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


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February 2, 2016


We appreciate the comments of Joseph Chen, Susan Christoffersen, Amit Goyal, David Hirshleifer, Petri Jylha, Jose Menchero, Stefan Nagel, Stephan Siegel, Jonathan Reuter, and seminar participants at Case Western University, Emory University, SAIF, Tulane University, UC Irvine, Vanderbilt University, the University of Stavanger, 2014 Helsinki Finance Summit, 2014 Rotterdam Behavioral Finance Conference, 2014 European Finance Association Meetings, 2014 Miami Behavioral Finance Conference, the Spring 2014 JOIM conference, 2015 CICF and the Ben Graham Centre's 4th Intelligent Investing Symposium. All errors are our own.

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

**Abstract**

When assessing a fund manager's skill, sophisticated investors will consider all factors (priced and unpriced) that explain cross-sectional variation in fund performance. We investigate which factors investors attend to by analyzing mutual fund flows as a function of recent returns decomposed into alpha and factor-related returns. Surprisingly, investors attend most to market risk (beta) when evaluating funds and treat returns attributable to size, value, momentum, and industry factors as alpha. Using proxies for investor sophistication (wealth, distribution channels, and periods of high investor sentiment), we find that more sophisticated investors use more sophisticated benchmarks when evaluating fund performance.

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. In theory, when assessing a fund manager's skill, investors should consider all factors that explain cross-sectional variation in fund performance, regardless of whether the factors are priced or unpriced (Grinblatt and Titman (1989), Pástor and Stambaugh (2002a)).

The intuition is straightforward. Consider size. Historically, the returns of small stocks have been correlated and small stocks have earned higher average returns than large stocks. A sophisticated investor will consider size when evaluating fund manager skill. In a year in which small stocks outperform large stocks, the investor will not conclude that all small cap fund managers are highly skilled. It doesn't matter whether the investor considers the return premium associated with size to result from risk, mispricing, or frictions. She will not confuse skill with returns that could be earned through passive investments (e.g., in small cap index funds).[1]

A sophisticated investor will also consider unpriced factors when evaluating mutual fund performance. Consider two industries that earn, on average, similar returns but perform well in different periods. Funds concentrated in one of the two industries will perform better in some periods but not others. The investor will not attribute these periodic performance differentials to fund manager skill.

Even factor returns that cannot be captured through passive investments should not be treated as alpha. Consider momentum. An investor might need to rely on active management to capture momentum returns. However, a sophisticated investor would not mistake recent positive or negative momentum returns as indicative of managerial skill. Rather the investor wishing to capture long-term momentum returns will invest in funds with high momentum loadings (and low fees).

Over the last twenty years, models such as the Fama-French three-factor model (Fama and French (1993)) and its four-factor cousin (Carhart (1997)) have become academic standards.

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[1] In this paper, we analyze fund flows in the U.S. equity mutual fund industry after 1997 when passive investment vehicles were available for broad market indexes, large cap, small cap, value, and growth.

The factors in these models have been shown empirically to be priced; stocks with higher market risk, smaller capitalization, higher book-to-market ratios, and recent momentum have earned greater returns on average. Though there is controversy within the profession as to whether the higher returns associated with small stocks, high book-to-market stocks, and positive momentum stocks are due to risk or mispricing,[2] sophisticated investors should consider these factors when assessing fund manager skill.

Because investors should consider all factors when assessing fund manager skill, one cannot infer that investors associate the factors they attend to with risk. However, investors are unlikely to ignore factors that they do associate with risk unless the costs of attending to those factors are higher than the benefits.

In this paper, we investigate whether investors pay attention to commonly used factors and industry tilts of mutual funds when assessing fund managers. The most surprising result to emerge from our analysis is the observation that flows do not respond as strongly to returns related to a fund's market risk (or beta). Consistent with this observation, we find that CAPM alphas are the best predictor of flows among competing performance evaluation models. In contrast to the results for market-related risk, flows respond strongly and nearly as much as alpha to other factor-related returns (size, value, momentum, and industry-related factors). As we discuss in detail below, we generally find that more sophisticated investors use more sophisticated benchmarks.

Our empirical analysis proceeds in two steps. To set the stage, we estimate mutual fund alphas using six competing empirical models of managerial skill: market-adjusted returns, the Capital Asset Pricing Model, the Fama and French (1993) three-factor model, a four-factor model that adds momentum (Carhart (1997)), a seven-factor model that adds the three industry factors of Pastor and Stambaugh (2002a, 2002b), and a nine-factor model that adds profitability and investment factors (Fama and French (2015)). In simple linear regressions of fund flows on the six performance measures, we find that the partial effect of CAPM alpha on fund flows is roughly double that of its nearest competitor (market-adjusted returns). To verify the robustness

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

of this result, we then 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 six 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 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.

In our second series of tests, we decompose the returns of a fund into eight components: seven factor-related returns (market (beta), size, value, momentum, and three industry factors) and the fund's alpha, all estimated using a seven-factor model. Here we find that returns related to a fund's beta do not generate the same flows as the fund's alpha or other factor-related returns. We find some evidence that investors attend to the value, size, and industry tilts of a fund when assessing managerial skill, but these effects are much weaker than those we observe for a fund's beta.

Sophisticated investors should attend to factor-related returns when assessing managerial skill. Viewed through this lens, our analysis is an investigation into how sophisticated investors are in assessing managerial skill. In aggregate, mutual fund investors do not attend to many aspects of fund performance. To test whether this lack of attention to factor returns is related to investor sophistication, we use three proxies for investor sophistication. First, we split our sample into direct v. broker sold. 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. Second, as suggested by Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2003) and Ben-Rephael, Kandel, and Wohl (2012), we use periods of high mutual fund trading as an indication of periods with high levels of investor sentiment and more trading by less sophisticated investors. Third, motivated by the evidence that correlates wealth with trading ability (Barber and Odean (2000); Geng, Li, Subrahmanyam, and Yu (2014)), diversification (Calvet, Campbell, and Sodini (2007)), and the disposition effect (Dhar and Zhu (2006)), we use wealth as a measure of investor sophistication in analyses that deploy data from a large discount broker over the 1991 to 1996 period. Consistent with the hypothesis that sophisticated investors use more sophisticated models for assessing fund performance, we consistently find that the flows of more sophisticated investors are less responsive to factor-related returns.

These results cannot be anticipated from prior research, which has documented a strong positive relationship between mutual fund flows and a variety of past performance measures including market-adjusted returns and alphas based on different factor models.[3] As discussed above, sophisticated investors should not reward fund managers with flows for returns attributable to factors to which the fund has a persistent exposure. However, unsophisticated investors may treat all components of return equally simply responding to market-adjusted returns. Because market-adjust returns and alphas are highly correlated (see Table 1, Panel E) a strong performance flow relationship for market-adjusted returns does not prove that investors ignore factors nor does a strong performance flow relationship for alphas prove that they attend to factors (rather than simply chasing market-adjusted returns). We are able to answer these questions by pitting performance measures based on competing models against one another and decomposing mutual fund returns into factor-related returns and alpha.

Barberis and Shleifer (2003) propose that rather than focusing on market-adjusted returns or on alphas, investors categorize assets into styles and do not distinguish between assets within a style. Using the nine Morningstar style boxes as a proxy for styles, Teo and Woo (2004) confirm that flows into funds within a style category are correlated with the past returns of that style category. Their results are evidence that investors do in fact reward managers for returns attributable to size and value styles. However, even if investors are oblivious to style categories, category flows and past returns will be positively correlated if investors are simply chasing

[3] Researchers have used a variety of return benchmarks when studying various mutual fund investor and managerial behaviors. Examples of studies using raw returns include Bergstresser and Poterba (2002) (tax-adjusted performance), Coval and Stafford (2007) (fund-flow price pressure relationship), Del Guercio and Tkac (2008) (Morningstar rating changes), and Ivkovic and Weisbenner (2009) (differential sensitivity of in and outflows to relative and absolute performance). Some that use market-adjusted returns include Chevalier and Ellison (1997) (strategic alteration of fund risk), Karceski (2002) (overweighting of high beta stocks), Barber, Odean, and Zheng (2005) (retail investor sensitivity to fees), and Spiegel and Zhang (2013) (alternative flow measure). Some that use alpha estimates include Khorana (2001) (fund manager replacements), Del Guercio and Tkac (2002) (retail investor versus pension fund behavior), Lynch and Musto (2003) (discarded strategies), Nanda, Wang, and Zheng (2004) (star spillover for fund families), Keswani and Stolin (2008) (smart-money effect in UK), Gil-Bazo and Ruiz-Verdu (2009) (performance fee relationship), and Sensoy (2009) (mismatched style indices).

market-adjusted returns. Thus, it remains an open question whether investors attend to factors or styles at all. Moreover, we show that one of our primary findings – that flows are less responsive to returns traced to a fund's market risk (beta) – is not driven by style chasing as the result is largely unaffected by the inclusion of month-style category fixed effects.

Consistent with Teo and Woo (2004), we confirm that flows chase style category returns. However, in contrast to the style-investing story, we find that flows are as, or more, responsive to deviations from style category returns as to the style category returns themselves. We also document that flows respond similarly to returns attributable to industry factors, to momentum, and to different specifications of alpha.

Our results largely support the story that unsophisticated investors chase market-adjusted performance with one surprising exception: market risk exposure. Flows are much less responsive to returns due to a fund's market risk (beta) than to other components of return. For the most part, investors do not reward fund managers for returns attributable to a fund's beta. Furthermore, investors who are likely to be more sophisticated—such as those who pay lower fees—are least likely reward managers for positive returns attributable to beta.

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. Style chasing does not explain this result for two reasons. First, when we include category-month fixed effects, which absorbs variation in fund flows across Morningstar style boxes, our main results are largely unaffected. Second, the average beta varies little across Morningstar style boxes. 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 flows.

In summary, our results provide insights into how investors evaluate mutual fund performance. Investors behave as if they expect mutual funds with high betas to outperform in strong markets and underperform in weak markets; they do not attribute these performance swings to managerial skill. Some investors attend to the value and size tilts of mutual funds when assessing fund manager performance, but returns traced to these factors generate flows that are nearly as large as those observed for fund's alpha. Returns traced to the momentum tilt of a fund garner virtually the same flows as a fund's alpha. Finally, investors discount the returns associated with industry factor returns not at all or very little. Put another way, investors behave as if they 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, momentum, or industry factors (suggesting these factors are the equivalent of alpha to most investors).[4] Moreover, if fund flow decisions are motivated by a desire to identify skilled mutual fund managers, our finding that investors respond to the category-level characteristics of a mutual fund indicates some investors misattribute category-level returns of a fund to managerial skill.

# I. Literature Review

## *A. Literature on Fund Flows*

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

[4] 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).

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) propose that investors should 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."

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. 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 return factors 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 factors investors attend to when picking actively managed mutual funds.

In a recent working paper, Agarwal, Green, and Ren (2015) adapt our methods to hedge funds and analyze the relation between hedge fund flows and returns. They also find that the CAPM alpha consistently wins a model horserace in predicting hedge fund flows. While factor-related returns garner flows for hedge funds, the relations are generally weaker than those we document for mutual fund investors. For example, when they decompose returns into alpha, traditional risks (e.g., market and size) and exotic risk (e.g., option factor risks), they find that traditional risks yield flow-return relations that are about half of that associated with alpha while exotic risks yield flow-return relations that are generally greater (see Table 7, p.40). These results dovetail neatly with our interpretation that more sophisticated investors use more sophisticated methods in two ways. First, hedge fund investors, who are likely more sophisticated than mutual fund investors, seem to attend to a wider variety of factor-related returns when assessing performance more than mutual fund investors. Second, hedge fund investors attend more to traditional risks, which are more easily measured and replicated in standard investments, than exotic risks.

### *B. Berk and van Binsbergen (2015)*

In independent work,[5] Berk and van Binsbergen (2015a) 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 (Berk and Green (2004) predicts future fund returns (Berk and van Binsbergen (2015b)). 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 63.42 percent of the time while the signs of alphas from the three- and four-factor models match the direction of flows only 62.91 and 62.94 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 62.18 percent of the time; and the sign of a fund's return in excess of the market matches the direction

[5] 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.

of flows 61.91 percent of the time. Results are similar at all horizons. 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 (2015a) 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, momentum tilts, and industry tilts.

The two papers reach the common conclusion that fund flows are better explained by CAPM alphas than competing models. However, the papers differ in motivation, methods, and interpretation. Berk and van Binsbergen motivate their analysis as a test of asset pricing models, while we are motivated to learn how sophisticated investors are in their evaluation of fund performance.

