Which risk factors matter to investors? Evidence from mutual fund flows

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Abstract

When selecting an actively managed equity fund, investors seek to identify fund managers who are able to generate positive risk-adjusted performance (alpha). To assess risk-adjusted performance, investors must apply a model of risk when ranking funds; thus, we can infer the risk model that investors use by the fund choices that they make. Based on this observation, we analyze the sensitivity of fund flows to alphas calculated using competing models of risk: market-adjusted returns, the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (which adds size and value factors), and the Carhart four-factor model (which adds a momentum factor). We first find that the CAPM-based alpha better explains fund flows than the three- or four-factor alphas. We then decompose fund returns into five categories – (1) four-factor alpha and returns that can be traced to the (2) market (beta), (3) size, (4) value, and (5) momentum tilts of the fund. We find that investors are most sensitive to a fund's alpha. Fund returns that can be traced to size, value, or momentum affect flows almost as much as a fund's alpha (with sensitivities ranging from 63-93% of that observed for alpha). However, fund returns that can be traced to the market beta of the fund affect flows little (with a sensitivity that is 26% of that observed for alpha). These results indicate investors account for a fund's market risk (beta) when assessing fund performance, but most do not treat other factor returns as compensation for risk when evaluating the performance of actively managed mutual funds. Auxiliary analyses document that fund flows respond strongly to the size- and value-related returns of a fund relative to other funds in the same Morningstar category. Flow do, though, also respond to mean category returns, suggesting that some investors confuse category-level fund performance with managerial skill. The mechanism by which investors tend to beta in assessing fund performance is a mystery.

Over the last twenty years, the Fama-French three-factor model (Fama and French (1993)) and its four-factor cousin (Carhart (1997)) have become academic standards. A multitude of academic papers measure the abnormal returns of anomaly-based equity trading strategies or the explanatory power of alternative factor models against the three-factor and four-factor models. Institutional investors also use these models and their factor returns as benchmarks.

The first factor in both models is the market-factor. Securities with higher market betas have the undesirable quality of outperforming other securities when the market does well (and the marginal utility of wealth is lower) and underperforming other securities when the market does poorly (and the marginal utility of wealth is higher). All else equal, investors should pay less for high beta securities leading these securities to earn higher expected returns.

In addition to the market factor, the three-factor model includes a size factor and a book-to-market factor to which the four-factor model adds a momentum factor. Empirically, these models better explain historical returns than does the one-factor market model. However, there is controversy within the profession as to whether the higher expected returns associated with small stocks, high book-to-market stocks, and positive momentum stocks are due to risk or mispricing.[1] To address the question of whether these factors represent risk that investors care about, empirical research to date searches for plausible risk factors that might explain the high returns of small, value, or momentum stocks.[2]

We take a different approach. Specifically, we analyze whether mutual fund investors treat these factors as risk characteristics when allocating capital to actively managed mutual funds. Most mutual fund investors allocate their savings to actively managed mutual funds, which seek to beat the market through some combination of fundamental and/or technical analysis. Mutual fund investors who perceive factor returns to be driven by risk should not react to these returns as if they were abnormal.

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[1] For the two sides of this debate, see Fama and French (2004) and Hirshleifer (2001)

[2] As examples of this approach, Fama and French (1993) suggest that a firm's book-to-market and size are proxies for distress risk. Campbell, Hilscher, and Szilagyi (2008) argue the returns on distressed stocks, which tend to be anomalously low, cannot explain the value and size effects. Daniel and Titman (1997) argue the high returns to small and value stocks cannot be explained by factor risk. Petkova and Zhang (2005) argue time-varying risk goes in the right direction and can partially explain the value premium.

For example, consider the problem from the perspective of an investor who views the world through the lens of the Capital Asset Pricing Model (CAPM), where market beta is the only priced risk factor. The CAPM investor expects mutual funds with higher market betas to outperform in up markets, so he would not interpret such outperformance as indicative of a fund manager's superior skill. If factors are capturing risk, then investors who hold portfolios with high factor loadings are compensated with high expected returns for, essentially, providing insurance to other investors against these risks. Both the insurer and the insured should be aware of the risk. Consequently, mutual fund flows—at least flows that emanate from a desire to find an exceptional fund manager—should not respond to returns that can be traced to risk factors. Indeed, this basic observation is the starting point of the theoretical work of Berk and Green (2004), who model fund flows and performance of actively managed funds, and Baks, Metrick, and Wachter (2001), who assess the wisdom of investing in actively managed funds from the perspective of a Bayesian investor.

Since a researcher cannot observe the model that investors use to assess the performance of mutual funds, empirical work on the topic uses a variety of benchmarks including raw returns, benchmark-adjusted returns (most commonly market-adjusted), or alphas estimated using empirical asset pricing models (most commonly the CAPM, three-factor, or four-factor model).[3] In many settings, the various performance measures are highly correlated. However, in some cases a mutual fund might be a top performer based on one measure (e.g., market-adjusted return) and a middling or bottom-tier fund based on another measure (e.g., four-factor alpha).

To explore the question of what model investors use to evaluate the performance of actively managed mutual funds, we use monthly return and flow data on over 3,900 U.S. diversified equity mutual funds that are actively managed over the period 1996 to 2012.[4] For each fund, we calculate the month *t* flow of new money into the fund and measure the

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[3] Examples of studies using raw returns include Bergstresser and Poterba (2002), Coval and Stafford (2007), Del Guercio and Tkac (2008), and Ivkovic and Weisbenner (2009). Some that use market-adjusted returns include Chevalier and Ellison (1997), Karceski (2002), Barber, Odean, and Zheng (2005), and Spiegel and Zhang (2013). Some that use alpha estimates include Khorana (2001), Del Guercio and Tkac (2002), Lynch and Musto (2003), Nanda, Wang, and Zheng (2004), Keswani and Stolin (2008), Gil-Bazo and Ruiz-Verdu (2009), and Sensoy (2009).

[4] The relatively small number of funds in our sample is a result of data requirements. Most importantly, we require a five-year history of fund returns for inclusion in our sample, which is necessary to estimate the factor tilts of a mutual fund.

performance of the fund over the year leading up to month *t* using four asset-pricing models: market-adjusted returns, the CAPM, the three-factor model, and the four-factor model.

Our first empirical tests exploit cases where a fund's ranking diverges across models to identify the model investors most commonly use to evaluate mutual fund performance. We use these cases to run a horserace of the four competing asset-pricing models. Our empirical tests involve pairwise comparisons of competing models, where we regress monthly flows of new money on decile ranks of prior annual performance estimated from the competing models. In general, we find greater flows to mutual funds with higher ranks based on CAPM alpha than to funds with higher ranks based on competing models. Thus, the CAPM is the clear victor of this horserace, suggesting investors rely most on the CAPM alpha when evaluating mutual fund performance.

The CAPM victory in this horserace suggests that investors consider beta (market risk) as a factor when evaluating mutual fund performance, but tend to disregard value, size, and momentum as risk factors. However, we suspect investors have differences of opinion regarding which factors constitute risk. Indeed, financial economists continue to debate whether the value premium can be traced to risk (Fama and French (1993)) or mispricing (Lakonishok, Shleifer, and Vishny (1994)). Assuming investors have differences of opinion about what constitutes a risk factor, our horserace results represent a referendum of investors on the preferred risk model., but do not provide an indication of whether a material subset of investors consider a particular factor in a risk model (e.g., value) to be related to risk.

To further explore which risk factors matter to investors, we decompose the annual return earned by each mutual fund into its four-factor alpha and returns related to its market, size, value, and momentum tilts. We then regress monthly flows on each of the five return components. We find that mutual funds are most responsive to the four-factor alpha; a 70 basis point increase in a fund's annual alpha (roughly the interquartile range of estimated alphas) is associated with an increase in monthly fund flows of 0.78 percentage points. In striking contrast to the flow-alpha relation, we find investors are much less responsive to returns associated with a fund's market risk (beta). Though flows respond to returns related to a fund's market risk, the magnitude of the flow-return relation is a mere 26% of that associated with a fund's four-factor alpha. Relative to the flow-alpha relation, this result indicates that high beta funds are not proportionately rewarded with flows in bull markets (nor penalized with withdrawals in bear markets). In aggregate, investors evaluate a mutual fund's performance after accounting for cross-sectional variation in the betas of mutual funds.

Of the remaining factor returns, we find flows are most responsive to factor tilts related to momentum, for which the magnitude of the flow-return relation is 93% of that associated with the fund's four-factor alpha. Flows also respond to factor tilts related to value and size, but the magnitude of the flow-return relation is 63% and 77% (respectively) of that associated with the fund's four-factor alpha.

We also explore the robustness of these results by separately analyzing the flow-return relation within performance quartiles, for different return horizons, for young v. old funds, for large v. small funds, using alternative measures of fund flows, and alternative specifications of our baseline regressions. Our main result – that investors account for cross-sectional variation in returns that can be traced to the market risk of a mutual fund when directing flows to funds – is quite robust. In contrast, we consistently find that investors' flows are about equally responsive to a fund's alpha and returns related to the fund's exposure to momentum factors. This result indicates investors do not consider momentum to be a risk factor when choosing mutual funds. The responsiveness of flows to returns traced to a fund's size or value tilts consistently lies between the high sensitivity that we observe to a fund's alpha and momentum-related returns and the low sensitivity we observe to returns traced to a fund's market risk (beta). These results dovetail neatly with those of our model horserace, where the CAPM emerges victorious.

If investors believe a fund's returns are related to factor risk, then investors should not respond to a fund's factor-related returns with flows. Thus, if investors do respond to factor-related returns with flows, investors must not consider returns related to the factor to be associated with risk. This basic argument allows us to conclude that investors do not consider momentum-related returns to be associated with a risk of material importance (since flows are equally responsive to a funds four-factor alpha and momentum-related returns).

Our results that investors do not respond as strongly to market-, size-, and value-related returns as they do to four-factor alpha and momentum returns suggests that investors use some mechanism that allows them to account for the beta, size tilt, and value tilts of funds when assessing performance. We do not believe it plausible that investors are running regressions to estimate fund exposures and four-factor alphas. Thus, we explore possible mechanisms that investors might use to adjust for a fund's market, size, and value tilts when assessing performance.

We find some evidence consistent with investors using Morningstar's style boxes categories as proxies for the size and value tilts of funds in each category.. Morningstar categorizes funds into nine style boxes based on the intersection of a fund's value tilt (value, blend, growth) and size tilt (small, medium, big). We decompose the size- and value-related returns of funds into two components: the portion of a fund's return that can be traced to category-level returns and the portion of the return that can be traced to the fund's deviation from its category-level return. We find that fund flows respond positively to category-level returns, but the category-level response is weaker than the response to the fund's deviation from category-level returns. This differential response indicates at least some investors assess performance relative to a fund's category assignment. However, the observation that flows respond to category-level returns suggests some investors confuse category-level returns with fund manager skill. Ultimately, a plausible interpretation of the slightly weaker response to the size- and value-related returns of funds is that some investors engage in category thinking as proposed by Barberis and Shleifer (2003).

Regardless of the underlying mechanism that drives these results, the differential response to category-level returns and to a fund's deviation from category-level returns provides an incentive for mutual fund managers to influence the category assignment of the funds they manage (or more generally the benchmark against which investors evaluate its performance) and is consistent with prior work that documents mutual funds strategically choose names and benchmarks to garner flows (Sensoy (2009) and Cooper, Gulen, and Rao (2005)).

The mechanism by which investors attend to a fund's market beta when assessing performance is a mystery, though we are able to reject several potential explanations Morningstar categories do not provide a convenient mechanism for assessing a fund's market-related risk because the average beta within each of the nine categories varies little across funds. Morningstar's ubiquitous star ratings of mutual funds, which have a large impact on fund flows, do not explain the proportionately weak response to returns related to a fund's market risk. While the inclusion of star ratings in our regressions dampens the relation between flows and the components of a fund's returns, the relative importance of the return components is similar to what we observe in our main results. Returns related to a fund's market risk are accompanied by the weakest flow response. Morningstar does provide information on a fund's beta and alpha with respect to various market indexes, but this information is not salient on websites and would require both knowledge of modern portfolio theory and Morningstar's detailed fund statistics to materially influence returns.

We also explore whether more sophisticated investors use more sophisticated benchmarks when evaluating mutual funds. Del Guercio and Reuter (2013) document that broker-sold mutual funds, which tend to have a less sophisticated investors clientele, experience flows that are more responsive to a fund's market-adjusted return than its four-factor alpha. When we break our sample into broker-sold and direct-sold mutual funds, we do observe some statistically significant differences in the flow-return relation. For example, investors in broker-sold funds respond more to the size- and value-related returns of a fund than do investors in direct-sold funds. This results suggests investors in broker-sold fund use less sophisticated benchmarks of mutual fund performance. However, the economic magnitude of the differences is modest.

In summary, our results provide interesting insights into how investors perceive mutual fund risk. Consistent with long-standing theories of asset pricing such as the CAPM, investors perceive mutual funds with high betas to be risky and account for this risk when assessing fund performance. The value and size tilts of mutual funds are generally not perceived to be risk; returns traced to these factors are only slightly discounted relative to a fund's alpha. Similarly, we find very little discounting of returns that can be traced to the momentum tilts of a mutual fund. Put another way, investors perceive the market risk of a fund to be an important consideration when assessing its performance (consistent with the theoretical view that market risk should be priced), but do not share the same perceptions of value, size, and momentum (suggesting these factors are the equivalent of alpha to most investors).[5] Moreover, if fund flow decisions are motivated by a desire to identify skilled mutual fund managers, our finding that investors respond to the market-adjusted returns of a mutual fund category when allocating capital to mutual funds indicates some investors misattribute the category-level return of a fund to managerial skill.

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[5] These results are also consistent with the survey responses of professionals reported in Bloomfield and Michaely (2004). Professionals expect firms with higher betas to be riskier investments and to generate higher returns. However, they consider firms with high market-to-book ratios to be overpriced (and riskier).

To sum up, we explicitly address the following question: How do investors account for risk when allocating capital to actively managed mutual funds? The remainder of the paper is organized as follows. In Section I, we review related literature. In section II, we describe our data and methods. We present our main results in Section III and make concluding remarks in Section IV.

I. Literature Review

Our results fit into the large literature on mutual fund flows. Early work establishes that fund flows respond to fund returns (Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)). Moreover, the relation between fund flows and returns tends to be convex; positive returns garner more new flows than those lost to negative returns (Chevalier and Ellison (1997), Sirri and Tufano (1998)). Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) argue mutual funds respond to these implicit incentives by altering the riskiness of their funds so as to secure a favorable year-end ranking. As noted above, this stream of research uses various measures of mutual fund performance ranging from raw returns to multi-factor alphas.

There is an emerging literature that goes beyond simple flow-return relations. Clifford, Fulkerson, Jordon, and Waldman (2013) focus on the impact of total risk (measured as a fund's trailing monthly standard deviation of returns) on fund flows and separately analyze inflows and outflows. They documents that *both* inflows and outflows are positively related to total risk. In contrast, we investigate whether investors differentially respond to the components of a fund's return that are arguably a result of the risk associated with the fund. Huang, Wei, and Yan (2012) investigate whether investors account for the precision of alpha estimates when allocating capital to mutual funds. They provide empirical support consistent with this hypothesis and argue the impact of precision on flows is more pronounced for sophisticated investors. In a spirit more similar to our work, De Andrade (2009) infers from flows investors' differential sensitivity to risk in up and down markets. He finds investor preference for funds with low down-market betas and suggesting that investors "…seek portfolio insurance, in addition to performance."

