Does Limited Investor Attention Explain Mutual Fund Flows? Evidence from Sector Funds*

Indraneel Chakraborty Alok Kumar
Tobias Mühlhofer Ravi Sastry

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Abstract

Recent mutual fund studies demonstrate that investors utilize the CAPM to allocate capital across various funds. We posit that investors *appear* to utilize the CAPM because funds provide information on market returns and investors use this easily available information due to their limited attention to additional factors. Among sector funds, where both sector and market returns are provided, although sector returns are not risk factors, investors respond to sector information in allocation decisions because it is easily available. Our evidence suggests that mutual funds can improve allocation decisions by providing appropriate fund performance benchmarks.

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Understanding how U.S. households make mutual fund allocation decisions is an important economic question since a growing proportion of aggregate household wealth is allocated to mutual funds. In particular, what fund-level information affects households' fund allocation decisions? Two recent studies (Barber, Huang, and Odean, 2016; Berk and van Binsbergen, 2016) suggest that aggregate investor behavior, as revealed by mutual fund flow data, is best explained by the CAPM.[1] Although this is preferable to some alternatives — e.g., raw-return chasing or simple market adjustment — investors appear to disregard much of the consensus regarding fund performance evaluation and the existence of additional risk factors. Barber, Huang, and Odean (2016) suggest that investor sophistication may explain the findings: investors with limited training or means are less equipped to evaluate fund managers. These findings are potentially puzzling because mutual fund investors exhibit some sophistication as implementing the CAPM requires computation of market betas. Yet, why does their sophistication end at the CAPM and not extend to multifactor models?

To understand this pattern in investor behavior, we investigate which dimension of investor sophistication generates allocation distortions. In particular, investors may (A) strictly prefer the CAPM over the class of multifactor models, or (B) accept multifactor models in principle but utilize the CAPM in practice because they ignore additional factors due to limited attention. We use "unsophisticated" to refer to the investors in hypothesis (A), and we use "underattentive" to refer to the investors in hypothesis (B). The argument behind hypothesis (B) is that, because paying attention is costly, investors limit this cost by utilizing readily available information to make allocation decisions. Further, since the most readily available information to investors is a broad market index, allocation decisions based on available information are observationally equivalent to decisions based on the CAPM. Hypothesis (B) is motivated by the literature that studies the impact of limited investor attention and processing power on financial market outcomes (e.g., Hirshleifer, 2001; Hirshleifer and Teoh, 2003; Barber and Odean, 2008; Cohen and Frazzini, 2008; Hirshleifer, Lim, and Teoh, 2009; Cohen and Lou, 2012).

The two hypotheses above have very different policy implications. If investors are unsophisticated, then financial education, additional regulation of mutual funds, or stronger fiduciary laws may lead to improved retail investor welfare. However, if investors are (merely) underattentive, then all that is necessary is im-

[1] The authors do not conclude that investors actually use the CAPM, but that the CAPM best explains patterns in aggregate fund flows, in comparison to a broad set of multifactor models. For brevity, in our paper we refer to these findings as an investor preference for the CAPM.

proved access to relevant information. This could be provided, either voluntarily or by mandate, by fund companies to investors.

Disentangling hypotheses (A) and (B) is difficult and not possible in the space of general equity mutual funds which is frequently analyzed in the literature. Distinguishing between a preference for the CAPM from reliance on readily available information is confounded in the general equity setting, since broad market indices such as the S&P 500 are good proxies for the market factor in the CAPM and are also the most common fund performance benchmarks.[2] Prior research has shown that investors respond to style category returns (Teo and Woo, 2004), benchmark adjusted fund returns (Sensoy, 2009), and style category adjusted fund returns (Barber, Huang, and Odean, 2016). However, because these style categories and benchmarks are proxies for the Fama-French value and size factors, it is not possible to distinguish sophisticated investors, who accept multifactor models and use them, from attentive investors, who use whatever factor/benchmark information is readily available to them. In the general equity fund setting, these investors are observationally equivalent.

Our innovation in this paper is to use the economic setting of sector funds to investigate why fund investors appear to use the CAPM in their capital allocation decisions. Sector funds provide an ideal setting to examine the potentially puzzling investor behavior and enables an out-of-sample test. Sector funds comprise 10–15% of total assets under management in the U.S. mutual fund industry. In addition to a broad market benchmark, investors in these funds are provided information regarding a sector benchmark.[3] In our tests, we separate the signal regarding the fund manager's skill obtained by comparing fund returns to the sector benchmark from the signal obtained from comparing fund performance with the CAPM/multifactor models. In such a case, the sector benchmark, despite its salience, cannot be considered a priced risk factor. Regardless of whether investors believe in the CAPM or a multifactor model, they should not respond to this placebo.[4]

[2] See Table I in Cremers, Petajisto, and Zitzewitz (2012) for a comprehensive summary of mutual fund benchmarks.

[3] Figure B.2 reports performance and benchmark information for a general equity fund; Figure B.3 reports the same for a sector fund. We do not claim that investors look only at funds' prospectuses for their information. We suggest that information regarding a sector benchmark is readily available to sector fund investors; the propectus is a proxy that demonstrates availability. Sophisticated investors, who by definition are informed, can always obtain returns data for pricing factors and relevant benchmarks.

[4] We compare fund flows to alphas (i.e. fund manager skill estimates) computed using both a baseline pricing model, and the same pricing model augmented by the sector benchmark. The augmented alpha cannot reflect the benchmark's exposure to the included risk factors as we orthogonalize it with respect to the baseline alpha. As shown in Table VI, our finding that investors respond to skill with respect to benchmark stripped of asset pricing information holds with respect to the CAPM and the Fama-French-Carhart model.