Regarding methods, both papers run a horserace of competing models. We extend this analysis by decomposing returns into alpha and factor-related returns. We also investigate whether these results differ depending on the sophistication of investors using distribution channels as a proxy for investor sophistication. Skeptical that investors are estimating factor exposures and alphas using statistical analyses, we also explore potential mechanisms that investors use to attend to factor-related returns when evaluating fund performance and find evidence that Morningstar category assignments allow investors to attend to the size and value tilts of funds when assessing performance.

Regarding interpretation, Berk and van Binsbergen conclude the CAPM victory in the horserace indicates the CAPM is closest to the "true asset pricing model." We disagree. Investors should consider all factor-related returns—priced and unpriced—when assessing the skill of a fund manager. The observation that investors attend to market risk (though as we show not completely) is both interesting and suggestive that market risk is a risk factor that many investors care about. However, this observation alone is not sufficient evidence to establish market risk as a priced risk factor.

Berk and van Binsbergen (2015a) write “Because we implement our method using mutual fund data, one might be tempted to conclude that our tests only reveal the preferences of mutual fund investors, rather than all investors. But this is not the case…. if our test rejects a particular asset pricing model, we are not simply rejecting the hypothesis that mutual fund investors use the model, but rather, we are rejecting the hypothesis that any investor who could invest in mutual funds uses the model.”

We disagree. Berk and van Binsbergen (2015a) argue that non-mutual fund investors who have access to mutual funds, will act to eliminate mispricing in the mutual fund market. However, the asset that is mispriced in this market is the skill of a fund manager, not necessarily the assets in a fund. Consider a hedge-fund manager who identifies a mutual fund manager whose skill has been overvalued by the market. The mutual fund manager has garnered more assets under management than can be justified by the fund manager’s ability. How can the hedge-fund manager exploit this mispricing? If she happens to own the mutual fund she can, of course, sell her shares. However, if she owns no shares, she can’t short the mutual fund. And, though the mutual fund manager’s skill is overpriced, that does not mean that the assets held by the fund are overpriced (e.g., imagine a market in which all assets are efficiently priced but active fund managers charged high fees). Thus there may be no positive net present value opportunity available for the hedge-fund manager to exploit. What if, instead, the hedge-fund manager identifies a mutual fund manager whose skill has been undervalued by the market? An undervalued fund manager who is skilled and whose strategies can potentially support larger positions. The hedge-fund manager could invest directly in the mutual fund. More likely though she will try to copy the mutual fund manager’s strategies through trades in equity (or other) markets. These trades will not show up in mutual fund flow data and thus mutual fund flow data will not provide information about the hedge-fund manager’s risk model. So mutual fund flow data does not inform us about the beliefs of non-mutual fund investors. In summary, we do not believe the results in either paper provide much evidence regarding the true asset pricing model. Both our paper and Berk and van Binsbergen (2015a) provide evidence on how investors assess fund performance.

# II. Data and Methods

## 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 2011 and includes about 4000 equity funds. Because we are interested in investors who are attempting to identify managerial skill in their fund allocation decisions, we exclude funds that CRSP identifies as 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:

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

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 $t$.[6] 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 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.

## B. Mutual Fund Performance

When selecting an equity 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 fund's exposure to factors

[6] 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.

known by the investor to affect cross-sectional equity returns (e.g. size).[7] What is less clear, and the focus of our research, is which factors mutual fund investors consider when estimating alpha. 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 by running a horserace between six 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 and French (1992) three-factor model (3F) which adds size and value factors, a four-factor model (4F) that adds momentum (Carhart (1997)), a seven-factor model (7F) that adds the three industry factors of Pastor and Stambaugh (2002a, 2002b), and a nine-factor model (9F) that adds profitability and investment factors (Fama and French (2015)). In many cases, these models yield similar rankings of mutual funds (i.e., the six 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 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 2011.[8] We proceed in two steps. First, we estimate the abnormal return (alpha) for each mutual fund using each of the six competing models. Alpha estimates are updated monthly based on a rolling estimation window. Consider the seven-factor model, which includes factors related to market, size, value, momentum, and three industry factors in the estimation of a fund's return. In this case, for each fund in month *t*

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[7] Some caveats are worth acknowledging. Ferson and Lin (2014) argue that investors might have different alphas for the same fund if markets are incomplete and investors have different marginal rates of substitution. Cremers et al. (2012) document that some indexes have positive alphas suggesting alphas do not precisely measure fund manager skill. Berk and van Binsbergen (2015b) argue the value-add of an active fund can be measured relative to the passive funds that are available to investors, which is time-varying.

[8] 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.

we estimate the following time-series regression using 60 months of returns data from months $\tau$ $= t\text{-}1, t\text{-}60$:

$$\left(R_{p\tau} - R_{f\tau}\right) = \alpha_{pt} + \beta_{pt}\left(R_{m\tau} - R_{f\tau}\right) + s_{pt}SMB_{\tau} + h_{pt}HML_{\tau} + s_{pt}UMD_{\tau} + \sum_{k=1}^{3} i_{pt}^{k} IND_{\tau}^{k} + e_{p\tau} \qquad (2)$$

where $R_{p\tau}$ is the mutual fund return in month $\tau$, $R_{f\tau}$ is the return on the riskfree rate, $R_{m\tau}$ is the return on a value-weighted market index, $SMB_{\tau}$ is the return on a size factor (small minus big stocks), $HML_{\tau}$ is the return on a value factor (high minus low book-to-market stocks), $UMD_{\tau}$ is the return on a momentum factor (up minus down stocks),[9] and $IND_{\tau}^{k}$ is the return on the k$^{th}$ industry portfolios which measure the industry tilts of a mutual fund. We construct the three industry portfolios by extracting the three main principal components of the Fama-French 17 industry portfolios as in Pastor and Stambaugh (2002a, 2002b), which we describe in detail in the online appendix. Readers can think of the industry portfolios as long-short portfolios constructed from the 17 Fama-French industry portfolios that capture common industry return that are orthogonal to the other factors that we consider. The parameters $\beta_{pt}$, $s_{pt}$, $h_{pt}$, $m_{pt}$, and $i_{pt}^{k}$ represent the market, size, value, momentum, and industry tilts (respectively) of fund $p$, while $\alpha_{pt}$ 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 $t$.) We then calculate the alpha for the fund in month t as its realized return less returns related to the fund's market, size, value, momentum, and industry exposures in month t:

$$\hat{\alpha}_{pt} = \left(R_{pt} - R_{ft}\right) - \left[\hat{\beta}_{pt}\left(R_{mt} - R_{ft}\right) + \hat{s}_{pt}SMB_{t} + \hat{h}_{pt}HML_{t} + \hat{m}_{pt}UMD_{t} + \sum_{k=1}^{3} \hat{i}_{pt}^{k} IND_{t}^{k}\right] \qquad (3)$$

We repeat this procedure for all months (t) and all funds (p) to obtain a time-series of monthly alphas and factor-related returns for each fund in our sample. Note that alpha captures returns due to stock selection as well as those resulting from the timing of factor exposures, relative to average past exposures.

[9] 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).

There is an analogous calculation of alphas and return components for the other factor models that we evaluate. For example, we estimate a fund's three-factor alpha using the regression of equation (2), but drop *UMD* and $IND^k$ as independent variables. To estimate the CAPM alpha, we retain only the market excess return as an independent variable. To estimate the market-adjusted return (*MAR*), we simply subtract the market return from the fund return.

## C. Horizon for Performance Evaluation

With rational expectations, investors respond to new information about the skill of fund managers – rewarding skilled managers with new deposits and penalizing poor managers with withdrawals. What is less clear is how investors should weight past returns when assessing fund manager skill; investors need to balance relevance (recent returns are likely more informative about the manager's current ability) versus the signal-to-noise ratio (short-term returns are mostly noise with very little signal about returns). In addition, numerous frictions (e.g., inertia, inattention, transaction costs) would also create delays in the response of flows to fund performance. This creates an empirical complication in our analysis, as we must make a decision about what performance horizon to analyze when we compare models.

To address this issue, we empirically estimate the rate of decay in the flow-return relation using monthly fund returns. To set the stage, we estimate the following unrestricted model of the flow-return relation:

$$F_{pt} = a + \sum_{s=1}^{18} b_s MAR_{p,t-s} + cX_{pt} + \mu_t + e_{pt} \qquad (4)$$

where $F_{pt}$ are flows for fund *p* in month *t* and $MAR_{p,t-s}$ represents the lagged market-adjusted return for the fund at lag s, where s=1 to 18 months. We settle on a lag length of 18 months based on the Akaike Information criterion (AIC) of models where we vary the number of lagged returns from 12 to 48. We include a matrix of control variable (*X*), which yields a vector of coefficient estimates (*c*). As controls, we include lagged fund flows from month t-19, 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 ($\mu_t$).

This regression yields a series of coefficient estimates, $b_s$, that represent the relation between flows in month *t* and the fund's market-adjusted return lagged s months, s=1,18. In Figure 1, the red line graphs the estimated *b* coefficients (y axis) at various lags (x axis) and shows a clear decay in the relation between past returns and fund flows. Recent returns are more important than distant returns.

To parsimoniously capture this decay in the flow-return relation, we model the flow-return relation using an exponential decay model, with decay rate λ:

$$F_{pt} = a + b\sum_{s=1}^{18} e^{-\lambda(s-1)} MAR_{t-s} + cX_{pt} + \mu_t + e_{pt} \tag{5}$$

The key parameters of interest in this model are *b*, which measures the relation between a weighted sum of the previous 18 monthly market adjusted returns, and $\lambda$, which measures the decay in the return-flow relation over time. In Figure 1, the smooth blue line represents the estimated decay function, which closely tracks the unconstrained estimates from the regression of equation (4).

We apply this decay function to the monthly alphas and factor-related returns for each fund-month observation. For example, when considering flows for funds in month *t*, we calculate the fund's alpha as a weighted average of the prior 18 monthly alphas:

$$ALPHA_{pt} = \frac{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)} \hat{\alpha}_{t-s}}{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}} \tag{6}$$

where monthly alpha estimates are based on one of the six models that we evaluate and the exponential decay is based on the estimates from equation (5).

## *D. Model Horserace*

We are interested in testing whether the mutual fund investment choices of investors are more sensitive to alphas calculated using one of six models. We begin by estimating a simple linear regression of fund flows on performance measures from the six competing models.

To more robustly address concerns about nonlinearities in the flow-return relation, we also consider pairwise comparisons of the competing models. To do so, we proceed as follows. In each month during our sample period we create deciles of mutual fund performance based on each of the six alpha estimates weighted by the 18-month exponential decay as described previously. Decile 10 contains top-performing funds, while decile 1 contains the worst funds. Thus, we ultimately have a time-series across months of six decile ranks (corresponding to the ranks based on the six competing models) for each mutual fund.

To fix ideas, consider the pairwise comparison of the CAPM and the 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:

$$F_{pt} = a + \sum_i \sum_j b_{ij} D_{ijpt} + cX_{pt} + \mu_t + \varepsilon_{pt} \qquad (7)$$

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. 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.

Figure 2 provides a visual representation of the key dummy variables, $D_{ijpt}$. In the regression, the omitted dummy variable (regression constant) is identified by funds with a decile rank of 5 based on both models (black square).  The grey and black cells represent funds with similar performance ranks based on both models. The empirical tests compare the coefficients corresponding to the 45 lower off-diagonal cells (where funds have better performance based on the CAPM) to the 45 upper off-diagonal cells (where funds have better performance based on the 3F Alpha). For example, we compare the coefficient estimate on the dummy variable for funds with a CAPM alpha in the 9th decile and 3F alpha in the 3rd decile (red cell, $b_{9,3}$) to funds with a CAPM alpha in the 3rd decile and 3F alpha in the 9th decile (green cell, $b_{3,9}$). 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 $b_{9,3} = b_{3,9}$ (i.e., do funds in the green cell or red cell of figure 2 garner more flows). 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, $b_{9,3} > b_{3,9}$; conversely, if investors place more weight on the three-factor alpha than the CAPM alpha, we will reject in favor of the alternative hypothesis, $b_{9,3} < b_{3,9}$. 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%.

## E. Return Decomposition

To preview our empirical results, we generally find that CAPM performance ranks better predict fund flows than performance ranks based on competing models. This result implies that investors are sufficiently sophisticated to account for market factors when assessing managerial performance. The result does not imply that investors fully account for market-related returns, that all investors use the CAPM, nor that mutual fund investors in aggregate completely ignore factors unrelated to market movements. Our second set of empirical tests addresses these issues by estimating the extent to which investors account for returns related to the factors we consider.

