0.26	52.3	−0.002	9.69	0.57	0.22	2.5
		(0.017)	(11.08)					(0.011)	(6.55)	(0.52)		
6	34.8	0.001	10.18	0.21	0.6	0.25	69.3	−0.007	9.94	0.39	0.20	2.0
		(0.014)	(5.87)					(0.016)	(5.17)	(0.28)		
8	39.9	0.004	6.25	0.16	0.6	0.25	82.8	0.005	4.88	0.55	0.13	1.5
		(0.011)	(3.44)					(0.010)	(2.30)	(0.28)		
10	41.1	0.008	4.16	0.13	0.6	0.24	83.5	0.011	2.44	0.82	0.10	1.5
		(0.009)	(2.31)					(0.008)	(1.42)	(0.51)		
12	39.4	0.011	2.97	0.11	0.6	0.24	81.4	0.012	2.26	0.62	0.10	1.6
		(0.007)	(1.73)					(0.006)	(1.04)	(0.34)		
15	38.9	**0.013**	1.96	0.10	0.6	0.25	83.3	0.018	0.71	2.17	0.09	1.5
		(0.006)	(1.19)					(0.006)	(0.62)	(1.90)		

Table A2: 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 $R^2 = 1 - \frac{Var_c\left(E_T(R_i^e)-\widehat{R}_i^e\right)}{Var_c\left(E_T(R_i^e)\right)}$, 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 $(1-LS_t)$. 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	R^2 (%)	α	γ	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	χ	HJ	$RMSE$
1	8.4	−0.001	**89.89**	0.61	0.7	0.30	16.7	0.002	66.27	0.73	0.54	3.4
		(0.013)	(42.40)					(0.009)	(43.84)	(0.69)		
4	31.6	−0.004	19.56	0.30	0.6	0.26	51.7	−0.003	11.57	0.84	0.23	2.5
		(0.017)	(11.08)					(0.012)	(7.35)	(0.81)		
6	34.8	0.001	10.18	0.21	0.6	0.25	79.0	0.006	3.43	2.40	0.16	1.7
		(0.014)	(5.87)					(0.011)	(3.30)	(2.26)		
8	39.9	0.004	6.25	0.16	0.6	0.25	86.0	0.010	2.71	2.21	0.16	1.4
		(0.011)	(3.44)					(0.010)	(2.30)	(1.83)		
10	41.1	0.008	4.16	0.13	0.6	0.24	84.0	0.012	2.13	1.82	0.12	1.5
		(0.009)	(2.31)					(0.008)	(1.44)	(1.29)		
12	39.4	0.011	2.97	0.11	0.6	0.24	83.3	0.015	1.49	2.15	0.10	1.5
		(0.007)	(1.73)					(0.006)	(1.06)	(1.63)		
15	38.9	**0.013**	1.96	0.10	0.6	0.25	82.4	0.019	0.63	4.57	0.09	1.5
		(0.006)	(1.19)					(0.006)	(0.63)	(4.67)		

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

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 $(1 - LS_t)$. 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	$\Delta c_{t+H,t}$	$\Delta\log(1-LS_{t+H,t})$	$\bar{R}^2$	H	Constant	$\Delta c_{t+H,t}$	$\Delta\log(1-LS_{t+H,t})$	$\bar{R}^2$
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 A5: 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 A6: 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 A7: 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. $\beta_{\Delta c} = \frac{Cov\left(r^e_{i,t+H,t}, \ln C_{t+H} - \ln C_t\right)}{Var(\ln C_{t+H} - \ln C_t)}$, $\beta_{\Delta \log(1-LS)} = \frac{Cov\left(r^e_{i,t+H,t}, \ln \frac{1-LS_{t+H}}{1-LS_t}\right)}{Var\left(\ln \frac{1-LS_{t+H}}{1-LS_t}\right)}$. Sample spans the period 1963Q1 to 2013Q3

Linear Expected Return-Beta Regressions

$$E_T\left(R^e_{i,t}\right) = \boldsymbol{\lambda}_0 + \boldsymbol{\lambda}'\boldsymbol{\beta} + \epsilon_i$$

