# CAPM, Factors, and Sectors: Do Investors Utilize Available Information?*

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**Abstract**

This paper utilizes sector fund flows data to test if investor behavior is best captured by the Capital Asset Pricing Model (CAPM) or if ready availability of information is driving investor behavior. Prospectuses of sector funds provide investors information regarding sector performance in addition to market and fund performance. We investigate whether investors respond to the outperformance of a sector with respect to the market, and the fund with respect to the sector. We find that investors respond to both performance metrics, with the elasticity of flow response to fund outperformance being twice that to sector outperformance. Thus, our results show that the average investor looks for and responds to all the performance level information readily available to her.

**JEL Classification:** G11, G12, D83.

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# 1 Introduction

A central strand of the finance literature dating back to Jensen (1968) has elucidated the best way to assess the performance of managed investment funds such as mutual funds. This literature has developed in tandem with the more general cross-sectional asset pricing literature.[1] Correspondingly, it has become widely accepted that multi-factor models (which are thought to capture the primary components of systematic risk and therefore marginal utility growth) are also the best tools in order to measure risk-adjusted performance by actively managed mutual funds, and thus provide the best indication of performance.[2]

Recent literature (Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016), however, has found that mutual fund capital flow data reveal that the asset pricing model that best explains investor behavior is the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965a, 1965b). This raises a puzzle: why is investor behavior best explained by the CAPM when more sophisticated models outperform the CAPM in explaining cross-sectional variation in expected returns? This paper argues that the reason may be availability of information. We show, in a natural laboratory of mutual funds, that when investors are provided additional information in the prospectus, then fund flows respond to the additional information with sensitivities in the same order of magnitude as the market benchmark.

Thus, we contend that investors look for, but do not find, *all* relevant benchmark information in mutual fund prospectuses. The alternative is that investors simply do not look at all. In other words, we propose that investors do not have an inherent preference for a one-factor model (perhaps because they are only averse to

[1] This is an extensive field of research, but seminal works in this vein include Fama and French (1993, 1996); Carhart (1997); Pastor and Stambaugh (2003); Fama and French (2015) who have identified risk factors that affect asset prices.

[2] An alternative to factor models lies in the non-parametric characteristic-based approach pioneered by Grinblatt and Titman (1993) and Daniel, Grinblatt, Titman, and Wermers (1997). However, even this type of methodology hinges crucially on making comparisons based on benchmark portfolios formed through characteristics that are ultimately derived from risk factors.

market risk). Instead, we argue that investors are only confronted with market-risk related information, because mutual-fund prospectuses and brokerage sites only report out-performance in relation to a broad market index.[3] Empirically distinguishing investor preference for the CAPM from investor reliance on readily available information is inherently difficult, since common market indices (such as the S&P 500) are a good proxy for the market factor in the CAPM, and are also the most frequently reported benchmark in prospectuses.

To disentangle the two competing hypotheses (that investors utilize CAPM or available information), we focus on a subset of the industry: sector mutual funds. Sector funds constitute a useful setting because, in addition to a market benchmark, prospectuses of these funds provide a sector-level benchmark that has relatively low correlation with the overall market return.[4,5] Sector funds are also a sizable fraction (approximately 10-15%) of total assets under management in the U.S. mutual fund industry. The fact that sector fund prospectuses contain information regarding sector-level benchmarks in addition to market performance information allows us to separately identify investor responses to broad market performance, sector performance, and fund performance. The empirical specification is based on the three choices made by the investor regarding investing a marginal dollar: (i) choice of investing the marginal dollar in the stock market, (ii) choice of investing in a sector compared to the overall market, and (iii) choice of a specific sector fund. If investors only use the CAPM, we would not expect that sector performance with respect to market performance would influence investors' capital allocations. This is our null hypothesis.

Using a fund-level monthly panel dataset of fund flows in U.S. sector funds from

[3]See, e.g., Figure 1, which shows performance and benchmark information from a typical equity fund's prospectus.

[4]See Figure 2, which shows performance and benchmark information for a sector fund, in comparison to Figure 1.

[5]Table 1 reports the correlation between monthly value weighted sector returns in our sample with monthly returns of the market index.

1999–2009, we find that investors respond to both performance metrics — sector return compared to market return, and fund return relative to sector benchmark. The elasticity of additional funds in response to previous month's performance is twice for fund out-performance compared to sector out-performance. These results are obtained in the presence of fund and month fixed effects and standard errors clustered at the fund level. Thus, we show that the average investor pays attention, and responds, to all of the performance level information that is readily available.[6]

This result is consistent with retail investors behaving as if information acquisition regarding benchmarks used by researchers and professionals such as HMB (value), SML (growth), and UMD (momentum) is too costly or insufficiently beneficial. Our paper does not take a stand on why investors exhibit this behavior. We just document it. One the one hand, this behavior is consistent with investors exhibiting bounded rationality (Rubinstein, 1998) or other behavioral biases (See, for example, Odean, 1998; Grinblatt and Keloharju, 2000; Barber, Huang, and Odean, 2016). On the other hand, our findings are also consistent with the argument that the costs of information acquisition for the average retail investor are high. Brokerages do not readily provide four/five factor alphas or time-series data of a fund's performance. The task of obtaining access to selected datasets of mutual fund time-series and then computing four/five-factor alphas for comparison imposes costs on retail mutual fund investors.[7]

An important concern regarding the results discussed above is that as Barber, Huang, and Odean (2016); Berk and van Binsbergen (2016) show, investors may be

[6] Berk and van Binsbergen (2015) propose evaluating managers based on value added as measured in dollars rather than basis points, building on the framework of Berk and Green (2004). We maintain the traditional returns-denominated approach, but in either approach, value must still be measured with respect to some explicit benchmark — usually a multi-factor model.

[7] The literature on search-theory considers financial and psychic costs separately. See, for example, Morgan and Manning (1985). While a comparison regarding whether a person should pay a financial cost in expectation of a financial benefit is relatively straightforward, the decision to bear psychic costs is a matter of individual ability and preference. Seminal work regarding the impact of psychic cost on job search decisions includes (Stigler, 1962; McCall, 1970). See Heckman, Lochner, and Todd (2006) for a comprehensive review of effects of individual psychic costs on education attainment decisions.

adjusting for risk. Hence, we calculate market risk-adjusted outperformance of the sector, and sector-risk outperformance of the fund. Again, we find that investors respond to both measures of outperformance. An alternative approach to test our hypothesis is provided by Berk and van Binsbergen (2016). We follow their approach to compute the signal of managerial skill using a single factor model (CAPM) and a two factor model that includes both the market return and the sector's benchmark return. A comparison of the models following the methods of Berk and van Binsbergen (2016) shows that investors utilize the sector index as well as the market index to determine managerial skill and therefore fund flows.

Why are sector funds a good natural laboratory for testing our hypothesis? Unlike sector funds, diversified (i.e. *generalist*) U.S. equity funds use a set of market benchmarks which is (at least statistically speaking) highly homogeneous. About 50% of equity funds state the S&P 500 as a benchmark.[8] Even among funds stating another benchmark, this is a distinction without a difference since most alternative benchmarks of the market correlate strongly with S&P 500. Arguing that investors who use alternative indices such as the S&P 400 or the Wilshire 5000 as benchmarks do not think of those as proxies for the market is problematic, as their correlations with the overall market's return is very high. Therefore, any statistical test attempting to separately identify the effects of the total market return and the benchmark return on fund flows will have very low power, as the independent variables are nearly collinear. Furthermore, a test of whether investors use benchmarks such as a Small Cap Value Index, if they are readily available in the prospectus, does not allow us to cleanly distinguish between investor recognition of a multi-factor model and their reliance on readily available information, since such an index approximates one of the other common asset-pricing factors. If, however, investors use sector-level benchmarks, which don't resemble traditional pricing factors, the conclusions are

[8]See Table 1 in Cremers, Petajisto, and Zitzewitz (2012) for the distribution of benchmarks across US equity funds as of 2007.

unambiguous; common asset pricing models do not state that sector risk should explain the cross-section of expected returns.

Given that sector-fund investors self-select to become so, a concern is that they are very different from other investors. We address this question first by examining the four-factor risk-adjusted returns of sector funds, which have a mean of -1.3% with a standard error of 1.1%. While this is negative as expected, it does not suggest extreme under-performance compared to investors in other fund classes (Carhart, 1997). We then conduct a horse race between a hypothetical investor that chooses funds for the next month using four factor alphas and another who uses market and sector indices to arrive at a similar decision. We find that the sector fund investor obtains statistically indistinguishable performance compared to other retail investors in non-sector funds.

The research on identifying the best set of risk factors to price assets is vast and still growing (Fama and French, 1993, 1996; Carhart, 1997; Pastor and Stambaugh, 2003; Fama and French, 2015). However, recent research suggests that investors are not adopting these insights and may still be using the CAPM (Berk and van Binsbergen, 2016; Barber, Huang, and Odean, 2016). The literature has explored the possibility of investor naiveté and overconfidence (Barber and Odean, 2000; Daniel, Hirshleifer, and Teoh, 2002; Malmendier and Shanthikumar, 2007), limited attention (Corwin and Coughenour, 2008), and the cost of information acquisition (Sirri and Tufano, 1998; Nieuwerburgh and Veldkamp, 2010; Abel, Eberly, and Panageas, 2013). Our results suggest that investors are using all performance related information readily available to them. Hence, a policy implication would be to include additional benchmarking information in the prospectus to reduce the cost of information acquisition.