In our main tests, we rearrange equation (3) to decompose the fund's return into its alpha and factor-related returns.

$$\left(R_{pt} - R_{ft}\right) = \hat{\alpha}_{pt} + \left[\hat{\beta}_{pt}\left(R_{mt} - R_{ft}\right) + \hat{s}_{pt} SMB_t + \hat{h}_{pt} HML_t + \hat{m}_{pt} UMD_t + \sum_{k=1}^{3} \hat{i}_{pt}^{k} IND_t^{k}\right] \qquad (8)$$

We base this return decomposition on the seven-factor model.[10] In this return decomposition, the fund's return consists of eight components – the fund's seven-factor alpha and returns related to the fund's market, size, value, momentum, and tilts with respect to three industry portfolios. In month *t*, we weight each of the return components over the prior 18 months (t-1 to t-18) using the exponential decay function analogous to the weighting of alphas described previously. For example, consider the portion of the fund's return related to market risk (or beta). We calculate the portion of the fund's return related to market risk as:

$$MKTRET_{pt} = \frac{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)} \left[ \hat{\beta}_{t-s} \left( R_{m,t-s} - R_{f,t-s} \right) \right]}{\sum_{s=1}^{18} e^{-\hat{\lambda}(s-1)}} \tag{9}$$

There are similar calculations for returns related to the funds size, value, momentum, and three industry tilts, which we label SIZRET, VALRET, MOMRET, INDRET1, INDRET2, and INDRET3 (respectively).

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:

$$\begin{aligned} F_{pt} = b_0 + b_1 ALPHA_{pt} + b_2 MKTRET_{pt} + b_3 SIZRET_{pt} + b_4 VALRET_{pt} \\ + b_5 MOMRET_{pt} + \sum_{k=1}^{3} b_{5+k} INDRETk_{pt} + \gamma X_{pt} + \mu_t + e_{pt} \end{aligned} \tag{10}$$

Where $b_0$ is the regression intercept, $e_{pt}$ is the regression error term, $\gamma$ is a coefficient vector associated with control variables ($X_{pt}$), and $\mu_t$ represents month fixed effects. The controls include 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 lagged fund flows.

The parameter estimates of interest in equation (10) are $b_i$, $i=1,8$. For expositional ease, call investors who rely on the seven-factor model when evaluating fund performance sophisticated investors, where the sophisticated adjective is used to describe their ability to

[10] We have also estimated results based on the nine-factor model and find qualitatively similar results.

account for the common return components when evaluating managerial skill. Sophisticated investors will direct capital based on the fund's alpha, but not returns related to known factors. Thus, we expect $b_1 > 0$, as investors *will* respond to a fund's seven-factor alpha, and $b_i = 0$, $i=2,8$, as investors with this sophisticated benchmark *will not* respond to fund returns that can be traced to factor loadings and factor realizations. In contrast, for investors who only consider market risk when assessing fund performance, we expect $b_1=b_3=b_4=b_5=b_6=b_7=b_8 >0$ and $b_2 = 0$; because investors who only adjust for market risk when assessing fund performance will discount returns that can be traced to market risk, but will treat returns that can be traced to the size, value, momentum, and industry 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 mutual fund 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.[11]

## F. 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 on fund characteristics across fund-month observations used in our main regression (Jan 1996 to Dec 2011). The average fund has a modestly negative monthly flow during our sample period (-0.53%), but with a standard deviation of 2.25% and interquartile range of more than 2% there is considerable cross-sectional variation in fund flows. The average fund has total net assets of about $1.4 billion, though the median fund is considerably smaller ($396 million). The average age of the fund is 202 months (about 17 years), while the median fund age is 154 months (11.8 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 annual expense ratio for

[11] As an alternative to decomposing the excess return of each fund into its components, we decompose the seven-factor alpha into components related to the fund's market-adjusted return and factor exposures by rearranging equation (4). This approach yields qualitatively similar results (see online appendix for details).

sample funds is 1.28%. A large proportion of funds (72%) 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%.

Table 1, Panel B presents descriptive statistics on the estimated alpha and factor loadings from the rolling window regressions, which include the 18-month period preceding this sample period (hence the greater number of observations for the regression statistics). The mean monthly alpha over the prior year is -2.3 bps per month (or about -28 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 0.95, 0.20, 0.03, and 0.02 (respectively), which suggests the average fund has close to average market risk with a modest tilt toward small stocks and virtually no tilt toward value stocks and stocks with strong recent returns. The mean industry tilt of mutual funds is also generally close to zero, which is what would expect if mutual funds in aggregate do not place large bets on particular industries. More importantly, there is considerable cross-sectional variation in factor loadings across funds. The standard deviations of beta, size, value, and momentum loadings are 0.19, 0.31, 0.35, and 0.14 (respectively), while industry loadings have a standard deviation of approximately 0.10.

Since investors evaluate the relative performance of funds at a particular point in time, we first want to verify that the product of factor loadings and factor realizations indeed generate economically meaningful cross-sectional variation in fund returns. To do so, we calculate descriptive statistics on each of the return components, which represent 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 across months.

The results of this analysis are presented in Table 1, Panel C. Not surprisingly, the seven-factor alpha generates the largest cross-sectional variation in performance (with a standard deviation of 0.815%). However, each of the factor loadings multiplied by the factor realizations over the 18 months leading up to month *t* generate large variation in the monthly returns earned on mutual funds. For example, the mean monthly return associated with market risk is 32 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, momentum, and industry); thus, the mean return associated with these return factors is small (ranging from -0.4 bps for momentum to 5.3 bps for the second industry factor). More importantly, we observe considerable cross-sectional variation in the returns due to these non-market return factors across funds, with standard deviations ranging from 12.6 bps for momentum to 36.5 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 D, 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 25% in absolute value).

In Panel E, we present the correlation matrix of alphas estimated based on the six models that we evaluate: MAR, CAPM, 3F, 4F, 7F, 9F. In contrast to the correlation matrix of the return decomposition, the correlation across the various alpha estimates is quite high. The high correlations explain why prior studies generally find a positive relation between flows and a variety of performance benchmarks (see footnote 4).

To further assess the reasonableness of our estimated factor loadings and set the stage for the analysis of Morningstar category assignments in moderating fund flows, 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) while we observe little difference in the industry tilts across the size or value dimensions of funds.

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 (0.141 to 0.253) is similar in magnitude to the overall standard deviation (0.171). Similarly, the cross-sectional standard deviation of momentum loadings within each of the nine style boxes (0.107 to 0.157) is similar in magnitude to the overall standard deviation (0.139). The within category standard deviation in the size (0.167 to 0.220) and value loadings (0.236 to 0.369) are somewhat less than the overall standard deviation (0.303 for size and 0.321 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 understand whether financial intermediaries such as Morningstar provide a mechanism by which investors can tend to factor-related returns when assessing fund performance.

# III. Results

## *A. Model Horserace*

To set the stage, we begin by estimating a simple linear regression where the dependent variable is percentage fund flow and the key independent variables are the six performance measures described in Table 1: market-adjusted returns and alphas from the CAPM, three-, four-, seven-, and nine-factor models. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, return volatility, and month fixed effects.

The results of this analysis are presented in Table 3. In column 1, we present results based on raw returns. In column 2, we standardize each performance measure by its cross-sectional standard deviation in month *t*. In column 3, we use percentile ranks based on each performance measure in month *t*. In all three versions, we find that the *partial* coefficient associated with the CAPM alpha is reliably greater than that observed on the other performance at conventional significance levels.[12] The differences are economically large. For example, consider the comparison of the coefficient estimate on the CAPM alpha versus that on market-adjusted returns. A one percentage point increase in a fund's CAPM alpha is associated with a 0.474 percentage point increase in monthly fund flow. A one percentage point increase in a fund's market-adjusted return has less than half that effect (0.221 v. 0.474), and the remaining performances have an even smaller marginal impact on flows. The same general pattern emerges when we consider standardized performance ranks (column 2) and percentile ranks (column 3). The marginal effect of an increase in the CAPM alpha is statistically and economically a more important determinant of fund flows than those from competing models.

One concern with these results is that we have assumed a linear relation between flows and performance. Our second approach, which relies on pairwise comparison of competing models and highly non-linear estimation of fund-flow relations, addresses these concerns. We present the pairwise comparison of models in Table 4.[13] Recall that we compare the dummy variables that correspond to the upper and lower off diagonals of the matrix depicted in Figure 2. To parsimoniously tabulate the results, the table presents the sum of the differences between the upper and lower off-diagonal elements and the percentage of coefficient differences that are greater than 0. Consider Panel A, where we present the pairwise comparisons where the CAPM emerges victorious. In all cases that we consider, the CAPM alpha is a better predictor of fund flows than the competing model. For example, the sum of the coefficient differences for the CAPM alpha versus market-adjusted returns is reliably positive (7.41, *t=3.46*) and significantly more than half are positive (77.8% or 35 of the 45 differences). The CAPM and market-adjusted horserace is the closest contest for the CAPM. The CAPM comfortably beats the remaining

[12] Results are qualitatively similar with category-month fixed effects, but the statistical significance of the spread between the CAPM alpha and market-adjusted return hovers around 0.10, but multicollinearity may render this test less powerful than our subsequent tests (pairwise horserace and return decomposition).
[13] See the online appendix for details of all 45 comparisons for the CAPM tests. The CAPM is also victorious in a pairwise comparison with category-adjusted returns. Detailed results are reported in the online appendix.

models that consider returns related to size, value, momentum, investment, profitability, and industry.[14]

In Figure 3, we graph key results of four of the horse races from Panel A of Table 4. For example, the top left graph shows 45 differences in the key dummy variables that emerge when we compare the CAPM alpha and market-adjusted returns as a predictor of flows. The biggest differences in coefficient corresponds to the tallest bar, which is identified by comparing flows for funds with a CAPM decile of 9 and market-adjusted return decile rank of 1 to flows for funds with a CAPM decile of 1 and market-adjusted return decile rank of 9 (labeled “9v1” on the horizontal axis). Clearly, funds with the better performance based on the CAPM garner more flows in this comparison. The remaining 44 bars represent the differences that we observe for all possible comparison for funds with different decile ranks based on the two competing models. The three remaining graphs in Figure 3 present the 45 comparisons for the horse races that depict the CAPM versus the three-factor, four-factor, or seven-factor model. The periodicity that becomes evident in these graphs emerges because the largest differences in coefficient estimates emerge when the decile ranks of the competing models are quite large (e.g., decile 9 v. decile 1 as discussed in the example above).

Returning to Table 4, we present results of comparisons of competing models where each panel presents results where a particular model is victorious. Consistent with the results in Panel A, in Panel B we find that market-adjusted returns are better able to predict fund flows that the remaining four models that we consider. (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.) In Panels C, D, and E we see that the model with fewer factors consistently provides a better forecast of flows.

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[14] We also consider a horse race of the CAPM alpha versus a fund’s Sharpe Ratio, where the CAPM alpha again defeats the Sharpe Ratio as a predictor of flows. The CAPM alpha also defeats category-adjusted fund returns (mutual fund return less the return of all sample funds in the same Morningstar style box).

### B. Do Investors Consider Factor-Related Returns when Evaluating Fund Performance?

The preceding analysis indicates the CAPM does the best job of predicting fund-flow relations. This result implies that investors tend to consider the market risk of funds when evaluating fund performance, but tend to ignore other factor-related determinants of fund flows (i.e., size, value, momentum, or industry-related factors). We view these results as suggestive that investors in aggregate are more likely to consider market risk when evaluating a fund's performance than other factors. However, the horse race results do not imply that investors fully account for market-related factors in their fund investment decision nor do the results imply that investors completely ignore other factors that affect fund performance (e.g., size, value, momentum, or industry). In this section we analyze this issue in more detail. To preview our results, we generally find that investors attend most to market risk when evaluating fund performance, though fund returns related to a fund's market risk do positively affect fund flows. Put differently, investors in aggregate do not completely account for the market risk of a fund when allocating capital to mutual funds. Investors attend to the size, value, and industry tilts of mutual funds to a much less extent than market risk when assessing performance. We find no evidence that investors attend to momentum.

#### B.1. Main Results – Return Decomposition

We regress fund flows on alphas and factor-related returns during the prior 18 months, where we use the seven-factor model to estimate the factor-related returns.[15] These results are presented in Table 5. 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.[16]

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[15] In prior drafts of this paper, we considered past performance based on horizons ranging from one month to three years and a return decomposition based on the four-factor model. The results of this analysis are qualitatively similar to those presented here.

[16] 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

In column 1, we present results for all funds using our main specification. In this main specification, we include standard control variables and month fixed effects, but exclude Morningstar Star ratings. In columns 2 and 3, we increase the granularity of the fixed effect control from month (column 1) to month-category (column 2) to month-category-star (column 3). The remaining six columns present subsample results (columns 4 through 9).