In independent work,[6] Berk and van Binsbergen (2014) also examine mutual fund performance and flow relationships. As a starting point to their analysis, they observe that managerial compensation, which is primarily determined by fund flows, predicts future fund returns (Berk and van Binsbergen (2013)). For six horizons (3 months, 6 months, 1 year, 2 years, 3 years, and 4 years), they measure the percent of time that the direction of a fund's flow is the same as the sign of its alpha as estimated for a variety of asset pricing models. For a 3-month horizon, the sign of the alpha from CAPM model, estimated using the CRSP Value Weighted index as a proxy for the market, matches the direction of flow 63.21 percent of the time; the signs of alphas from the three- and four-factor models match the direction of flows 62.94 and 63.02 percent of the time; the sign of the CAPM alpha estimated using the S&P 500 index as a proxy for the market match the direction of flows 62.04 percent of the time; and the sign of a fund's return in excess of the market matches the direction of flows only 61.75 percent of the time;. Over the five of the six horizons that they analyze, the sign of CAPM alpha (using the CRSP value weighted index as market proxy) matches the direction of flows best with differences across models that are similar in magnitude to those observed at the 3-month horizon. Over a 3-year horizon the three-factor model dominates. Other models that Berk and van Binsbergen examine, including the consumption CAPM (Breeden (1979)), the habit formation model (Campbell and Cochrane (1999)), and long-run risk model (Bansal and Yaron (2004)) perform less well over all horizons. While Berk and van Binsbergen (2013) measure the correspondence between the sign of alpha under different risk models and the sign of flows, we focus primarily on the sensitivity of flows to components of returns attributable to market risk, size tilts, book-to-market tilts, and momentum tilts. Though the two papers differ in focus and methods, they reach the common conclusion that fund flows are better explained by CAPM alphas than three- or four-factor alphas.

As discussed above, mutual funds appear to pick benchmarks or adopt names that garner flows. Sensoy (2009) documents that one-third of the actively managed US equity mutual funds specify a benchmark index in the fund prospectus that does not match the fund's actual style.

[6] In September 2013, Berk and van Binsbergen and we became aware that both sets of authors had independently derived similar findings. Berk and van Binsbergen first posted their paper to SSRN in October 2013. We posted our paper to SSRN in March 2014.

Moreover, he documents that fund flows respond to these mismatched benchmarks. Cooper, Gulen, and Rao (2005) document that mutual funds change names to a hot investment style garner additional fund flows. In contrast to the inquiry into the self-selected benchmarks of mutual funds, we ask a more general question: How do investors adjust for risk when evaluating fund performance? Note that the positive evidence in Sensoy (2009) and Cooper et al. (2005) that investors pay attention to self-selected benchmarks and fund names does not address the more general question of what risk factors investors tend to when picking actively managed mutual funds.

II. Data and Methods

II.A. Fund Flows

Our dependent variable of interest is fund flows and is estimated using data from the CRSP mutual fund database. The CRSP database contains monthly data beginning in 1991. Since we use an estimation window of five years in our empirical analysis described below, our sample period covers the years 1996 to 2012 and includes about 4000 equity funds yielding about 330,000 fund-month observations. Because we are interested in investors who are attempting to identify managerial skill in their fund allocation decisions, we exclude index funds from our analysis.

Following the majority of the prior literature on fund flows, we calculate flows for fund p in month t as the percentage growth of new assets assuming that all flows take place at the end of the month:

$$F_{pt} = \frac{TNA_{pt}}{TNA_{p,t-1}} - (1 + R_{pt}), \tag{1}$$

where TNA_{pt} is the total net assets under management of fund p at the end of month t, and R_{pt} is the total return of fund p in month t.[7] We aggregate the flows and compute the value-weighted returns across multiple share classes within one fund portfolio. We restrict our analysis to funds with total net assets data (required to calculate fund flows), a minimum of $10 million in assets at the end of month $t-1$, and month t flows of more than -90% and less than 1,000%. We

[7] In the rare cases where two funds merge into a single fund during month t, beginning-of-period TNA is set equal to the combined assets of the two funds while end-of-period TNA is set equal to the merged assets of the remaining fund.

merge the CRSP data with the fund style box from Morningstar equity fund universe by matching on fund CUSIPs. Our final sample consists of observations with successful merges.

II.B. Mutual Fund Performance

When selecting a mutual fund that actively manages its investments, an investor seeks to identify a mutual fund that is able to deliver an alpha, where the fund's alpha is estimated after stripping out any fund return that can be traced to the risk associated with the fund's investments. What is less clear, and the focus of our research, is what model investors use to assess the risk-adjusted returns of mutual funds. At one extreme, investors may simply rank funds based on their raw returns; at the other, they may rank funds based on a multifactor model of returns such as those commonly found in the academic literature on asset pricing.

We begin be running a horserace between four competing models that investors might reasonably employ when evaluating the performance of mutual funds: market-adjusted returns (MAR), the Capital Asset Pricing Model (CAPM), the Fama-French three-factor model (FF3) and the Fama-French version of the Carhart (1997) four-factor model (FF4). In many cases, these models yield similar rankings of mutual funds (i.e., the four performance measures are highly correlated). However, we exploit the cases where rankings differ across models to answer the question of which model best explains the choices that investors make when allocating capital to actively managed mutual funds.

We proceed in two steps. First, we estimate the abnormal return (alpha) for each mutual fund over an annual horizon using each of the four competing models (MAR, CAPM, FF3, FF4). Alpha estimates are updated monthly based on a rolling estimation window. Consider the four-factor model, which includes factors related to market, size, value, and momentum in the estimation of a fund's return. In this case, for each fund in month *t* we estimate the following time-series regression using 60 months of returns data from months τ = *t-1, t-60*:

$$(R_{p\tau} - R_{f\tau}) = \alpha_{pt} + y_{pt} YDUM_{\tau} + \beta_{pt}(R_{m\tau} - R_{f\tau}) + s_{pt} SMB_{\tau} + h_{pt} HML_{\tau} + m_{pt} UMD_{\tau} + e_{p\tau} \qquad (2)$$

where $R_{p\tau}$ is the mutual fund return in month τ, $R_{f\tau}$ is the return on the riskfree rate, $R_{m\tau}$ is the return on a value-weighted market index, SMB_{τ} is the return on a size factor (small minus big stocks), HML_{τ} is the return on a value factor (high minus low book-to-market stocks), and UMD_{τ}

is the return on a momentum factor (up minus down stocks).[8] The parameters β_{pt}, s_{pt}, h_{pt}, and m_{pt} represent the market, size, value, and momentum tilts (respectively) of fund p, while α_{pt} is the mean return unrelated to the factor tilts and $e_{p\tau}$ is a mean zero error term. (The subscript t denotes the parameter estimates used in month t, which are estimated over the 60 months prior to month t.) YDUM is a dummy variable that takes a value of 1 for fund returns in the most recent 12-month period ($\tau = t\text{-}1,\ t\text{-}12$) and 0 otherwise. Thus, the estimated annual four-factor alpha for the most recent 12-month period is $(\alpha_{pt} + y_{pt})$.[9] To estimate the three-factor alpha, we estimate the regression of equation (2), but drop *UMD* as an independent variable. To estimate the CAPM alpha, we drop *SMB, HML,* and *UMD*. To estimate the market-adjusted return, we calculate the average difference between the fund return and market return over the prior 12 months:

$$\sum_{\tau=t-1}^{t-12} \frac{(R_{p\tau} - R_{m\tau})}{12}. \tag{3}$$

Second, in each month during our sample period we create deciles of mutual fund performance based on each of the four alpha estimates. Decile 10 contains top-performing funds, while decile 1 contains the worst funds. Thus, we ultimately have a time-series across months of four decile ranks (corresponding to the ranks based on the four competing models) for each mutual fund.

II.C. Model Horserace

We are interested in testing whether the mutual fund investment choices of investors are more sensitive to alphas calculated using one of four models: market-adjusted returns, CAPM, three-factor, and four-factor models. To empirically test this hypothesis, we proceed as follows. To fix ideas, consider alphas calculated using the CAPM and three-factor model. We estimate the relation between flows and a fund's decile ranking based on the CAPM and three-factor models by estimating the following regression:

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[8] We obtain the market, size, book-to-market, and momentum factors from Ken French's online data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

[9] We focus on performance over the most recent 12 months given the evidence in the fund flow literature that flows are more sensitive to performance in recent periods (e.g., Sirri and Tufano (1998); Chevalier and Ellison (1997)). However, using only 12 months of data to estimate the average exposure of a fund to market, size, value, and momentum factors would yield imprecise estimates of factor exposures. Consequently, we use 60 months (5 years) of data to estimate a fund's average factor exposure.

$$F_{pt} = a + \sum_i \sum_j b_{ij} D_{ijpt} + cX_{pt} + \mu_t + \varepsilon_{pt} \tag{4}$$

where the dependent variable (F_{pt}) is the fund flow for mutual fund p in month t. D_{ijpt} is a dummy variable that takes on a value of one if fund p in month t is in decile i based on the CAPM and decile j based on the three-factor model. To estimate the model, we exclude the dummy variable for $j=5$ and $i=5$. The matrix X_{pt} represents control variables, while c represents a vector of associated coefficient estimates. As controls, we include lags of a fund's total expense ratio (TNA-weighted across share classes), a dummy variable for no-load funds (if all share classes are no-load funds), a fund's return standard deviation estimated over the prior 12 months, the log of fund size in month t-1, and the log of fund age in month t-1. We also include time fixed effects (μ_t).

The key coefficients of interest are b_{ij}, $i=1,\ldots, 10$ and $j=1,\ldots, 10$, which can be interpreted as the percentage flows received by a fund in decile i for the CAPM and decile j for the three-factor model relative to a mutual fund that ranks in the fifth decile on both performance measures. For example, $b_{10,9}$ would represent the incremental flows for funds with a top decile (10) CAPM alpha and a 9th decile three-factor alpha, while $b_{9,10}$ represents incremental flows for a 9th decile CAPM alpha and top decile three-factor alpha.

To determine whether investors are more sensitive to the CAPM or three-factor alpha, we test the null hypothesis that $b_{ij} = b_{ji}$ for all $i \neq j$. For example, we test the null hypothesis that $b_{10,9} = b_{9,10}$. If investors place more weight on the CAPM alpha than the three-factor alpha, we would expect to reject the null in favor of the alternative hypothesis, $b_{10,9} > b_{9,10}$; conversely, if investors place more weight on the three-factor alpha than the CAPM alpha, we will reject in favor of the alternative hypothesis, $b_{10,9} < b_{9,10}$. Note that we can make, at most, 45 comparisons. Thus, we test the null hypothesis that the summed difference across all 45 comparisons is equal to zero, and we calculate a binomial test statistic to test the null hypothesis that the proportion of differences equals 50%.

II.D. Are Factor Returns Discounted?

To preview our empirical results, we generally find that CAPM performance ranks better predict fund flows than performance ranks based on market-adjusted returns, the three-factor model, or the four-factor model. This result implies that investors discount mutual fund returns that can be traced to market risk (since the CAPM outperforms market-adjusted returns as a predictor of flows), but do not heavily discount returns that can be traced to size, value, or momentum factors (since the CAPM outperforms ranks based on three- and four-factor models). This raises the obvious question of how much do investors discount mutual fund returns that can reasonably be traced to factor returns (e.g., a small cap mutual fund performing well when small cap stocks perform well). Our second set of empirical tests addresses this question.

D. 1. Return Decomposition

We use the regression in equation (2) to decompose the excess return of a mutual fund over the year leading up to month *t* into its four-factor alpha and returns that can be traced to the market, size, value, and momentum tilts of the fund. In month t, we calculate the mean excess return for the mutual fund over the prior 12 months (t-1 to t-12):

$$\overline{R_{pt} - R_{ft}} = \sum_{\tau=t-1}^{t-12} \frac{\left(R_{p\tau} - R_{f\tau}\right)}{12} \tag{5}$$

We similarly calculate the mean realizations on the market risk premium, size factor, value factor, and momentum factor ($\overline{R_{mt} - R_{ft}}$, $\overline{\mathrm{SMB}_t}$, $\overline{\mathrm{HML}_t}$, and $\overline{\mathrm{UMD}_t}$, respectively) over the 12 months prior to month *t*. The estimates of a fund's four-factor alpha $\left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right)$ and factor tilts ($\hat{\beta}_{pt}$, $\hat{s}_{pt}$, $\hat{h}_{pt}$, $\hat{m}_{pt}$) from the regression of equation (2) allow us to decompose the return into five components:

$$\overline{R_{pt} - R_{ft}} \equiv \left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) + \left[\hat{\beta}_{pt}\overline{R_{mt} - R_{ft}}\right] + \left(\hat{s}_{pt}\overline{SMB_t}\right) + \left(\hat{h}_{pt}\overline{HML_t}\right) + \left(\hat{m}_{pt}\overline{UMD_t}\right) \tag{6}$$

Note the mean residual over the 12 months leading up to month *t* in equation (2) is mechanically zero because of the inclusion of a dummy variable for the most recent year.

With this return decomposition, we can determine whether investors respond differently to the components of returns by estimating the following panel regression across *p* funds and *t* months:

$$\begin{aligned} F_{pt} = b_0 + b_1\left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) + b_2\left[\hat{\beta}_{pt}\overline{R_{mt} - R_{ft}}\right] + b_3\left(\hat{s}_{pt}\overline{SMB_t}\right) \\ + b_4\left(\hat{h}_{pt}\overline{HML_t}\right) + b_5\left(\hat{m}_{pt}\overline{UMD_t}\right) + \gamma X_{pt} + e_{pt} \end{aligned} \tag{7}$$

Where b_0 is the regression intercept, e_{pt} is the regression error term, and γ is a coefficient vector associated with control variables (X_{pt}). The controls are the same as in the horserace regressions:

total expense ratio, a dummy variable for no-load, fund's return standard deviation, the log of fund size, the log of fund age, and time fixed effects.

The parameter estimates of interest in equation (7) are b_i, $i=1,5$. For four-factor investors, we expect $b_1 > 0$, as investors *will* respond to a fund's four-factor alpha, and $b_2=b_3=b_4=b_5=0$, as four-factor investors *will not* respond to fund returns that can be traced to factor loadings and factor realizations. Alternatively stated, we expect four-factor investors to fully discount returns associated with factor tilts and factor realizations when assessing the managerial skill of a fund manager. In contrast, for CAPM investors (who only consider market risk when assessing fund performance), we expect $b_1=b_3=b_4=b_5>0$ and $b_2 = 0$. CAPM investors will discount returns that can be traced to market risk, but will treat returns that can be traced to the size, value, and momentum tilts of a fund as alpha.

Because we are measuring these relations using fund-level rather than investor-level fund flows, the coefficient estimates can be viewed as the weight placed on a particular factor by investors in aggregate. The empirical question addressed by this approach is *which* factors do investors attend to when assessing the skill of a fund manager.

D. 2. Alpha Decomposition

As an alternative to decomposing the excess return of each fund into its components, we decompose the four-factor alpha into components related to the fund's market-adjusted return and factor exposures by rearranging equation (6):

$$\left(\hat{\alpha}_{pt}+\hat{y}_{pt}\right) \equiv \overline{R_{pt}-R_{mt}}-\left[\left(\hat{\beta}_{pt}-1\right)\left(\overline{R_{mt}-R_{ft}}\right)+\left(\hat{s}_{pt}\overline{SMB_t}\right)+\left(\hat{h}_{pt}\overline{HML_t}\right)+\left(\hat{m}_{pt}\overline{UMD_t}\right)\right] \quad (8)$$

With this alpha decomposition, we can determine whether investors respond differently to the components of a fund's four-factor alpha by estimating the following panel regression across p funds and t months:

$$\begin{aligned} F_{pt} = c_0 + c_1\left(\overline{R_{pt}-R_{mt}}\right) + c_2\left[\left(\hat{\beta}_{pt}-1\right)\left(\overline{R_{mt}-R_{ft}}\right)\right] + c_3\left(\hat{s}_{pt}\overline{SMB_t}\right) \\ + c_4\left(\hat{h}_{pt}\overline{HML_t}\right) + c_5\left(\hat{m}_{pt}\overline{UMD_t}\right) + \gamma X_{pt} + e_{pt} \end{aligned} \quad (9)$$

Where c_0 is the regression intercept, e_{pt} is the regression error term, and γ is a coefficient vector associated with control variables (X_{pt}).

The parameter estimates of interest in equation (9) are c_i, $i=1,5$. For four-factor investors, we expect $c_1 = -c_2 = -c_3 = -c_4 = -c_5 > 0$; fund flows will respond to market-adjusted returns, but the portion of this return that can be traced to factor tilts will be fully discounted. In contrast, for CAPM investors, we expect $c_1 = -c_2 > 0$ and $c_3 = c_4 = c_5 = 0$. CAPM investors will discount returns that can be traced to a fund's market exposure, but will not similarly discount returns that can be traced to the size, value, and momentum tilts of the fund.