Our empirical approach uses a fund-level monthly panel dataset of fund flows in U.S. sector funds from 1999–2016. We test whether a model that includes sector benchmark information is *better* than the CAPM (and the Fama-French-Carhart model) in explaining fund flows. To identify which asset pricing model performs best in explaining investor behavior, we measure abnormal fund returns (alpha) for two competing models, and assess which of the two measures better explains subsequent fund flows. Berk and van Binsbergen (2016) provide a test which focuses on the relation between the *sign* of estimated alphas and the *sign* of subsequent flows. In comparison, Barber, Huang, and Odean (2016) project the *actual* flows onto indicators representing the *decile rank* of estimated alphas. While both approaches are robust to nonlinearities in the flow-performance relation, the former paper's approach — by considering only the sign of fund flows — is also robust to aggregation across funds. In contrast, the latter paper's specification assumes that a single (nonlinear) flow-performance relation holds across all funds. Under this assumption, their test is more efficient statistically. Thus, the two approaches come with a tradeoff between robustness and efficiency. We utilize the strengths of both methods in our tests.

Our results show that investors use sector benchmark returns along with market returns to determine whether managers outperformed in a specific period, and that this model explains fund flows better than the null that the investors are using the CAPM to assess managers. These results obtain in the presence of fund-specific fixed effects, suggesting that differences in fund specific investor priors or other persistent differences such as how the funds are marketed (Del Guercio and Reuter, 2014) are not driving the results. We control for fund size in every period along with fund fixed effects. Thus, differences in skill and returns to scale of managers (Berk and Green, 2004; Berk and van Binsbergen, 2015) do not explain our findings. Inclusion of time fixed effects addresses potential concerns that aggregate economic characteristics or high investor sentiment in certain periods (Chiu and Kini, 2014) are driving the results.

To evaluate the potential welfare loss to investors due to limited attention, we compare the performance of investors who utilize the Fama-French-Carhart four factor model and those who utilize the benchmark model. In our hypothetical horse race, investors redistribute their assets to the funds that finish in the top decile based on the two models in the previous month. Clearly, chasing returns is not a profitable strategy, but our focus is on the difference between the returns from the two strategies. We find that while the mean return is higher for the four-factor model investor (-0.14% monthly) compared to the sector benchmark investor (-0.23% monthly) the distribution of returns is statistically insignificant. A Kolmogorov-Smirnov test does not reject the null that the distributions are the same (p-value of 0.81). This evidence suggests that limited attention investors do not perform much worse, as far as statistical differences are concerned. As paying attention is costly, this statistically insignificant difference may even be acceptable to some retail investors.

In addition to our main results using fund flows, we also conduct an experiment to test our hypothesis out-of-sample using micro-data. An advantage of the experimental setting is that we can conduct within respondent comparisons. The experimental evidence also suggests that when benchmark information is provided, respondents utilize it to make allocation decisions.[5]

Collectively, these findings suggest that investors with limited attention respond to sector benchmarks *because* the information is provided, even though such benchmark returns are not proxies for priced risk factors. Information availability leads to investor usage, conditional on plausible relevance. We do not claim that investors will respond to whatever information is included in fund prospectuses or other materials, however irrelevant. We can not directly test whether investors ignore obviously irrelevant information, as such information is not routinely provided. Choi, Laibson, and Madrian (2010), however, provide evidence that index mutual fund investors place high weight on annualized returns since inception, which supports our hypothesis that investors pay attention to readily available information.

More broadly, our results suggest that investors *appear* to utilize the CAPM in the general equity fund setting because they exhibit limited attention, rather than a conscious adoption of the CAPM. When funds provide them with broad market benchmark returns, investors take the (possibly unintended) cue and use that information to evaluate fund managers. Among sector funds, investors use sector benchmark returns when they are provided, even when they are not informative with respect to any omitted risk factors, and, therefore, should not be used. The reason investors include the benchmark nonetheless is that it is salient, plausibly relevant information. To improve the skill evaluation and capital allocation process, a policy suggestion would be to provide investors with returns for plausible benchmarks and risk factors.

Our findings are consistent with the literature on limited investor attention and processing power (see Hirshleifer, 2001; Hirshleifer and Teoh, 2003, among others). Barber and Odean (2008) show that investors

[5]Given that experimental subjects are not representative mutual fund investors, we interpret these results as additional suggestive evidence only.

respond to information that easily attracts their attention, allowing them to manage the problem of choosing among thousands of possible stock purchases (Odean, 1999). Huberman and Regev (2001) show that investors may pay attention to even stale news if it is reported prominently. At the same time, response to other information that is also important but harder to process is delayed (DellaVigna and Pollet, 2009; Cohen and Frazzini, 2008; Cohen and Lou, 2012), suggesting investor information processing constraints. Investor inattention may even be rational (Sims, 2003, 2006; Stokey, 2009). In the context of capital markets, Abel, Eberly, and Panageas (2013) shows that in the presence of costs to obtain information, a consumer will remain optimally inattentive to the stock market for finite intervals of time.[6] While this literature has argued in favor of optimal inattention over *time* and over *stocks*, we demonstrate that retail investors exhibit limited attention over the *space of benchmarks*, and utilize the ones that are readily available and plausibly relevant in their decision-making process.[7]

In addition, our work relates to the well-established literature on the determinants of flow decisions of mutual fund investors. Barber, Odean, and Zheng (2005) find that when choosing funds, investors pay attention to salient fees such as loads, but not to hidden fees. Bergstresser, Chalmers, and Tufano (2009) investigate whether mutual fund brokers help investors improve allocation, but do not find evidence of such tangible benefits. Christoffersen, Evans, and Musto (2013) find that brokers' incentives have significant effects on mutual funds' flows. Kumar (2009) finds that stock categorization influences investors' allocation decisions. Froot and Teo (2008) find that institutional investors also have style preferences. Bailey, Kumar, and Ng (2011) find that investors who do not pay attention to news trade mutual funds frequently, buy higher expense funds, prefer active funds, and overall achieve lower returns. Extending these findings, our paper shows that fund flows are affected by information costs of obtaining benchmark information.