Our findings are consistent with the literature on rational inattention (Sims, 2003, 2006; Stokey, 2009). A rationally inattentive agent translates external data into action while being constrained by a finite Shannon "capacity" to process information (Shannon, 1949). Such an agent will therefore not use some freely available information or use it imperfectly. In the context of capital markets, Abel, Eberly, and Panageas (2013) show that in presence of costs to obtain information, which consist of costs of gathering and processing information about stock values and costs of deciding how to respond to this information, a consumer remains optimally inattentive to the stock market for finite intervals of time. Thus, if the cost of information acquisition and processing is not taken into account, it would appear that the standard intertemporal Euler equation that relates asset returns and consumption growth does not hold (Lynch, 1996). While the above literature has argued in favor of optimal inattention over *time*, we are arguing that retail investors also exhibit inattention over the *space* of benchmarks, and utilize the ones that are readily available in their decision making process. The literature has also identified search costs over the space of mutual funds as a determinant of fund flows (Sirri and Tufano, 1998). The authors find that fund flows are directly related to the size of the fund's family as well as the current media attention received by the fund, which lower consumers' search costs.

These results leave open the question of which pricing model is correct, and consequently which risk-adjustment procedure investors *should* employ. Berk and van Binsbergen (2016) emphasize that their results should not be construed to suggest that the CAPM is the "correct" model, nor that investors believe the CAPM to be the correct model. They conclude only that, among the set of models under consideration, the CAPM explains fund flows as well, or better than, any other model. Similarly, we conclude that if additional benchmarking information were presented to investors, they *might* alter their capital allocation decisions. If information acquisition is costly, then availability of such information could be welfare improving.

Section 2 discusses data. Section 3 provides a description of the methodology employed. Section 4 presents results; Section 5 discusses additional and robustness tests. Section 6 concludes.

# 2 Data

We use a monthly panel of sector funds as our main dataset. Data and methodology are adopted from Hartzell, Mühlhofer, and Titman (2016); we largely use their terminology in describing the data construction process.

To find our fund universe, we begin by considering the entire sample of mutual funds present in the Center for Research in Security Prices (CRSP) Survivorship-Bias Free Mutual Fund Database from 1990 to the end of 2009. We eliminate index funds. We then look for specialized *Sector Funds*, by examining the Lipper Objective Codes to find funds that invest in US Equity with strategies that are concentrated in one industry, or sector. Over our time period, the sectors on which funds focus are *Health and Biotechnology* (henceforth *Healthcare*), *Natural Resources*, *Real Estate*, *Science and Technology*, *Telecommunications*, and *Utilities*. A sector *Specialty* also exists, but we do not include these funds in our results, as these do not constitute a group of funds with a homogeneous investment objective (or benchmark), but rather a set of funds in small numbers which invest in single industries which do not fit into any of the aforementioned categories. Because Sector funds did not appear in significant numbers before the year 1998 (roughly), we begin our sample at that point in time.

As stated above, Sector Funds benchmark themselves according to sector indices, in addition to the overall market, and we need returns data for these sector benchmarks for our study. Even though there may be some variation in the specific index chosen by each fund, each of these sector indices approximates a value-weighted portfolio of securities in that sector. Finding the specific index used by each fund for benchmarking would be very time consuming; in addition, many such indices are proprietary and, once found, index returns would be difficult to obtain. The alternative of using returns data to exchange-traded funds (ETFs) in each sector as a proxy for the sector index is also infeasible, as many sectors do not have ETFs over the entire time sample. Alternatively, if an ETF does exist in a given sector, it may not be liquid enough to provide accurate return information. Therefore, we elect to construct our own sector benchmarks as vaule-weighted portfolios of sector securities, following the methodology of Hartzell, Mühlhofer, and Titman (2016). Given that commercially available sector benchmarks are highly correlated with a value-weighted portfolio of sector securities, these should provide a good proxy for the actual indices quoted by funds. We show below that, in a setting in which this question is tractable, this is indeed the case.

To construct our benchmarks, we begin by using MFLinks to identify unique fund portfolios among share classes, and then adding stock holdings for each portfolio, obtained from the Thomson-Reuters S12 Mutual Fund Holdings database. For each equity position, at each time period, for each fund, we include additional stock information from the CRSP monthly stock database. We also determine S&P 500 membership for each held security at any given time, from CRSP's S&P-500 constituent file.

We then assemble security universes for each of the sectors covered by Sector Funds, in order to construct value-weighted benchmarks. For some of our sectors, exogenous specification of sector universes (such as, for example, SIC codes) would not be well-suited because these sector universes might span many such categorizations. As a result, we alternatively elect to define sector universes endogenously. Specifically, we define a sector universe as the set of unique securities held in a given year by at least five percent of Sector Funds within a sector, or two portfolios (whichever is greater). For example the *Real Estate* sector universe for 2005 is the set of all stocks held in at least five percent of Real Estate sector fund portfolios during the year 2005. There exists a natural overlap between Sector-Fund universes, so we allow these to be non-orthogonal.[9] The benchmark portfolio for each sector is the value-weighted portfolio of all stocks within the sector, and the returns to this

[9] For example, many firms that are classified as *Science and Technology* can also be classified as *Healthcare*, or *Natural Resources*, if these firms develop biotechnology or mineral extraction technology, respectively.

portfolio constitute our sector index.

Our condition that, to be considered as part of a sector universe, a stock must be held by at least five percent of funds or two portfolios, is designed to avoid including equities that are clearly outside of a fund's natural sector universe but are still held by a small number of managers. For example, at several times in our data set, a small number of Real Estate funds holds Microsoft in their portfolios, in small quantities. When forming a benchmark portfolio with weights that are based on relative market capitalization, Microsoft (a large, non-sector stock) would become the largest holding in this sector's benchmark portfolio. This would clearly be unwarranted, as Microsoft is not a Real Estate stock. We test our filter by comparing, for each sector, the returns to the benchmark portfolio assembled according to this filter to value-weighted returns of all Sector Funds in the respective sector and find a close match between the two series. We therefore believe that this filter is effective in defining sector universes.[10]

Table 2 shows summary statistics for our data, for each sector. Then, for comparison, we also show our statistics for a group of Generalist Funds, large diversified funds, which closely track the S&P 500 (see Hartzell, Mühlhofer, and Titman (2016)). We begin by showing the number of unique portfolios that we identify in each sector. This number ranges from 20 for Telecommunications to 156 for Science and Technology. We identify 808 unique Generalist Fund portfolios. The table also shows distributional statistics for the number of unique portfolios that exist in a given year. Once again, the Telecommunications sector has the smallest number of these, with only 10.1 (10) portfolios in the mean (median) year, followed by Natural Resources with 22 (23). Health and Biotechnology and Utilities show similar numbers of funds with 33 (28) and 31 (34), respectively. Real Estate is the second most populated sector in this respect, with 43 (60) and Science and Technology the most populated, with 66

[10] In the Real Estate sector, where benchmark choice is fairly homogeneous, in that funds use either the Dow Jones Real Estate or the FTSE-NAREIT index (see e.g. Hartzell, Mühlhofer, and Titman (2010)), we also find that our benchmark portfolio has a correlation of more than .99 with these two indices.

(57). Once again, Generalist Funds are much more numerous than any single sector, with an average (median) year featuring 411 (450) portfolios. The median fund's net asset value is comparable across sectors, at around $ 100 million, except for Utilities, where the median is almost twice as large, at $180 million. The median Generalist Fund is also about twice as large as the median (non-Utility) sector fund, at $201 million. While all size distributions show some positive skewness, the upper halves of size distributions differ markedly among sectors as evidenced by the variation in means, ranging from $205 million for Telecommunications, to almost $500 million for Utilities. The upper tail of the Generalist Fund distribution is much larger as shown by the mean of $1.3 billion.

# 3 Methodology

Section 3.1 describes a simple test driven by first principles of whether investors are using all available information. Section 3.2 presents a different approach, using the framework of Berk and van Binsbergen (2016), to provide an alternative way to test our hypothesis.

## 3.1 A Simple Approach

We argue that mutual-fund investors react to the information with which they are confronted, rather than follow a particular asset-pricing model. Since for a general fund, only market and fund performance is available, it is difficult to distinguish whether investors are using the CAPM to allocate funds or are using all possible information which happens to be market and fund performance. Hence, we utilize data on sector fund flows. As stated before, sector funds quote both performance in relation to the market benchmark, as well as a sector-based benchmark in their prospectus, providing an ideal environment to disentangle these two hypotheses.

If our hypothesis that investors use all readily available performance information is correct, then we should expect that the investor choices (measured through fund flows) depend on both of these performance metrics. On the other hand, if investors use the CAPM, then fund flows should not depend on sector-benchmark performance.

### The Simple Information Model

In the case of sector funds, an investor can make three choices based on three performance measures available to her: (i) market performance information helps an investor to decide whether to allocate capital to the stock market, (ii) sector performance data with respect to market performance data enables an investor to decide whether to allocate to the specific sector, and (iii) fund performance information within a sector helps an investor choose a specific fund. This logic inspires the following empirical specification for fund $j$ in sector $s$ in market $m$ at time $t+1$ based on returns at time $t$ given by $r_{k,t}$, where $k \in \{j, s, m\}$ (fund index, sector index and market respectively):

$$\text{flow}_{j,t+1} = \gamma_0 + \gamma_M r_{m,t} + \gamma_{SM}(r_{s,t} - r_{m,t}) + \gamma_{FS}(r_{j,t} - r_{s,t}) + \epsilon_{j,t}, \qquad (1)$$

In the equation above, the second, third, and fourth term, each account for the three components of information that a sector-fund investor has at her disposal, and which are outlined above. If these information components drive investment choice, we should see each of them statistically affect fund flows.