II.E. Sample Descriptive Statistics

In Table 1, we provide descriptive statistics for our final sample, which consists of nearly 4,000 diversified U.S. equity funds that are actively managed. Panel A presents descriptive statistics across the 333,723 fund-month observations. The average fund has a modestly negative monthly flow during our sample period (-0.33%), but with a standard deviation of 7.42% there is considerable cross-sectional variation in fund flows. The rather modest interquartile range of fund flows (about 2.4%) relative to the high standard deviation suggests our sample contains extreme measures of fund flows. The average fund has total net assets of about $1.3 billion, though the median fund is considerably smaller ($330 million). The average age of the fund is 183.59 months (about 15 years), while the median fund age is 138 months (11.5 years). Our sample tends to be tilted toward larger and older funds since we require a five-year track record to estimate a fund's factor loadings. The average expense ratio for sample funds is 1.29%. A large proportion of funds (71%) has either a front-end or back-end load. (Recall that we categorize a fund as having a load if any of its share classes have a load attached to it). The mean monthly return standard deviation of sample funds is 4.92%.

The factor regressions yield reasonable estimates of the one-year alpha, beta, size, value, and momentum coefficients. The mean monthly alpha over the prior year is -3.4 bps per month (or about -41 bps per year), which is consistent with the well-documented aggregate underperformance of mutual funds. The average fund has beta, size, value, and momentum coefficients of 0.97, 0.18, 0.06, and 0.03 (respectively), which suggests the average fund has close to average market risk with a modest tilt toward small stocks and slight tilts toward value stocks and stocks with strong recent returns. Median estimates of the factor loadings are close to mean estimates. More importantly, there is considerable cross-sectional variation in factor loadings across funds. The standard deviations of beta, size, value, and momentum loadings are 0.18, 0.32, 0.36, and 0.15 (respectively).

Since investors evaluate the relative performance of funds at a particular point in time, we first want to verify that our estimates of factor loadings and realizations indeed generate economically meaningful cross-sectional variation in fund returns. To do so, we calculate descriptive statistics on our key independent variables in two steps. First, in each month during our sample period we calculate the mean, standard deviation, median, and $25^{th}/75^{th}$ percentile for each variable across funds. Second, we average the monthly statistics over time (i.e., across months).

The results of this analysis are presented in Table 1, Panel B. Not surprisingly, the four-factor alpha generates the largest cross-sectional variation in performance (with a standard deviation of 0.707%). However, each of the factor loadings multiplied by the factor realizations over the year leading up to month *t* generate economically large variation in the monthly returns earned on mutual funds. For example, the mean monthly return associated with market risk is 46.6 bps during our sample period, with a standard deviation of 25.4 bps. The average fund does not load heavily on the remaining return factors (size, value, and momentum); thus, the mean return associated with these return factors is small (ranging from 0.4 bps for momentum to 6.5 bps for value). More importantly, we observe considerable cross-sectional variation in the returns due to these return factors across funds, with standard deviations ranging from 21.0 bps for momentum to 34.4 bps for value. It is this variation that is the key to our empirical analysis, as we seek to estimate how sensitive investors are to fund returns that are reasonably attributed to factor returns when selecting actively managed mutual funds.

In Panel C, we present the correlation matrix of return components based on overlapping fund-month observations. We are interested to learn whether there is a high degree of correlation among the components of return, as high correlation between the return components would potentially limit our ability to identify whether investors respond differently to the components of returns. The pairwise correlations are generally low (less than 20% in absolute value). Auxiliary analyses of variance inflation factors for the return components are all less than 1.06 indicating multicollinearity is not a major concern when we turn to our main results.

In Panel D, we present the correlation matrix of annual abnormal return measures across all fund-month observations for the four models we evaluate: market-adjusted returns, CAPM alpha, three-factor alpha, and four-factor alpha. In contrast to the correlation matrix of the return decomposition, the correlation across the various abnormal return measures is quite high and the (unreported) variance inflation factors for the four performance measures range from 6.5 (for market-adjusted returns) to 10.4 (for three-factor alpha). The high correlations in the abnormal return estimates across the four models indicates the importance of exploiting cases where fund rankings differ across models (as we do in our horserace tests) and using the return components to assess the relative importance of the different components of returns (as we do in our return/alpha decomposition regressions).

To further assess the reasonableness of our estimated factor loadings, we present descriptive statistics on factor loadings across Morningstar style boxes in Table 2. Morningstar categorizes diversified equity funds into one of nine style boxes. The style boxes have two dimensions: size (small, mid, large) and fund investment style (value, blend, growth). We expect our factor loadings to line up with a fund's style box assignment and they do. There is modest variation in beta estimates (Panel A) across the style boxes, though growth funds tend to have higher betas than value firms. As expected, small funds have large relative loadings on the SMB factor while there is modest variation in size loadings across the value dimension (Panel B). Similarly, value funds have relatively large loadings on HML, while there is relatively modest variation in value loadings across size categories (Panel C). Finally, growth (value) funds tend to have a modest tilt toward stocks with strong (poor) recent returns (Panel D).

More importantly, we observe considerable cross-sectional variation in factor loadings within each style box. For example, the cross-sectional standard deviation of beta within each of the nine style boxes (0.153 to 0.232) is similar in magnitude to the overall standard deviation (0.185). Similarly, the cross-sectional standard deviation of momentum loadings within each of the nine style boxes (0.124 to 0.175) is similar in magnitude to the overall standard deviation (0.151). The within category standard deviation in the size (0.167 to 0.219) and value loadings (0.239 to 0.387) are somewhat less than the overall standard deviation (0.320 for size and 0.355 for value). This is expected since the categories explicitly sort on funds' size and value tilts. However, there is still considerable cross-sectional variation in the size and value loadings within a category, which we later exploit to test the hypothesis that investor flows respond to category-level rather than fund-level returns.

III. Results

III.A. Model Horserace

We present the pairwise comparison of models in Table 3. Consider first Panel A, where we pit the CAPM against the three-factor model. There is clear evidence that investors are more responsive to fund performance based on the CAPM alpha than the three-factor alpha. For example, consider the row labeled "9 v 3", which compares the flows for funds with a CAPM decile rank of 9 and 3F decile rank of 3 ($b_{9,3}$, $N_{9,3}$=506 observations) to the flows for funds with a CAPM decile of 3 and 3F decile of 9 ($b_{3,9}$, $N_{3,9}$=424). It is clear that in this comparison, investors are more responsive to the funds with the higher CAPM rank (with incremental flows of 0.95%) than those with higher 3F ranks (with incremental flows of 0.02%). In this case, the difference in flows is 0.93% per month and is reliably positive (p<.05). Of the 45 cases presented, in 43 (95.6%) flows are greater (i.e., more positive or less negative) for the funds with the higher CAPM rank. Furthermore, the sum of the differences in the 45 cases is reliably positive. Thus, there is compelling evidence that flows are more responsive to a fund's CAPM rank than its 3F rank.

In Panel B, we compare the CAPM to a simple market-adjusted return model. (Note that the market-adjusted return model is the equivalent of using raw returns to cross-sectionally rank funds, so we can also think of these results as comparing the responsiveness of flows to ranks based on raw returns to ranks based on the CAPM.) Inspection of the coefficient estimates in the 45 cases reveals the majority of the differences (84.4%) are positive, which indicates flows are generally greater for funds with the higher CAPM rank. The summed differences at the bottom of the table are also reliably positive (p<.10). In this case, there is tight competition between the CAPM and market-adjusted returns, though flows are reliably more responsive to CAPM rank.

In Panel C, we compare market-adjusted returns to the three-factor model. In general, flows are reliably more responsive to ranks based on market-adjusted returns than to the ranks based on the 3F alpha. In Panel D, we compare the three-factor and four-factor models. This is the only case where the summed difference for the 45 cases is not reliably different from zero (indicating we can not distinguish between the two models as predictors of flows). Of the 45 cases in 32 (71.1%) the flows are greater (i.e., more positive or less negative) which suggests investors are somewhat more responsive to ranks base on a fund's 3F alpha than to those based on the 4F alpha. Again, there is tight competition between the 3F and 4F models, though there is some evidence that the 3F model is a better predictor of cross-sectional variation in fund flows.

In the Table A1 of the online appendix, we also run a horserace between a fund's Sharpe Ratio over the prior year (mean fund return divided by its standard deviation) and alphas from the alternative models. This analysis indicates that flows are more responsive to the CAPM alpha than to a fund's Sharpe Ratio, though there is no reliable difference in the responsiveness of flows when we compare the Sharpe Ratio and market-adjusted returns.

III.B. Are Factor Returns Discounted?

The preceding analysis indicates the CAPM does the best job of predicting fund-flow relations. This result implies that fund flows respond to returns that can be traced to the size, value, and momentum characteristics of a fund. However, it is still possible that flows are less sensitive to the portion of a fund's return that can be traced to factor loadings.

B. 1. Full Sample Results – Return Decomposition

To address this question, we regress fund flows on four-factor alphas and fund returns during the prior year that result from market, size, value, and momentum tilts of a fund (see the regression of equation (7)). These results are presented in Table 4. All regressions include as controls lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, return volatility, and month fixed effects. To address issues of residual cross-sectional dependence within a month (a time effect) or residual serial dependence for a fund over time (a fund effect), we double-cluster standard errors by month and fund.[10]

In column 1, we present results for all funds. Fund flows respond positively to the four-factor alpha with an estimated sensitivity of 1.113, which is highly significant at conventional levels. The parameter estimate suggests a 70 bps increase in the estimated four-factor alpha (roughly the interquartile range of estimated alphas observed in Table 1) is associated with an increase in fund flows of 0.78 percentage points. The sensitivity of flows to returns traced to market, size, value, and momentum factor returns are all reliably positive. These results suggest that, in aggregate, investors respond to fund returns that can be traced to a fund's investment style and do not fully discount returns that might be traced to these factors when assessing fund performance.

Of more interest are the magnitudes of the returns traced to factors loadings relative to the four-factor alpha. All of the estimated coefficients on the returns due to factor loadings

[10] In this and all subsequent analyses, we present results excluding outliers (defined as observations with a Cook's D statistic greater than 4/n in the full sample analysis where n is the number of observations used to estimate the regression). The coefficient estimates including influential observations are qualitatively similar to those presented, though less precisely estimated.

(except momentum) are reliably different from that for the four-factor alpha ($p<.01$ for market, size, and value factors). This suggests that, in aggregate, investors tend to discount returns traced to factor loadings when assessing fund performance. For example, the estimated coefficient on returns traced to market risk is 0.288 or 26% of the estimated coefficient on the four-factor alpha (1.113). Thus, in aggregate, investors seem to pay some attention to the market risk (i.e., beta) of a fund when assessing fund performance. In contrast to market risk, the discounts associated with size, value, and momentum returns are much smaller. The estimated coefficients on the returns traced to a fund's size and value tilts are 0.853 and 0.705, 77% and 63% of the estimated coefficient on the four-factor alpha; the estimated coefficient on the return traced to a fund's momentum tilt is 1.036, or 93% of the estimated coefficient on the four-factor alpha. When we formally test the null hypothesis that the coefficients on the returns traced to factor tilts differ from that for the fund's alpha, we can reject the null hypothesis of equality for the market, size, and value coefficients ($p<.01$), but not for the momentum tilts.

The regression of column 1 imposes a linear relationship between fund flows and returns. Since prior research suggests the relationship is convex (e.g., Chevalier and Ellison (1997)), we test the robustness of our results by separately estimating the four-factor model regression for different quartiles of fund returns. To do so, in each month, we construct fund return quartiles based on the raw return of the fund over the prior year and separately analyze the flow regression within each return quartile. The results of this analysis are presented in columns 2 through 5 of Table 4 and generally confirm the conclusions from the simple linear regression. Within each return category, the estimated coefficients on returns traced to market risk are consistently the smallest. Consistent with prior research documenting a convexity in the fund flow relation, we do observe a lower coefficient on the four-factor alpha among funds in the lowest return quartile (0.691) relative to the full sample (1.113). Similarly, the estimated coefficient on returns traced to market, size, and value factors are lower in the bottom return quartile (-0.138, 0.565, 0.552, and 0.357, respectively) relative to those for the full sample (0.288, 0.853, 0.705, 1.036, respectively).

Within each performance quartile, three results remain robust. First, the fund flows are sensitive to returns that can be traced to the each of the factor tilts of a fund as well as to a fund's four-factor alpha. Second, fund returns that can be traced to factor tilts of a fund are discounted relative to a fund's four-factor alpha. Third, fund returns that can be traced to the market risk of a fund are discounted most heavily. In three of the four performance quartiles, the sensitivity of flows to a fund's momentum tilt is greater than that of other factors and not reliably different from that associated with the fund's alpha; however, in the bottom performance quartile this result reverses.

We test the robustness of these conclusions across four different return horizons: 1, 6, 12, and 24 months. To do so, we reestimate the rolling five-year regression of fund returns on factor returns (equation (2)) but vary the horizon dummy variable (YDUM) to correspond to 1 month (or alternatively, 6, 12, or 24 months). We then estimate the return decomposition regression (equation (7)). The results of this analysis are presented in Figure 1. Panel A presents coefficient estimates on each of the return components where each cluster of bars depicts results for a particular horizon ranging from 1 month to 24 months. The size of the coefficient estimates increases with horizon, but not linearly in time. For example, the 6-, 12-, and 24-month coefficient estimate on a fund's four-factor alpha are 4.3, 6.8, and 9.5 times that of the coefficient estimate at a 1-month horizon (0.116). This indicates investors weight recent returns more heavily than distant returns when assessing fund performance. However, the relative importance of the components of returns is quite consistent across horizons. This is made clear in Figure 1, Panel B, where each coefficient estimate is divided by the coefficient estimate on alpha for the same horizon. For each horizon, alpha and momentum-related returns sport the largest coefficients, followed by returns traced to the fund's size and value tilts. For each horizon, the coefficient estimate on returns traced to a fund's market risk is the smallest.

B. 2. Full Sample Results – Alpha Decomposition

One possible explanation for why the coefficient estimates are small on returns attributable to market risk is that these returns are estimated imprecisely leading to attenuation bias in the coefficients. In this section, we present flow-return relations by decomposing the four-factor alpha into components related to the fund's market-adjusted return and those related to the fund's factor tilts. As discussed above, for four-factor investors, we expect $c_1 = -c_2 = -c_3 = -c_3 = -c_5 > 0$ (equation 9); however, if returns attributable to market risk are estimated less precisely than returns attributable to other factors, attenuation bias will now cause $-c_2 < -c_3 = -c_4 = -c_5$, that is, attenuation bias should lead the magnitude of the coefficient on return attributable to market risk to be smaller than the magnitudes of coefficients attributable to size, value, and momentum. That is, however, not the case.

The results of this regression are presented in Table 5. When we decompose a fund's four-factor alpha, we find that flows respond positively to the fund's market-adjusted return. Consistent with the results from the return decomposition regression in Table 4, we find that investors heavily discount the portion of a fund's four-factor alpha that can be traced to the fund's market risk.

For example, consider the coefficient estimate on the fund's market factor return exposure from the regressions that use the decomposition of returns as the independent variable. In the return decomposition regression, a coefficient estimate of zero on the market factor return indicates investors completely discount the component of returns that can be traced to a fund's market risk exposure. In the return decomposition regression of Table 4, we find a reliably positive coefficient estimate on the market factor return component (0.288, $p<.01$), but the coefficient estimate is reliably less than those related to a fund's alpha (1.113) and the components of a fund's return that can be traced to its size, value, and momentum exposures (coefficient estimates ranging from 0.705 to 1.036). Thus, we conclude that investor flows are much less responsive to the portion of a fund's return that can be traced to its exposure to market risk.

In the alpha decomposition regression, a coefficient estimate of zero on the market factor return indicates investors *do not discount* the component of a fund's alpha that can be traced to its market risk exposure. In this specification, we find a reliably negative coefficient estimate on the market factor return component (-0.821, $p<.01$), but the absolute value of the coefficient estimate is reliably less than that associated with the fund's market-adjusted return (1.068, $p<.01$). Consistent with the results from our return decomposition regression, these results indicate investors to a large extent *do* adjust for market risk when assessing fund performance.