Our results leave open the question of which pricing model is correct, and consequently which risk-adjustment procedure investors *should* employ. We conclude that if additional benchmarking information were presented to investors, they would alter their capital allocation decisions. Our findings make policy

[6] 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).

[7] The literature has also identified search costs over the space of mutual funds as a determinant of fund flows (Sirri and Tufano, 1998). Beyond mutual funds, for assets in general, Nieuwerburgh and Veldkamp (2010) show that information acquisition costs can rationalize under-diversification.

remedies for sub-optimal investor capital allocation simple. If paying attention requires costly effort, then easier availability of relevant information could be welfare improving.

I Data

We use a monthly panel of sector fund returns as our main dataset with a sample period of Jan 1999–Dec 2016 (observations from Dec 1998 are included to calculate lagged measures). To identify our fund universe, we begin by considering the entire sample of mutual funds in the Center for Research in Security Prices (CRSP) Survivorship-Bias Free Mutual Fund Database. We eliminate index funds. We then look for specialized sector funds, by examining the Lipper Objective Codes to find funds that invest in U.S. equity with strategies that are concentrated in one industry, or sector. Over our time period, the only industry specialty sectors with significant fund presence are *Health and Biotechnology*, *Natural Resources*, *Real Estate*, *Science and Technology*, *Telecommunications*, and *Utilities*.[8] Because sector funds did not appear in significant numbers before the year 1999, we begin our sample from Jan 1999.

I.A Constructing Sector Benchmark Returns

For our study, we need returns data for sector benchmarks. 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. Using returns data for exchange-traded funds (ETFs) in each sector as a proxy for the sector index is infeasible, as many sectors do not have ETFs over the entire time sample. Therefore, we construct our own sector benchmarks as value-weighted portfolios of sector securities (Hartzell, Mühlhofer, and Titman, 2016).

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 then assemble security universes for each of the sectors covered by sector funds, in order to construct value-weighted benchmarks. For some

[8] 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 and do not fit into any of the aforementioned categories.

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 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).[9] The benchmark portfolio for each sector is the value-weighted portfolio of all stocks within the sector, and the returns to this portfolio constitute our sector index.

Our condition that a stock must be held by at least five percent of funds (or two portfolios) to be a part of a sector universe is designed to avoid including equities that are clearly outside of a fund's natural sector universe but are nevertheless held by a small number of managers. For example, at several times in our data set, several real estate funds hold small positions in Microsoft. 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]

I.B Summary Statistics

Panel A of Table I reports summary statistics for our data, for each sector. For comparison, we also report summary statistics for generalist funds, a group of large diversified funds, which closely track the S&P 500. We begin by showing the number of unique portfolios that we identify in each sector. This number ranges from 32 for telecommunications to 205 for science and technology. We identify 1337 unique generalist fund portfolios. The table also reports 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 14 portfolios in the median year, followed by natural resources with 41. Real estate is the second most

[9] As an 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 share securities, as appropriate. For example, many firms that are classified as *Science and Technology* can also be classified as *Health and Biotechnology*, or *Natural Resources*, if these firms develop biotechnology or mineral extraction technology, respectively.

[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, we also find that our benchmark portfolio has a correlation of more than 0.95 with these two indices.

populated sector with 79 funds in the median year. Science and technology is the most populated with 83 funds. Generalist funds are more numerous than any single sector, with a median year featuring 743 portfolios.

The median fund's net asset value is comparable across sectors, at around $100 million. Utilities has a median asset size of $158 million, while health and biotechnology has a median asset size of $177 million. The median generalist fund is also around $227 million in terms of median asset size. As expected, fund distributions exhibit a positive skew.

Panel B of Table I provides descriptive statistics regarding fund and benchmark performance. Data are at a monthly frequency and returns are in decimal points. The summary statistics are for the sample period 1999 to 2016. The average sector fund has positive mean raw return at 0.68 percentage point, but almost no alpha with respect to the Fama-French-Carhart four factor model. Figure 1 reports the four-factor risk-adjusted three-year rolling alphas of sector funds in the sample. The unit of observation is fund-month. Table B.1 reports correlations between monthly value weighted sector returns in our sample with monthly returns of the market index.

I.C Flow-to-Performance Sensitivity of Sector Funds

The tests of which model is better at capturing investors' assessments of fund managers' skill are dependent on the shape of the flow-to-performance relationship in sector funds, i.e. whether the relationship is linear or not. Empirical literature on equity mutual funds documents a convex shape: fund flows are sensitive to good performance while outflows are relatively insensitive to bad performance (see Brown, Harlow, and Starks, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Lynch and Musto, 2003). In contrast, Spiegel and Zhang (2013) argue that the flow response function convexity result is driven by misspecification of the empirical model. The authors conclude that the flow-return relation is linear. Recently, Goldstein, Jiang, and Ng (2016) show that bond funds do not exhibit the convexity observed in equity funds, and the flow-to-performance sensitivity may even be concave.

Figure 2 depicts a non-parametric univariate analysis and reports the flow-to-performance sensitivity of sector funds to alpha of the fund with respect to the sector benchmark, to alpha of the sector with respect to the market benchmark, and to alpha of the fund with respect to the market benchmark (CAPM). In the leftmost panel, 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 shows that sector fund investors do not behave very differently from investors in other equity funds. The middle panel reports the sensitivity of fund flows into the sector with respect to the market. The rightmost panel reports the fund flows with respect to alpha where CAPM is the model to determine skill.