Consider first the results for our main specification in column 1. Fund flows respond positively to the seven-factor alpha with an estimated sensitivity of 0.884, which is highly significant at conventional levels. The parameter estimate suggests a 87 bps increase in alpha (roughly the interquartile range of estimated alphas observed in Table 1, Panel C) is associated with an increase in fund flows of 0.77 percentage points. The sensitivity of flows to returns traced to market, size, value, momentum, and industry 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 fund's alpha. In the main specification of column 1, fund returns related to a fund's market, size, and value factors do not generate the same flows as a fund's alpha. For example, the coefficient on the returns related to a fund's market risk (0.253) is 29% of the alpha coefficient (0.884), while the size and value coefficients are 86% and 75% (respectively) of those associated with a fund's alpha. In contrast, the coefficient on the momentum-related returns is not reliably different from those associated with a fund's alpha. We do find some evidence that investors consider the industry tilts of mutual funds in the second and third industry factors, which yield coefficient estimates that are 79% and 80% of those associated with a fund's alpha (respectively). However, the coefficient on returns associated with the first industry factor is not reliably different from those associated with a fund's alpha. When we formally test the null

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regression). The coefficient estimates including influential observations are qualitatively similar to those presented, though less precisely estimated.

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, value, and two of the three industry coefficients. Thus, in aggregate, investors seem to tend most to the market risk (i.e., beta) of a fund when assessing fund performance. Investors in aggregate do some accounting for the size, value, and industry tilts of a fund, but the responsiveness of flows to these return components is much stronger than that observed for returns related to a fund's market risk.

In column 2, we replace month fixed effects with month-category fixed effects, which absorb variation in average fund flows across the nine Morningstar style boxes. The results are qualitatively similar to our main specification. Flows respond less to returns related to a fund's market risk than to alpha or other factor-related returns.

### B.2. Morningstar Fund Ratings

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.[17] Ratings range from one star for poor performing funds to five 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 and, to a lesser extent, other factor-related returns by following Morningstar fund ratings when allocating capital to mutual funds.

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[17] 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 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%).

To investigate whether star ratings are a potential mechanism by which investors tend to factor-related returns (particularly returns traced to market risk), we replace the month fixed effects of our main specification with month-category-star fixed effects. The star component of the fixed effect is based on five categories that we construct based on a fund's star rating. First, we calculate the TNA-weighted overall star rating[18] across share classes for a fund. (There is generally little variation in star ratings across share classes.) We then create five categories of star ratings based on the following intervals: (1.0,1.5), [1.5,2.5), [2.5,3.5), [3.5,4.5), [4.5,5.0).

The results of this analysis are presented in column 3, Table 5. Because star ratings are highly correlated with fund performance, the month-category-star fixed effects reduce the coefficient estimates relative to those in our main specification of column 1. However, the relative importance of factor-related returns and alpha in explaining flows is once again qualitatively similar to that observed in our main specification. Thus, star ratings do not appear to explain the result that investors attend most to a fund's market risk when assessing performance and pay much less, but some, attention to the fund's size, value, and industry characteristics.

### B.3. Fund Size and Age

To further test the robustness of our findings, we partition our sample into small vs. large funds and young vs. old funds. 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. 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

[18] 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.

of return history. We estimate subsample results by interacting a fund size (or fund age) dummy variable with the return components.

We present the results based on the fund size partition in columns 4 and 5, Table 5.[19] In general, the results are quite similar between small and large funds with one exception – the importance of a fund's size-related returns. Among small funds, the coefficient estimate on returns related to a fund's size tilt is only 63% of that associated with the fund alpha (i.e., 0.529/0.843). In contrast, for large funds, the responsiveness of flows to size-related returns (0.885) is very similar to the flow response to a fund's alpha. We present the results based on the fund age partition in columns 6 and 7, Table 5. We find very little difference in the flow response to return components between young and old funds.

### B.4. Nonlinearities in Flow-Returns

Our main regression 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 interacting a dummy variable that takes on a value of one for funds that are above the median fund return in a particular month with the fund return components. We summarize the results of this regression in the last two columns of Table 5. Consistent with prior work that documents a convex relation between flows and returns, we find that seven of the eight return components generate higher coefficient estimates in the flow regressions for funds that are above-median returns. However, we continue to find that returns related to a fund's market risk do not generate the same flow response as other return components.

We succinctly summarize the main message of these analyses in Figure 4, which presents eight graphs that each correspond to one of the eight return components that we analyze. Consider the graph that summarizes results responsiveness of flows to market-related returns (top left graph of Figure 4). Each bar in the graph represents the estimated coefficient on the fund's market-related return divided by the coefficient on the fund's alpha, and the nine bars

[19] Results with month-category fixed effects yield results qualitatively similar to those in columns 4 to 9; see online appendix for details.

correspond to the nine different sets of results that we present in Table 5. In this graph, regardless of the specification or subsample considered, we find that flows are much less responsive to a fund's market-related returns than to the fund's alpha. Scanning the remaining six graphs in the figure also reveals the main message of these analyses; fund flows have a very muted response to market-related returns of mutual funds but tend to have a much stronger response to other return components. We find robust evidence that investors have a mildly muted response to value-related returns and somewhat weaker evidence of a muted response for size-related and industry-related returns (in that two of the three industry components yield ratios less than one). Fund flows respond to momentum-related returns as much (if not more) than to a fund's alpha.

### *C. Persistence in Factor Loadings*

One possible explanation for our results is that investors do not respond to factor-related returns because they rationally anticipate that factor loadings are not persistent and will "shrink" toward their global mean out of sample. Assume that an investor estimates the tilt of a fund towards value stocks, but recognizes the estimate does not reliably predict the future value tilt of a fund. Since the investor believes the estimated value tilt is not informative, she will estimate a fund's alpha assuming no value tilt. In our regression framework, if investors believe there is no persistence in the value tilt of a fund, we would observe a coefficient estimate on the value-related return that is close to that for the fund's alpha. In contrast, assume that the investor believes the estimate of a fund's market beta is quite reliable and also predicts the fund's future beta with respect to the market; she would not treat returns related to the fund's market beta as alpha. In our regression framework, the estimated coefficient on the fund's market-related return would be zero. If rational variation in the persistence of factor loadings explains our observed results, we would expect to observe greater persistence in estimated market betas relative to the other factor loadings.

To investigate this conjecture, we analyze the out-of-sample persistence in our factor loadings as follows. Consider estimates of market betas for mutual funds. In month *t*, we sort all funds into quintiles based on the estimated beta for the five years ending in month *t*. To compute the in-sample beta estimates for each beta quintile for month *t*, we calculate the cross-sectional mean of the estimated beta within that quintile; we then calculate the average and standard error of the cross-sectional means across months. To compute the out-of-sample beta estimates, we first construct a time series of monthly fund returns during month t+1 for each beta quintile. We then estimate the out-of-sample market beta for each quintile using the out-of-sample return series. We repeat this analysis for each of the factor loadings.

The results of this analysis are presented in Table 6. In Panel A, we present the in-sample and out-of-sample beta estimates for fund quintiles formed on the basis of in-sample betas. The in-sample betas range from a low of 0.677 for quintile 1 to a high of 1.154 for quintile 5 yielding a spread (Hi-Lo) of 0.477. As expected, the out-of-sample estimates tend to shrink toward the global beta for funds, which is slightly less than one, and the spread (Hi-Lo) thus declines to 0.254. The "Shrinkage Ratio" for the beta estimates is calculated as the out-of-sample to in-sample Hi-Lo spread of the beta estimates: 0.254/0.477 = 53.2%. Panels B through G present similar results for each of the other estimated factor loadings. For each factor that we analyze, the rank ordering of the loadings across quintile portfolios is preserved out-of-sample, which indicates the estimated in-sample loadings are indeed informative. However, as expected, all out-of-sample parameter estimates shrink toward their global mean. The most persistent factor loadings are those related to size, value, and the first industry factor, while the remaining factors (beta, momentum, and the other industry factors) tend to shrink more toward the global mean. Thus, if investors rationally account for shrinkage when responding to factor-related returns, we would expect investors to respond least to returns related to the size, value, and first industry factor. This is not what we observe. In fact, investors tend to respond less to returns related to a fund's market beta *despite* the fact that the beta estimate is less persistent.

# IV. Investor Sophistication and Fund-Flow Relations

Our primary analysis treats mutual fund investors as a homogenous group. However, different investors almost certainly use different methods to assess the performance of mutual funds. In this section, we test and find strong support for the conjecture that more sophisticated investors use more sophisticated benchmarks to evaluate mutual fund performance. We do so in three ways. First, we use direct-sold versus broker-sold distribution channels as a proxy for investor sophistication. Second, we compare the flow-return dynamics during periods of high sentiment, when less sophisticated investors arguably represent a higher proportion of fund investors, to periods of low sentiment. Third, we use a separate dataset of fund purchases and sales at a discount broker fund marketplace to compare the flow-return relations for wealthy and other investors.

### *A. Distribution Channels*

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. Thus, we hypothesize that investors in the direct-sold channel will respond less to factor-related returns than investors in the broker-sold channel.

To test this hypothesis, 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 (10) by interacting the each of the return components of a fund with a dummy variable that takes a value of one if the fund is primarily broker-sold.

We summarize the results of this single interaction regression for the full sample and main regression specification in the first three columns of Table 7. Column 1 presents the coefficient estimates for the direct-sold channel. Column 2 presents the corresponding estimates for the broker-sold channel (i.e., the sum of the coefficient estimate on the return component for the direct-sold channel and coefficient on the interaction of the return component with the broker-sold dummy). Column 3 presents the difference between the direct-sold and broker-sold channel (i.e., the estimated interaction terms). With the exception of momentum, we consistently find that investors in the broker-sold channel respond more to factor-related returns than do investors in the direct-sold channel. These results are consistent with the notion that investors in the broker-sold channel are less sophisticated in their assessment of fund performance than investors in the broker-sold channel.[20]

These results provide strong support for the notion that more sophisticated investors use more sophisticated models to assess fund manager skill. Nonetheless, the *relative* importance of the various factors is generally similar for the two distribution channels. Perhaps most strikingly, the coefficient estimates on a fund's market-related return are smaller than other factor-related returns for both the direct-sold and broker-sold channels.

[20] Investors in the direct-sold channel also respond less to a fund's alpha. When we calculate the ratio of the factor-related coefficient and the alpha coefficient (as in Figure 4), for all factor-related returns except momentum we consistently find the ratio is less for direct-sold subsample than the broker-sold subsample.

## B. Periods of High v. Low Sentiment Trading

Brown, Goetzmann, Hiraki, Shiraishi, and Watanabe (2003) and Ben-Rephael, Kandel, and Wohl (2012) provide evidence that aggregate fund flows are a measure of overall investor sentiment. Our second test builds on this observation to identify periods of extreme sentiment trading. Specifically, for each month in our sample period we create a sentiment measure ($SENT_t$) that captures temporal variation in aggregate trading in mutual funds:

$$SENT_t = \frac{\sum_{i=1}^{n} |F_{it}|}{\sum_{i=1}^{n} TNA_{i,t-1}} \tag{11}$$

where the numerator sums the absolute value of fund flows ($F_{it}$) across $n$ funds and scales by the sum of lagged TNAs. This measure will be high when we observe high levels of inflows or outflows in funds. Note that we do not care about the sign of sentiment, but are merely interested in identifying periods when sentiment-motivated investors are more likely to be present in the market. Accordingly, we define high sentiment months as those where $SENT_t$ exceeds the median value across our sample period.[21]

We conjecture that more sophisticated investors will use more sophisticated benchmarks and thus expect to observe flows being relatively less responsive to factor-related returns during low sentiment periods. We present the results of this analysis in columns 4 to 6 of Table 7. Consistent with our conjecture, we consistently find that flows are more responsive to factor-related returns during high sentiment periods. These results support our conjecture that more sophisticated investors use more sophisticated benchmarks.

## C. Wealthy v. Other Investor Trades at Broker

In our third analysis, we identify mutual fund purchases and sales of wealthy versus other investors using trades and position data for 78,000 households who have accounts with a large discount broker (LDB) over the period 1991 to 1996 (see Barber and Odean (2000) for details).

[21] We prefer using aggregate flows across mutual funds to identify periods of high sentiment trading as this will also capture trading between types of funds (e.g., large flows from small cap to large cap funds), but our results are qualitatively similar if we sum signed flows rather than the absolute value of flows.