The results from the alpha decomposition related to a fund's size, value, and momentum factor exposures also mirror those from the return decomposition regression. Investors partially adjust for size and value risk when assessing fund performance, but the magnitude of the adjustment is much less than that associated with a fund's market exposure. Moreover, the full sample results do not indicate investors adjust for a fund's momentum exposure.

Within each performance quartile, the factor return with the most negative coefficient is consistently associated with a fund's market exposure. Moreover, with the exception of funds within the top performance quartile, the coefficient estimates on a fund's size, value, or momentum exposure are negative with one exception (momentum among top quartile funds), but smaller in absolute value than those associated with a fund's market risk exposure. Overall, these results are consistent with those from the return decomposition regression: Investors appear to adjust for the market risk of a fund when evaluating its performance; to a lesser extent, they adjust for a fund's size, value, and momentum exposure.

B. 3. Results by Fund Age and Fund Size

To further test the robustness of our findings, we partition our sample into young vs. old funds and small vs. large funds. Since young funds tend to have shorter track records, we anticipate that the sensitivity of flows to returns will be greater for young funds. However, given that we require a minimum of five years of performance data for funds, our sample omits the youngest funds where these effects are most dramatic (Chevalier and Ellison (1997)). As a result, we define young (old) funds as those with less (more) than 10 years of return history. To partition on fund size, in December of each year we split funds on the sample median of total net assets for funds and define below-median funds as small funds and above-median funds as large funds for the following year.

The results of this analysis are presented in Table 5. For reference, the column (1) repeats our full sample results. When we partition by fund age (columns (2) and (3)), we still generally find that for both young and old funds fund flows are sensitive to both a fund's factor returns and alpha but less sensitive to market, size, and value factor returns than alpha. In contrast, investors tend not to discount momentum-related returns when picking funds. Moreover, the largest discounting of fund returns occurs for returns that can be traced to the market risk of the fund. When we partition by fund size (columns (4) and (5)), we find similar results.

B. 4. Alternative Measures of Fund Flows

Spiegel and Zhang (2013) argue that changes in mutual fund market share offer an alternative specification for flows that is more resilient to heterogeneity in fund-flow relations across funds. Specifically, they propose using the change in a fund's market share as a measure of flow (Δm_{it}):

$$\Delta m_{it} = \frac{TNA_{it}}{\sum_{i=1}^{n_{t-1}} TNA_{it}} - \frac{TNA_{i,t-1}}{\sum_{i=1}^{n_{t-1}} TNA_{i,t-1}} \tag{10}$$

where TNA_{it} is the total net assets of fund i in month t, and n_{t-1} is the number of funds in existence in month t-1. Using this alternative market-share measure of flow, Spiegel and Zhang (2013) find no evidence of convexity in the flow-performance relation.

We estimate the return decomposition regression using this alternative flow measure as the dependent variable. The results are qualitatively similar to our prior results using this alternative measure of fund flows. Specifically, we observe strong responses of flows to a fund's four-factor alpha, a similar response to returns traced to a fund's momentum tilt, weaker responses to returns traced to a fund's size and value tilts, and no response to returns that can be traced to a fund's market risk. (See Table A2 of the online appendix for these results.)

III.C. Do Investors Respond to Category Returns?

C. 1. Return Decomposition

Our primary results indicate investors in aggregate place more weight on the CAPM than other models when ranking mutual funds. Moreover, they partially discount returns related to size, value, and momentum tilts. It is possible that the muted response to size and value factors results from investors using Morningstar style categories when picking funds (e.g., treating all small cap funds as similar despite having different exposures to small cap stocks). However, there is considerable variation in the size and value tilts of funds within each Morningstar category box (see Table 2). Thus, if investors use Morningstar category boxes to assess mutual fund performance, we would observe a muted response to fund returns that can be traced to a fund's value or size tilts. However, we should not observe fund flows responding to category-level returns (e.g., small funds should not see inflows when small funds outperform funds from other categories). In this section, we present evidence that these category assignments influence how investors respond to fund returns.

To investigate this issue, we decompose the size (or value) factor exposure of a fund into the average exposure of the Morningstar category to which it belongs and the fund's deviation from the mean category exposure. For example, the mean category exposure for small cap funds would be the mean size coefficient from equation (2) across all funds categorized by Morningstar as small cap funds. In general, we calculate the mean size coefficient for a category $\hat{s}_{ct}$ as:

$$\hat{s}_{ct} = \sum_{p=1}^{N_c} \frac{\hat{s}_{pt}}{N_c} \tag{11}$$

where $\hat{s}_{pt}$ is the estimated size coefficient for fund p from the regression of equation (2) and N_c are the number of funds in size category c (small cap, mid cap, or large cap). There is an analogous calculation for the three value categories (value, blend, and growth).

We now decompose the fund's return and isolate the size factor exposure that is related to the fund's category assignment ($\hat{s}_{ct}$) and the deviation of the fund's factor exposure from the average factor exposure for the category ($\hat{s}_{pt} - \hat{s}_{ct}$):

$$\begin{aligned}\overline{R_{pt} - R_{ft}} \equiv \left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) + \left[\hat{\beta}_{pt}\overline{R_{mt} - R_{ft}}\right] + \left(\hat{s}_{pt} - \hat{s}_{ct}\right)\overline{SMB_t} + \hat{s}_{ct}\overline{SMB_t} \\ + \left(\hat{h}_{pt} - \hat{h}_{ct}\right)\overline{HML_t} + \hat{h}_{ct}\overline{HML_t} + \hat{m}_{pt}\overline{UMD_t}\end{aligned} \tag{12}$$

This return decomposition yields an augmented version of the regression from equation (7):

$$\begin{aligned}F_{pt} = b_0 + b_1\left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) + b_2\left[\hat{\beta}_{pt}\overline{R_{mt} - R_{ft}}\right] + b_{3f}\left(\left(\hat{s}_{pt} - \hat{s}_{ct}\right)\overline{SMB_t}\right) + b_{3c}\left(\hat{s}_{ct}\overline{SMB_t}\right) \\ + b_{4f}\left(\left(\hat{h}_{pt} - \hat{h}_{ct}\right)\overline{HML_t}\right) + b_{4c}\left(\hat{h}_{ct}\overline{HML_t}\right) + b_5\left(\hat{m}_{pt}\overline{UMD_t}\right) + \gamma X_{pt} + e_{pt}\end{aligned} \tag{13}$$

In this regression, the key parameters of interest are b_{3f}, b_{3c}, b_{4f}, and b_{4c}. If investors benchmark returns at the category level, then we should observe $b_{3c}=b_{4c}=0$; investors should not respond to returns that can be traced to the category-level exposure to size or value factors. However, if some investors treat category-level returns as alpha we would expect to observe positive coefficients on these category-level coefficients. Note also that if investors do not distinguish between a fund's category-level size exposure and its fund-level size exposure then we would observe $b_{3f}=b_{3c}$. Thus, this framework also allows us to test whether investors treat the source of a fund's factor exposure (category assignment v. deviation from category averages) equally.

We present the results of this analysis in Table 7. Consider first the results based on the decomposition of the size exposure. The coefficient on the mean category exposure of a fund is reliably positive, which indicates fund flows indeed respond to the category-level exposure of a fund. However, the response of flows to the fund's size category exposure is less than that associated with the fund's deviation from this category average (1.011 v. 0.746, $p<.05$). The results are quite similar for the decomposition of a fund's value exposure, where the response of flows to the fund's value category exposure is less than that associated with the fund's deviation from this category average (0.807 v. 0.495, p<.01). These results are generally consistent across fund performance quartiles (see columns 2 to 5 of the table). Taken together, these results indicate some investors treat returns that can be traced to the category-level exposures as alpha. However, the response of flows to these category-level exposures is not as strong as the response to the fund's deviation from its category-level exposure. These results suggest that some investors use a fund's category assignment to benchmark returns, which in turn can explain why investors are slightly less responsive to the portion of a fund's return that can be traced to its size and value tilts.

C. 2. Alpha Decomposition

As an alternative to the return decomposition, we also augment the alpha decomposition of equation (8) by incorporating the mean fund return for each of the nine Morningstar category boxes into our specification. To estimate the category-adjusted return for each fund, we calculate the average difference between the fund return and category return over the prior 12 months:

$$\overline{R_{pt} - R_{ct}} = \sum_{\tau=t-1}^{t-12} \frac{\left(R_{p\tau} - R_{c\tau}\right)}{12} \quad . \tag{14}$$

where $R_{c\tau}$ is the equally weighted mean return across all funds in category c during month τ. In this specification, we calculate category-level returns for each of the nine Morningstar style boxes. Similarly, we calculate the market-adjusted return for each of the nine Morningstar style boxes, $\overline{R_{ct} - R_{mt}}$. In the alpha decomposition of equation (8), we replace the market-adjusted return with the category-adjusted return for each fund and the market-adjusted return for each category:

$$\begin{aligned} \left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) &\equiv \left(\overline{R_{pt} - R_{ct}}\right) + \left(\overline{R_{ct} - R_{mt}}\right) \\ &-\left[\left(\hat{\beta}_{pt} - 1\right)\left(\overline{R_{mt} - R_{ft}}\right) + \left(\hat{s}_{pt}\overline{SMB_t}\right) + \left(\hat{h}_{pt}\overline{HML_t}\right) + \left(\hat{m}_{pt}\overline{UMD_t}\right)\right]. \end{aligned} \tag{15}$$

This yields the following variation of the regression of equation (9):

$$\begin{aligned} F_{pt} = c_0 &+ c_{1\mathrm{f}}\left(\overline{R_{pt} - R_{ct}}\right) + c_{1\mathrm{c}}\left(\overline{R_{ct} - R_{mt}}\right) + c_2\left[\left(\hat{\beta}_{pt} - 1\right)\left(\overline{R_{mt} - R_{ft}}\right)\right] \\ &+ c_3\left(\hat{s}_{pt}\overline{SMB_t}\right) + c_4\left(\hat{h}_{pt}\overline{HML_t}\right) + c_5\left(\hat{m}_{pt}\overline{UMD_t}\right) + \gamma X_{pt} + e_{pt}. \end{aligned} \tag{16}$$

In this regression, the key parameters of interest are c_{1f}, which measures the sensitivity of flows to category-adjusted returns of the fund, and c_{1c}, which measures the sensitivity of flows to the market-adjusted returns of the category.

The results of this analysis are presented in Table 8. Fund flows respond to both the category-adjusted return of the fund and the market-adjusted return of the category. However, the response of flows to the category-adjusted return of the fund (1.097) is greater than that of the market-adjusted return of the category (0.899) at p-values less than 0.01. In addition, the inclusion of the category-adjusted return of the fund reduces the impact of the fund's size and value tilts on fund flows. For example, in Table 5 where we estimate the same regression with just market-adjusted returns as an independent variable, the coefficient estimate on the portion of the fund's alpha that can be traced to its size tilt is -0.250. When we decompose the market-adjusted return into two components (category-adjusted return of the fund and market-adjusted return of the category), the coefficient estimate on a fund's size-related return is reduced in magnitude by about half to -0.133 and the reduction is statistically significant ($p<.01$). The inclusion of category-level returns also reduces the coefficient estimates on a fund's value-related return ($p<.01$).

These results are quite consistent with the results of the prior section based on the return decomposition of a fund. In both specifications, we find that fund flows respond to *category-level* returns. If fund flow decisions are motivated by a desire to identify skilled mutual fund managers, these results indicate some investors misattribute the market-adjusted returns of a category to managerial skill.

III.D. Can Star Ratings explain Our Results?

Each month, Morningstar issues mutual fund ratings that are based on a fund's risk and return relative to its peer group over three-, five-, and ten-year horizons. Morningstar ranks funds within fund categories based on a risk-adjusted return, where the risk-adjustment is a modified measure of standard deviation.[11] Ratings range from one star for poor performing funds to five

[11] Morningstar website (http://www.morningstar.com/help/data.html#StarRating) describes their risk measure as "…the variation in a fund's month-to-month return, with an emphasis on downward variation. But unlike standard deviation, which treats upside and downside variability equally, Morningstar Risk places greater emphasis on downward variation. Like beta, Morningstar Risk is a relative measure. It compares the risk of funds in each Morningstar category." Returns are measures as the fund's excess return over a risk-free rate after adjusting for

stars for top performers. Moreover, Morningstar fund ratings have a causal impact on fund flows (Del Guercio and Tkac (2008)). Given Morningstar penalizes funds for volatility and star ratings influence fund flows, it's plausible that investors account for market risk indirectly by following Morningstar fund ratings when allocating capital to mutual funds.

To investigate whether star ratings are a potential mechanism by which investors tend to factor-related returns (particularly returns traced to market risk), we augment our main return decomposition regression of equation (7) to include dummy variables for a fund's star ratings as follows. First, we calculate the TNA-weighted overall star rating[12] across share classes for a fund. (There is generally little variation in star ratings across share classes.) We create a dummy variable for one-star funds that takes on a value of one if the TNA-weighted star rating is less than 1.5. We similarly create dummy variables for two- to five-star funds based on the following star rating categories: [1.5,2.5), [2.5,3.5), [3.5,4.5), [4.5,5.0). When estimating the regression, we omit the lowest star rating category and report results for the remaining star-category dummy variables.

The results of this analysis are presented in Table 9. For comparison purposes, we present the regression results for all funds with star ratings, but omitting the star rating dummy variables, in column 1. In column 2, we estimate the regression including the star rating dummy variables. Consistent with prior work, we find that funds with high star ratings enjoy greater net flows. For example, funds in the top star-rating category have monthly net flows that are 2.39% greater than other funds. The inclusion of star ratings reduces the effect of each return component on fund flows. For example, the impact of a fund's four-factor alpha on fund flows is reduced by about 20% (from 1.116 to 0.884). However, the relative importance of the components of returns is largely unaffected. Returns traced to size, value, and momentum risk receive a modest discount relative to a fund's four-factor alpha, while returns traced to a fund's market risk receive steep discounts. This analysis suggests that star ratings do affect the flow-return relations, but are not the primary mechanism through which investors tend to market beta when allocating capital to mutual funds.

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loads and sales charges. The distribution of funds within stars are: one star (10%), two star (22.5%), three star (35%), four star (22.5%), five star (10%).

[12] Morningstar's overall star rating is a weighted average of the three-, five-, and ten-year star ratings for a fund with more weight given to the three-year rating.

III.E. Fund Distribution Channel and Flow Relations

Our primary analysis treats mutual fund investors as a homogenous group. However, investors vary and different groups of investors may perceive risk differently. Chalmers and Reuter (2013) report that investors who purchase mutual funds through a broker tend to be younger, less well educated, and less wealthy than investors who buy funds sold directly from fund companies and that investors in broker-sold funds underperform investors in direct-sold funds. Del Guercio and Reuter (2013) find that flows are more sensitive to alpha for direct-sold funds than broker-sold funds, while Christoffersen, Evans, and Musto (2013) report that flows to broker-sold funds are heavily influenced by payments made by fund companies to brokers. If investors in direct-sold funds are more knowledgeable than those in broker-sold funds, they are likely to have more sophisticated models for benchmarking mutual fund performance.

To investigate this possibility, we analyze the impact of a fund's distribution channel on the flow-return relations. To do so, we first identify the primary distribution channel for each fund. As in Sun (2014), we classify a fund as broker-sold if 75% of its assets are held in a share class that meets any of the following three criteria: the fund charges a front-end load, a back-end load, or a 12b-1 fee greater than 25 bps. Bergstresser, Chalmers, and Tufano (2009) document that broker-sold funds tend to charge front-end loads, back-end loads, or 12b-1 fees as a means to provide compensation to brokers who sell funds to investors. Conversely, a fund is direct-sold if 75% of its assets are held in a share class that charges no front-end load, no back-end load, and no 12b-1 fee. In the average month during our sample period, 40% of funds are direct-sold, 53% are broker-sold, and the remaining 7% have an indeterminate distribution channel.