II Methodology

Section II.A describes a preliminary intuitive test which shows that investors are using information when it is made available to them. Section II.B explains why a more robust methodology is called for, and describes the related approaches in the literature. Section II.C presents our primary specification.

II.A A Simple Intuitive Approach

Before considering the more robust methodologies of Berk and van Binsbergen (2016) and Barber, Huang, and Odean (2016), we first implement two simpler pooled specifications that measure the influence — if any — that fund performance relative to a sector benchmark has on subsequent fund flows. In section II.A.1, we measure the relationship between outperformance (fund return minus sector benchmark return) and fund flows. In section II.A.2, we measure the relationship between *risk-adjusted* outperformance and fund flows.

II.A.1 The Simple Information Model

In the case of sector funds, an investor can make choices based on three performance measures available to her: (i) market performance information helps an investor 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 a specific sector, and (iii) fund performance information within a sector helps an investor choose a specific fund. This logic motivates 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 $k \equiv \{j, s, m\}$ (fund index, sector index and market, respectively):

$$flow_{j,t+1} = \gamma_0 + \gamma_m r_{m,t} + \gamma_{sm}(r_{s,t} - r_{m,t}) + \gamma_{fs}(r_{j,t} - r_{s,t}) + \gamma_t + \gamma_j + \varepsilon_{j,t}, \quad (1)$$

In the equation above, the second, third, and fourth terms account for the three components of information that a sector-fund investor has at her disposal, as outlined above. If these information components drive investment choice, we should see each of them statistically affect fund flows. Time and fund fixed effects are denoted by γ_t and γ_j, respectively.

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

$$flow_{j,t} = \left(\frac{TNA_{j,t}}{TNA_{j,t-1}} - 1 \right) - r_{j,t}, \tag{2}$$

where, $TNA_{j,t}$ is the Total Net Assets for fund j at time t.

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 a slower response to fund performance.[11] Thus, our identification strategy requires that at least some investors respond quickly. Since the remaining investors may respond slowly, our results provide a conservative lower bound on the sensitivities.

(1) does not adjust for risk. It is intended to reflect a marginal investor who is not especially sophisticated but who is nevertheless attentive to realized performance.

II.A.2 Risk-Adjusted Outperformance

We modify the simple specification in (1), maintaining the focus on the three salient components of the marginal investor's information set (market return, sector outperformance, and fund outperformance), but measuring each of these after adjusting for risk exposure. The specification is then expressed in terms of

[11] However, Sialm, Starks, and Zhang (2015) show that this possibility of "sticky" flows may not be a major concern. They find that flows into funds from defined contribution assets are more volatile and exhibit more performance sensitivity than non-defined contribution flows. Additionally, there is general evidence that individual investors also exhibit high turnover in their brokerage accounts (Barber and Odean, 2000; Grinblatt and Keloharju, 2000; Ivkovic and Weisbenner, 2009).

alphas rather than the raw return differentials in (1):

$$flow_{j,t+1} = \gamma_0 + \gamma_m(r_{m,t} - r_{f,t}) + \gamma_{fs}\alpha(Fund - Sec)_{j,t} + \gamma_{sm}\alpha(Sec - Mkt)_{s,t} + \gamma_j + \gamma_t + \varepsilon_{j,t}. \tag{3}$$

(3) contains an intercept followed by the excess returns of the market over the risk-free rate (notation as defined before, where $r_{f,t}$ is the risk-free rate). The next two terms are, respectively, alpha of the fund over its sector benchmark, and of the sector over the market. We also include time and fund fixed effects.

The two alpha measures are obtained as follows. We begin by estimating betas for each of the alphas. For $\alpha(Fund - Sec)$, we estimate the following model for each fund j:

$$(r_{j,t} - r_{f,t}) = \alpha + \beta_{j,s}(r_{s,t} - r_{f,t}) + \beta_{j,m}(r_{m,t} - r_{f,t}) + \varepsilon_t. \tag{4}$$

The estimates are obtained 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 with respect to the market at time t). We then calculate the $\alpha(Fund - Sec)$) as:

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

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

$$\begin{aligned} (r_{s,t} - r_{f,t}) &= \alpha + \beta_{s,m}(r_{m,t} - r_{f,t}) + \varepsilon_t \\ \alpha(Sec - Mkt)_{s,t} &= (r_{s,t} - r_{f,t}) - \beta_{s,m,t}(r_{m,t} - r_{f,t}). \end{aligned} \tag{6}$$

While (3) effectively reflects the spirit of our hypothesis, it makes certain implicit assumptions. Section II.B relaxes these assumptions and discusses a robust approach that is our main test.

II.B A Robust Approach

The specifications described in section II.A are intuitive and efficient, conditional on certain assumptions. In particular, (1) and (3) require a linear flow-performance relationship that is common to all funds. To ensure that our results are not an artifact of this assumption, we now consider the more robust methodologies of Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) in some detail.

The primary specification from Barber, Huang, and Odean (2016) is:

$$F_{p,t} = a + \sum_i \sum_j b_{i,j} D_{i,j,p,t} + cX_{p,t} + \mu_t + \varepsilon_{p,t}, \tag{7}$$

where flows for fund p and time t are projected onto a set of control variables, X, and a collection of indicators, D, corresponding to the fund's alpha decile rankings according to two competing models, i and j. For example, if the estimated alpha according to model i is in decile 4 while the estimated alpha according to model j is in decile 7, then $D_{4,7,p,t} = 1$ and $D_{i\neq 4,j\neq 7,p,t} = 0$. This specification abstracts away from the numerical estimates of alpha and considers only relative rankings. It is therefore robust to nonlinearities in the flow-performance relationship.