In this analysis, we conjecture that wealthy investors will generally be more sophisticated than others, consistent with the evidence on trading ability (Barber and Odean (2000); Geng, Li, Subrahmanyam, and Yu (2014)), diversification (Calvet, Campbell, and Sodini (2007)), and the disposition effect (Dhar and Zhu (2006)). We define a wealthy investor as a household with total average account size (including stock, bond, cash, and mutual fund investments) that is above the median account size in the broker sample.[22]

The broker offers a mutual fund marketplace for buying and selling mutual funds. We use the trades in mutual funds to construct a measure of flows by summing the value buys (*B*) less the value of sells (*S*) of fund *i* across *n* wealthy households (*j=1,n*) in month *t*, which we scale by the positions (*P*) of fund *i* summed across these households:

$$F_{it}^{wealthy} = \frac{\sum_{j=1}^{n}\left(B_{ijt} - S_{ijt}\right)}{\sum_{j=1}^{n}\left(P_{ij,t-1}\right)} \tag{12}$$

There is an analogous calculation for mutual fund trades made by the less wealthy households. The results of this analysis are presented in columns 7 to 9 of Table 7. It is quite noteworthy that using this limited sample period and dataset, which at times yields imprecisely estimated flow-return relations, we again generally find that flows are less responsive to returns related to a fund's market risk for *both* the wealthy and less wealthy households. Moreover, consistent with our conjecture that more sophisticated investors use more sophisticated benchmarks, we consistently find that flows that emanate from wealthy investors are less responsive to factor-related returns.

The tests in Table 7 focus on the difference in flow-return coefficients interacted with proxies for sophistication (broker distribution channel, periods of high sentiment, or wealth). In each of the three analyses the less sophisticated investors respond more to a fund's alpha, consistent with the evidence in Bailey, Kumar, and Ng (2011) that less sophisticated investors chase fund performance. When we calculate the ratio of the factor-related coefficient and the

[22] Our results are qualitatively similar when we split the LDB sample based on the top quartile versus below median account size. We also have self-reported income for a subset of the LDB sample and find qualitatively similar results when we split the sample on income.

alpha coefficient (as in Figure 4), our results are qualitatively similar to the conclusions based on the unscaled differences in coefficient estimates (presented in Table 7). The online appendix also provides results that are qualitatively similar when we use category-month (rather than month) fixed effects. To sum up, all three proxies for investor sophistication are consistent with the conjecture that more sophisticated investors use more sophisticated benchmarks.

# V. Fund Categories and Flows

Our primary results indicate investors in aggregate place more weight on the CAPM than other models when ranking mutual funds. Moreover, they partially adjust for returns related to fund's size and value tilts. We hypothesize that the muted response to size and value factors results from some 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). If investors use Morningstar category boxes to assess mutual fund performance then we would observe a muted response to the fund returns that can be traced to a fund's value or size tilts since Morningstar categories capture some of the variation in size and value tilts (see Table 2). These predictions dovetail neatly with our main results, where we indeed observe a muted response to returns that can be traced to a fund's size and value tilts (see Table 5 and Figure 4).

A secondary prediction, which we test in this section, is that investors will be less responsive to returns that can be traced to a fund's category characteristics (e.g., all Morningstar small value funds will likely have some tilt toward small value stocks) than to returns that can be traced to a fund's deviation from mean category characteristics (i.e., the relative tilt toward small/value cap for a fund identified as a Morningstar small value fund).

To test this second prediction, we decompose the size (and 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 size category exposure for a small value fund is the mean size-related return across all funds categorized by Morningstar as small value funds. In general, we calculate the mean category return for the size factor as:

$$CATSIZ_{ct} = \frac{1}{N_c}\sum_{p=1}^{N_c} SIZRET_{pt} \tag{13}$$

where $SIZRET_{pt}$ is the size-related return for fund p and $N_c$ are the number of sample funds in category *c*, where we consider the nine Morningstar categories. There is an analogous calculation for a fund's value exposure.

This return decomposition yields an augmented version of the regression from equation (10), where the single independent variable for size-related returns (*SIZRET*) is now replaced with two independent variables associated the with size tilt of the fund's category (*CATSIZ*) and the deviation of the fund's size tilt from the category average (*FUNDSIZ=SIZRET-CATSIZ*). Similarly, the single independent variable for value-related returns (*VALRET*) is replaces with two independent variables that capture the fund's value category (*CATVAL*) and deviation from category (*FUNDVAL=VALRET-CATVAL*). If investors benchmark returns at the category level, then we should observe coefficients of zero on the *CATSIZ* and *CATVAL* variables; 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 equal coefficient estimates on *CATSIZ* and *FUNDSIZ* (or *CATVAL* and *FUNDVAL*). 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 8. Consider first the results based on the decomposition of the size exposure. The coefficient on the mean category exposure of a fund (*CATSIZ*) 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 (*FUNDSIZ* v. *CATSIZ* coefficients, 0.849 > 0.681, $p<.05$). 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 (*FUNDVAL* v. *CATVAL* coefficients, 0.736 v. 0.542, p<.01). These results are quite consistent across the alternative specifications (columns 2 and 3) and subsamples (columns 4 to 9) that we consider. 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.

# VI. Conclusion

What factors do investors consider when evaluating equity mutual fund performance? We address 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 a fund's exposure to factors known to affect cross-sectional equity returns. Fund flows should respond to alpha, but how do investors calculate a fund's alpha? At one extreme, unsophisticated investors may evaluate funds based solely on their market-adjusted returns. At another extreme, sophisticated investors will consider all available factors, both priced and unpriced, to assess a fund's performance.

Our empirical analysis reveals that investors behave as if they are concerned about market risk but are largely unaware of other factors that drive equity returns. Thus when we run a horserace between six asset-pricing models, the CAPM is able to best explain variation in flows across mutual funds. In additional analyses, we decompose the returns of each mutual fund into eight components: a seven-factor alpha, and flows associated with market, size, value, momentum factors, and three industry factors. We find that flows respond to each of the eight return components, but to varying degrees. In general, the fund alpha generates the largest flow response. The response of flows to a fund's momentum-related return rivals that of the response to alpha. At the other extreme, flows are least sensitive to the fund returns that can be traced to market risk (beta). We find some evidence that investors attend to the value, size, and industry tilts of a fund when assessing managerial skill, but these effects are much weaker than those we observe for a fund's beta. Moreover, we find that investors respond strongly to the factor-related return associated with a fund's Morningstar category. Since the category-level return is not under the control of the manager, this result suggests some mutual fund investors confuse a fund's category-level performance and manager skill. However, we find evidence that some investors use Morningstar categories to assess fund performance as the flow response to the size and value factor-related returns of a category are generally weaker than the response to the fund's deviation from its category mean.

Investors will obtain the most precise estimates of managerial skill when they strip out all factor-related returns when assessing fund performance. Hence, we interpret these results as suggestive that investors vary in their sophistication level, and more sophisticated investors use more sophisticated benchmarks.

To more directly test the hypothesis that investor sophistication plays a role in the fund-flow relations that we document, we partition our sample based on funds' distribution channel and on periods of high and low sentiment. We separately analyze return and fund flow relationships for wealthy and less wealthy investors at a large discount brokerage. We find that the flows of investors who are likely more sophisticated—direct-sold fund investors, investors trading during low sentiment periods, and wealthier investors—are generally less responsive to factor-related returns suggesting that they are more aware that those returns are not indicative of fund manager skill.

To adjust for factor related returns when evaluating a fund, an investor needs to know the factor return. Sophisticated investors will seek out this information. But less sophisticated investors may not be aware of size, value, momentum, or industry returns. The market's performance, however, is ubiquitously reported which may be one reason why investors do pay attention to market risk when evaluating mutual fund managers.

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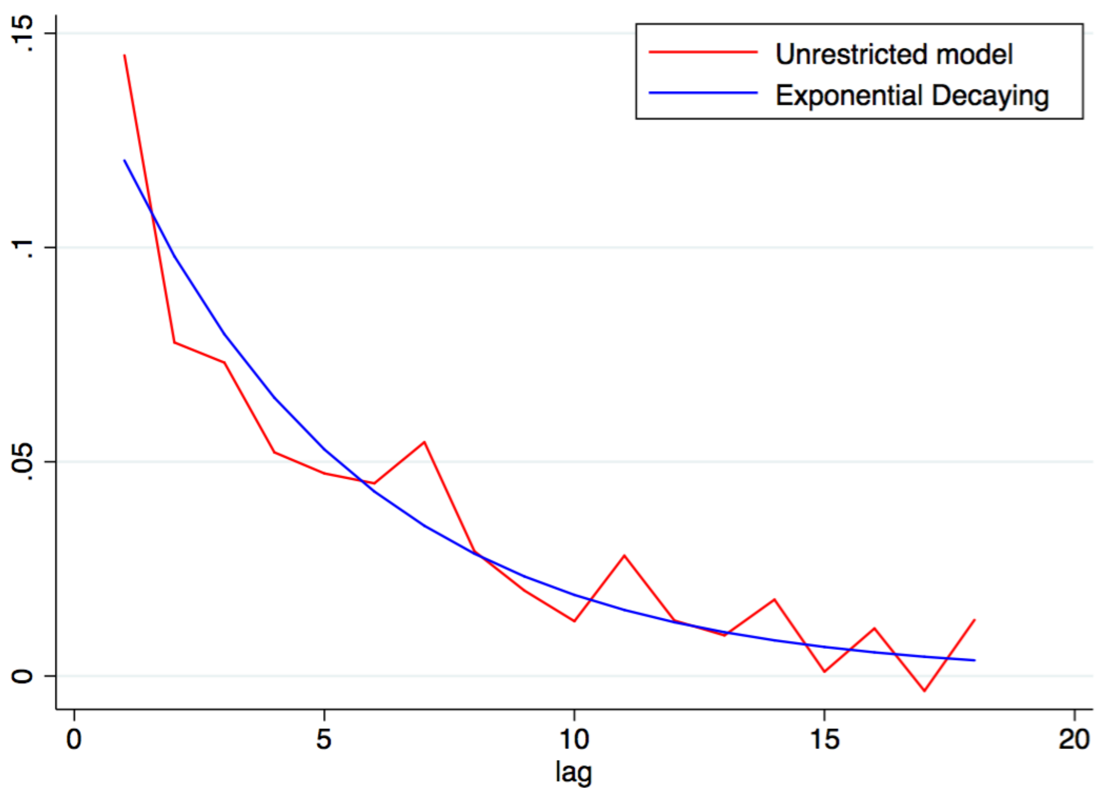
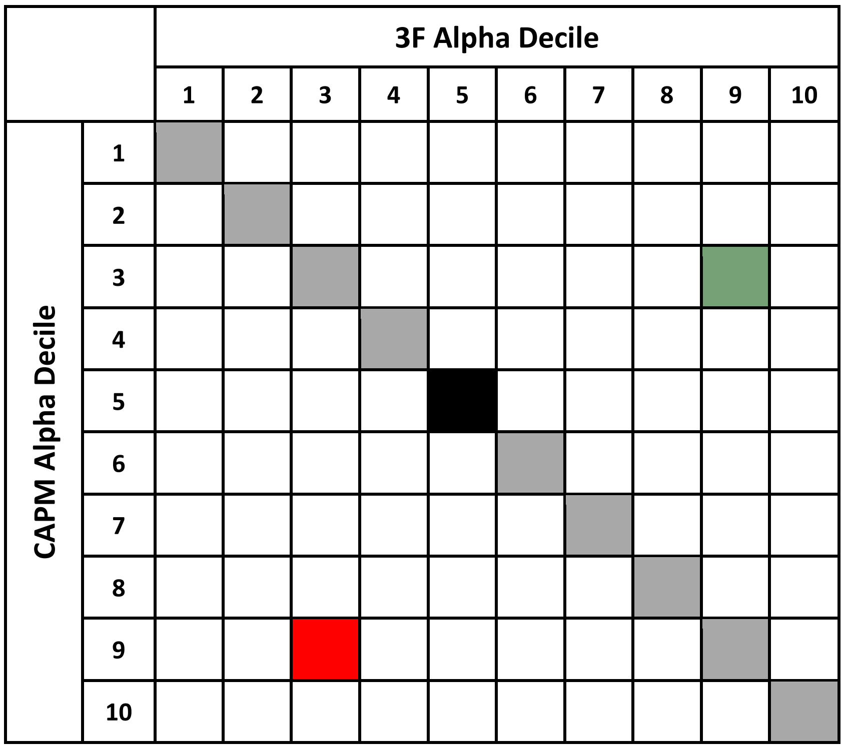
## Figure 1: Decay in Fund Flow Relation

The graph presents the regression coefficient estimates (y axis) by horizon (x axis) for two models of monthly fund flows (dependent variable): (1) Unrestricted model (with 18 lags of monthly fund returns and individual coefficient estimates on each lagged return), and (2) Exponential decay model (where the coefficient estimates on the lagged monthly returns are restricted to follow an exponential decay function with decay parameter lambda).