To test the hypothesis that flow-return relations differ across distribution channels, we modify the main return decomposition regression of equation (7) by interacting the return components of a fund with a dummy variable (B_{pt}) that takes a value of one if the fund is primarily broker-sold:

$$\begin{aligned}
&F_{pt} = b_0 + \\
&b_{d1}\left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) + b_{d2}\left[\hat{\beta}_{pt}\overline{R_{mt} - R_{ft}}\right] + b_{d3}\left(\hat{s}_{pt}\overline{SMB_t}\right) + b_{d4}\left(\hat{h}_{pt}\overline{HML_t}\right) + b_{d5}\left(\hat{m}_{pt}\overline{UMD_t}\right) + \\
&b_{b1}B_{pt}\left(\hat{\alpha}_{pt} + \hat{y}_{pt}\right) + b_{d2}B_{pt}\left[\hat{\beta}_{pt}\overline{R_{mt} - R_{ft}}\right] + b_{d3}B_{pt}\left(\hat{s}_{pt}\overline{SMB_t}\right) + b_{d4}B_{pt}\left(\hat{h}_{pt}\overline{HML_t}\right) + b_{d5}B_{pt}\left(\hat{m}_{pt}\overline{UMD_t}\right) \\
&+\gamma X_{pt} + e_{pt}
\end{aligned} \tag{17}$$

The coefficient estimates b_{d1} to b_{d5} represent the flow-return relation for direct-sold funds, while the coefficient estimates b_{b1} to b_{b5} represent the incremental flow-return relation for broker-sold funds. We exclude funds with an indeterminate distribution channel from this analysis.

We summarize the results of this single regression across the three columns of Table 10. Column (1) presents the coefficient estimates for the direct-sold channel (b_{d1} to b_{d5}). Column (2) presents the corresponding estimates for the broker-sold channel (b_{d1}+b_{b1} to b_{d5}+b_{b5}, e.g., the impact of alpha on broker-sold fund flows is b_{d1}+b_{b1}). Column (3) presents the difference between the direct-sold and broker-sold channel (i.e., b_{b1} to b_{b5}). While we observe statistically significant differences in the fund flow relations between broker-sold and direct-sold channels (see column (3) of Table 10), the differences are economically small in magnitude. Moreover, the general pattern of results—modest discounts for size and value related returns and heavy discounts for market-related returns—are similar for both distribution channels. Consistent with the view that investors who buy direct-sold funds are more sophisticated, they tend to discount market, size, and value-related returns more heavily than investors who buy through broker-sold funds. We interpret this evidence as suggestive that more sophisticated investors, who gravitate toward direct-sold mutual fund channels, use more sophisticated models to benchmark fund returns.

IV. Conclusion

What factors do investors view as risks in equity markets? We analyze this question by analyzing the net flows into actively managed funds. Our key insight is that investors who attempt to identify a skilled active manager will strip out any fund-level returns that can reasonably be traced to the risk taken on by the manager. Fund flows should respond to alpha, but how do investors calculate a fund's alpha? At one extreme, investors might merely evaluate funds based on their market-adjusted returns and essentially assume all funds have similar levels of risk. At another extreme, investors might use the four-factor model, with factors related to a fund's market, size, value, and momentum tilts, to assess a fund's performance.

Our empirical analysis reveals that the CAPM is able to best explain variation in flows across mutual funds. When we run a horserace between four asset-pricing models (market-adjusted returns, the CAPM, the three-factor model, and the four-factor model), the CAPM emerges as the clear victor. In additional analyses, we decompose the returns of each mutual fund into five components: four-factor alpha, market risk, size tilt, value tilt, and momentum tilt.

We find that flows respond to both the four-factor alpha and returns that can be traced to the size, value, and momentum tilts of the fund. The response of flows to a fund's momentum-related return rivals that of alpha. However, the size and value related returns of a fund generate a slightly weaker flow response than that associated with a fund's four-factor alpha. Consistent with the results of our model horserace, we find returns that can be traced to a fund's market risk (beta) garner the weakest flow response from investors.

We do not claim that all, or even most, investors use the same benchmark when evaluating the skill of a mutual fund manager. Indeed, we find evidence that category assignments, fund ratings, and distribution channels affect fund-flow relations, but our main observation that mutual fund investors seem to account for market risk in their fund selection decisions remains robust.

We also provide evidence that investors respond strongly to the market-adjusted return of a fund's Morningstar category. Since the category level return is not under the control of a mutual fund manager, this suggests that some mutual fund investors confuse strong category performance and a skilled mutual fund manager

In contrast to asset pricing tests, which look for state variables that might explain the high returns to small, value, or high-momentum stocks, our results indicate that mutual fund investors do not generally view these characteristics as risk factors when evaluating the performance of mutual funds. However, consistent with a long theoretical literature suggesting market risk should be important to investors, we find investors actually do care about market risk.

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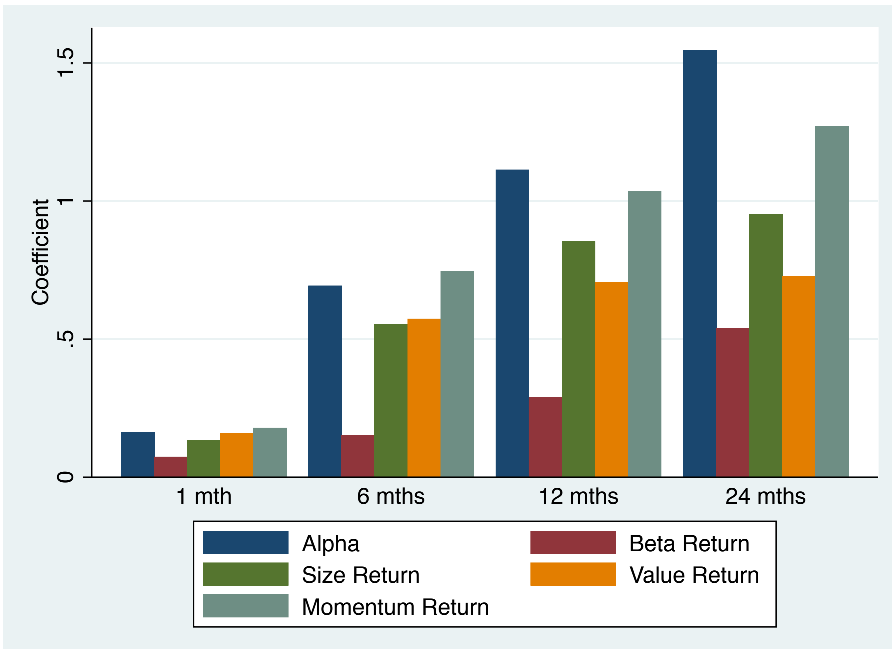
Figure 1: Return Decomposition Results for Different Horizons

Panel A depicts the coefficient estimates on the components of returns for 1, 6, 12, and 24 months; Panel B depicts the coefficient estimates scaled by the coefficient estimate on alpha. For each horizon, the estimated regression for each horizon is the same as that in our main results (i.e., 12 months) with the exception being the change in the horizon dummy variable.

Panel A: Coefficient Estimates on Return Components



Panel B: Coefficient Estimates Scaled by Alpha Coefficient

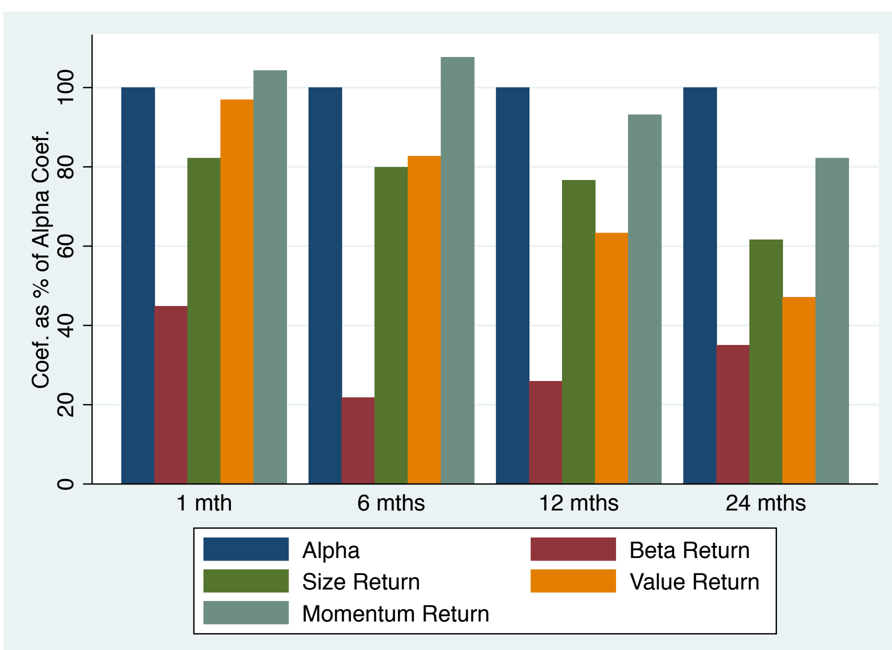


Table 1: Descriptive Statistics for Mutual Fund Sample

The table presents descriptive statistics for 333,723 fund-month observations across 204 months (January 1996 to December 2012). Share class data are aggregated at the fund level. Panel A presents statistics across fund-month observations. Panel B presents descriptive statistics on fund return components that are calculated by month and then averaged across months. Panel C presents the correlation matrix between fund return components based on fund-month observations. Panel D presents the correlation matrix between annual abnormal return measures calculated from four models: market-adjusted returns, the CAPM, Fama-French three-factor model, and Fama-French four-factor model. Percentage fund flow is percentage change TNA from month t-1 to t adjusted for the fund return in month t. The Load Fund Dummy takes a value of one if any share class for the fund has a front or back-end load. Alpha, factor coefficients (beta, size, value, and momentum) and Adjusted R-squared for month t are estimated using a five-year rolling regression of fund excess return (market less riskfree return) on market, size, value, and momentum factors. Returns due to factor tilts of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimating factor loading. Percentage fund flow is winsorized at -90% and 1000%; all other variables are winsorized at the 1 and 99% levels.

Table 1, continued

	Mean	Std	25th Perc.	Median	75th Perc.
Panel A: 333,723 Fund-Month Observations					
Percentage fund flow	-0.329%	7.424%	-1.670%	-0.534%	0.689%
Fund Size at month t-1 (in millions)	1315.70	3061.31	105.64	330.43	1048.82
Fund Age in Months at month t-1	183.59	147.72	94.00	138.00	207.00
Expense ratio (TNA-weighted across classes)	1.29%	0.45%	1.00%	1.24%	1.55%
Load Fund Dummy	0.71	0.46	0.00	1.00	1.00
Monthly Return Std. Deviation (t-12 to t-1)	4.92%	2.02%	3.35%	4.71%	6.15%
Four-Factor Alpha (t-12 to t-1)	-0.034%	0.751%	-0.416%	-0.064%	0.317%
Beta	0.97	0.18	0.87	0.97	1.07
Size Coefficient	0.18	0.32	-0.07	0.12	0.40
Value Coefficient	0.06	0.36	-0.17	0.06	0.30
Momentum Coefficient	0.03	0.15	-0.06	0.01	0.10
Adjusted R-Squared	0.81	0.17	0.76	0.87	0.92
Panel B: Mean Descriptive Statistics Across 204 Months (Jan 1996 to Dec 2012)					
Four-Factor Alpha (t-12 to t-1)	-0.061%	0.707%	-0.472%	-0.078%	0.319%
Return due to Market Risk (t-12 to t-1)	0.466%	0.254%	0.328%	0.468%	0.607%
Return due to Size Risk (t-12 to t-1)	0.032%	0.235%	-0.140%	0.025%	0.200%
Return due to Value Risk (t-12 to t-1)	0.065%	0.344%	-0.161%	0.053%	0.297%
Return due to Momentum Risk (t-12 to t-1)	0.004%	0.210%	-0.123%	-0.001%	0.130%

Panel C: Correlation between Fund Return Components

	(a)	(b)	(c)	(d)	(e)
(a) Four-Factor Alpha (t-12 to t-1)	1.00				
(b) Return due to Market Risk (t-12 to t-1)	0.06	1.00			
(c) Return due to Size Risk (t-12 to t-1)	-0.01	0.01	1.00		
(d) Return due to Value Risk (t-12 to t-1)	0.00	-0.12	0.03	1.00	
(e) Return due to Mom. Risk (t-12 to t-1)	-0.18	-0.14	-0.09	0.01	1.00

Panel D: Correlation between Fund Alphas

	(a)	(b)	(c)	(d)
(a) Market-Adjusted Return	1.00			
(b) CAPM Alpha	0.92	1.00		
(c) Three-Factor Alpha	0.75	0.80	1.00	
(d) Four-Factor Alpha	0.72	0.76	0.94	1.00

Table 2: Descriptive Statistics by Morningstar Style Box

This table presents the mean and standard deviation of estimated factor coefficients (beta, size, value, and momentum) across fund-month observations for each of the nine Morningstar style boxes. Factor coefficients (beta, size, value, and momentum) and Adjusted R-squared for month t are estimated using a five-year rolling regression of fund excess return (market less riskfree return) on market, size, value, and momentum factors.

	Large	Medium	Small	Agg by Value
Panel A: Beta				
Value	0.935	0.841	0.869	0.906
	(0.153)	(0.232)	(0.172)	(0.180)
Blend	0.952	0.940	0.954	0.950
	(0.172)	(0.182)	(0.136)	(0.169)
Growth	1.000	1.018	1.045	1.013
	(0.184)	(0.202)	(0.165)	(0.186)
Agg by Size	0.966	0.956	0.985	0.967
	(0.174)	(0.218)	(0.173)	(0.185)
Panel B: Size Coefficient				
Value	-0.048	0.236	0.591	0.091
	(0.167)	(0.204)	(0.201)	(0.282)
Blend	-0.018	0.311	0.633	0.134
	(0.191)	(0.202)	(0.191)	(0.307)
Growth	0.054	0.387	0.695	0.261
	(0.215)	(0.219)	(0.202)	(0.329)
Agg by Size	0.002	0.332	0.657	0.179
	(0.200)	(0.220)	(0.203)	(0.320)
Panel C: Value Coefficient				
Value	0.280	0.375	0.473	0.324
	(0.239)	(0.286)	(0.265)	(0.262)
Blend	0.084	0.246	0.336	0.149
	(0.235)	(0.299)	(0.285)	(0.273)
Growth	-0.179	-0.131	-0.067	-0.145
	(0.305)	(0.387)	(0.286)	(0.329)
Agg by Size	0.034	0.083	0.153	0.063
	(0.324)	(0.412)	(0.366)	(0.355)
Panel D: Momentum Coefficient				
Value	-0.037	-0.061	-0.053	-0.044
	(0.126)	(0.156)	(0.124)	(0.133)
Blend	0.013	-0.017	-0.003	0.005
	(0.127)	(0.150)	(0.131)	(0.132)
Growth	0.071	0.100	0.076	0.080
	(0.143)	(0.175)	(0.144)	(0.153)
Agg by Size	0.022	0.033	0.028	0.025
	(0.140)	(0.180)	(0.147)	(0.151)

Table 3: Results of Model Horserace

This table presents results of a pairwise comparison of competing asset pricing models ability to predict fund flows. The four panels present the following pairwise comparisons: Panel A, CAPM v. Three-Factor Model; Panel B, CAPM v. Market-Adjusted; Panel C, Market-Adjusted v. Three-Factor Model; Panel D, Three-Factor Model v. Four-Factor Model.

For example, we estimate the relation between flows and a fund's decile ranking based on the CAPM and three-factor models by estimating the following regression:

$$F_{pt} = a + \sum_i \sum_j b_{ij} D_{ijpt} + cX_{pt} + \mu_t + \varepsilon_{pt}$$

where the dependent variable (F_{pt}) is the fund flow for mutual fund p in month t. D_{ijpt} is a dummy variable that takes on a value of one if fund p in month t is in decile i based on the CAPM and decile j based on the three-factor model. To estimate the model, we exclude the dummy variable for $j=5$ and $i=5$. The matrix X_{pt} represents control variables, while the c contains a vector of associated coefficient estimates. As controls, we include lags of a funds total expense ratio (TNA-weighted across share classes), a dummy variable for no-load funds (if all share classes are no-load funds), a funds return standard deviation estimated over the prior 12 months, the log of fund size in month t-1, and the log of fund age in month t-1. We also include time fixed effects (μ_t).