To assess the relative predictive powers of models of i and j, the authors compare $\sum_{i>j} b_{i,j}$ and $\sum_{i<j} b_{i,j}$. If the difference is statistically significant, then it can be reasonably concluded that one model is more consistent with investors' decisions than the other.[12] Note, however, that the $b_{i,j}$'s are assumed not to depend on the fund — the exact (nonlinear) flow-performance relationship is common to all funds.

The methodology proposed by Berk and van Binsbergen (2016) is robust to this assumption as well, allowing heterogeneous (nonlinear) flow-performance relationships. They estimate:

$$\operatorname{sign}(F_{p,t}) = \gamma_0 + \gamma_1 \left(\frac{\operatorname{sign}\left(\alpha^i_{p,t}\right)}{\operatorname{Var}\left(\operatorname{sign}\left(\alpha^j_{p,t}\right)\right)} - \frac{\operatorname{sign}\left(\alpha^j_{p,t}\right)}{\operatorname{Var}\left(\operatorname{sign}\left(\alpha^j_{p,t}\right)\right)} \right) + \varepsilon_{p,t}, \tag{8}$$

where the nomenclature has been slightly modified to allow straightforward comparison with (7). $\gamma_1 > 0$ if and only if model i is a better pricing model than model j with respect to explaining fund flows. By

[12] An alternative test could impose a monotonicity constraint, such that the b coefficients are weakly monotonic in both i and j. This would still allow for a nonlinear flow-performance relationship, but it would disallow some locally suboptimal behaviors (for example, negative marginal flows for improving rank) that would otherwise be admissible.

considering only the signs of both flows and alphas, (8) makes no assumptions about the functional form of the flow-performance relationship, either within or across funds. Positive alphas should be associated with positive flows, and vice-versa.

While the specification is robust to fund-level heterogeneity, we note that — in keeping with its Berk and Green (2004) frame of reference — it does not control for any potential determinants of flows other than realized performance. In contrast, (7) has an overall mean, a, time fixed effects, μ_t, and fund-level controls, $X_{p,t}$. We include fund and month-year fixed effects and fund-level controls in our tests. Overall, the two approaches are largely consistent. We implement two robust specifications, described in section II.C, that build on the strengths of both previous approaches.

II.C Implementation

To implement a robust specification, we first redefine fund flows. Over a horizon of length T, this is:

$$F_{p,t} = q_{p,t} - q_{p,t-T}\left(1 + R^V_{p,t}\right), \tag{9}$$

where $R^V_{p,t}$ is defined as the projection of fund p's returns on the space of available Vanguard index funds — i.e. the passive alternative investment opportunity. We take $R^V_{p,t}$ to be the return on the relevant sector benchmark. Note that the imputation of fund flows in (9), which follows Berk and van Binsbergen (2016), is different from the one we used in (2). The latter approach, used by other researchers, corresponds to a 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:

$$R_{p,t} = R^V_{p,t} + \Delta R_{p,t}. \tag{10}$$

Thus, (9) can be re-written as

$$F_{p,t} = q_{p,t} - q_{p,t-T}\left(1 + R_{p,t}\right) + q_{p,t-T}\,\Delta R_{p,t}, \tag{11}$$

where the last "adjustment" term is not present in the usual flow measure, i.e., (2).

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

$$\alpha^{j}_{p,t+1} = R^{e}_{p,t+1} - R^{j}_{p,t+1}, \tag{12}$$

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

$$R^{j}_{p,t+1} = F^{j}_{t+1}\,\widehat{\beta}^{j}_{p} \tag{13}$$

and

$$\alpha^{j}_{p,t} = \prod_{s=t-T+1}^{t} \left(1 + R^{e}_{p,s} - F^{j}_{s}\widehat{\beta}^{j}_{p}\right) - 1. \tag{14}$$

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 one could estimate (13) once for each fund, over the entire sample, we employ rolling regressions to estimate the factor loadings in (13) and, in turn, the managerial skill in (14). Our approach increases the noise in the estimates. At the same time, it corresponds to the information set actually available to investors in real time and avoids any look-ahead bias.

Finally, in addition to estimating (8) as a test for the limited attention hypothesis, we draw upon the strengths of both approaches and develop a hybrid specification. We compute decile ranks for funds with respect to both the CAPM and the sector model, as in Barber, Huang, and Odean (2016). Then, we create an indicator variable $D_{i,j,p,t}$ that equals one when the decile rank according to model i is higher than the decile rank according to model j. This effectively collapses the upper off-diagonal 45 cells of the 10×10 matrix into a single statistic and allows us to conduct a joint test of the superiority of the sector fund model over the CAPM. We estimate the following specification:

$$\operatorname{sign}(F_{p,t}) = a + b_{i,j}D_{i,j,p,t} + cX_{p,t} + \mu_t + \eta_p + \varepsilon_{p,t}, \tag{15}$$

As the cells have non-linear flow effects, Barber, Huang, and Odean (2016) compare the differences in a pairwise manner and report the sum of coefficient differences. We sidestep this issue by utilizing the sign of fund flows, as in Berk and van Binsbergen (2016), allowing for robust aggregation across funds.

III Results

This section presents our main result: investors are responding to readily available information — rather than explicitly adopting the CAPM or any other pricing model — when making fund flow decisions. Section III.A reports the results of the simple and intuitive tests described in Section II.A. Section III.B reports the results of our main test and shows that a model that includes the sector benchmark is better able to explain fund flows than the CAPM. Section III.C utilizes a nested model test to provide further evidence that investors use additional information provided by the sector benchmark when making investment decisions.

III.A Raw and Risk Adjusted Outperformance

We first test whether investor fund flows in sector funds respond at all to raw sector benchmark returns. Then, we risk-adjust the returns and test the sensitivity of fund flows to sector benchmark returns. Note that this section cannot test whether the sector benchmark model is able to better explain fund flows that the CAPM or any other model. Section III.B explicitly tests which model is better able to explain investor behavior.