Throughout this part, we define fund flows using the measure that is common in this literature (see e.g. Sirri and Tufano (1998) or Barber, Huang, and Odean (2016)), as fractional change in the fund's total net assets, scaled by fund returns:

$$\text{flow}_{j,\tau} = \left(\frac{TNA_{j,\tau}}{TNA_{j,\tau-1}} - 1\right) - r_{j,\tau} \qquad (2)$$

In the above expression, $TNA_{j,\tau}$ is the Total Net Assets for fund $j$ at time $\tau$. Note that in Equation 1 we use flow at time $t+1$ while measuring returns at time $t$. We do this to avoid the possibility of spurious results' being introduced by having $r_{j,t}$ (i.e. the fund's return) on both sides. At the same time, however, this raises the hurdle on the quality of association we aim to find, in that performance does not just have to be simultaneously associated with flows, but must actually *predict* flows, in order for us to find significant results.

We conduct all tests at a monthly time horizon (i.e. $t$ is in months). By using this time horizon we impose a stricter test for the presence of the relationship that we explore with regards to both speed of information flow, as well as the power of the tests. This is because information flows may be slower or administrative restrictions on, for example, retirement accounts may lead to slower response to fund performance. Thus, our identification strategy requires that at least some investors respond soon. Since the remaining investors may respond slowly, our results provide a conservative lower bound on the sensitivities.

Despite the advances in our understanding of risk factors, true mutual-fund alphas are not readily accessible to an investor who is "just" paying attention. Instead, mutual funds emphasize raw outperformance with respect to their benchmark. When looking at a prospectus, it is quite unclear whether the relative performance is due to Beta or Alpha. Thus, Eq. 1, in our opinion, provides the empirical specification that truly tests whether investors pay attention to readily available information.

### Risk-Adjusted Outperformance

While the most immediate information available to mutual-fund investors emphasizes raw returns, finance theory, of course, states that investment performance must be measured on a risk-adjusted basis. Many investors are likely aware of this idea, and it is possible with only a little more effort for an investor to access information necessary to risk-adjust returns compared to a benchmark.[11] We therefore now proceed to testing a risk-adjusted version of the simple information model. In addition to providing a further refinement that investors might be making, doing this also provides us with a more rigorous framework to test our information hypothesis.

We therefore make an improvement on the simple specification in Eq. 1 which maintains the focus on the three components of investor decision making (market return, outperformance of the sector, and outperformance of the fund), but measures each of these with respect to an instantaneous measure of alpha, rather than to raw returns. The specification then becomes:

$$flow_{j,t+1} = \gamma_0 + \gamma_M(r_{m,t} - r_{f,t}) + \gamma_{FS}\alpha(Fund - Sec)_{j,t} + \gamma_{SM}\alpha(Sec - Mkt)_{s,t} + \epsilon_t \quad (3)$$

The above regression contains an intercept followed by the excess returns of the market over the risk-free rate (notation as defined before, with $r_{f,t}$ the risk-free rate). The next two terms are, respectively, an instantaneous alpha of the fund over its sector benchmark, and of the sector over the market.

Specifically, to derive these two measures we proceed as follows. We begin by estimating Betas for each of the instantaneous alphas. For $\alpha(Fund - Sec)$, we run the following regression, in the spirit of factor models, for each fund j:

$$(r_{j,t} - r_{f,t}) = \alpha + \beta_{j,s}(r_{s,t} - r_{f,t}) + \beta_{j,m}(r_{m,t} - r_{f,t}) + \epsilon_t \quad (4)$$

This is a standard factor-model regression of the excess returns to fund j on excess returns to its sector benchmark and the market, respectively. We run this regression for each fund j and month t, over a three-year rolling window (i.e. from month $t-35$ to month t). We thus derive, for each fund at each time a $\beta_{j,s,t}$ (three-year Beta of fund j with respect to its sector at time t), and a $\beta_{j,m,t}$ (three-year Beta of fund j

[11]Morningstar, for example, publishes estimates of funds' betas.

with respect to the market at time $t$). Doing these calculations over a rolling window is largely consistent with the practices of data providers such as Morningstar and therefore reflects the type of information that an investor is likely to see.

Then, we calculate the measure of instantaneous alpha (in this case $\alpha(Fund - Sec)$) as:

$$\alpha(Fund - Sec)_{j,t} = (r_{j,t} - r_{f,t}) - \beta_{j,s,t}(r_{s,t} - r_{f,t}) - \beta_{j,m,t}(r_{m,t} - r_{f,t}) \tag{5}$$

In the terminology of factor models, we subtract from the fund's excess returns in a particular period each factor realization the same period multiplied by its respective Beta.[12]

To compute $\alpha(Sec - Mkt)$ we proceed analogously, but estimate a one-factor model of the *sector benchmark* over the market. Specifically we run the following regression:

$$(r_{s,t} - r_{f,t}) = \alpha + \beta_{s,m}(r_{m,t} - r_{f,t}) + \epsilon_t \tag{6}$$

Once again, we run this regression for each sector $s$ at each time $t$ over a three-year horizon, obtaining for each combination a $\beta_{s,m,t}$. Analogously, we then compute a measure of instantaneous alpha as:

$$\alpha(Sec - Mkt)_{s,t} = (r_{s,t} - r_{f,t}) - \beta_{s,m,t}(r_{m,t} - r_{f,t}) \tag{7}$$

The specifications above are driven by first principles. Below we adopt an alternative approach from the recent literature, which allows additional insights related to our hypothesis.

[12]This approach is equivalent to the $\epsilon$ used in Berk and van Binsbergen (2016), and which we compute below.

## 3.2 An Alternative Approach

While the setup in the previous section is driven by our hypothesis of how investors make mutual-fund allocation decisions, the previous setup cannot explicitly reject the competing hypothesis that investors use the CAPM in order to do this. In order to explicitly disentangle this, in this section we adopt the empirical framework of Berk and van Binsbergen (2016), which will allow us to directly trade off these two competing hypotheses, by testing which model better explains flows.[13] The idea behind this framework is to test whether there exists a significant difference in the fraction of flows explained by the CAPM, versus that explained by our information-based model.

For this section, we first re-define the measure of fund flows according to that of Berk and van Binsbergen (2016). Over a horizon of length $T$ this is:

$$F_{i,t} = q_{i,t} - q_{i,t-T}\left(1 + R^V_{i,t}\right), \tag{8}$$

where $R^V_{i,t}$ is defined in Berk and van Binsbergen (2015) as the the projection of fund $i$'s returns on the space of available Vanguard index funds — i.e. the passive alternative investment opportunity. We will take $R^V_{i,t}$ to be the return on the relevant sector benchmark, as constructed in Hartzell, Mühlhofer, and Titman (2016).[14]

Note that the approach in (8) to imputing fund flows, which follows Berk and van Binsbergen (2016), is different from the one we use in the previous section (Eq 2). The approach from the previous section follows the more typical approach in this literature (see e.g. Sirri and Tufano (1998), or Barber, Huang, and Odean (2016)). More typically, fund assets at time $t-1$ would be scaled by the fund's own return, rather

[13]Throughout this section we closely follow the empirical setup of Berk and van Binsbergen (2016) and largely adopt their notation as well.

[14]In Section 5, we show that our results are not sensitive to whether funds' AUMs are scaled by the return on the constructed benchmark or by the return on the appropriate Vanguard ETF. An important reason why we use the benchmarks constructed in Hartzell, Mühlhofer, and Titman (2016) is because it allows us to have a longer time series than the Vanguard ETF benchmarks.

than the return on the fund-mimicking passive portfolio. The usual approach corresponds to a literal measure of investors' explicit actions. If a fund ends a period with more (or less) assets than its own returns can explain, it must be due to investors' fund flows.

To understand the alternative flow measurement approach, we decompose the fund's actual return into two components, the return on the fund-mimicking passive portfolio and the difference between these returns:

$$R_{i,t} = R^V_{i,t} + \Delta R_{i,t}. \tag{9}$$

Thus, (8) can be re-written as

$$F_{i,t} = q_{i,t} - q_{i,t-T}\,(1 + R_{i,t}) + q_{i,t-T}\,\Delta R_{i,t}, \tag{10}$$

where the last "adjustment" term is included in the flow measure of Berk and van Binsbergen (2016) but not in the usual flow measure. Under the assumptions of Berk and Green (2004), the return difference has zero mean in expectation, $\mathbb{E}\left[\Delta R_{i,t}\right] = 0$, so making the "adjustment" has no effect on the level of flows, but is likely to reduce measurement error, as returns on the passive portfolio do not include the idiosyncratic noise present in the fund's actual returns. This is not an innocuous assumption, however, as it holds only in expectation, and only when a fund's risk-adjusted performance is assumed to be zero.

In practice, the passive portfolios are likely to be very highly correlated with most funds, in which case the distinction is not empirically relevant. In some cases, however, funds' performance does deviate materially from the performance of the passive benchmark, and this deviation is positively correlated with risk-adjusted performance. Cremers and Petajisto (2009) demonstrates this by analyzing funds' holdings, while Amihud and Goyenko (2013) employs a simple returns-based analysis. For the sake of consistency, we maintain the definition in (8).

We define the signal of managerial skill on fund $i$ with respect to pricing model $j$ to be

$$\epsilon^j_{i,t+1} = R^e_{i,t+1} - R^j_{i,t+1}, \tag{11}$$

the difference between the fund's excess return and its risk-adjusted return. If model $j$ is a standard linear factor (beta) model, then

$$R^j_{i,t+1} = F^j_{t+1}\,\widehat{\beta}^j_i \tag{12}$$

and

$$\epsilon^j_{i,t} = \prod_{s=t-T+1}^{t}\left(1 + R^e_{i,s} - F^j_s \widehat{\beta}^j_i\right) - 1. \tag{13}$$

We compute this signal of skill conditional on two simple models: a single factor model (CAPM), and a two-factor model that includes both the market return and the sector's benchmark return. While Berk and van Binsbergen (2016) estimate (12) once for each fund, over the entire sample, we employ rolling regressions to estimate the factor loadings in (12) and, in turn, the managerial skill in (13). While this increases the noise in the estimates, it corresponds to the information set actually available to investors in real time and avoids any look-ahead bias.