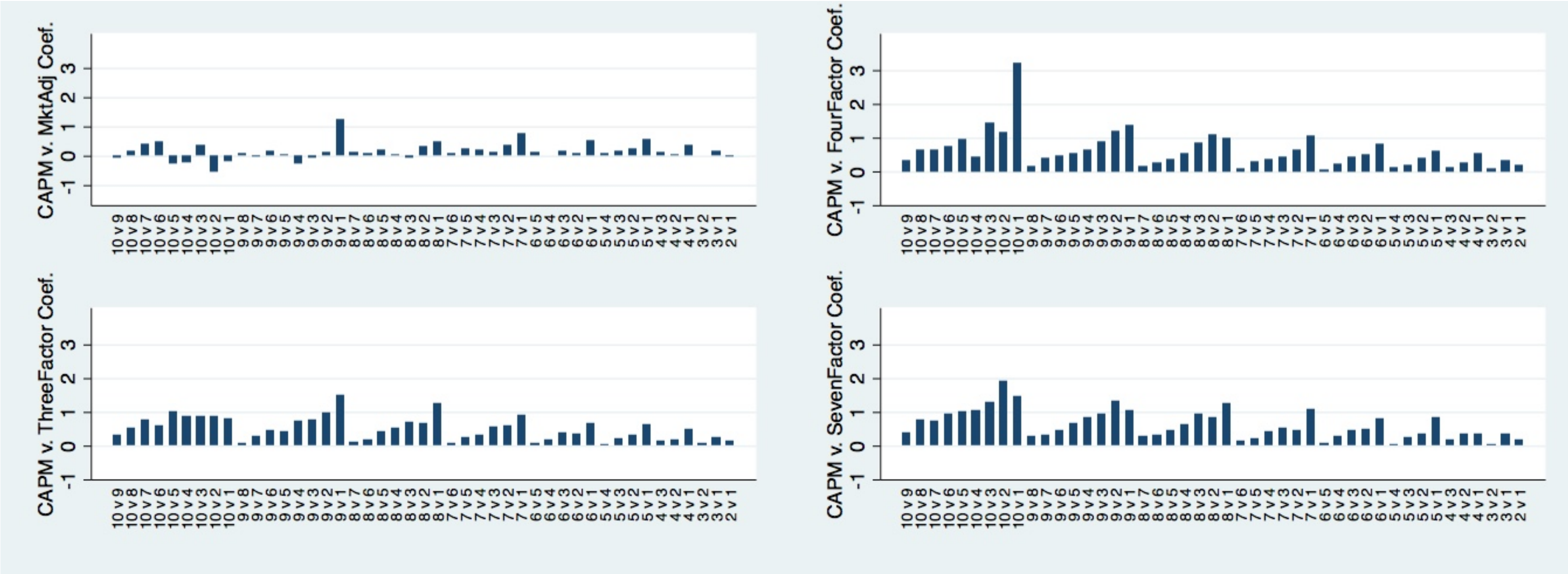
## Figure 2: Horse Race Dummy Variables

The figure shows the 100 possible dummy variables for the flow regression that compares relative fund flows based on a fund's CAPM alpha versus three-factor alpha, where 10 is a top decile fund and 1 a bottom decile fund. In the regression, the omitted dummy variable (regression constant) are funds with a decile rank of 5 based on both models (black square). The grey and black cells represent funds with similar ranks based on both models. The empirical tests compare the coefficients corresponding to the 45 lower off-diagonal cells (where funds have better performance based on the CAPM) to the 45 upper off-diagonal cells (where funds have better performance based on the 3F Alpha). For example, we compare the coefficient estimate on the dummy variable for funds with a CAPM alpha in the 9th decile and 3F alpha in the 3rd decile (red cell) to funds with a CAPM alpha in the 3rd decile and 3F alpha in the 9th decile (green cell).



## Figure 3: Flow Differences for Funds with Different Decile Ranks

This figure shows the 45 differences in coefficient estimates on dummy variables that compare funds with similar but opposite rankings based on two models used to estimate performance. For example, the leftmost bar in each graph is the coefficient estimate on dummy variables for funds with a CAPM decile rank of 10 and competing model decile rank of 9 less the coefficient estimate on the dummy variable for funds with a CAPM decile rank of 9 and competing model decile rank of 10. The four graphs compare the CAPM to four competing models (market-adjusted returns, three-factor model, four-factor model, and seven-factor model).



## Figure 4: Relative Importance of Return Components

Monthly fund flows are regressed on eight return components (alpha and seven factor-related returns). Each graph displays the ratio of the coefficient estimate for a return component to the coefficient estimate on alpha, where the red line indicates the effect of the return component on flows is equal to that of alpha. Within each graph, the bars correspond to different models (see text for details):

1) Main Results: All funds, basic controls, month fixed effects
2) All funds, basic controls, month-category fixed effects
3) All funds, basic controls, month-category-star rating fixed effects
4) Small funds
5) Big funds
6) Young funds
7) Old funds
8) Below median return
9) Above median return

## Table 1: Descriptive Statistics for Mutual Fund Sample

Panel A presents statistics across fund-month observations. Statistics on fund characteristics are across fund-month observations from May 1997 to November 2011, the period where these data are used in subsequent regression analyses. 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.

Panel B presents statistics across fund-month observations from January 1996 to November 2011 of estimated coefficients from monthly rolling regressions using the seven-factor model.

Panel C presents time-series averages of cross-sectional descriptive statistics on monthly fund return components, which are the independent variables of interest in our fund-flow regressions. Returns due to factor tilts of a fund are estimated as the mean monthly factor return times the fund's estimated factor loading. In each month, return components represent an exponentially weighted average of the return component over the prior 18 months (see text for details). We first calculate descriptive statistics across funds in each month; the table presents the average of each statistic across months.

Panel D presents the correlation matrix between fund return components based on fund-month observations.

Panel E presents the correlation matrix between annual abnormal return measures calculated from six models: market-adjusted returns (MAR), the Capital Asset Pricing Model (CAPM), a three-factor model (3F) that adds size and value factors, a four-factor model (4F) that adds momentum, a seven-factor model (7F) that adds the three industry factors, and a nine-factor model (9F) that adds profitability and investment factors. Percentage fund flow is winsorized at -90% and 1000%; all other variables are winsorized at the 1 and 99% levels.

Table 1, continued

| | #Obs | Mean | Std | 25th Perc. | Median | 75th Perc. |
|---|---|---|---|---|---|---|
| **Panel A: Fund Charactieristics (Fund-Month Obs.)** | | | | | | |
| Percentage fund flow | 257053 | -0.533% | 2.254% | -1.620% | -0.609% | 0.453% |
| Fund size ($mil) | 257053 | 1443.500 | 2941.297 | 125.132 | 396.577 | 1240.571 |
| Fund Age (months) | 257053 | 202.450 | 148.946 | 111.000 | 154.000 | 225.000 |
| Expense ratio | 257053 | 1.276% | 0.438% | 0.995% | 1.230% | 1.517% |
| Load Fund Dummy | 257053 | 0.723 | 0.448 | 0.000 | 1.000 | 1.000 |
| Volatility (t-12 to t-1) | 257053 | 4.926% | 2.007% | 3.358% | 4.705% | 6.137% |
| **Panel B: Fund Alpha and Factor Exposures (Fund-Month Obs.)** | | | | | | |
| Alpha | 328705 | -0.023% | 2.478% | -1.134% | -0.034% | 1.087% |
| Beta | 328705 | 0.945 | 0.186 | 0.862 | 0.960 | 1.043 |
| Size Coefficient | 328705 | 0.196 | 0.306 | -0.049 | 0.141 | 0.398 |
| Value Coefficient | 328705 | 0.032 | 0.350 | -0.181 | 0.034 | 0.256 |
| Momentum Coefficient | 328705 | 0.015 | 0.137 | -0.066 | 0.005 | 0.085 |
| Industry 1 Coefficient | 328705 | 0.041 | 0.101 | -0.013 | 0.020 | 0.071 |
| Industry 2 Coefficient | 328705 | 0.004 | 0.086 | -0.043 | 0.003 | 0.051 |
| Industry 3 Coefficient | 328705 | -0.002 | 0.100 | -0.050 | -0.002 | 0.043 |
| Adjusted R-Squared | 328705 | 0.831 | 0.151 | 0.784 | 0.878 | 0.932 |
| **Panel C: Mean Descriptive Statistics on Return Components across 175 Months (Jan 1996 to Nov 2011)** | | | | | | |
| ALPHA | 175 | -0.048% | 0.815% | -0.484% | -0.056% | 0.384% |
| MKTRET | 175 | 0.320% | 0.254% | 0.190% | 0.325% | 0.461% |
| SIZRET | 175 | 0.045% | 0.365% | -0.193% | 0.028% | 0.292% |
| VALRET | 175 | 0.015% | 0.229% | -0.083% | 0.005% | 0.101% |
| MOMRET | 175 | -0.004% | 0.126% | -0.077% | -0.003% | 0.066% |
| INDRET1 | 175 | -0.012% | 0.177% | -0.102% | -0.016% | 0.075% |
| INDRET2 | 175 | 0.053% | 0.272% | -0.150% | 0.040% | 0.239% |
| INDRET3 | 175 | 0.021% | 0.214% | -0.115% | 0.016% | 0.153% |

**Panel D: Correlation between Fund Return Components**

| | ALPHA | MKTRET | SIZRET | VALRET | MOMRET | INDRET1 | INDRET2 |
|---|---|---|---|---|---|---|---|
| (a) ALPHA | 1 | | | | | | |
| (b) MKTRET | 0.0479 | 1 | | | | | |
| (c) SIZRET | -0.0821 | 0.0698 | 1 | | | | |
| (d) VALRET | 0.0255 | -0.1220 | 0.0114 | 1 | | | |
| (e) MOMRET | -0.2240 | -0.0791 | -0.0134 | 0.0225 | 1 | | |
| (f) INDRET1 | -0.0321 | 0.0233 | -0.0221 | -0.0311 | 0.0451 | 1 | |
| (g) INDRET2 | -0.1620 | -0.0157 | 0.0115 | 0.0494 | -0.0131 | -0.1170 | 1 |
| (h) INDRET3 | -0.1690 | 0.0288 | -0.0516 | -0.1350 | 0.0798 | 0.0030 | -0.0488 |

**Panel E: Correlation between Fund Alphas**

| | MAR | CAPM | 3F | 4F | 7F | 9F |
|---|---|---|---|---|---|---|
| (a) MAR | 1 | | | | | |
| (b) CAPM | 0.92 | 1 | | | | |
| (c) 3F | 0.74 | 0.78 | 1 | | | |
| (d) 4F | 0.70 | 0.73 | 0.89 | 1 | | |
| (e) 7F | 0.65 | 0.68 | 0.82 | 0.86 | 1 | |
| (f) 9F | 0.59 | 0.64 | 0.76 | 0.81 | 0.89 | 1 |