III.A.1 Raw Outperformance

Table II 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-year) fixed effects in column (4). The standard errors are clustered at the fund level across all specifications.

Column (1) reports estimates obtained from a pooled OLS model that puts equal weight on all funds. 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) of sector outperformance, the aggregate assets under management (AUM) in the sector increase by 20 basis points (bps). In addition, one pp of superior performance of a fund compared to its sector leads to an additional 36 bps flow into the fund in the next month. Fund size is included following Sirri and Tufano (1998), who point out that fund size reduces search costs for retail investors. The negative coefficient shows that larger funds have lower fund flow sensitivity. A potential concern may be that our results are driven by a specific sector. Column (2) includes sector fixed effects to address this concern. Our results remain statistically and quantitatively similar. Column (3) includes fund fixed effects. The results remain similar in magnitude. This shows that persistent fund specific characteristics are not driving our results: within funds, periods with higher sector benchmark returns (relative to the market return) experience higher fund flows.

The most exhaustive specification (Column 4) with fund-level fixed effects and month fixed effects shows that the results remain robust across specifications. Thus, even after controlling for persistent fund-level characteristics and aggregate characteristics that include S&P 500 returns and additional economic outcomes, we find that the fund flows show similar sensitivity to sector benchmark returns. 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 21 bps. For each pp outperformance of a fund in a sector, the AUM increases by 34 bps.

III.A.2 One Factor Risk-adjusted Outperformance

Table III reports the estimation results for the specification that uses alphas rather than raw returns (Eq. 3). Column (1) reports estimates obtained from a pooled specification. It shows that for each pp increase in the alpha of a fund with respect to the sector benchmark, the fund flows increase by 32 bps in the next month. In addition, for each pp increase in the alpha of the sector compared to the market, fund flows increase by 19 bps. Column (2) includes sector fixed effects and obtains similar qualitative and quantitative results. Column (3) obtains similar results in a within fund framework.

Column (4), which is the most exhaustive specification with fund and month-year fixed effects, reports that for each pp outperformance of a sector relative to the market, as measured by the alpha of the sector compared to the market index, the assets under management (AUM) of a fund in the sector grow by 20 bps.

In addition, for each pp outperformance of a fund in a sector relative to the sector as measured by the alpha of the fund in a one factor (sector) model, the AUM grows by 34 bps. These numbers are statistically and economically significant and are similar in magnitude to those obtained in Table II. As before the flows are twice as sensitive to fund outperformance with respect to the sector as they are to sector outperformance with respect to the market.

III.B Robust Approach

The results above provide evidence that investors utilize sector benchmark data when making allocation decisions. To establish that a model that includes sector benchmarks is "better" at explaining fund flows than the CAPM, we use the semi-parametric approach of Berk and van Binsbergen (2016). The authors point out that whenever mutual fund investors observe a manager out- or under-performing the benchmark, investors update their signal about the manager's talent. In turn, the fund will experience a corresponding inflow or outflow. However, without assumptions regarding the distribution of investors' priors and posteriors, and the fund's (presumably decreasing) return to scale function in terms of AUM, the magnitude of the capital response is hard to quantify. A way to sidestep the issue is to focus only on the direction of the capital response. The sign of the realized return outperformance given the null of a specific model and the sign of the capital inflows should correlate positively. To compare two models, i and j, (8) regresses the sign of capital flow on the difference in the standardized signs of fund outperformance with respect to models i and j.

Table IV presents the results. The main variable of interest is "Diff of Signs" 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 the CAPM to capture investor allocation of funds. An important note is that this approach is applicable when comparing models which may be behavioral in nature. In our case, we argue that investors respond to sector benchmarks when that information is provided, despite sector returns not being priced risk factors. The first column shows a pooled OLS estimate. In the second column, we add indicator variables for funds in each sector. This addresses concerns regarding persistent differences in sectors regarding fund flows. Column (3) reports a regression with fund fixed effects, which controls for time-independent differences in returns to scale of funds and distribution of investors' priors and posteriors. Column (4) provides a regression with both fund- and time-period fixed effects. All specifications include fund size to address search cost differences (Sirri and Tufano, 1998) and differences in returns to scale of funds (Berk and Green, 2004; Stambaugh, 2014; Pastor, Stambaugh, and Taylor, 2015).

Column (1) shows that the coefficient on "Diff of Signs" is positive and significant. This suggests that investors use the sector benchmark along with market returns to determine whether the manager outperformed in a specific period, and that this model explains fund flow signs better than the null that the investors are using the CAPM to evaluate the skill of fund managers. Column (2) includes sector fixed effects and obtains similar results. Column (3) includes fund-specific fixed effects. The coefficient remains similar in magnitude, suggesting that differences in fund specific investor priors or posteriors or other persistent differences such as how the funds are marketed (Del Guercio and Reuter, 2014) are not driving the results. In addition, the presence of fund size in every period as an additional control along with the fund fixed effects suggests that differences in skill and returns to scale of managers (Berk and Green, 2004; Berk and van Binsbergen, 2015) do not explain away the results. Finally, Column (4) includes time fixed effects to address the possibility that aggregate economic characteristics or high investor sentiments in certain periods (Chiu and Kini, 2014) are driving the results. The results remain similar in statistical power and magnitude.

Table V utilizes a hybrid approach as described in Section II.C. We rank funds based on how they perform with respect to both the CAPM and the sector model, as in Barber, Huang, and Odean (2016). Then, we create an indicator variable that equals one when the sector model rank is superior to the CAPM rank. The indicator variable collapses the upper off-diagonal cells into one metric and allows for a joint test. We regress the indicator variable on the sign of fund flows to compare the models in a manner that allows robust aggregation across funds.