From this explanation it should become apparent that $\epsilon^j_{i,t}$ computed for the two-factor model, using a one-month time horizon is equivalent to our instantaneous alpha ($\alpha(Fund - Sec)_{j,t}$) from the previous section (Eq 5). Note that in Eq 3 we use both $\alpha(Fund - Sec)$ as well as $\alpha(Sec - Mkt)$ to model flows. Here, on the other hand, we will only use the former term to trade off against CAPM alphas. This choice is consistent with the Berk and van Binsbergen (2016) framework, which conditions flows upon pure fund-level outperformance. It does, however, set a higher hurdle for us, as we need to show that even without the sector-level outperformance our model can explain a larger fraction of flows than the CAPM.

Finally, we estimate

$$\text{sign}\left(F_{i,t}\right) = \gamma_0 + \gamma_1 \left( \frac{\text{sign}\left(\epsilon_{i,t}^{\text{sector}}\right)}{\text{Var}\left(\text{sign}\left(\epsilon_{i,t}^{\text{sector}}\right)\right)} - \frac{\text{sign}\left(\epsilon_{i,t}^{\text{CAPM}}\right)}{\text{Var}\left(\text{sign}\left(\epsilon_{i,t}^{\text{CAPM}}\right)\right)} \right) + \xi_{i,t}. \tag{14}$$

where

$$\text{sign}(x) \quad = \quad \begin{cases} x/|x| & \text{if } x \neq 0 \\ 0 & \text{if } x = 0. \end{cases} \tag{15}$$

From Proposition 5 in Berk and van Binsbergen (2016), $\gamma_1 > 0$ if and only if the two-factor "sector" model is a better pricing model than the CAPM.

# 4 Results

Section 4.1 describes the results of a simple test driven by first principles of whether investors are using all available information. Section 4.2 shows that our results hold using a different approach based on the framework of (Berk and van Binsbergen, 2016). Section 4.3 conducts tests using aggregate sector-level fund flows and finds additional evidence in favor of our argument.

## 4.1 Raw and Risk Adjusted Outperformance

### Raw Outperformance

Table 3 estimates fractional fund flow at time $t+1$ (next month) into a specific sector fund based on returns to the S&P 500 ($S\&P_t$), the difference between returns to the sector benchmark and returns to the S&P 500 ($Sec - S\&P$), and the difference between returns to the fund and returns to the sector benchmark ($Fund - Sec$) (Eq. 1). The columns progressively include additional fixed effects, starting from sector fixed effects in column (2), fund fixed effects in column (3) and time period (month) fixed effects in column (4). The standard errors are clustered at the fund level across all specifications.

Column (1) reports estimates obtained from pooled OLS that weighs all fund equally. The specification shows that sector performance compared to market performance is an important driver of capital flows into sector funds. For each percentage point (pp) over-performance of a sector, the aggregate assets under management (AUM) in the sector increase by 13 basis points (bps). In addition, 1 pp superior performance of a fund compared to its sector leads to an additional 30 bps flow into the fund in the next month. Including fund size is based on Sirri and Tufano (1998) who point out that fund size reduces search costs for retail investors.

A potential concern maybe that our results are driven by a specific sector. Column (2) includes sector fixed effects to address this concern. These consist of Natural Resources ($sec.\mathrm{NR}$), Real Estate ($sec.\mathrm{RE}$), Science and Technology ($sec.\mathrm{TK}$), Telecommunications ($sec.\mathrm{TL}$), and Utilities ($sec.\mathrm{UT}$). Our results remain statistically and quantitatively similar. The most exhaustive specification (Column 4) with fund-level fixed effects and month fixed effects shows that the results remain robust across specifications. Column (4) reports that for each percentage point outperformance of a sector compared to the market, the AUM of a fund in the sector grows by 13 bps. For each pp outperformance of a fund in a sector, the AUM grows by 23 bps, which is approximately twice the sensitivity of the sector outperformance.

### One Factor Risk-adjusted Outperformance

Table 4 reports the estimation results for the specification that uses alphas rather than raw returns (Eq. 3). As before, the dependent variable is fund flow in the next month. The first column shows a pooled OLS estimate. In the second column, we add indicator variables for funds in each sector. We then show a regression with fund fixed effects, and lastly a regression with both fund- and time-period fixed effects. All columns continue to show that investors allocate more funds based on fund performance against the sector and sector performance compared to the market. The most exhaustive specification, i.e., column (4) shows that the sensitivities of additional fund flows in response to sector and fund alphas are quantitatively similar to those in Table 3.

The column reports that for each percentage point outperformance of a sector compared to the market, as measured by alpha of the sector compared to the market index, the AUM of a fund in the sector grows by 15 bps. In addition, for each pp outperformance of a fund in a sector compared to the sector as measured by the alpha of the fund in a one factor (sector) model, the AUM grows by 31 bps. These numbers are statistically and economically significant and are similar in magnitude to those obtained in Table 3. As before the flows are twice as sensitive to fund outperformance with respect to the sector compared to sector outperformance compared to the market.

## 4.2 Alternative Approach

So far, we have shown that a fund flow panel data suggests that investors respond to fund outperformance compared to sector and sector outperformance with respect to the market. However, we have not addressed the question whether this model of fund flows is a better model than another that suggests that investors utilize CAPM. This section compares our sector fund performance model with CAPM and tests whether the former is able to better explain investor behavior.

Table 5 estimates the specification discussed in Eq. 14, which is based on Berk and van Binsbergen (2016). The dependent variable is the sign of index-adjusted fund flow. The first column shows a pooled OLS estimate. In the second column, we add dummy variables for funds in each sector. We then show a regression with fund fixed effects, and lastly a regression with both fund- and time-period fixed effects.

The main variable of interest is the "Diff of Signs" variable which is the difference in signs of fund outperformance measured by the two-factor sector-plus-market model and the one-factor market model. A statistically and economically significant coefficient suggests that the two-factor "sector" model is a better model than CAPM to capture investor allocation of funds.

Column (1) shows that the average investor is responding to the two-factor "sector" fund model as the coefficient of "Diff of Signs" variable is positive and significant. When we include sector fixed effects, the results grow slightly stronger in Column (2). Column (3) shows that inclusion of fund-specific fixed effects still produces a coefficient of similar magnitude. Finally, Column (4) includes time fixed effects as well and the results remain similar in statistical power and magnitude.

## 4.3 Fund flows at the Aggregate Level

So far our results have been obtained using equal weights to all funds. Even though, we have included fund fixed effects, another potential concern maybe that the fund flow results are driven by small and therefore unrepresentative funds. In this section, we therefore utilize aggregate sector-level monthly flows to determine whether these flows respond to sector outperformance compared to the market index.

Table 6 reports the results. In column (1), we include month fixed effects. Column (2) includes month and sector fixed effects. Columns (3) and (4) repeat the exercise with an indicator variable that is 1 if the sector outperforms the market index. Standard errors are clustered at the sector level. Column (1) shows that aggregate fund flows into the sector funds increase by 14 bps for each percentage point outperformance of the sector with respect to the market index. This magnitude is very similar to that obtained in Section 4.1 which conducted an analysis at individual fund level. Columns (3) and (4) estimate the sensitivity based on an indicator variable for whether the sector outperformed the market index, and again find a statistically significant result.

These results suggest that our results are present at fund and sector level flows.

# 5 Additional Discussion and Robustness

Section 5.1 investigates if sector fund investors are very different from investors in non-sector funds by looking at sector-fund return distribution during our sample period. Section 5.2 tests the difference in returns investors who use a two factor sector model compared to a four-factor model. Section 5.3 reports performance sensitivity of sector funds in a non-parametric setting. Section 5.4 conducts additional robustness tests.

## 5.1 Do Sector Fund Investors Under-perform?

Next, we plan to test if sector fund investors are truly different from other investors. As long as the returns obtained by sector fund investors is similar to those obtained by generalist fund investors, our results should have external validity.

Figure 3 reports the four factor risk-adjusted three year rolling alpha of sector funds in the sample. Unit of observation is fund-month and the sample period is from Dec 1999–Dec 2009. The mean four factor alpha is -1.3%, the median is -1.2%, and the standard deviation is 1.06%. The four factor alpha for the 90th percentile fund is -0.04% or about zero. Thus, we believe that sector fund investors are not a self-selected group of irrational investors making decisions that are clearly detrimental to capital protection, and would very much belong in the setup of active portfolio management that Berk and Green (2004) have in mind.

## 5.2 A Horse Race

We conduct a horse race between an investor who uses readily available information, and an investor who utilizes the four factor model to invest. This provides us an idea of the magnitude of loss in return faced by the former investor to obtain an estimate of the cost of information acquisition. This exercise will also provide a welfare estimate of the benefit of better information provision in mutual fund prospectuses.

Figure 4 reports the distribution of returns for an investor who invests next month in the top decile performers in terms of four factor alpha in the current month. Unit of observation is fund-month and the sample period is from Dec 1999–Dec 2009. The universe of funds is all sector funds. It is expected that such a strategy will not deliver outperformance since the literature has shown that mutual fund outperformance in terms of the four factor model is not very persistent (Carhart, 1997; Bollen and Busse, 2005).