Each panel compares the coefficients where the decile ranks based on the two competing models differ. For example, the row "10 v 9" in Panel A compares $b_{10,9}$ (decile 10 CAPM alpha funds and decile 9 three-factor alpha funds) to $b_{9,10}$ (decile 9 CAPM alpha funds and decile 10 three-factor alpha funds).

The last two rows of each panel present tests of the null hypothesis that the summed difference between the coefficients is zero and the null hypothesis that the percentage of positive coefficients is equal to 50%.

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Panel A: CAPM v. Three-Factor Model

	CAPM alpha > 3F Alpha			3F Alpha > CAPM Alpha				
	b_{ij}	$se(b_{ij})$	N_{ij}	b_{ji}	$se(b_{ji})$	N_{ji}	b_{ij} - b_{ji}	$se(b_{ij}$-$b_{ji})$
10 v 9	2.03***	(0.16)	6069	1.69***	(0.16)	5761	0.35*	(0.18)
10 v 8	1.88***	(0.20)	2105	1.89***	(0.46)	2129	-0.01	(0.47)
10 v 7	1.41***	(0.24)	1004	1.38***	(0.26)	1038	0.04	(0.30)
10 v 6	1.38***	(0.34)	515	0.83***	(0.28)	520	0.55	(0.42)
10 v 5	1.87***	(0.72)	323	0.30	(0.21)	362	1.57**	(0.74)
10 v 4	0.64**	(0.31)	199	0.48*	(0.27)	250	0.15	(0.39)
10 v 3	0.03	(0.70)	106	0.23	(0.31)	176	-0.20	(0.81)
10 v 2	0.11	(0.42)	62	-0.26	(0.35)	103	0.37	(0.53)
10 v 1	-0.77	(0.89)	15	-0.89**	(0.42)	27	0.11	(1.00)
9 v 8	1.21***	(0.12)	6638	1.14***	(0.12)	6785	0.06	(0.12)
9 v 7	1.30***	(0.20)	3650	0.84***	(0.17)	3691	0.46**	(0.23)
9 v 6	1.28***	(0.27)	2145	0.46***	(0.14)	2136	0.82***	(0.26)
9 v 5	0.92***	(0.17)	1381	0.37*	(0.20)	1218	0.55**	(0.23)
9 v 4	0.66***	(0.23)	881	0.38	(0.23)	756	0.28	(0.32)
9 v 3	0.95**	(0.38)	506	0.02	(0.23)	424	0.93**	(0.43)
9 v 2	0.74***	(0.22)	326	-0.48	(0.33)	226	1.23***	(0.39)
9 v 1	0.03	(0.46)	90	-1.21**	(0.48)	73	1.23*	(0.70)
8 v 7	0.79***	(0.11)	5943	0.58***	(0.10)	6403	0.21*	(0.11)
8 v 6	0.58***	(0.11)	3855	0.33***	(0.11)	4205	0.25**	(0.10)
8 v 5	0.62***	(0.13)	2684	0.09	(0.12)	2636	0.53***	(0.14)
8 v 4	0.83***	(0.19)	1777	0.18	(0.13)	1606	0.65***	(0.19)
8 v 3	0.46**	(0.18)	1140	0.13	(0.34)	970	0.33	(0.37)
8 v 2	0.19	(0.20)	609	-0.05	(0.23)	457	0.24	(0.30)
8 v 1	-0.07	(0.34)	225	-1.19***	(0.42)	133	1.12**	(0.54)
7 v 6	0.41***	(0.11)	5499	0.28***	(0.10)	5899	0.13	(0.11)
7 v 5	0.52***	(0.12)	3830	0.08	(0.11)	4346	0.44***	(0.13)
7 v 4	0.44***	(0.13)	2841	-0.09	(0.12)	2939	0.53***	(0.15)
7 v 3	0.13	(0.15)	1745	-0.12	(0.21)	1648	0.25	(0.22)
7 v 2	0.01	(0.26)	1067	-0.32	(0.20)	832	0.34	(0.30)
7 v 1	0.25	(0.35)	393	-0.99***	(0.30)	260	1.24***	(0.43)
6 v 5	0.23	(0.16)	5352	0.03	(0.10)	5862	0.19	(0.14)
6 v 4	0.12	(0.12)	3842	-0.08	(0.10)	4452	0.19	(0.13)
6 v 3	0.01	(0.13)	2738	-0.46***	(0.12)	2750	0.46***	(0.14)
6 v 2	-0.23	(0.17)	1556	-0.46**	(0.18)	1380	0.23	(0.22)
6 v 1	0.64	(0.39)	625	-0.51*	(0.30)	415	1.14**	(0.52)
5 v 4	0.06	(0.12)	5312	-0.08	(0.16)	5883	0.14	(0.18)
5 v 3	-0.18	(0.13)	3824	-0.29**	(0.13)	4344	0.11	(0.15)
5 v 2	-0.28*	(0.16)	2375	-0.77***	(0.15)	2296	0.49**	(0.19)
5 v 1	-0.08	(0.29)	906	-1.01***	(0.22)	739	0.93***	(0.33)
4 v 3	-0.29***	(0.10)	5647	-0.52***	(0.09)	6378	0.23**	(0.09)
4 v 2	-0.46***	(0.12)	3752	-0.59***	(0.22)	4232	0.13	(0.21)
4 v 1	-0.54***	(0.20)	1425	-0.86***	(0.24)	1259	0.32	(0.27)
3 v 2	-0.78***	(0.11)	6235	-0.83***	(0.11)	7384	0.05	(0.11)
3 v 1	-0.61***	(0.21)	2631	-1.25***	(0.13)	2449	0.63***	(0.23)
2 v 1	-0.99***	(0.12)	5951	-1.21***	(0.12)	6913	0.22*	(0.12)
						Sum of Differences	20.23***	(3.46)
						Percent of Differences > 0	95.56***	

Panel B: CAPM v. Market-Adjusted

	CAPM Alpha > Market-Adjusted Return			Market-Adjusted Return > CAPM Alpha				
	b_{ij}	$se(b_{ij})$	N_{ij}	b_{ji}	$se(b_{ji})$	N_{ji}	$b_{ij} - b_{ji}$	$se(b_{ij}-b_{ji})$
10 v 9	1.73***	(0.14)	4694	1.39***	(0.14)	4639	0.34*	(0.18)
10 v 8	1.37***	(0.26)	1055	1.26***	(0.35)	1032	0.11	(0.44)
10 v 7	0.89***	(0.33)	530	1.57**	(0.68)	534	-0.68	(0.76)
10 v 6	1.11***	(0.40)	283	0.23	(0.31)	307	0.88*	(0.52)
10 v 5	1.27**	(0.57)	171	-0.15	(0.39)	199	1.42**	(0.65)
10 v 4	-0.45	(0.61)	117	-0.64	(0.93)	144	0.19	(1.11)
10 v 3	-0.14	(0.53)	62	-0.53	(0.53)	81	0.39	(0.84)
10 v 2	1.86	(1.28)	40	1.25*	(0.65)	40	0.61	(1.48)
10 v 1	1.62**	(0.82)	19	0.02	(1.38)	7	1.60	(1.24)
9 v 8	1.23***	(0.11)	5994	1.04***	(0.12)	6047	0.18	(0.14)
9 v 7	0.94***	(0.13)	1904	0.75***	(0.18)	1770	0.20	(0.22)
9 v 6	1.59***	(0.59)	858	0.76***	(0.27)	821	0.83	(0.61)
9 v 5	0.32	(0.25)	500	0.59**	(0.23)	499	-0.28	(0.31)
9 v 4	0.88	(0.61)	266	0.34	(0.26)	322	0.54	(0.64)
9 v 3	0.15	(0.62)	186	1.08	(1.25)	187	-0.93	(1.40)
9 v 2	-0.73	(0.52)	110	0.17	(0.87)	101	-0.90	(1.04)
9 v 1	0.26	(1.04)	51	-1.01**	(0.48)	62	1.26	(1.09)
8 v 7	0.99***	(0.17)	6250	0.63***	(0.09)	6411	0.37*	(0.20)
8 v 6	0.68***	(0.13)	2234	0.50***	(0.12)	2144	0.19	(0.17)
8 v 5	0.68***	(0.20)	1132	0.63***	(0.22)	1056	0.05	(0.27)
8 v 4	0.42*	(0.25)	617	0.34	(0.32)	576	0.08	(0.40)
8 v 3	0.01	(0.45)	314	-0.31	(0.28)	358	0.32	(0.51)
8 v 2	0.04	(0.34)	199	-0.23	(0.33)	203	0.27	(0.47)
8 v 1	1.41	(1.01)	85	1.83	(2.52)	68	-0.41	(2.76)
7 v 6	0.60***	(0.09)	6234	0.22**	(0.10)	6293	0.38***	(0.11)
7 v 5	0.48***	(0.13)	2353	0.02	(0.16)	2385	0.46**	(0.20)
7 v 4	0.45***	(0.16)	1217	0.10	(0.17)	1210	0.35	(0.25)
7 v 3	0.28	(0.35)	658	0.17	(0.29)	619	0.11	(0.44)
7 v 2	0.29	(0.25)	350	-0.17	(0.24)	368	0.46	(0.33)
7 v 1	-0.61	(0.48)	146	-1.27**	(0.62)	137	0.66	(0.83)
6 v 5	0.22***	(0.07)	6274	0.10	(0.08)	6200	0.13	(0.10)
6 v 4	0.56*	(0.30)	2412	0.03	(0.12)	2568	0.53	(0.33)
6 v 3	-0.17	(0.16)	1244	-0.19	(0.15)	1158	0.01	(0.20)
6 v 2	-0.40*	(0.24)	629	-0.51*	(0.29)	618	0.10	(0.36)
6 v 1	0.88*	(0.49)	252	-0.62**	(0.29)	244	1.51***	(0.53)
5 v 4	0.15	(0.11)	6405	-0.10	(0.09)	6224	0.25**	(0.12)
5 v 3	-0.13	(0.12)	2359	-0.04	(0.16)	2444	-0.09	(0.20)
5 v 2	-0.22	(0.18)	1095	-0.25	(0.22)	1161	0.03	(0.25)
5 v 1	-0.51*	(0.26)	461	-0.70***	(0.23)	385	0.19	(0.30)
4 v 3	-0.19**	(0.08)	6312	-0.35***	(0.11)	6372	0.16	(0.10)
4 v 2	-0.40***	(0.12)	2244	-0.27	(0.31)	2175	-0.13	(0.34)
4 v 1	-0.42*	(0.22)	669	-0.82***	(0.17)	689	0.40	(0.25)
3 v 2	-0.55***	(0.10)	6440	-0.63***	(0.12)	6569	0.08	(0.13)
3 v 1	-0.47*	(0.25)	1569	-0.87***	(0.20)	1544	0.40	(0.31)
2 v 1	-0.69***	(0.18)	5510	-1.10***	(0.11)	5617	0.42**	(0.19)
						Sum of Differences	13.03*	(6.82)
						Percent of Differences > 0	84.44***	

Panel C: Market-Adjusted v. Three-Factor Model

	Market-Adjusted Return > 3F Alpha			3F Alpha > Market-Adjusted Return				
	b_{ij}	$se(b_{ij})$	N_{ij}	b_{ji}	$se(b_{ji})$	N_{ji}	$b_{ij} - b_{ji}$	$se(b_{ij}-b_{ji})$
10 v 9	2.03***	(0.18)	6269	1.77***	(0.16)	5986	0.26	(0.21)
10 v 8	1.62***	(0.19)	2384	1.48***	(0.17)	2310	0.14	(0.23)
10 v 7	1.14***	(0.23)	1166	2.14***	(0.75)	1255	-1.00	(0.79)
10 v 6	0.83***	(0.31)	614	1.26***	(0.28)	783	-0.43	(0.36)
10 v 5	1.31**	(0.53)	453	1.04***	(0.22)	494	0.27	(0.56)
10 v 4	0.94***	(0.26)	314	0.61*	(0.35)	293	0.34	(0.44)
10 v 3	0.95	(0.64)	229	-0.02	(0.50)	210	0.97	(0.79)
10 v 2	1.83**	(0.81)	127	0.92**	(0.44)	141	0.91	(0.90)
10 v 1	1.09	(0.95)	51	0.65	(0.73)	91	0.44	(1.19)
9 v 8	1.27***	(0.11)	6460	1.09***	(0.10)	6664	0.19	(0.13)
9 v 7	1.25***	(0.19)	3682	0.76***	(0.12)	3648	0.49**	(0.21)
9 v 6	1.10***	(0.23)	2271	1.06***	(0.25)	2156	0.03	(0.33)
9 v 5	1.09***	(0.24)	1401	0.59***	(0.14)	1328	0.50*	(0.27)
9 v 4	0.81***	(0.25)	889	0.29*	(0.17)	884	0.53*	(0.31)
9 v 3	0.80**	(0.32)	635	0.59*	(0.31)	528	0.21	(0.44)
9 v 2	0.31	(0.24)	455	-0.03	(0.30)	337	0.35	(0.38)
9 v 1	0.44	(0.43)	212	-0.73*	(0.41)	182	1.17**	(0.59)
8 v 7	0.70***	(0.11)	5710	0.50***	(0.09)	6085	0.20*	(0.11)
8 v 6	0.60***	(0.11)	3899	0.38***	(0.09)	4154	0.23*	(0.12)
8 v 5	0.51***	(0.11)	2607	0.14	(0.12)	2592	0.37***	(0.14)
8 v 4	0.81***	(0.16)	1796	0.30	(0.21)	1737	0.52**	(0.25)
8 v 3	0.19	(0.15)	1105	0.00	(0.15)	1088	0.18	(0.19)
8 v 2	0.39	(0.32)	777	-0.02	(0.17)	567	0.41	(0.33)
8 v 1	0.89*	(0.53)	399	-0.11	(0.52)	251	1.00	(0.74)
7 v 6	0.44***	(0.10)	5309	0.35***	(0.09)	5743	0.10	(0.10)
7 v 5	0.30***	(0.11)	4011	0.17*	(0.09)	4292	0.12	(0.13)
7 v 4	0.24*	(0.14)	2892	-0.04	(0.10)	3024	0.28*	(0.14)
7 v 3	-0.13	(0.14)	1952	-0.03	(0.18)	1838	-0.10	(0.21)
7 v 2	0.06	(0.17)	1147	-0.31*	(0.17)	967	0.37	(0.23)
7 v 1	-0.16	(0.42)	550	-0.32	(0.27)	418	0.16	(0.56)
6 v 5	0.23***	(0.08)	5220	0.09	(0.09)	5546	0.15	(0.09)
6 v 4	0.06	(0.09)	4001	-0.11	(0.09)	4478	0.17	(0.12)
6 v 3	-0.11	(0.12)	2681	-0.23**	(0.11)	2883	0.12	(0.15)
6 v 2	-0.26	(0.16)	1732	-0.55***	(0.14)	1669	0.29	(0.19)
6 v 1	-0.05	(0.33)	796	-0.68***	(0.25)	576	0.63	(0.39)
5 v 4	-0.08	(0.09)	5263	0.17	(0.20)	5751	-0.26	(0.21)
5 v 3	-0.08	(0.12)	4090	-0.38***	(0.09)	4318	0.30**	(0.14)
5 v 2	-0.39***	(0.15)	2526	-0.80***	(0.14)	2531	0.42**	(0.18)
5 v 1	-0.33	(0.24)	1114	-0.82***	(0.23)	959	0.49	(0.35)
4 v 3	-0.25**	(0.11)	5599	-0.43***	(0.11)	6090	0.18	(0.13)
4 v 2	-0.52***	(0.12)	3706	-0.71***	(0.10)	4252	0.18	(0.14)
4 v 1	-0.66***	(0.22)	1573	-0.68***	(0.17)	1558	0.01	(0.28)
3 v 2	-0.82***	(0.09)	6263	-0.83***	(0.11)	6837	0.02	(0.10)
3 v 1	-0.75***	(0.16)	2811	-0.86***	(0.17)	2864	0.11	(0.23)
2 v 1	-1.17***	(0.12)	6259	-1.13***	(0.15)	6882	-0.05	(0.14)
						Sum of Differences	11.95***	(4.08)
						Percent of Differences > 0	88.89***	