Columns (1) and (2) report the estimates when we divide outperformance into deciles as in Barber, Huang, and Odean (2016). We also conduct robustness tests in columns (3) and (4) where we divide the funds into terciles. This is a more stringent test because the disagreement has to be stronger: top tercile by sector fund rank and bottom tercile by CAPM. Columns (1)–(4) confirm that when the two models disagree with respect to the quantile rank of alpha, investors allocate capital in the direction of the sector model alpha.

III.C A Nested Model Test

Another approach to test whether investors exhibit limited attention but utilize additional information when it is easily available, is to test if a model that nests additional information regarding sector benchmarks is a better predictor of fund flows. Hence, we nest the alpha estimated with respect to the sector benchmark in a specification that uses the CAPM alpha to explain the fund flows. Given the non-linearities in fund flows, we again use the nested specification to predict the sign of fund flows. Further, given that the skill of a fund manager estimated against the sector benchmark may have a correlated component with the skill estimated using the CAPM, we take the component of alpha that is orthogonal to the alpha estimated using the CAPM. The specification is below:

$$\text{sign}(flow_{j,t+1}) = \gamma_0 + \gamma_{fm}\alpha(Fund - Mkt)_{s,t} + \gamma_{fs}\text{Orthog.}\alpha(Fund - Sec)_{j,t} + \varepsilon_{j,t}. \tag{16}$$

Panel A of Table VI reports the results. The CAPM α and orthogonalized α compared to the sector benchmark are standardized. Comparing the adjusted R^2 in columns (1) and (2), we note that the skill of the manager estimated using the sector benchmark, even after orthogonalization, explains almost the same amount of the variance in the sign of next month fund flows as the CAPM alpha. When we include fund and month fixed effects, we obtain similar increases in explanatory power between columns (3) and (4).

To test whether the nested model is superior we conduct a two-step test. First, we regress the sign of fund flow on the controls (fund size, fund fixed effects, year-month fixed effects). We then include the CAPM α, and finally the orthogonalized sector α. We calculate both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion. In both cases, the criteria suggest that the relative likelihood of the model with only the CAPM α being the right model over the model with the orthogonalized α is statistically negligible.

Panel A orthogonalizes fund alpha with respect to the CAPM — in line with the conclusions of Barber, Huang, and Odean (2016) and Berk and van Binsbergen (2016) — while, for the sake of robustness, panel B orthogonalizes fund alpha with respect to the alpha calculated using the four-factor model. The potential concern is that the benchmark could be a collection of factors, and hence investors responding to it are simply responding to a multifactor model. For example, Moskowitz and Grinblatt (1999) find that sector funds may be betting on momentum. Hence, to demonstrate that investors are responding to information beyond the projection of any omitted factors on the benchmarks, we orthogonalize the skill of the manager measured by the alpha of the fund with respect to the skill of the manager as measured by the Fama-French-Carhart model. A comparison of columns 1 and 2 in Panel B shows that the skill inferred from the orthogonalized alpha explains at least as much of the variance in fund flow direction as the Fama-French-Carhart alpha. This supports our conclusion that investors use benchmarks to estimate fund manager skill over and beyond their preferred asset pricing model. As before, we conduct a two-step test to compare the models. Both AIC and BIC suggest that including the orthogonalized sector α is the preferred model.

IV Additional Discussion and Robustness

Section IV.A tests the difference in returns of investors who use a two-factor sector model compared to a four-factor model. Section IV.B conducts tests using aggregate sector-level fund flows and finds additional evidence in favor of our limited attention argument. Section IV.C provides additional experimental evidence. Section IV.D conducts additional robustness tests.

IV.A A Horse Race

We conduct a horse race between an investor with limited attention who uses readily available information, and an investor who utilizes the four-factor model to invest. This provides an estimate of the magnitude of investors' losses in risk-adjusted returns as well as 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. We do not believe that an investor should chase returns as in this exercise as monthly returns provide a noisy signal of the skill of the manager. As we note below, chasing returns in both cases lead to negative mean returns. The calculations below are for comparison of the models only.

Figure 3 reports the distribution of returns for an investor who invests next month in the top decile performers in terms of the four-factor alpha in the current month. The universe of funds is all sector funds. It is expected that such a strategy will not deliver strong 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).

A comparison shows that a strategy where an investor allocates capital based on the four-factor alpha has a mean return of -0.14% monthly. An investor who utilizes sector benchmark information and fund benchmark information with a relative loading as given in Column (4) of Table III, i.e. approximately half the weight on sector outperformance of S&P compared to fund outperformance of sector, will receive an average return of -0.23% monthly. Thus, the four-factor model slightly outperforms, even though the difference during our sample period and for our universe of sector funds is not statistically significant. A Kolmogorov-Smirnov test yields a p-value of 0.81, which suggests that the null (that the distributions are the same) cannot be rejected in our sample. A t-test of the difference of the mean four-factor alphas of the two strategies also provides a statistically insignificant result.

These results suggest that sector fund investors are giving up a small amount of returns, and welfare, as a result of limited attention.

IV.B Fund Flows at the Aggregate Level

The results in Section III have been obtained using equal weights on all funds. Though we have included fund fixed effects, a potential concern may be that the fund flow results are driven by small, and therefore, under-representative funds. We now utilize aggregate sector-level monthly flows to determine whether these flows respond to sector outperformance compared to the market index.

Table VII 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 one 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 15 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 III.A which conducted an analysis at the individual fund level. Columns (3) and (4), using an indicator variable, again find statistically significant results.