Estimates of Factor Risk Prices λ, Non-overlapping Samples

	25 Size/Book-Market Portfolio					10 Momentum Portfolio				
H	λ_0	$\frac{1-LS_{t+H}}{1-LS_t}$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$	λ_0	$\frac{1-LS_{t+H}}{1-LS_t}$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
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 A8: 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	$\frac{C_{t+H}}{C_t}$	$\frac{1-LS_{t+H}}{1-LS_t}$	$Rm_{t+H,t}$	$SMB_{t+H,t}$	$HML_{t+H,t}$	$\bar{R}^2$	$RMSE$	$\frac{RMSE}{RMSR}$
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 A9: 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 A10: 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	R^2 (%)	α	γ	$\chi^{top\ 10\%}$	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	36.4	0.005	29.94	1.08	0.69	0.58	0.25	36.4	0.005	30.13	0.001	0.69	0.58	0.25
		(0.011)	(84.35)	(3.48)					(0.012)	(106.91)	(0.90)			
4	64.1	0.001	5.28	1.80	0.53	0.44	0.19	64.1	0.000	6.02	0.001	0.53	0.44	0.19
		(0.012)	(6.60)	(2.11)					(0.014)	(5.85)	(2.29)			
6	82.9	0.005	3.82	1.58	0.50	0.30	0.13	82.9	0.005	3.66	0.002	0.50	0.30	0.13
		(0.011)	(3.12)	(1.30)					(0.011)	(3.13)	(2.75)			
8	87.0	0.010	2.89	1.46	0.47	0.26	0.11	87.0	0.010	2.89	0.001	0.47	0.26	0.11
		(0.010)	(2.10)	(1.08)					(0.012)	(2.20)	(5.30)			
10	84.5	0.012	1.98	1.42	0.46	0.29	0.12	84.5	0.012	1.98	0.004	0.46	0.29	0.12
		(0.008)	(1.36)	(1.06)					(0.008)	(1.28)	(10.65)			
12	83.4	**0.014**	1.69	1.33	0.45	0.30	0.13	83.4	**0.014**	1.69	0.005	0.45	0.30	0.13
		(0.006)	(1.00)	(0.90)					(0.006)	(0.90)	(9.98)			
16	83.8	**0.016**	**1.07**	**1.72**	0.50	0.29	0.13	83.6	**0.015**	1.21	0.001	0.50	0.29	0.13
		(0.006)	(0.47)	(0.86)					(0.005)	(1.55)	(11.38)			

Table A11: 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 $R^2 = 1 - \frac{Var_c\left(E_T\left(R_i^e\right)-\widehat{R}_i^e\right)}{Var_c\left(E_T\left(R_i^e\right)\right)}$, 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 $(1-LS_t)$. 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	R^2 (%)	α	γ	$\chi^{<90\%}$	HJ	$RMSE$	$\frac{RMSE}{RMSR}$	R^2 (%)	α	γ	$\omega^{<90\%}$	HJ	$RMSE$	$\frac{RMSE}{RMSR}$
1	40.2	−0.001	62.83	1.14	0.34	0.74	0.43	40.2	−0.000	67.10	**1.000**	0.34	0.74	0.43
		(0.008)	(54.91)	(1.31)					(0.011)	(61.40)	(0.14)			
4	95.4	**0.016**	9.77	2.31	0.27	0.21	0.12	95.4	0.016	9.76	0.999	0.27	0.21	0.12
		(0.008)	(8.19)	(2.58)					(0.018)	(8.65)	(0.84)			
6	94.1	**0.016**	2.43	6.63	0.29	0.23	0.14	94.1	0.016	2.41	1.000	0.29	0.23	0.14
		(0.007)	(4.72)	(14.77)					(0.015)	(4.84)	(0.92)			
8	90.4	**0.014**	0.24	49.15	0.33	0.30	0.17	94.5	−0.005	2.96	**0.757**	0.33	0.23	0.13
		(0.007)	(2.93)	(61.2)					(0.019)	(3.62)	(0.07)			
10	88.7	0.013	0.07	121.25	0.33	0.32	0.19	91.5	0.008	2.16	**0.775**	0.33	0.28	0.16
		(0.006)	(2.05)	(364.4)					(0.012)	(3.71)	(0.07)			
12	86.2	0.011	0.04	174.30	0.33	0.36	0.21	94.1	0.009	1.72	**0.756**	0.33	0.23	0.14
		(0.006)	(1.68)	(799.8)					(0.010)	(2.29)	(0.07)			
16	87.1	0.011	0.03	199.72	0.34	0.35	0.20	95.6	0.010	1.64	**0.724**	0.26	0.20	0.12
		(0.006)	(1.39)	(1525.7)					(0.007)	(1.70)	(0.082)			

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 $(1-LS_t)$. 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.