Having said that, a comparison shows that a strategy where an investor chases returns based on four-factor alpha has a mean return of -1.68% annually, with a median of -1.63% with the 90th percentile return at 2.18%. An investor who utilizes sector benchmark information and fund benchmark information with a relative loading as given in Column (4) of Table 4, i.e. approximately half the weight on sector outperformance of S&P compared to fund outperformance of sector, will receive an average return of -1.81% with a median of -1.76% and a 90% return of 1.31%.

Thus, the four factor model slightly outperforms, even though the difference during our sample period and for our sample of the universe of sector funds is not statistically significant. The Kolmogorov-Smirnov test yields a p-value of 0.696, which suggests that the null that the distributions are the same cannot be rejected given the small sample size. A t-test of the difference of the mean four factor alphas of the two strategies also provides a statistically insignificant result.

These results again suggest that sector fund investors may be losing a little on performance but not an exorbitant amount, and could be thought of as the investors in the Berk and Green (2004) setup as discussed above in Section 5.1.

## 5.3 Flow-to-Performance Sensitivity of Sector Funds

An important question is whether sector fund performance sensitivity is different from other mutual funds. Empirical literature on equity mutual funds document a convex shape, i.e. fund flows are sensitive to good performance while outflows are not as sensitive to bad performance (see Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003). Recently, Goldstein, Jiang, and Ng (2016) show that bond funds exhibit no such convexity, and the flow-to-performance sensitivity may even be concave.

Figure 5 conducts a non-parametric univariate analysis and reports the flow-to-performance sensitivity of sector funds with respect to alpha of the fund with respect to the sector benchmark, alpha of the sector with respect to the market benchmark, and alpha of the fund with respect to the market benchmark (CAPM), respectively. The leftmost figure shows that, consistent with previous research, we find that sector equity funds exhibit a convex flow-to-performance sensitivity with respect to the benchmark, which is the sector. This univariate analysis thus again shows that sector fund investors are not behaving very differently from investors in other equity funds.

## 5.4 Robustness Tests

Our results are robust to a variety of robustness tests. In particular, Table 7 tests whether our results are driven by a sub-sample of fund-month observations where performance sensitivity is either high or low. The reason may be that investors who are more/less sensitive to short term performance may be different in behavior compared to other investors. Such sensitivity to short-term performance may be related to investor sophistication. Then, for example, more performance-sensitive investors may use the CAPM more or less than the sector benchmark model.

We first calculate the fund flows in the next month scaled by the four factor alpha of the fund in a particular month. Focusing on the sample where the fund flow sensitivity thus calculated is positive, we divide the observations into terciles based on fund flow sensitivity. Columns (1) and (2) report the estimates of (3). We find that funds with lower fund-flow sensitivity respond with lower sensitivities to the two benchmark, and those with higher sensitivity to performance measured by four factor alpha have higher sensitivity to the sector and fund outperformance. However, results remain across the cross-section of observations in a statistically significant manner. Columns (3) and (4) test whether CAPM better described investor behavior in the two subsamples by reporting the coefficients of Eq. (14). Again, by noting the statistically significant and positive coefficient of difference of signs variable in both columns, we find that the sector benchmark model better explains investor behavior in both subsamples.

Table 8 reports the results of a regression where we estimate fund flows against the binary variables of whether funds outperform the sector and whether a specific sector outperforms the market. The results remain similar to those reported in Section 3.1. To address the possibility that investors are not just using a two-factor model that includes the sector benchmark, but the four factor model, Table 9 includes the monthly fund four factor alpha as an additional control. The results obtained in Table 4 remain robust.

# 6 Conclusion

In this paper we shed new light on a puzzling result of recent literature, namely that mutual-fund flows look as if investors are pricing assets through the CAPM. This seems to be happening despite clear theoretical and empirical evidence that multi-factor models provide the best inferences in terms of assessing performance.

We argue that investors, rather than being averse to only market risk, simply pay attention to readily-available information (i.e. benchmark information in mutual-fund prospectuses and on brokerage websites). However, since most mutual funds list a primary benchmark that approximates the market portfolio, in a traditional setting these two hypotheses are observationally equivalent.

We use the natural laboratory of sector funds (which provide a sector benchmark in addition to a market benchmark in their prospectuses) in order to disentangle these two hypotheses. We show empirically that sector-fund flows respond to performance in relation to both the types of benchmark with which investors are confronted. This result holds both on a raw-returns and risk-adjusted basis. We thus find our information hypothesis supported. Next, we show that our information-based model explains a significantly higher fraction of flows than the CAPM. This allows us to statistically reject the hypothesis that investors follow the CAPM, in favor of our information hypothesis. All empirical setups are robust to various model specifications. Further tests reveal that sector-fund performance overall resembles that of mutual funds overall. We further show that selecting funds based on our information model yields returns that are statistically indistinguishable from those realized by selecting funds through a four-factor model. Both these results lend credibility to the setting which we examine and our information hypothesis.

The conclusion which we present in this paper, that investors simply pay attention to the information with which they are confronted, has important implications regarding how to improve investor welfare. This understanding might lead to a policy recommendation to include additional (relevant) benchmark information in the prospectuses of general equity funds to reduce the cost of information acquisition for investors. To our knowledge, our study is the first to present an environment in which it is possible to understand the importance of this aspect of investor decision making, over traditional risk-based explanations.

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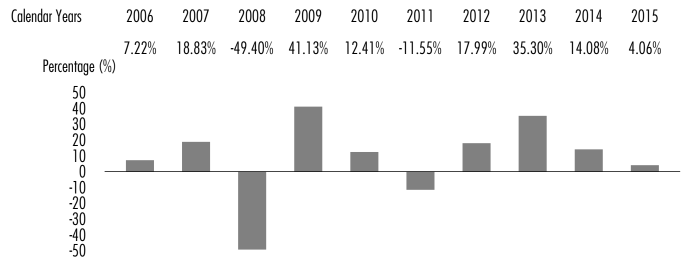
**Year-by-Year Returns**




| *During the periods shown in the chart:* | *Returns* | *Quarter ended* |
|---|---|---|
| *Highest Quarter Return* | *19.09%* | *June 30, 2009* |
| *Lowest Quarter Return* | *–27.07%* | *December 31, 2008* |
| *Year-to-Date Return* | *–2.15%* | *March 31, 2016* |

**Average Annual Returns**

After-tax returns are calculated using the historical highest individual federal marginal income tax rates, but do not reflect the impact of state or local taxes. Actual after-tax returns may differ depending on your individual circumstances. The after-tax returns shown are not relevant if you hold your shares in a retirement account or in another tax-deferred arrangement. Return After Taxes on Distributions and Sale of Fund Shares may be higher than other returns for the same period due to a tax benefit of realizing a capital loss upon the sale of fund shares.

| For the periods ended December 31, 2015 | Past 1 year | Past 5 years | Past 10 years |
|---|---|---|---|
| **Fidelity® Magellan® Fund** | | | |
| **Return Before Taxes** | 4.06% | 10.88% | 5.54% |
| **Return After Taxes on Distributions** | 2.27% | 9.23% | 4.13% |
| **Return After Taxes on Distributions and Sale of Fund Shares** | 3.81% | 8.39% | 4.41% |
| S&P 500® Index<br>**(reflects no deduction for fees, or expenses, or taxes)** | 1.38% | 12.57% | 7.31% |

**Investment Adviser**

Fidelity Management & Research Company (FMR) (the Adviser) is the fund's manager. FMR Co., Inc. (FMRC) and other investment advisers serve as sub-advisers for the fund.

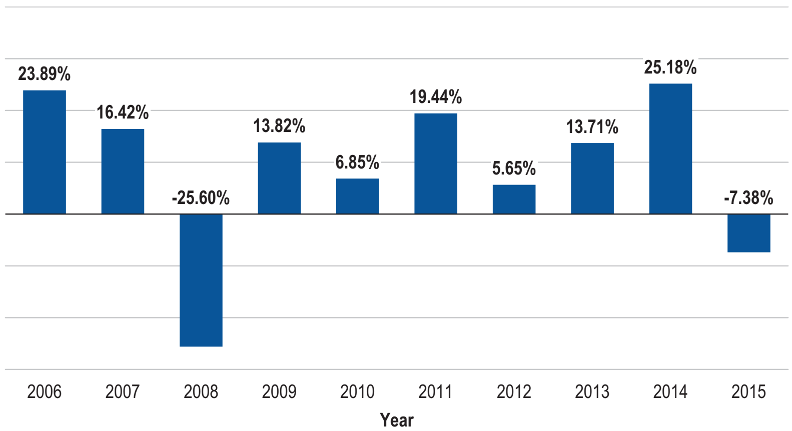
5 *Prospectus*

Figure 1: Performance information from Fidelity Magellan's prospectus.

This figure shows the performance page of an average fund on Morningstar. The page illustrates that besides fund performance, market-index performance is available to investors.

FRANKLIN UTILITIES FUND
SUMMARY PROSPECTUS

**Class A Annual Total Returns**




| | | |
|---|---|---|
| Best Quarter: | Q3'10 | 12.21% |
| Worst Quarter: | Q3'08 | -13.14% |

**Average Annual Total Returns**
(figures reflect sales charges)
For the periods ended December 31, 2015

| | 1 Year | 5 Years | 10 Years |
|---|---|---|---|
| **Franklin Utilities Fund - Class A** | | | |
| Return Before Taxes | -11.33% | 9.77% | 7.59% |
| Return After Taxes on Distributions | -12.66% | 8.75% | 6.64% |
| Return After Taxes on Distributions and Sale of Fund Shares | -5.32% | 7.77% | 6.19% |
| **Franklin Utilities Fund - Class C** | -8.71% | 10.16% | 7.52% |
| **Franklin Utilities Fund - Class R** | -7.75% | 10.32% | 7.68% |
| **Franklin Utilities Fund - Class R6** | -7.15% | 4.90%[1] | — |
| **Franklin Utilities Fund - Advisor Class** | -7.31% | 10.88% | 8.22% |
| S&P 500® Utilities Index (index reflects no deduction for fees, expenses or taxes) | -4.85% | 11.04% | 7.41% |
| S&P 500® Index (index reflects no deduction for fees, expenses or taxes) | 1.38% | 12.57% | 7.31% |

1. Since inception May 1, 2013.

No one index is representative of the Fund's portfolio.