## Table 2: Descriptive Statistics by Morningstar Style Box

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

| | Large | Medium | Small | Agg by Value |
|---|---|---|---|---|
| **Panel A: Beta** | | | | |
| Value | 0.932 | 0.843 | 0.888 | 0.908 |
| | (0.144) | (0.253) | (0.170) | (0.179) |
| Blend | 0.929 | 0.916 | 0.945 | 0.929 |
| | (0.143) | (0.189) | (0.141) | (0.152) |
| Growth | 0.944 | 0.933 | 0.985 | 0.949 |
| | (0.163) | (0.205) | (0.166) | (0.177) |
| Agg by Size | 0.936 | 0.908 | 0.955 | 0.932 |
| | (0.152) | (0.217) | (0.164) | (0.171) |
| **Panel B: Size Coefficient** | | | | |
| Value | -0.02 | 0.247 | 0.637 | 0.112 |
| | (0.167) | (0.220) | (0.198) | (0.285) |
| Blend | 0.004 | 0.319 | 0.652 | 0.154 |
| | (0.179) | (0.202) | (0.189) | (0.301) |
| Growth | 0.042 | 0.338 | 0.653 | 0.227 |
| | (0.192) | (0.205) | (0.198) | (0.305) |
| Agg by Size | 0.013 | 0.312 | 0.650 | 0.176 |
| | (0.183) | (0.211) | (0.195) | (0.303) |
| **Panel C: Value Coefficient** | | | | |
| Value | 0.186 | 0.271 | 0.311 | 0.218 |
| | (0.254) | (0.351) | (0.236) | (0.279) |
| Blend | 0.056 | 0.18 | 0.204 | 0.099 |
| | (0.253) | (0.308) | (0.251) | (0.271) |
| Growth | -0.09 | -0.068 | -0.116 | -0.089 |
| | (0.295) | (0.369) | (0.310) | (0.319) |
| Agg by Size | 0.033 | 0.072 | 0.060 | 0.046 |
| | (0.292) | (0.381) | (0.336) | (0.321) |
| **Panel D: Momentum Coefficient** | | | | |
| Value | -0.055 | -0.063 | -0.051 | -0.056 |
| | (0.108) | (0.145) | (0.118) | (0.118) |
| Blend | -0.014 | -0.028 | -0.009 | -0.015 |
| | (0.107) | (0.138) | (0.116) | (0.115) |
| Growth | 0.059 | 0.092 | 0.086 | 0.073 |
| | (0.131) | (0.157) | (0.140) | (0.141) |
| Agg by Size | 0.004 | 0.027 | 0.032 | 0.013 |
| | (0.127) | (0.165) | (0.142) | (0.139) |

| | Large | Medium | Small | Agg by Value |
|---|---|---|---|---|
| **Panel E: Industry 1 Coefficient** | | | | |
| Value | 0.048 | 0.055 | 0.027 | 0.047 |
| | (0.076) | (0.101) | (0.070) | (0.082) |
| Blend | 0.054 | 0.051 | 0.027 | 0.050 |
| | (0.082) | (0.099) | (0.069) | (0.084) |
| Growth | 0.035 | 0.062 | 0.034 | 0.042 |
| | (0.097) | (0.149) | (0.120) | (0.117) |
| Agg by Size | 0.045 | 0.058 | 0.030 | 0.046 |
| | (0.087) | (0.128) | (0.099) | (0.100) |
| **Panel F: Industry 2 Coefficient** | | | | |
| Value | -0.029 | -0.017 | -0.011 | -0.024 |
| | (0.072) | (0.091) | (0.062) | (0.075) |
| Blend | -0.008 | -0.001 | -0.008 | -0.007 |
| | (0.076) | (0.082) | (0.059) | (0.075) |
| Growth | 0.011 | -0.002 | -0.023 | 0.001 |
| | (0.097) | (0.110) | (0.083) | (0.099) |
| Agg by Size | -0.006 | -0.005 | -0.016 | -0.008 |
| | (0.086) | (0.099) | (0.073) | (0.087) |
| **Panel G: Industry 3 Coefficient** | | | | |
| Value | -0.013 | -0.009 | -0.007 | -0.012 |
| | (0.081) | (0.100) | (0.082) | (0.086) |
| Blend | 0.001 | -0.002 | -0.022 | -0.003 |
| | (0.086) | (0.102) | (0.087) | (0.090) |
| Growth | 0.012 | 0.008 | -0.004 | 0.008 |
| | (0.109) | (0.132) | (0.093) | (0.113) |
| Agg by Size | 0.001 | 0.002 | -0.010 | 0.000 |
| | (0.095) | (0.119) | (0.090) | (0.100) |

## Table 3: Fund Flows and Competing Measures of Fund Performance

This table presents regression coefficient estimates from panel regressions of percentage fund flow (dependent variable) on six different measures of mutual fund performance: Market-Adjusted Returns, and alphas estimated using CAPM, Three-, Four-, Seven-, and Nine-Factor models. See Table 1 and text for details. "Raw Returns" are unscaled; "Standardized Returns" are scaled by the cross-sectional standard deviation of the performance measure in month *t*, and "Percentile Ranks" are based on percentile ranks in month *t*. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, return volatility, and month fixed effects.

| | Scale for Independent Variables | | |
|---|---|---|---|
| | Raw Returns | Standardized Returns | Percentile Rank |
| CAPM alpha | 0.474*** | 0.415*** | 1.357*** |
| | (0.061) | (0.043) | (0.130) |
| Market-adjusted | 0.221*** | 0.277*** | 0.852*** |
| | (0.056) | (0.042) | (0.126) |
| Three-factor alpha | 0.186*** | 0.063 | 0.361*** |
| | (0.063) | (0.049) | (0.139) |
| Four-factor alpha | -0.072 | -0.028 | 0.039 |
| | (0.045) | (0.049) | (0.139) |
| Seven-factor alpha | 0.071 | 0.083** | 0.285*** |
| | (0.046) | (0.035) | (0.105) |
| Nine-factor alpha | 0.005 | -0.054* | -0.177* |
| | (0.036) | (0.030) | (0.092) |
| Controls | Yes | Yes | Yes |
| Month Fixed Effects | Yes | Yes | Yes |
| Obs | 257053 | 257053 | 257053 |
| Adj. R-squared | 0.174 | 0.174 | 0.172 |

Standard errors (double-clustered by fund and month) are in parentheses.
***, **, * - significant at the 1, 5, and 10% level.

## Table 4: Results of Pairwise Model Horserace

This table presents results of a pairwise comparison of competing asset pricing models ability to predict fund flows.

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 lagged fund flows from month t-19, 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 ($\mu_t$).

We compare the coefficients where the decile ranks are the same magnitude but the ordering is reversed. For example, we compare $b_{10,1}$ (mean flows for a top decile CAPM alpha fund and bottom decile three-factor alpha fund) to $b_{1,10}$ (mean flows for a bottom decile CAPM alpha funds and top decile three-factor alpha funds).

The table presents the results of two hypothesis tests for each horserace: (1) Ho: The sum of the differences in coefficient estimates is zero and (2) Ho: The proportion of differences that are positive is equal to 50%.

**Panel A: CAPM Victories**

| | | | | | |
|---|---|---|---|---|---|
| Winning Model | CAPM | CAPM | CAPM | CAPM | CAPM |
| Losing Model | MAR | 3 Factor | 4 Factor | 7 Factor | 9 Factor |
| Sum of Coefficient Differences | 7.41*** | 22.94*** | 27.50*** | 28.52*** | 33.03*** |
| t-stat | (3.46) | (10.55) | (13.29) | (14.68) | (17.56) |
| % of Coefficient Differences > 0 | 77.78 | 100.00 | 100.00 | 100.00 | 100.00 |
| Binomial p-value | <.01 | <.01 | <.01 | <.01 | <.01 |

**Panel B: Market-Adjusted Return (MAR) Victories**

| | | | | |
|---|---|---|---|---|
| Winning Model | MAR | MAR | MAR | MAR |
| Losing Model | 3 Factor | 4 Factor | 7 Factor | 9 Factor |
| Sum of Coefficient Differences | 15.93*** | 20.41*** | 25.11*** | 28.89*** |
| t-stat | (7.39) | (9.28) | (13.37) | (15.08) |
| % of Coefficient Differences > 0 | 100.00 | 100.00 | 100.00 | 100.00 |
| Binomial p-value | <.01*** | <.01*** | <.01*** | <.01*** |

**Panel C: 3 Factor Victories**

| | | | |
|---|---|---|---|
| Winning Model | 3 Factor | 3 Factor | 3 Factor |
| Losing Model | 4 Factor | 7 Factor | 9 Factor |
| Sum of Coefficient Differences | 19.62*** | 22.49*** | 24.79*** |
| t-stat | (9.85) | (11.89) | (14.68) |
| % of Coefficient Differences > 0 | 91.11 | 95.56 | 100.00 |
| Binomial p-value | <.01*** | <.01*** | <.01*** |

**Panel D: 4 Factor Victories**

| | | |
|---|---|---|
| Winning Model | 4 Factor | 4 Factor |
| Losing Model | 7 Factor | 9 Factor |
| Sum of Coefficient Differences | 19.44*** | 22.72*** |
| t-stat | (9.95) | (12.74) |
| % of Coefficient Differences > 0 | 93.33*** | 100.00*** |
| Binomial p-value | <.01 | <.01 |

**Panel E: 7 Factor Victory**

| | |
|---|---|
| Winning Model | 7 Factor |
| Losing Model | 9 Factor |
| Sum of Coefficient Differences | 16.35*** |
| t-stat | (7.97) |
| % of Coefficient Differences > 0 | 100.00 |
| Binomial p-value | <.01*** |

***, **, * - significant at the 1, 5, and 10% level.

## Table 5: 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 seven factor-related returns. The seven factor-related returns are estimated based on the fund's factor exposure (e.g., tilt toward small versus large stocks) and the factor return (e.g., performance of small versus large stocks). The seven factors include the market (i.e., a fund's beta times the excess return on the market index), size, value, momentum, and three industry portfolios that capture the industry tilts of a mutual fund. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Fund Sample: | All Funds | All Funds | All Funds | Small Funds | Big Funds | Young Funds | Old Funds | Below Median Ret. | Above Median Ret. |
| ALPHA | 0.884*** | 0.789*** | 0.738*** | 0.843*** | 0.899*** | 0.918*** | 0.868*** | 0.701*** | 0.891*** |
| | (0.027) | (0.030) | (0.027) | (0.033) | (0.030) | (0.036) | (0.028) | (0.036) | (0.036) |
| MKTRET | 0.253*** | 0.207*** | 0.194*** | 0.236*** | 0.255*** | 0.252*** | 0.253*** | 0.163*** | 0.244*** |
| | (0.056) | (0.050) | (0.041) | (0.056) | (0.055) | (0.057) | (0.055) | (0.058) | (0.056) |
| SIZRET | 0.759*** | 0.685*** | 0.639*** | 0.529*** | 0.885*** | 0.725*** | 0.775*** | 0.714*** | 0.591*** |
| | (0.054) | (0.053) | (0.048) | (0.061) | (0.062) | (0.062) | (0.062) | (0.063) | (0.075) |
| VALRET | 0.665*** | 0.590*** | 0.568*** | 0.698*** | 0.647*** | 0.697*** | 0.653*** | 0.523*** | 0.684*** |
| | (0.063) | (0.057) | (0.053) | (0.066) | (0.066) | (0.070) | (0.064) | (0.073) | (0.071) |
| MOMRET | 1.059*** | 0.940*** | 0.851*** | 0.933*** | 1.106*** | 1.202*** | 0.996*** | 0.906*** | 0.999*** |
| | (0.060) | (0.062) | (0.050) | (0.067) | (0.071) | (0.080) | (0.060) | (0.076) | (0.075) |
| INDRET1 | 0.920*** | 0.820*** | 0.838*** | 0.914*** | 0.915*** | 0.937*** | 0.918*** | 0.705*** | 0.945*** |
| | (0.074) | (0.073) | (0.075) | (0.083) | (0.084) | (0.101) | (0.077) | (0.093) | (0.098) |
| INDRET2 | 0.701*** | 0.593*** | 0.630*** | 0.681*** | 0.714*** | 0.691*** | 0.701*** | 0.539*** | 0.741*** |
| | (0.095) | (0.084) | (0.089) | (0.115) | (0.108) | (0.124) | (0.103) | (0.103) | (0.129) |
| INDRET3 | 0.692*** | 0.642*** | 0.479*** | 0.739*** | 0.664*** | 0.726*** | 0.684*** | 0.431*** | 0.776*** |
| | (0.087) | (0.082) | (0.081) | (0.112) | (0.091) | (0.110) | (0.096) | (0.104) | (0.102) |
| Month Fixed Effects | YES | NO | NO | YES | YES | YES | YES | YES | YES |
| Month-Cat. Fixed Effects | NO | YES | NO | NO | NO | NO | NO | NO | NO |
| Month-Cat.-Rating FEs | NO | NO | YES | NO | NO | NO | NO | NO | NO |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 257053 | 257053 | 248463 | 257053 | | 257053 | | 257053 | |
| Adj. R-squared | 0.173 | 0.190 | 0.216 | 0.175 | | 0.173 | | 0.175 | |

Standard errors (double-clustered by fund and month) are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

## Table 6: In-Sample v. Out-of-Sample Factor Loadings

The table presents in-sample versus out-of-sample factor loadings for quintiles based on in-sample factor loadings. In month *t*, we sort all funds into quintiles based on the estimated beta for the five years ending in month t. For each beta quintile, we construct two time series of returns: in-sample and out-of-sample. The in-sample time series is based on monthly fund returns during the five-year estimation period (t-59 to t); the out-of-sample time series is based on the monthly fund returns during month t+1. We repeat this analysis for every month during our sample period. Armed with the in-sample and out-of-sample time-series of monthly fund returns for each beta quintile, we estimate the market beta for each quintile using the in-sample and out-of-sample return series yielding a total of ten beta estimates. We repeat this analysis for each of the factor loadings. The "Shrinkage Ratio" is the ratio of the out-of-sample spread in extreme quintiles (Hi-Lo) to the in-sample spread.