Panel D: Three-Factor Model v. Four-Factor Model

	3F Alpha > 4F Alpha			4F Alpha > 3F Alpha				
	b_{ij}	$se(b_{ij})$	N_{ij}	b_{ji}	$se(b_{ji})$	N_{ji}	b_{ij} - b_{ji}	$se(b_{ij}-b_{ji})$
10 v 9	1.57***	(0.16)	3148	1.58***	(0.25)	3111	-0.01	(0.29)
10 v 8	1.87***	(0.30)	489	1.18***	(0.34)	434	0.69	(0.49)
10 v 7	5.74	(4.94)	184	2.08**	(0.99)	205	3.66	(5.13)
10 v 6	0.94*	(0.52)	93	-0.21	(0.68)	103	1.14	(0.70)
10 v 5	0.21	(0.67)	62	0.89**	(0.40)	53	-0.68	(0.75)
10 v 4	-0.63	(0.46)	38	1.77	(1.13)	43	-2.41*	(1.44)
10 v 3	-1.69	(1.83)	21	0.65	(1.01)	40	-2.34	(2.04)
10 v 2	-0.66	(1.80)	15	2.85	(2.36)	33	-3.52	(2.61)
10 v 1	-0.55	(.)	3	-0.35	(1.55)	27	-0.19	(1.53)
9 v 8	1.04***	(0.13)	4700	0.90***	(0.14)	4897	0.13	(0.16)
9 v 7	0.60***	(0.18)	1213	0.49**	(0.25)	1024	0.11	(0.30)
9 v 6	0.44	(0.33)	455	0.29	(0.37)	410	0.15	(0.45)
9 v 5	0.84***	(0.29)	221	0.40	(0.27)	185	0.45	(0.37)
9 v 4	0.36	(0.39)	96	2.11*	(1.10)	96	-1.75	(1.19)
9 v 3	0.60	(0.39)	64	2.58	(2.82)	65	-1.97	(2.84)
9 v 2	-0.81**	(0.33)	33	-0.54	(0.45)	45	-0.27	(0.48)
9 v 1	1.09*	(0.65)	19	-1.25	(1.99)	29	2.35	(1.98)
8 v 7	0.64***	(0.11)	5163	0.34***	(0.09)	5565	0.29***	(0.10)
8 v 6	0.63***	(0.13)	1485	0.53	(0.36)	1401	0.10	(0.39)
8 v 5	0.45*	(0.25)	635	0.22	(0.28)	557	0.23	(0.39)
8 v 4	-0.12	(0.35)	322	0.09	(0.26)	235	-0.21	(0.47)
8 v 3	-0.04	(0.30)	139	-0.81*	(0.49)	143	0.77	(0.59)
8 v 2	0.06	(0.38)	86	-0.51	(1.11)	78	0.57	(1.15)
8 v 1	-2.09	(2.10)	39	0.12	(0.48)	33	-2.21	(2.20)
7 v 6	0.32***	(0.09)	5433	0.16*	(0.09)	5941	0.16	(0.11)
7 v 5	0.86***	(0.33)	1747	0.01	(0.17)	1643	0.85**	(0.36)
7 v 4	0.29	(0.20)	748	0.05	(0.40)	636	0.24	(0.42)
7 v 3	0.09	(0.23)	325	-0.43	(0.26)	284	0.52	(0.32)
7 v 2	0.37	(0.47)	156	-0.37	(0.29)	148	0.74	(0.55)
7 v 1	0.57	(0.45)	62	-1.20*	(0.68)	66	1.77**	(0.81)
6 v 5	0.09	(0.09)	5432	0.16	(0.15)	6091	-0.07	(0.17)
6 v 4	0.20*	(0.12)	1819	-0.28**	(0.12)	1774	0.47***	(0.15)
6 v 3	0.16	(0.25)	769	-0.51**	(0.23)	620	0.67**	(0.31)
6 v 2	-0.17	(0.24)	346	-0.97**	(0.42)	253	0.80	(0.49)
6 v 1	-0.69	(0.54)	89	-0.48*	(0.27)	96	-0.21	(0.55)
5 v 4	0.01	(0.12)	5483	-0.19**	(0.09)	6067	0.19	(0.14)
5 v 3	-0.24*	(0.13)	1644	-0.53***	(0.20)	1648	0.29	(0.24)
5 v 2	-0.13	(0.18)	622	-0.62***	(0.17)	526	0.49**	(0.22)
5 v 1	-0.32	(0.30)	203	-1.12**	(0.52)	148	0.80	(0.62)
4 v 3	-0.08	(0.20)	5393	-0.41***	(0.08)	5926	0.33	(0.21)
4 v 2	-0.30**	(0.15)	1347	-0.70***	(0.16)	1286	0.40*	(0.21)
4 v 1	0.14	(0.23)	385	-0.71**	(0.35)	268	0.85**	(0.37)
3 v 2	-0.60***	(0.09)	5070	-0.67***	(0.10)	5459	0.07	(0.12)
3 v 1	-0.16	(0.17)	747	-0.72***	(0.23)	720	0.56**	(0.23)
2 v 1	-0.84***	(0.16)	3848	-0.91***	(0.16)	3992	0.07	(0.20)
						Sum of Differences	5.08	(10.14)
						Percent of Differences > 0	71.11***	

Table 4: Return Decomposition Results
Response of Fund Flows to Components of Fund Returns

This table presents regressions coefficient estimates from panel regressions of percentage fund flow (dependent variable) on the components of a fund's return—a fund's alpha and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund (see regression equation (7)). Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Column 1 presents results for all funds. Columns 2 to 5 present results for fund return quartiles, which are reconstituted monthly based on the excess return of the fund (fund return less riskfree rate) from period t-12 to t-1. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)	(3)	(4)	(5)
		Results by Quartiles of Fund Returns			
	All Funds	Group 1 (Lowest)	Group 2	Group 3	Group 4 (Highest)
Alpha (t-12 to t-1)	1.113***	0.691***	0.909***	1.058***	1.125***
	(0.040)	(0.067)	(0.089)	(0.084)	(0.072)
Return due to Market Risk (t-12 to t-1)	0.288***	-0.138	0.0335	0.247*	0.330**
	(0.076)	(0.104)	(0.126)	(0.129)	(0.133)
Return due to Size Risk (t-12 to t-1)	0.853***	0.565***	0.598***	0.595***	1.003***
	(0.082)	(0.115)	(0.135)	(0.115)	(0.155)
Return due to Value Risk (t-12 to t-1)	0.705***	0.552***	0.592***	0.654***	0.895***
	(0.083)	(0.091)	(0.114)	(0.112)	(0.120)
Return due to Momentum Risk (t-12 to t-1)	1.036***	0.357***	0.908***	1.069***	1.141***
	(0.076)	(0.110)	(0.121)	(0.114)	(0.129)
Controls	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES
Observations	327202	81703	82130	82197	81172
R-squared	0.119	0.093	0.061	0.065	0.090

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table 5: Alpha Decomposition Results
Response of Fund Flows to Components of Fund Alphas

This table presents estimated regressions coefficients from panel regressions of percentage fund flow (dependent variable) on the components of a fund's four-factor alpha—a fund's market-adjusted return and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund (see the regression of equation (9)). Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Columns 2 to 5 present results for fund return quartiles, which are reconstituted monthly based on the excess return of the fund (fund return less riskfree rate) from period t-12 to t-1. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)	(3)	(4)	(5)
		Results by Quartiles of Fund Returns			
	All Funds	Group 1 (Lowest)	Group 2	Group 3	Group 4 (Highest)
Market adjusted return (t-12 to t-1)	1.068***	0.772***	1.043***	1.205***	1.087***
	(0.039)	(0.066)	(0.097)	(0.089)	(0.076)
(Beta-1) * market excess return (t-12 to t-1)	-0.821***	-0.855***	-0.902***	-0.910***	-0.689***
	(0.085)	(0.109)	(0.101)	(0.099)	(0.139)
Return due to Size Risk (t-12 to t-1)	-0.250***	-0.129	-0.374***	-0.543***	-0.0308
	(0.081)	(0.107)	(0.117)	(0.107)	(0.136)
Return due to Value Risk (t-12 to t-1)	-0.433***	-0.159**	-0.337***	-0.449***	-0.152
	(0.084)	(0.078)	(0.072)	(0.091)	(0.108)
Return due to Momentum Risk (t-12 to t-1)	-0.0484	-0.334***	-0.0504	-0.0224	0.133
	(0.082)	(0.100)	(0.086)	(0.086)	(0.128)
Controls	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES
Observations	327218	81717	82134	82196	81171
R-squared	0.117	0.094	0.060	0.065	0.087

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table 6: Return Decomposition Results by Fund Age and Fund Size

This table presents main results (column 1) by fund age (columns 2 and 3) and fund size (columns 4 and 5). Young (old) funds are defined as funds with less than (greater than or equal to) 10 years of return history in month t. Small (large) funds have below (above) median TNA as of the year-end prior to month t. The table presents estimated regressions coefficients from panel regressions of percentage fund flow (dependent variable) on a fund's alpha and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund. Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)	(3)	(4)	(5)
		By Fund Age		By Fund Size	
	All Funds	Young Funds	Old Funds	Small Funds	Large Funds
Alpha (t-12 to t-1)	1.113***	1.188***	1.060***	1.051***	1.137***
	(0.040)	(0.050)	(0.043)	(0.045)	(0.049)
Return due to Market Risk (t-12 to t-1)	0.288***	0.321***	0.265***	0.228***	0.349***
	(0.076)	(0.097)	(0.083)	(0.087)	(0.092)
Return due to Size Risk (t-12 to t-1)	0.853***	0.945***	0.796***	0.689***	1.010***
	(0.082)	(0.102)	(0.091)	(0.088)	(0.100)
Return due to Value Risk (t-12 to t-1)	0.705***	0.672***	0.740***	0.731***	0.665***
	(0.083)	(0.095)	(0.080)	(0.092)	(0.088)
Return due to Momentum Risk (t-12 to t-1)	1.036***	1.225***	0.886***	0.951***	1.054***
	(0.076)	(0.100)	(0.079)	(0.089)	(0.096)
Controls	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES
Observations	327202	132577	194625	149762	159257
R-squared	0.119	0.131	0.113	0.101	0.153

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table 7: Return Decomposition
Response of Fund Flows to Category v. Fund Characteristics

This table presents regressions coefficient estimates from panel regressions of percentage fund flow (dependent variable) on the components of a fund's return—a fund's alpha and returns attributable to the category-level factor loadings (size and value), the fund's deviation from its category-level factor loadings (size and value), and the fund's market and momentum tilts (see regression equation (13)). Category-level loadings are based on a fund's size (small, mid-cap, or large) or value (value, blend, growth) Morningstar assignment. Returns due to factor loadings of a fund (category) are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's (category's) estimated factor loading. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)	(3)	(4)	(5)
		Results by Quartiles of Fund Returns			
	All Funds	Group 1 (Lowest)	Group 2	Group 3	Group 4 (Highest)
Alpha (t-12 to t-1)	1.125***	0.687***	0.941***	1.117***	1.115***
	(0.041)	(0.064)	(0.087)	(0.079)	(0.073)
Return due to market risk (t-12 to t-1)	0.291***	-0.150	0.0771	0.325***	0.299**
	(0.076)	(0.104)	(0.125)	(0.123)	(0.132)
Return traced to category-level size risk (t-12 to t-1)	0.746***	0.614***	0.519***	0.426***	0.867***
	(0.094)	(0.141)	(0.155)	(0.120)	(0.167)
Return traced to size risk deviation from category average (t-12 to t-1)	1.011***	0.537***	0.805***	0.995***	1.091***
	(0.114)	(0.155)	(0.161)	(0.142)	(0.202)
Return traced to category-level value risk (t-12 to t-1)	0.495***	0.337***	0.379***	0.486***	0.580***
	(0.099)	(0.118)	(0.108)	(0.118)	(0.177)
Return traced to value risk deviation from category average (t-12 to t-1)	0.807***	0.581***	0.795***	0.903***	0.928***
	(0.087)	(0.093)	(0.128)	(0.115)	(0.130)
Return due to momentum risk (t-12 to t-1)	1.060***	0.369***	0.957***	1.130***	1.122***
	(0.075)	(0.111)	(0.120)	(0.107)	(0.129)
Control Variables	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES
Observations	327192	81701	82132	82189	81170
R-squared	0.119	0.093	0.062	0.066	0.090
Difference (Across-category response - Within-category response):					
Size risk	-0.265**	0.077	-0.286*	-0.569***	-0.223
	(0.126)	(0.192)	(0.164)	(0.137)	(0.208)
Value risk	-0.312***	-0.244**	-0.416***	-0.417***	-0.348**
	(0.080)	(0.112)	(0.080)	(0.089)	(0.173)

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table 8: Alpha Decomposition
Response of Fund Flows to Category v. Fund Characteristics

This table presents regressions coefficient estimates from panel regressions of percentage fund flow (dependent variable) on the components of a fund's four-factor alpha—a fund's category-adjusted return, the market-adjusted return of the category, and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund (see the regression of equation (16)). Category-level returns are based on the nine Morningstar style boxes. Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)	(3)	(4)	(5)
		Results by Quartiles of Fund Returns			
	All Funds	Group 1 (Lowest)	Group 2	Group 3	Group 4 (Highest)
Fund - category return (t-12 to t-1)	1.097***	0.709***	1.057***	1.198***	1.136***
	(0.041)	(0.064)	(0.096)	(0.096)	(0.077)
Category - market return (t-12 to t-1)	0.899***	0.539***	0.842***	0.937***	0.868***
	(0.053)	(0.074)	(0.097)	(0.094)	(0.106)
(Beta-1) * market excess return (t-12 to t-1)	-0.807***	-0.843***	-0.876***	-0.868***	-0.682***
	(0.085)	(0.108)	(0.101)	(0.099)	(0.138)
Return due to Size Risk (t-12 to t-1)	-0.133*	-0.0383	-0.253**	-0.385***	0.115
	(0.080)	(0.107)	(0.118)	(0.103)	(0.137)
Return due to Value Risk (t-12 to t-1)	-0.324***	-0.0931	-0.241***	-0.307***	-0.0742
	(0.079)	(0.078)	(0.078)	(0.089)	(0.108)
Return due to Momentum Risk (t-12 to t-1)	-0.0262	-0.332***	0.000562	0.0133	0.153
	(0.080)	(0.098)	(0.084)	(0.086)	(0.126)
Control Variables	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES
Observations	327221	81720	82136	82190	81175
R-squared	0.117	0.093	0.061	0.066	0.088
Difference in response to Fund-category return vs Category-market return					
	0.198***	0.171***	0.215***	0.262***	0.268***
	(0.049)	(0.060)	(0.052)	(0.056)	(0.089)
Difference in absolute value of coefficients between category alpha decomposition and alpha decomposition					
Return due to Size Risk (t-12 to t-1)	-0.114***	-0.076***	-0.123***	-0.163***	-0.142***
	(0.009)	(0.017)	(0.014)	(0.016)	(0.021)
Return due to Value Risk (t-12 to t-1)	-0.108***	-0.060***	-0.098***	-0.141***	-0.067***
	(0.008)	(0.013)	(0.012)	(0.014)	(0.014)

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table 9: The Impact of Star Ratings on Flow-Return Relations

This table presents regressions coefficient estimates from panel regressions of percentage fund flow (dependent variable) on the components of a fund's return—a fund's alpha and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund (see regression equation (7)). Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Column 1 presents results for all funds. Column 1 contains results for all funds with available star ratings (about 12,000 fund-month observations are missing star ratings), which are similar to the main results. Column 2 contains regression results when we add dummy ratings for star rating categories to the baseline regression (where a star rating of 1 is the omitted category). Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)
Alpha (t-12 to t-1)	1.116***	0.884***
	(0.041)	(0.038)
Return due to Market Risk (t-12 to t-1)	0.291***	0.234***
	(0.078)	(0.069)
Return due to Size Risk (t-12 to t-1)	0.849***	0.638***
	(0.084)	(0.072)
Return due to Value Risk (t-12 to t-1)	0.709***	0.521***
	(0.085)	(0.070)
Return due to Momentum Risk (t-12 to t-1)	1.042***	0.689***
	(0.079)	(0.066)
Rating = 2	--	0.000756*
		(<0.001)
Rating = 3	--	0.00521***
		(<0.001)
Rating = 4	--	0.0133***
		(0.001)
Rating = 5	--	0.0239***
		(0.001)
Control Variables	YES	YES
Month Fixed Effects	YES	YES
Observations	315508	315508
R-squared	0.120	0.159

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table 10: The Impact of Fund Distribution Channels on Flow-Return Relations

This table presents regressions coefficient estimates from single panel regressions of percentage fund flow (dependent variable) on the components of a fund's return and interaction of the components with a dummy variable that takes a value of one for broker-sold funds (see regression equation (17)). Column 1 presents the results for direct-sold funds, column 2 presents results for broker-sold funds (the sum of the direct-sold coefficient and the broker-sold interaction coefficient for each return component), and column 3 presents the difference between broker-sold and direct-sold channels (i.e., the coefficient estimate on the interaction between the broker-sold dummy variable and the return component). The components of a fund's return include fund's alpha and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund. Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility. The regression is estimated excluding funds with an indeterminate distribution channel (see text for details).