Click to view the fund's prospectus or statement of additional information.

6 | Summary Prospectus franklintempleton.com

Figure 2: Performance information from the Franklin Utilities Fund prospectus. This figure shows the performance information from the prospectus of a typical sector fund. In addition to the fund's historical performance, investors are shown benchmark performance for the overall market (S&P 500) as well as the relevant sector index (S&P 500 Utilities).

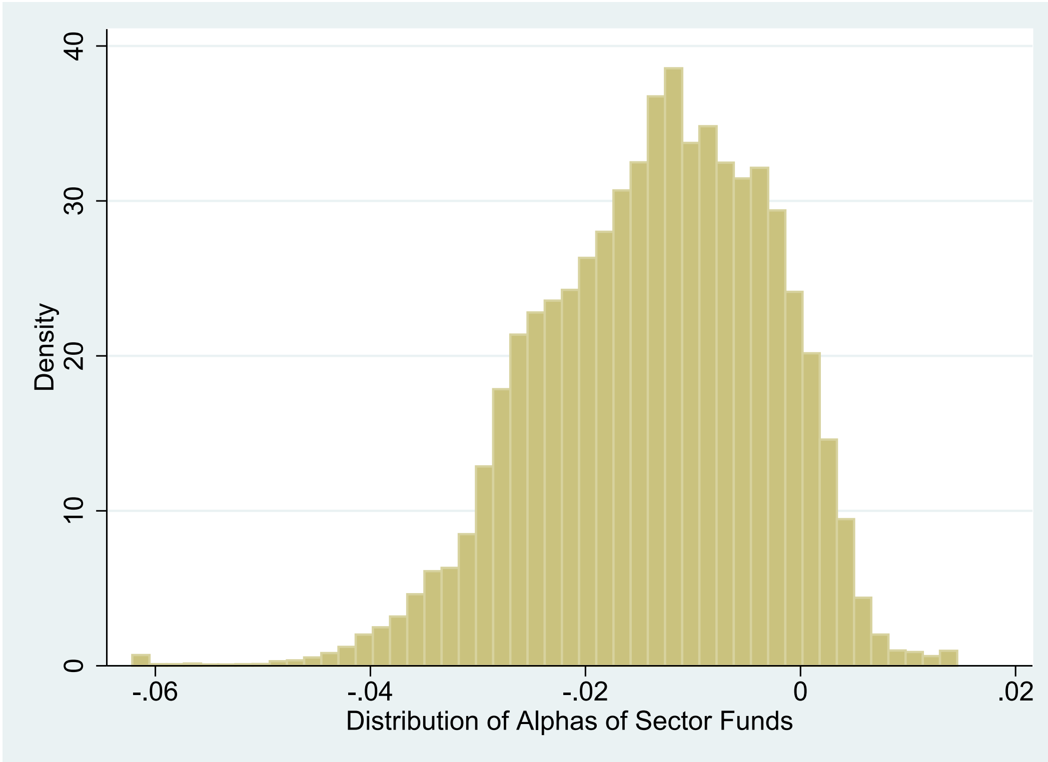



Figure 3: Risk-Adjusted Out-performance of Sector Funds

This figure reports the four factor risk-adjusted three year rolling alpha of sector funds in the sample. Unit of observation is fund-month and the sample period is from Dec 1999–Dec 2009.

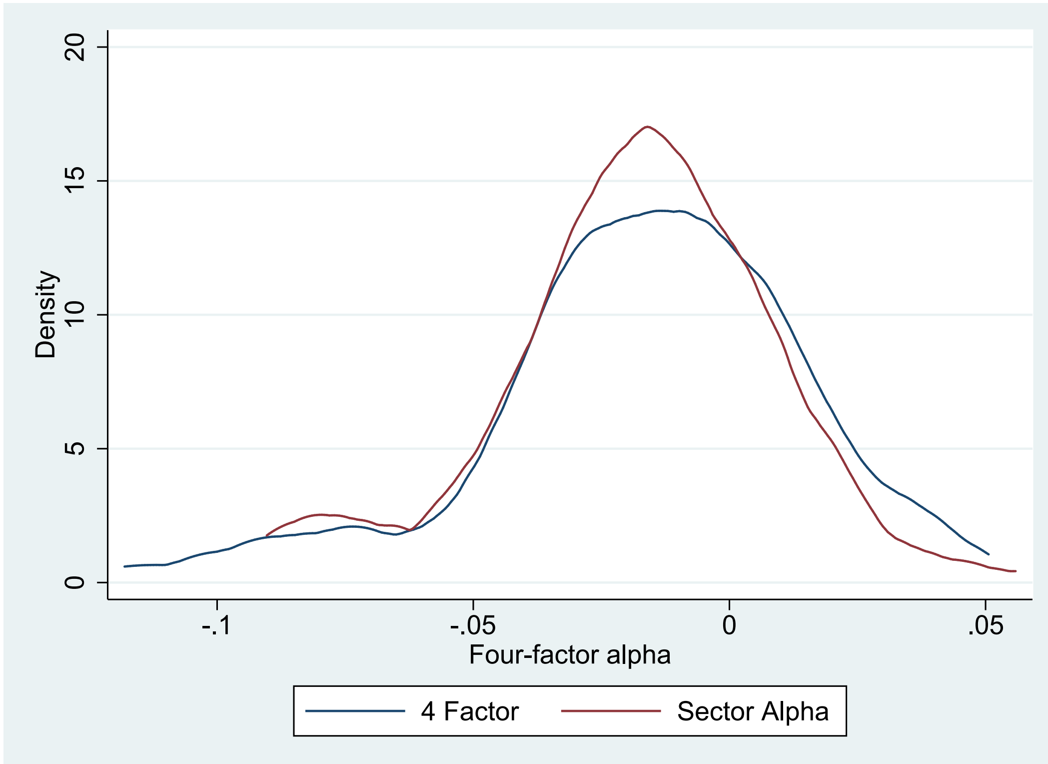



Figure 4: Horse race between the four factor model and sector benchmark model

This figure reports the distribution of returns for an investor who invests next month in the top decile performers in terms of four factor alpha in the current month. Unit of observation is fund-month and the sample period is from Dec 1999–Dec 2009, all sector funds.

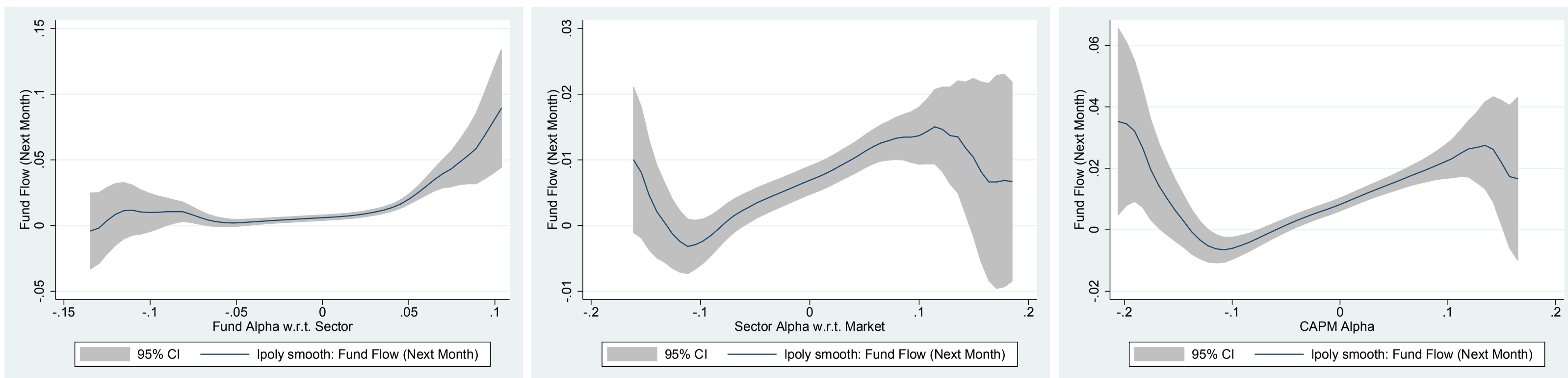



Figure 5: Flow Performance Sensitivity

This figure reports the flow-to-performance sensitivity of Sector Funds with respect to Alpha of the Fund with respect to the Sector Benchmark, Alpha of the Sector with respect to the Market Benchmark, and Alpha of the fund with respect to the Market Benchmark (CAPM), respectively.