| | Quintile Portfolios | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 (Lo) | 2 | 3 | 4 | 5 (Hi) | Hi-Lo | Shrinkage Ratio |
| **Panel A: Beta Estimates**, Fund Quintiles based on Market Beta | | | | | | | |
| In-Sample | 0.677*** | 0.874*** | 0.951*** | 1.015*** | 1.154*** | 0.477 | |
| | (0.0053) | (0.0036) | (0.0025) | (0.0024) | (0.0050) | | |
| Out-of-Sample | 0.762*** | 0.915*** | 0.961*** | 0.986*** | 1.016*** | 0.254 | 53.2% |
| | (0.0202) | (0.0139) | (0.0106) | (0.0135) | (0.0266) | | |
| **Panel B: Size Coefficient**, Fund Quintiles based on Size Coefficient | | | | | | | |
| In-Sample | -0.175*** | -0.020*** | 0.135*** | 0.337*** | 0.677*** | 0.852 | |
| | (0.0015) | (0.0018) | (0.0028) | (0.0034) | (0.0063) | | |
| Out-of-Sample | -0.122*** | -0.026 | 0.118*** | 0.273*** | 0.525*** | 0.647 | 75.9% |
| | (0.0122) | (0.0166) | (0.0227) | (0.0220) | (0.0240) | | |
| **Panel C: Value Coefficients**, Fund Quintiles based on Value Coefficient | | | | | | | |
| In-Sample | -0.450*** | -0.117*** | 0.042*** | 0.207*** | 0.474*** | 0.924 | |
| | (0.0064) | (0.0040) | (0.0038) | (0.0062) | (0.0078) | | |
| Out-of-Sample | -0.265*** | -0.040* | 0.089*** | 0.242*** | 0.451*** | 0.716 | 77.5% |
| | (0.0292) | (0.0211) | (0.0193) | (0.0222) | (0.0257) | | |
| **Panel D: Momentum Coefficients**, Fund Quintiles based on Momentum Coefficient | | | | | | | |
| In-Sample | -0.159*** | -0.053*** | 0.007*** | 0.075*** | 0.212*** | 0.371 | |
| | (0.0042) | (0.0025) | (0.0022) | (0.0032) | (0.0059) | | |
| Out-of-Sample | -0.080*** | -0.032*** | -0.014 | 0.014 | 0.071*** | 0.152 | 40.8% |
| | (0.0140) | (0.0103) | (0.0099) | (0.0118) | (0.0152) | | |
| **Panel E: Industry Coefficient 1**, Fund Quintiles based on Industry 1 Coefficient | | | | | | | |
| In-Sample | -0.050*** | -0.006** | 0.019*** | 0.056*** | 0.186*** | 0.236 | |
| | (0.0010) | (0.0008) | (0.0010) | (0.0016) | (0.0034) | | |
| Out-of-Sample | -0.012** | 0.004 | 0.020*** | 0.051*** | 0.167*** | 0.179 | 75.9% |
| | (0.0060) | (0.0045) | (0.0059) | (0.0082) | (0.0169) | | |
| **Panel F: Industry Coefficient 2**, Fund Quintiles based on Industry 2 Coefficient | | | | | | | |
| In-Sample | -0.110*** | -0.030*** | 0.004*** | 0.041*** | 0.116*** | 0.226 | |
| | (0.0023) | (0.0014) | (0.0013) | (0.0016) | (0.0025) | | |
| Out-of-Sample | -0.050*** | -0.023*** | -0.004 | 0.004 | 0.013 | 0.063 | 27.9% |
| | (0.0113) | (0.0083) | (0.0084) | (0.0113) | (0.0170) | | |
| **Panel G: Industry Coefficient 3**, Fund Quintiles based on Industry 3 Coefficient | | | | | | | |
| In-Sample | -0.125*** | -0.039*** | -0.002 | 0.033*** | 0.124*** | 0.249 | |
| | (0.0031) | (0.0017) | (0.0014) | (0.0016) | (0.0020) | | |
| Out-of-Sample | -0.025 | -0.009 | -0.002 | 0.008 | 0.044*** | 0.070 | 27.9% |
| | (0.0228) | (0.013) | (0.0098) | (0.0111) | (0.0157) | | |

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

## Table 7: Investor Sophistication and Flow-Return Relations

This table presents regressions coefficient estimates from three interactive panel regressions of fund flows (dependent variable) on the components of a fund's return and an interaction dummy variable that proxies for investor sophistication. We consider three proxies: funds sold through broker-sold distribution channels (the model of columns 1-3), periods of high investor sentiment as measured by above median trading of mutual funds (the model of columns 4-6), and less wealthy investors at a large discount brokerage firm (the model of columns 7-9). When we use broker data, fund flows are measured using trades and positions made at the broker over the period 1991 to 1996 (see text for details). Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | CRSP Fund Flows: Direct v. Broker Sold Funds | | | CRSP Fund Flows: Periods of High v. Low Sentiment | | | Broker Data: Wealthy v. Other Investors | | |
| | Direct | Broker | Diff (Brok.-Dir.) | Low Sentiment | High Sentiment | Diff (High-Low) | Wealthy | Others | Diff (Oth.-Wlthy) |
| ALPHA | 0.816*** | 0.914*** | 0.0972*** | 0.816*** | 0.956*** | 0.140*** | 3.554*** | 4.127*** | 0.573** |
| | (0.032) | (0.031) | (0.032) | (0.029) | (0.040) | (0.046) | (0.676) | (0.649) | (0.269) |
| MKTRET | 0.225*** | 0.291*** | 0.0662*** | 0.133* | 0.374*** | 0.241** | 1.273 | 2.211 | 0.937** |
| | (0.051) | (0.055) | (0.013) | (0.075) | (0.067) | (0.095) | (1.619) | (1.821) | (0.462) |
| SIZRET | 0.616*** | 0.839*** | 0.223*** | 0.734*** | 0.788*** | 0.0537 | 1.632 | 4.094*** | 2.462** |
| | (0.065) | (0.061) | (0.061) | (0.063) | (0.074) | (0.090) | (1.264) | (0.860) | (0.972) |
| VALRET | 0.527*** | 0.750*** | 0.223*** | 0.477*** | 0.874*** | 0.396*** | 3.906*** | 4.873*** | 0.967 |
| | (0.067) | (0.064) | (0.044) | (0.068) | (0.093) | (0.113) | (0.801) | (1.445) | (1.472) |
| MOMRET | 1.095*** | 1.019*** | -0.0762 | 0.979*** | 1.091*** | 0.112 | 5.648** | 5.872*** | 0.224 |
| | (0.067) | (0.067) | (0.070) | (0.068) | (0.081) | (0.101) | (2.405) | (2.277) | (1.870) |
| INDRET1 | 0.770*** | 1.004*** | 0.234** | 0.727*** | 1.072*** | 0.345*** | 2.132* | 2.73 | 0.597 |
| | (0.090) | (0.086) | (0.100) | (0.091) | (0.096) | (0.124) | (1.089) | (1.694) | (0.933) |
| INDRET2 | 0.581*** | 0.876*** | 0.295** | 0.642*** | 0.713*** | 0.0711 | 2.691 | 0.223 | -2.469 |
| | (0.118) | (0.110) | (0.128) | (0.105) | (0.142) | (0.162) | (1.851) | (1.848) | (1.728) |
| INDRET3 | 0.561*** | 0.693*** | 0.132 | 0.426*** | 1.034*** | 0.608*** | 3.706*** | 7.196*** | 3.490*** |
| | (0.095) | (0.096) | (0.094) | (0.099) | (0.111) | (0.140) | (1.399) | (1.077) | (0.741) |
| Month Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | | 234690 | | | 256972 | | | 24629 | |
| R-squared | | 0.181 | | | 0.177 | | | 0.061 | |

Standard errors (double-clustered by fund and month) are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.

## Table 8: Morningstar Categories and Fund Flows

This table presents a modified version of the main regression of Table 5. The single independent variable for size-related returns (SIZRET) is now replaced with two independent variables associated the with size tilt of the fund's Morningstar category (CATSIZ) and the deviation of the fund's size tilt from the Morningstar category average (FUNDSIZ). Similarly, VALRET is replaced with CATVAL and FUNDVAL. Key coefficient estimates are presented in bold. Tests for differences in the coefficient estimates on category-related returns and deviation from category are presented at the bottom of the table. Controls include lagged fund flows from month t-19, lagged values of log of fund size, log of fund age, expense ratio, load fund dummy, and return volatility.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Fund Sample: | All Funds | All Funds | Small Funds | Big Funds | Young Funds | Old Funds | Below Median Return | Above Median Return |
| ALPHA | 0.893*** | 0.743*** | 0.840*** | 0.910*** | 0.919*** | 0.881*** | 0.732*** | 0.915*** |
| | (0.028) | (0.027) | (0.033) | (0.030) | (0.036) | (0.029) | (0.039) | (0.037) |
| MKTRET | 0.253*** | 0.191*** | 0.233*** | 0.261*** | 0.240*** | 0.256*** | 0.213*** | 0.268*** |
| | (0.056) | (0.042) | (0.056) | (0.055) | (0.057) | (0.055) | (0.059) | (0.055) |
| **CATSIZ** | **0.681*** ** | **0.574*** ** | **0.477*** ** | **0.799*** ** | **0.743*** ** | **0.646*** ** | **0.667*** ** | **0.539*** ** |
| | **(0.069)** | **(0.062)** | **(0.073)** | **(0.078)** | **(0.077)** | **(0.076)** | **(0.086)** | **(0.085)** |
| **FUNDSIZ** | **0.849*** ** | **0.712*** ** | **0.699*** ** | **0.928*** ** | **0.753*** ** | **0.908*** ** | **0.675*** ** | **0.830*** ** |
| | **(0.070)** | **(0.065)** | **(0.091)** | **(0.080)** | **(0.101)** | **(0.078)** | **(0.082)** | **(0.097)** |
| **CATVAL** | **0.542*** ** | **0.529*** ** | **0.613*** ** | **0.519*** ** | **0.551*** ** | **0.546*** ** | **0.413*** ** | **0.541*** ** |
| | **(0.079)** | **(0.068)** | **(0.078)** | **(0.085)** | **(0.091)** | **(0.080)** | **(0.081)** | **(0.094)** |
| **FUNDVAL** | **0.736*** ** | **0.591*** ** | **0.724*** ** | **0.737*** ** | **0.724*** ** | **0.732*** ** | **0.639*** ** | **0.790*** ** |
| | **(0.062)** | **(0.050)** | **(0.075)** | **(0.063)** | **(0.070)** | **(0.067)** | **(0.079)** | **(0.072)** |
| MOMRET | 1.077*** | 0.858*** | 0.926*** | 1.126*** | 1.205*** | 1.008*** | 0.955*** | 1.062*** |
| | (0.060) | (0.050) | (0.067) | (0.071) | (0.080) | (0.060) | (0.076) | (0.073) |
| INDRET1 | 0.923*** | 0.839*** | 0.930*** | 0.903*** | 0.972*** | 0.912*** | 0.726*** | 0.909*** |
| | (0.074) | (0.074) | (0.083) | (0.084) | (0.101) | (0.076) | (0.093) | (0.097) |
| INDRET2 | 0.732*** | 0.642*** | 0.700*** | 0.740*** | 0.730*** | 0.727*** | 0.549*** | 0.893*** |
| | (0.095) | (0.089) | (0.115) | (0.107) | (0.125) | (0.102) | (0.104) | (0.128) |
| INDRET3 | 0.720*** | 0.476*** | 0.720*** | 0.713*** | 0.710*** | 0.736*** | 0.604*** | 0.761*** |
| | (0.085) | (0.079) | (0.114) | (0.087) | (0.112) | (0.094) | (0.104) | (0.095) |
| **CATSIZ – FUNDSIZ** | **-0.168*** | **-0.138*** | **-0.222** ** | **-0.129** | **-0.01** | **-0.261*** ** | **-0.008** | **-0.291*** ** |
| | **(0.088)** | **(0.083)** | **(0.104)** | **(0.101)** | **(0.122)** | **(0.094)** | **(0.112)** | **(0.109)** |
| **CATVAL – FUNDVAL** | **-0.194*** ** | **-0.062** | **-0.111** | **-0.218*** ** | **-0.173** ** | **-0.186** ** | **-0.226*** ** | **-0.249*** ** |
| | **(0.064)** | **(0.055)** | **(0.078)** | **(0.074)** | **(0.081)** | **(0.073)** | **(0.068)** | **(0.090)** |
| Month Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Star Ratings | NO | YES | NO | NO | NO | NO | NO | NO |
| Controls | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 257053 | 248463 | 257053 | | 257053 | | 257053 | |
| R-squared | 0.173 | 0.216 | 0.177 | | 0.175 | | 0.179 | |

Standard errors (double-clustered by fund and month) are in parentheses. ***, **, * - significant at the 1, 5, and 10% level.