	(1)	(2)	(3)
	Direct-sold	Broker-sold	Diff (Broker - Direct)
Alpha (t-12 to t-1)	1.035***	1.121***	0.0858*
	(0.045)	(0.045)	(0.046)
Return due to Market Risk (t-12 to t-1)	0.231***	0.283***	0.0518***
	(0.073)	(0.076)	(0.015)
Return due to Size Risk (t-12 to t-1)	0.760***	0.919***	0.159*
	(0.090)	(0.093)	(0.083)
Return due to Value Risk (t-12 to t-1)	0.545***	0.796***	0.251***
	(0.083)	(0.085)	(0.053)
Return due to Momentum Risk (t-12 to t-1)	1.134***	0.945***	-0.189**
	(0.085)	(0.091)	(0.096)
Control Variables		YES	
Month Fixed Effects		YES	
Observations		299581	
R-squared		0.126	

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Table A1: Sharpe Ratio Horserace

This table presents results of a horserace between (Panel A) CAPM Alpha v. Sharpe Ratio and (Panel B) Sharpe Ratio v. Market-Adjusted Returns. Fund Sharpe Ratios are calculated as the mean fund return divided by its standard deviation using 12-month trailing returns.

For example, we estimate the relation between flows and a fund's decile ranking based on the the CAPM alpha and Sharpe Ratio (SR) by estimating the following regression:

$$F_{pt} = a + \sum_i \sum_j b_{ij} D_{ijpt} + cX_{pt} + \mu_t + \varepsilon_{pt}$$

where the dependent variable (F_{pt}) is the fund flow for mutual fund p in month t. D_{ijpt} is a dummy variable that takes on a value of one if fund p in month t is in decile i based on the CAPM and decile j based on the SR. To estimate the model, we exclude the dummy variable for $j=5$ and $i=5$. The matrix X_{pt} represents control variables, while the c contains a vector of associated coefficient estimates. As controls, we include lags of a funds total expense ratio (TNA-weighted across share classes), a dummy variable for no-load funds (if all share classes are no-load funds), a funds return standard deviation estimated over the prior 12 months, the log of fund size in month t-1, and the log of fund age in month t-1. We also include time fixed effects (μ_t).

Each panel compares the coefficients where the decile ranks based on the two competing models differ. For example, the row "10 v 9" in Panel A compares $b_{10,9}$ (decile 10 CAPM alpha funds and decile 9 SR funds) to $b_{9,10}$ (decile 9 SR funds and decile 10 CAPM alpha funds).

The last two rows of each panel present tests of the null hypothesis that the summed difference between the coefficients is zero and the null hypothesis that the percentage of positive coefficients is equal to 50%.

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

Panel A: CAPM Alpha v. Sharpe Ratio

	CAPM alpha > Sharpe Ratio			Sharpe Ratio > CAPM Alpha				
	b_{ij}	$se(b_{ij})$	N_{ij}	b_{ji}	$se(b_{ji})$	N_{ji}	$b_{ij} - b_{ji}$	$se(b_{ij}-b_{ji})$
10 v 9	1.58***	(0.13)	6875	1.70***	(0.15)	7290	-0.12	(0.17)
10 v 8	1.43***	(0.20)	2060	1.18***	(0.17)	2549	0.25	(0.26)
10 v 7	1.27***	(0.27)	978	0.60**	(0.23)	931	0.67**	(0.34)
10 v 6	1.18***	(0.26)	656	0.53**	(0.25)	431	0.66*	(0.37)
10 v 5	0.91**	(0.41)	403	0.78*	(0.42)	224	0.13	(0.62)
10 v 4	0.73	(0.65)	233	0.91	(0.91)	130	-0.18	(1.17)
10 v 3	1.86***	(0.53)	159	0.52	(0.43)	103	1.34**	(0.68)
10 v 2	0.43	(0.40)	186	-0.54	(0.51)	71	0.97	(0.70)
10 v 1	0.60	(0.62)	226	-1.29**	(0.54)	30	1.89**	(0.80)
9 v 8	0.94***	(0.10)	6932	1.16***	(0.15)	7285	-0.22	(0.17)
9 v 7	0.78***	(0.15)	2403	0.63***	(0.13)	2658	0.15	(0.18)
9 v 6	0.67***	(0.19)	1094	0.33**	(0.15)	1099	0.35*	(0.20)
9 v 5	0.59**	(0.24)	587	0.09	(0.31)	517	0.51	(0.39)
9 v 4	0.09	(0.32)	349	-0.37	(0.26)	324	0.45	(0.38)
9 v 3	1.20**	(0.55)	241	0.05	(0.27)	211	1.15*	(0.65)
9 v 2	1.55**	(0.66)	154	-0.54	(0.50)	121	2.09***	(0.79)
9 v 1	1.27**	(0.63)	117	-0.66	(0.55)	71	1.93**	(0.88)
8 v 7	0.79***	(0.17)	6355	0.56***	(0.10)	6954	0.22	(0.17)
8 v 6	0.66***	(0.16)	2492	0.21*	(0.12)	2661	0.45**	(0.19)
8 v 5	0.51**	(0.22)	1030	0.40*	(0.22)	1143	0.11	(0.31)
8 v 4	-0.16	(0.22)	550	-0.27	(0.19)	591	0.11	(0.25)
8 v 3	0.01	(0.27)	298	0.03	(0.40)	317	-0.01	(0.45)
8 v 2	0.34	(0.53)	242	-0.66**	(0.27)	164	1.00*	(0.59)
8 v 1	0.35	(0.51)	125	-1.49***	(0.56)	77	1.84**	(0.74)
7 v 6	0.51***	(0.09)	6139	0.38***	(0.14)	6893	0.13	(0.14)
7 v 5	0.21*	(0.12)	2429	0.06	(0.12)	2612	0.15	(0.15)
7 v 4	-0.32	(0.21)	1048	0.91	(0.87)	1096	-1.23	(0.87)
7 v 3	0.41	(0.28)	592	-0.14	(0.52)	520	0.55	(0.63)
7 v 2	-0.72**	(0.32)	336	-0.23	(0.25)	298	-0.50	(0.40)
7 v 1	0.15	(0.27)	168	-1.75**	(0.78)	87	1.90***	(0.68)
6 v 5	0.11	(0.09)	6301	-0.03	(0.09)	7021	0.14	(0.10)
6 v 4	-0.07	(0.12)	2285	-0.17	(0.12)	2386	0.10	(0.15)
6 v 3	-0.17	(0.18)	1007	-0.33**	(0.15)	963	0.16	(0.18)
6 v 2	-0.52	(0.33)	448	-0.74***	(0.28)	442	0.21	(0.35)
6 v 1	-0.45	(0.35)	232	-0.48	(0.36)	193	0.03	(0.43)
5 v 4	-0.22**	(0.10)	6411	-0.08	(0.14)	6925	-0.14	(0.16)
5 v 3	-0.45***	(0.13)	2125	-0.39***	(0.11)	2397	-0.06	(0.14)
5 v 2	-0.30*	(0.17)	862	0.42	(1.09)	906	-0.72	(1.08)
5 v 1	-0.99**	(0.44)	365	-0.90***	(0.29)	313	-0.09	(0.51)
4 v 3	-0.44***	(0.08)	6315	-0.43***	(0.09)	6866	-0.02	(0.09)
4 v 2	-0.39**	(0.18)	2128	-0.45***	(0.15)	2154	0.07	(0.21)
4 v 1	-0.86***	(0.26)	579	-0.84***	(0.18)	592	-0.02	(0.32)
3 v 2	-0.77***	(0.10)	6480	-0.64***	(0.13)	7074	-0.13	(0.15)
3 v 1	-0.59*	(0.30)	1533	-0.54***	(0.17)	1584	-0.05	(0.32)
2 v 1	-0.90***	(0.16)	6014	-1.08***	(0.16)	6415	0.18	(0.16)
						Sum of Differences	16.41***	(5.54)
						Percent of Differences > 0	68.89***	

Panel B: Sharpe Ratio v. Market-Adjusted Return

	Sharpe Ratio > Market-Adjusted Return			Market-Adjusted Return > Sharpe Ratio				
	b_{ij}	$se(b_{ij})$	N_{ij}	b_{ji}	$se(b_{ji})$	N_{ji}	b_{ij} - b_{ji}	$se(b_{ij}$-$b_{ji})$
10 v 9	1.95***	(0.15)	6130	1.71***	(0.14)	6140	0.24	(0.18)
10 v 8	1.51***	(0.16)	2512	1.44***	(0.25)	2430	0.07	(0.31)
10 v 7	1.08***	(0.17)	1359	1.48***	(0.21)	1286	-0.40	(0.24)
10 v 6	1.74***	(0.62)	735	1.42***	(0.24)	834	0.33	(0.61)
10 v 5	0.65**	(0.31)	408	0.73**	(0.29)	499	-0.08	(0.47)
10 v 4	0.65	(0.64)	237	0.77*	(0.44)	290	-0.12	(0.85)
10 v 3	-0.05	(0.60)	168	0.28	(0.56)	205	-0.33	(0.77)
10 v 2	0.37	(0.55)	136	-0.28	(0.53)	104	0.66	(0.62)
10 v 1	0.83	(0.63)	162	-1.73	(1.13)	88	2.57**	(1.29)
9 v 8	1.38***	(0.17)	6132	1.23***	(0.11)	6059	0.15	(0.18)
9 v 7	0.76***	(0.12)	2969	0.90***	(0.19)	2818	-0.14	(0.22)
9 v 6	0.72***	(0.16)	1539	0.89***	(0.18)	1498	-0.17	(0.24)
9 v 5	0.84***	(0.21)	791	0.51**	(0.21)	906	0.33	(0.31)
9 v 4	0.40*	(0.21)	465	0.02	(0.29)	547	0.38	(0.33)
9 v 3	-0.03	(0.39)	277	1.40**	(0.56)	333	-1.43**	(0.68)
9 v 2	0.08	(0.48)	178	-0.71	(0.53)	196	0.78	(0.72)
9 v 1	-0.27	(0.92)	100	0.09	(0.60)	105	-0.36	(1.22)
8 v 7	0.62***	(0.09)	6023	0.83***	(0.09)	5753	-0.20*	(0.11)
8 v 6	0.60***	(0.10)	3088	0.60***	(0.11)	2955	0.00	(0.13)
8 v 5	0.40**	(0.16)	1511	0.62***	(0.14)	1604	-0.22	(0.19)
8 v 4	0.30*	(0.18)	784	0.61***	(0.22)	816	-0.31	(0.29)
8 v 3	0.13	(0.18)	432	0.16	(0.21)	476	-0.03	(0.25)
8 v 2	0.08	(0.21)	233	0.47	(0.54)	304	-0.38	(0.55)
8 v 1	0.38	(0.80)	124	-1.32	(1.28)	114	1.70	(1.58)
7 v 6	0.48***	(0.09)	6326	0.36***	(0.10)	5961	0.12	(0.12)
7 v 5	0.44***	(0.10)	2981	0.63***	(0.16)	2884	-0.19	(0.17)
7 v 4	1.22*	(0.72)	1613	0.00	(0.16)	1524	1.22*	(0.72)
7 v 3	0.19	(0.33)	789	-0.07	(0.30)	807	0.26	(0.44)
7 v 2	-0.45	(0.34)	386	0.46*	(0.26)	443	-0.91**	(0.44)
7 v 1	-0.10	(0.38)	159	-0.62	(0.55)	177	0.52	(0.64)
6 v 5	0.17**	(0.08)	6474	0.23***	(0.08)	6071	-0.06	(0.10)
6 v 4	0.26***	(0.10)	3090	-0.01	(0.11)	2858	0.27**	(0.13)
6 v 3	0.19	(0.15)	1452	0.08	(0.13)	1417	0.12	(0.18)
6 v 2	-0.14	(0.20)	657	-0.23	(0.27)	801	0.08	(0.33)
6 v 1	0.25	(0.47)	229	0.20	(0.27)	307	0.05	(0.55)
5 v 4	0.16	(0.15)	6182	0.02	(0.09)	6157	0.15	(0.17)
5 v 3	-0.11	(0.10)	2928	-0.04	(0.13)	2663	-0.08	(0.15)
5 v 2	0.54	(0.73)	1352	-0.15	(0.23)	1356	0.69	(0.76)
5 v 1	-0.08	(0.18)	467	-0.44	(0.34)	526	0.35	(0.33)
4 v 3	-0.24***	(0.08)	5916	-0.16	(0.12)	5754	-0.08	(0.13)
4 v 2	-0.34***	(0.11)	2491	-0.38**	(0.16)	2454	0.04	(0.19)
4 v 1	-0.58***	(0.22)	892	-0.04	(0.42)	899	-0.53	(0.46)
3 v 2	-0.52***	(0.09)	5791	-0.65***	(0.10)	5436	0.13	(0.11)
3 v 1	-0.38***	(0.14)	1783	-0.63***	(0.21)	1846	0.25	(0.24)
2 v 1	-0.69***	(0.18)	5247	-0.96***	(0.14)	5089	0.27	(0.20)
						Sum of Differences	5.67	(6.18)
						Percent of Differences > 0	57.78	

Table A2: Return Decomposition Results using Market-Share Measure of Flow
Response of Fund Flows to Components of Fund Returns

This table presents regressions coefficient estimates from panel regressions of change in a fund's market share (Δm_{it}, dependent variable) on the components of a fund's return—a fund's alpha and returns attributable to the factor loadings (beta, size, value, and momentum) of the fund (see regression equation (7)). Change in market share for fund i in month t is estimated as:

$$\Delta m_{it} = \frac{TNA_{it}}{\sum_{i=1}^{n_{t-1}} TNA_{it}} - \frac{TNA_{i,t-1}}{\sum_{i=1}^{n_{t-1}} TNA_{i,t-1}}$$

where TNA_{it} is the total net assets of fund i in month t, and n_{t-1} is the number of funds in existence in month t-1. Returns due to factor loadings of a fund are estimated as the mean monthly factor return from month t-12 to t-1 times the fund's estimated factor loading. Column 1 presents results for all funds. Columns 2 to 5 present results for fund return quartiles, which are reconstituted monthly based on the excess return of the fund (fund return less riskfree rate) from period t-12 to t-1. Controls include lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

	(1)	(2)	(3)	(4)	(5)
		Results by Quartiles of Fund Returns			
	All Funds	Group 1 (Lowest)	Group 2	Group 3	Group 4 (Highest)
Alpha (t-12 to t-1)	0.0241***	0.0190***	0.0271***	0.0199***	0.0135***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Return due to Market Risk (t-12 to t-1)	0.000264	0.00124	0.000327	-0.000970*	-0.00203***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Return due to Size Risk (t-12 to t-1)	0.0179***	0.0117***	0.0196***	0.0147***	0.0109***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
Return due to Value Risk (t-12 to t-1)	0.0207***	0.0189***	0.0236***	0.0120***	0.00818***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
Return due to Momentum Risk (t-12 to t-1)	0.0252***	0.0204***	0.0279***	0.0177***	0.00906**
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Controls	YES	YES	YES	YES	YES
Month Fixed Effects	NO	NO	NO	NO	NO
Observations	324672	81349	81395	81495	80433
R-squared	0.047	0.117	0.044	0.014	0.067

Standard errors are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.