Table 1: Cross-correlation table

The table reports the correlation between monthly value weighted sector returns in our sample with monthly returns of the market index.

| Variables | S&P 500 Index | Health & Biotech | Natural Rsrcs. | Real Estate | Science and Tech. | Telecom | Utils. |
|---|---|---|---|---|---|---|---|
| S&P 500 Index | 1.000 | | | | | | |
| Health and Biotech. | 0.765 | 1.000 | | | | | |
| Natural Resources | 0.593 | 0.473 | 1.000 | | | | |
| Real Estate | 0.612 | 0.552 | 0.372 | 1.000 | | | |
| Science and Tech. | 0.836 | 0.615 | 0.483 | 0.392 | 1.000 | | |
| Telecom. | 0.917 | 0.675 | 0.561 | 0.509 | 0.917 | 1.000 | |
| Utilities | 0.822 | 0.718 | 0.744 | 0.525 | 0.603 | 0.736 | 1.000 |

## Table 2: Summary Statistics for Funds by Sector

The table reports summary statistics for all fund-years by sector. For each sector, we list distributional statistics for the number of funds (defined as distinct portfolios, thus combing share classes) active each year, the total value of all equity positions for each fund, the number of unique securities in each portfolio, the number of S&P 500 securities in each portfolio, as well as the number of unique securities and unique S&P 500 securities in each sector universe. Data are obtained from Hartzell, Mühlhofer, and Titman (2016).

| | Mean | Stdev | 1st Quartile | Median | 3rd Quartile |
|---|---|---|---|---|---|
| **Sector Health and Biotechnology**: 71 unique portfolios. | | | | | |
| Number of Funds | 32.85 | 22.6 | 12.75 | 27.5 | 55 |
| Equity Net Asset Value ($ Millions) | 600.4 | 1,821 | 23.31 | 137.4 | 482.2 |
| Number of Unique Securities Held | 62.89 | 37.3 | 41 | 54 | 74 |
| Number of Unique S&P 500 Securities Held | 19.44 | 11.39 | 11 | 19 | 26 |
| Number of Securities in Sector Universe | 220.3 | 67.9 | 165.5 | 243 | 257 |
| Number of S&P 500 Securities in Sector Universe | 39.42 | 12.4 | 25.5 | 41 | 50.5 |
| **Sector Natural Resources**: 38 unique portfolios. | | | | | |
| Number of Funds | 21.7 | 7.901 | 15.75 | 22.5 | 28.25 |
| Equity Net Asset Value ($ Millions) | 401.7 | 1,027 | 33.59 | 96.83 | 330.6 |
| Number of Unique Securities Held | 54.68 | 28.19 | 36 | 49 | 71 |
| Number of Unique S&P 500 Securities Held | 19.81 | 11.94 | 10 | 19 | 27 |
| Number of Securities in Sector Universe | 199.7 | 73.48 | 163.5 | 201 | 240.5 |
| Number of S&P 500 Securities in Sector Universe | 58.37 | 9.305 | 52 | 60 | 65 |
| **Sector Real Estate**: 94 unique portfolios. | | | | | |
| Number of Funds | 43.3 | 28.38 | 13.75 | 59.5 | 67 |
| Equity Net Asset Value ($ Millions) | 373.8 | 877 | 28.87 | 97.88 | 366.3 |
| Number of Unique Securities Held | 45.81 | 24.54 | 32 | 40 | 51.25 |
| Number of Unique S&P 500 Securities Held | 6.536 | 4.098 | 3 | 6 | 10 |
| Number of Securities in Sector Universe | 120.4 | 53.21 | 106 | 144 | 157.5 |
| Number of S&P 500 Securities in Sector Universe | 6.625 | 4.717 | 2 | 5 | 10.25 |
| **Sector Science and Technology**: 156 unique portfolios. | | | | | |
| Number of Funds | 65.5 | 48.37 | 17.75 | 56.5 | 106.5 |
| Equity Net Asset Value ($ Millions) | 446.2 | 1,083 | 17.6 | 84.4 | 342.5 |
| Number of Unique Securities Held | 62.71 | 40.61 | 40 | 54 | 73 |
| Number of Unique S&P 500 Securities Held | 23.67 | 16.06 | 12 | 20 | 31 |
| Number of Securities in Sector Universe | 263.5 | 84.19 | 215 | 270 | 320.5 |
| Number of S&P 500 Securities in Sector Universe | 72.68 | 23.49 | 55 | 70 | 95 |
| **Sector Telecommunications**: 20 unique portfolios. | | | | | |
| Number of Funds | 10.11 | 5.943 | 6 | 10 | 13.5 |
| Equity Net Asset Value ($ Millions) | 205.9 | 338.3 | 12.75 | 71.14 | 266.7 |
| Number of Unique Securities Held | 51.7 | 40.78 | 29 | 42 | 59 |
| Number of Unique S&P 500 Securities Held | 16.83 | 10.81 | 10 | 16 | 21 |
| Number of Securities in Sector Universe | 83.26 | 51.34 | 46 | 80 | 113 |
| Number of S&P 500 Securities in Sector Universe | 29.11 | 14.76 | 19 | 27 | 35 |
| **Sector Utilities**: 46 unique portfolios. | | | | | |
| Number of Funds | 31.3 | 8.591 | 31.5 | 34 | 37 |
| Equity Net Asset Value ($ Millions) | 494.5 | 760.3 | 51.28 | 182.5 | 581.5 |
| Number of Unique Securities Held | 56.05 | 27.17 | 38 | 49 | 70 |
| Number of Unique S&P 500 Securities Held | 28.05 | 14.97 | 19 | 25 | 33 |
| Number of Securities in Sector Universe | 218 | 49.85 | 183 | 227 | 241 |
| Number of S&P 500 Securities in Sector Universe | 91.53 | 42.97 | 63 | 68 | 137.5 |
| **Generalist Funds**: 808 unique portfolios. | | | | | |
| Number of Funds | 410.6 | 163.4 | 302.2 | 450 | 554 |
| Equity Net Asset Value ($ Millions) | 1,329 | 5,037 | 60.45 | 201.8 | 760.7 |
| Number of Unique Securities Held | 142.4 | 195.7 | 57 | 85 | 141 |
| Number of Unique S&P 500 Securities Held | 93.86 | 96.44 | 43 | 64 | 101 |
| Number of Securities in Sector Universe | 3,784 | 829.3 | 3,633 | 3,980 | 4,294 |
| Number of S&P 500 Securities in Sector Universe | 519.2 | 12.1 | 510.8 | 518 | 524.5 |

## Table 3: Benchmark Returns and Fund Flows

Dependent variable: Fund flow, time $t+1$. This table shows regressions of fractional fund flow at time $t+1$, on an intercept, returns to the S&P 500 ($S\&P_t$), the difference between returns to the sector benchmark and returns to the S&P 500 ($Sec - S\&P$), and the difference between returns to the fund and returns to the sector benchmark ($Fund - Sec$). We show for a panel of individual funds, a pooled-OLS regression, a regression with sector fixed effects, a regression with fund fixed effects, and a regression with fund and time-period fixed effects. We use monthly data.

| | Next Month Fund Flows | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $S\&P_t$ | 0.00157 | 0.00277 | 0.0126 | |
| | (0.07) | (0.12) | (0.56) | |
| $Sec_t - S\&P_t$ | 0.131*** | 0.121*** | 0.128*** | 0.134*** |
| | (6.00) | (5.32) | (5.92) | (4.93) |
| $Fund_t - Sec_t$ | 0.302*** | 0.298*** | 0.251*** | 0.233*** |
| | (4.84) | (4.74) | (3.97) | (3.55) |
| log TNA | -0.00837*** | -0.00845*** | -0.0352*** | -0.0366*** |
| | (-7.32) | (-7.49) | (-7.31) | (-7.42) |
| Constant | 0.0417*** | 0.0375*** | 0.139*** | 0.167*** |
| | (7.28) | (6.49) | (7.84) | (7.52) |
| Sector FE | No | Yes | No | No |
| Fund FE | No | No | Yes | Yes |
| Month FE | No | No | No | Yes |
| Observations | 62581 | 62581 | 62581 | 62581 |
| Adjusted $R^2$ | 0.006 | 0.007 | 0.012 | 0.018 |

*t* statistics in parentheses, standard errors are clustered at fund level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Impact of Risk Adjusted Out-performance on Fund Flows

Dependent variable: Fund flow, time $t+1$. This table shows regressions of fractional fund flow at time $t+1$, on an intercept, two risk-adjusted outperformance measures ($\alpha$), first of a fund over its sector benchmark, then of the fund's sector benchmark over the S&P-500, as well as excess returns to the S&P 500 ($S\&P$). $\alpha$ is computed as the difference between realized excess returns in month $t$ minus realized excess returns to a set of benchmarks the same month, each multiplied by its respective Beta. For $\mathtt{fund} - \mathtt{sec}$ the subject returns are the returns to a fund, and benchmarks are the fund's sector benchmark and the S&P 500. For $\mathtt{sec} - S\&P$ the subject returns are the return to the fund's sector benchmark, and the benchmark is the S&P 500. The first column shows a pooled OLS estimate. In the second column, we add dummy variables for funds in each sector. We then show a regression with fund fixed effects, and lastly a regression with both fund- and time-period fixed effects. We use monthly data.

| | Next Month Fund Flows | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\alpha$(fund - sec)$_t$ | 0.308*** | 0.320*** | 0.297*** | 0.312*** |
| | (4.70) | (4.87) | (4.36) | (4.39) |
| $\alpha$(sec - S&P)$_t$ | 0.142*** | 0.138*** | 0.134*** | 0.151*** |
| | (6.27) | (5.61) | (5.60) | (4.89) |
| (S&P - Risk-free)$_t$ | 0.0112 | 0.0111 | 0.0131 | |
| | (0.49) | (0.48) | (0.59) | |
| log TNA | -0.00831*** | -0.00831*** | -0.0350*** | -0.0363*** |
| | (-7.28) | (-7.38) | (-7.28) | (-7.38) |
| Constant | 0.0422*** | 0.0370*** | 0.140*** | 0.163*** |
| | (7.41) | (6.44) | (7.87) | (7.27) |
| Sector FE | No | Yes | No | No |
| Fund FE | No | No | Yes | Yes |
| Month FE | No | No | No | Yes |
| Observations | 62302 | 62302 | 62302 | 62302 |
| Adjusted $R^2$ | 0.006 | 0.007 | 0.012 | 0.018 |

*t* statistics in parentheses, standard errors are clustered at fund level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Regressions of Sign of Index-Adjusted Fund Flow, on Differences of Signs in Outperformance

Dependent variable: sign of Index-Adjusted Fund Flow. This table shows results for a fund-level panel regression of the sign of the index-adjusted flow of funds to a mutual fund, on the difference in signs of fund outperformance measured by the two-factor sector-plus-market model and the one-factor market (CAPM) model. The first column shows a pooled OLS estimate. In the second column, we add dummy variables for funds in each sector. We then show a regression with fund fixed effects, and lastly a regression with both fund- and time-period fixed effects. We use monthly data.

| | Sign of Index-Adjusted Fund Flow | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Diff of Signs | 0.0366*** | 0.0444*** | 0.0425*** | 0.0510*** |
| | (8.77) | (9.25) | (12.17) | (14.40) |
| log TNA | 0.00402 | -0.00329 | 0.0512*** | 0.0547*** |
| | (0.85) | (-0.79) | (5.15) | (5.01) |
| Constant | -0.324*** | -0.372*** | -0.495*** | -0.314*** |
| | (-18.67) | (-12.81) | (-13.61) | (-4.69) |
| Sector FE | No | Yes | No | No |
| Fund FE | No | No | Yes | Yes |
| Month FE | No | No | No | Yes |
| Observations | 62576 | 62576 | 62576 | 62576 |
| Adjusted $R^2$ | 0.004 | 0.031 | 0.006 | 0.036 |

*t* statistics in parentheses, standard errors are clustered at fund level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Table 6: Benchmark Returns and Aggregate Sector Flows

Dependent variable: Fund flow, time $t+1$. This table shows regressions of aggregate fractional fund flow to a value-weighted portfolio of mutual funds in each sector at time $t+1$, on an intercept, and the difference between returns to the sector benchmark and returns to the S&P 500 ($Sec - S\&P$). The first two columns use as a primary independent variable the raw sector outperformance, while the third and fourth columns use an indicator variable equal to one when sector return weakly exceed S&P-500 returns and zero otherwise. We show for a panel of value-weighted fund portfolios (one for each sector), a pooled-OLS regression and a regression with time-period fixed effects. We use monthly data.

| | Next Month Flows into Sector Funds | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Sec_t - S\&P_t$ | 0.143** | 0.143** | | |
| | (4.75) | (4.57) | | |
| $Sec_t \geqslant S\&P_t$ | | | 0.0157** | 0.0153** |
| | | | (4.57) | (4.11) |
| Constant | 0.0135 | 0.0123 | 0.00535 | 0.00463 |
| | (0.69) | (0.61) | (0.29) | (0.24) |
| Sector FE | No | Yes | No | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Observations | 852 | 852 | 852 | 852 |
| Adjusted $R^2$ | 0.342 | 0.343 | 0.341 | 0.341 |

*t* statistics in parentheses, errors clustered at sector level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Table 7: Performance Sensitivity and Fund Flows

This table shows versions of the Risk-Adjusted Outperformance model (Table 4) and the Difference-of-Signs model (Table 5), each using a split of the data by sensitivity of flow to performance. Columns (1) and (2) show the Risk-Adjusted Outperformance model for the least sensitive and most sensitive tercile of flow to performance, respectively. Columns (3) and (4) show this for the Difference-of-Signs model. Fixed effects are as note. We use monthly data.

| | Next Month Fund Flows | | Sign of Index-Adjusted Fund Flow | |
|---|---|---|---|---|
| | (Less Sensitive) | (More Sensitive) | (Less Sensitive) | (More Sensitive) |
| | (1) | (2) | (3) | (4) |
| α(fund - sec)_t | 0.182*** | 3.718*** | | |
| | (26.27) | (11.76) | | |
| α(sec - S&P)_t | 0.136*** | 2.136*** | | |
| | (39.56) | (11.58) | | |
| Diff of Signs | | | 0.0619*** | 0.0259*** |
| | | | (7.42) | (4.15) |
| log TNA | 0.000860*** | -0.0460*** | 0.0574** | 0.0723*** |
| | (4.30) | (-6.40) | (3.24) | (4.25) |
| Constant | 0.000588 | 0.178** | -0.310 | -0.157 |
| | (0.29) | (2.64) | (-1.91) | (-0.95) |
| Sector FE | No | Yes | No | No |
| Fund FE | No | No | Yes | Yes |
| Month FE | No | No | No | Yes |
| Observations | 12603 | 12476 | 12536 | 12403 |
| Adjusted $R^2$ | 0.435 | 0.106 | 0.045 | 0.047 |

*t* statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Table 8: Impact of Signed Outperformance on Fund Flows

Dependent variable: Fund flow, time $t+1$. This table shows regressions of fractional fund flow at time $t+1$, on an intercept, returns to the S&P 500 ($S\&P_t$), and two indicator variables. The first $Sec_t \geqslant S\&P_t$ is equal to one if the difference between returns to the sector benchmark and returns to the S&P 500 is weakly positive and zero otherwise; the second $Fund_t \geqslant Sec_t$ is equal to one if the difference between returns to the fund and returns to the sector benchmark is weakly positive and zero otherwise. We show for a panel of individual funds, a pooled-OLS regression, a regression with sector fixed effects, a regression with fund fixed effects, and a regression with fund and time-period fixed effects. We use monthly data.

| | Next Month Fund Flows | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $S\&P_t$ | 0.0183 | 0.0182 | 0.0263 | |
| | (0.79) | (0.78) | (1.20) | |
| $Sec_t \geqslant S\&P_t$ | 0.0128*** | 0.0118*** | 0.0125*** | 0.0137*** |
| | (6.17) | (5.53) | (6.22) | (5.51) |
| $Fund_t \geqslant Sec_t$ | 0.0130*** | 0.0127*** | 0.00796** | 0.00768** |
| | (4.85) | (4.81) | (3.07) | (2.85) |
| log TNA | -0.00837*** | -0.00847*** | -0.0351*** | -0.0369*** |
| | (-7.31) | (-7.50) | (-7.32) | (-7.46) |
| Constant | 0.0288*** | 0.0262*** | 0.128*** | 0.155*** |
| | (5.36) | (4.77) | (7.39) | (7.16) |
| Sector FE | No | Yes | No | No |
| Fund FE | No | No | Yes | Yes |
| Month FE | No | No | No | Yes |
| Observations | 62582 | 62582 | 62582 | 62582 |
| Adjusted $R^2$ | 0.006 | 0.007 | 0.012 | 0.018 |

*t* statistics in parentheses, standard errors are clustered at fund level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Impact of Risk Adjusted Outperformance on Fund Flows

Dependent variable: Fund flow, time $t+1$. This table shows regressions of fractional fund flow at time $t+1$, on an intercept, three risk-adjusted outperformance measures ($\alpha$), first of a fund over its sector benchmark, then of the fund's sector benchmark over the S&P-500, and then four-factor alpha, as well as excess returns to the S&P 500 (S&P). $\alpha$ is computed as the difference between realized excess returns in month $t$ minus realized excess returns to a set of benchmarks the same month, each multiplied by its respective Beta. For $\mathtt{fund} - \mathtt{sec}$ the subject returns are the returns to a fund, and benchmarks are the fund's sector benchmark and the S&P 500. For $\mathtt{sec} - \mathrm{S\&P}$ the subject returns are the return to the fund's sector benchmark, and the benchmark is the S&P 500. For 4 factor $\alpha$, the subject returns are the returns to the fund, and the benchmark returns are the common asset pricing factors of excess market return, size, book-to-market, and momentum. The first column shows a pooled OLS estimate. In the second column, we add dummy variables for funds in each sector. We then show a regression with fund fixed effects, and lastly a regression with both fund- and time-period fixed effects. We use monthly data.

| | Next Month Fund Flows | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\alpha$(fund - sec)$_t$ | 0.329$^{***}$ | 0.324$^{***}$ | 0.249$^{**}$ | 0.319$^{***}$ |
| | (4.07) | (4.12) | (3.21) | (3.82) |
| $\alpha$(sec - S&P)$_t$ | 0.157$^{***}$ | 0.140$^{***}$ | 0.0983$^{**}$ | 0.156$^{***}$ |
| | (4.41) | (3.92) | (2.77) | (3.58) |
| 4 factor $\alpha_t$ | -0.0273 | -0.00457 | 0.0652 | -0.00981 |
| | (-0.45) | (-0.08) | (1.12) | (-0.14) |
| (S&P - Risk-free)$_t$ | 0.0120 | 0.0112 | 0.0115 | |
| | (0.52) | (0.49) | (0.52) | |
| log TNA | -0.00830$^{***}$ | -0.00831$^{***}$ | -0.0351$^{***}$ | -0.0363$^{***}$ |
| | (-7.28) | (-7.39) | (-7.30) | (-7.40) |
| Constant | 0.0420$^{***}$ | 0.0370$^{***}$ | 0.140$^{***}$ | 0.163$^{***}$ |
| | (7.44) | (6.43) | (7.90) | (7.30) |
| Sector FE | No | Yes | No | No |
| Fund FE | No | No | Yes | Yes |
| Month FE | No | No | No | Yes |
| Observations | 62302 | 62302 | 62302 | 62302 |
| Adjusted $R^2$ | 0.006 | 0.007 | 0.012 | 0.018 |

*t* statistics in parentheses, standard errors are clustered at fund level.

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$