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

IV.C Additional Experimental Evidence

Our empirical results are based on fund level data. In this section, we conduct an out-of-sample micro-level test of our argument that availability of information regarding benchmarks affects investment choices. A benefit is that we are able to control for respondent characteristics and conduct within respondent comparisons. An important caveat, which is generally applicable, is that experimental subjects are not representative of mutual fund investors. Therefore, the results in this section are only suggestive.

IV.C.1 Experimental Setup and Design

We conduct an online survey on the Amazon Mechanical Turk (mTurk) platform.[13] The survey recruited a sample of 149 individuals living in the U.S.[14] We collect demographic characteristics that include age, gender, race, and education. In addition, we collect financial information such as income, employment status, industry of employment, investing experience, and risk tolerance. Summary statistics of the complete set of respondent characteristics are provided in Panel A of Table VIII.

In a randomized control trial, the main task we assign to the participants is to allocate $100 into three funds: a fund investing in government securities, a generalist mutual fund, and a sector fund. Each respondent is provided five allocation scenarios where the performance numbers are randomly drawn from uniform distributions. In each scenario respondents are given performance figures for the government fund, the generalist fund, a market index, and the sector fund. The returns are drawn from independent uniform distributions. Market and sector returns are drawn from an interval of $[0\%, 20\%]$, where return of government securities range from 0% to 4%. Further, the treatment group only is also provided performance figures for a sector index. Given their respective performance figures, respondents are then asked to allocate their capital. The summary statistics of allocation decisions are also provided in Panel A of Table VIII. Appendix A provides additional details and Figure A.1 shows the screens viewed by respondents.

[13] Recent studies that use the same platform include Horton, Rand, and Zeckhauser (2011) and Kuziemko, Norton, Saez, and Stantcheva (2015), among others. Casler, Bickel, and Hackett (2013) compared the online responses of participants recruited via Amazon's Mechanical Turk (MTurk), social media, and face-to-face behavioral testing, and found that mTurk respondents are more diverse, yet their behavioral test results are indistinguishable from the other groups of participants.

[14] The survey on average lasted approximately 5 minutes 18 seconds. Participants received 75 cents, which is competitive in the mTurk marketplace.

IV.C.2 Experimental Findings

Using the allocation decisions of survey respondents, we conduct two simple tests. First, we test a relevance condition: whether the presence of information regarding benchmarks affects allocation decisions at all. This test can shed some light on why many investors do not invest in sector funds: they may find information about sector funds difficult to obtain because paying to attention to a new class of funds requires costly effort.

Column (1) of Panel B in Table VIII reports that in presence of the treatment of benchmark information, survey investors allocate on average 6.3% of their portfolio to sector funds. This result remains similar after including fund and market performance metrics in column (2), demographic controls (age, income, education, marital status, gender, race and state of residence) in column (3), and financial controls (home owner status, employment status, industry of employment, investing experience, investing experience in mutual funds and risk aversion) in column (4). Thus, the presence of information regarding benchmark returns positively affects allocation to sector funds on average. In column (4), our most exhaustive specification, investors allocate approximately 5.1% of their portfolio to sector funds in the presence of benchmark information.

Second, we test *how* the presence of benchmark information affects investment decisions. To compare the experimental data with real fund level data, we run an analysis similar to that of Section III.A (Table II) within the subset of survey respondents who received sector benchmark performance information. Panel C of Table VIII reports the results. Since the portfolio allocation decision requires investors to allocate between government securities and the equity market (both market fund and sector fund), we find that when the market performs well, investors invest more in equities. In addition, as in Table II, we find that investors respond in a statistically and economically significant manner to the fund outperformance with respect to the sector and sector outperformance with respect to the market.

An important observation is that even after controlling for variation in demographic characteristics in column (2) and financial characteristics in column (3), the results obtain. The results that investors respond to the fund outperformance with respect to the sector and the sector outperformance with respect to the market obtain even after all individual investor fixed effects are included in column (4). This finding is consistent with the argument that inherent differences between sector fund investors and other investors are not driving the allocation results. In sum, the experiment provides suggestive evidence in support of the argument that if investors are provided plausibly relevant information (such as the sector benchmark), they respond to it, and that this might generalize to the space of general equity funds.

IV.D Robustness Tests

Table IX tests whether our results are driven by a subsample of fund-month observations, in which performance sensitivity is either high or low. It may be that investors who are more/less sensitive to short-term performance may behave differently compared to other investors. Such sensitivity to short-term performance may be related to investor sophistication. In this case, 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 Eq. (3). We find that funds with lower fund-flow sensitivity respond with lower sensitivities to the two benchmarks, and those with higher sensitivity to performance measured by four-factor alpha have higher sensitivity to the sector and fund outperformance. However, our results remain statistically significant in the cross-section of observations. Columns (3) and (4) test whether the CAPM better describes investor behavior in the two subsamples by reporting the coefficients of Eq. (8). Again, by noting the statistically significant and positive coefficient of the difference of signs variable in both columns, we find that the sector benchmark model better explains investor behavior in both subsamples.

Table X 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 II.A. 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 XI includes the monthly fund four-factor alpha as an additional control. The results obtained in Table III remain robust.

V Conclusion

We shed new light on a puzzling finding in the recent mutual fund literature, namely that mutual fund flows suggest that investors are utilizing the CAPM to allocate funds, despite the consensus that multifactor models provide better performance assessment. We show that investors, rather than consciously accepting and utilizing the CAPM, exhibit limited attention and therefore pay attention, and respond, to readily available information. Since most mutual funds list a primary benchmark that approximates the market portfolio, it *appears* as if investors are utilizing the CAPM.

We use the natural laboratory of sector funds, which provide a sector benchmark in addition to a market benchmark, to disentangle the limited attention hypothesis from a belief in the CAPM. Our results show that investors respond to the sector benchmarks to evaluate fund managers. We also conduct an experiment to obtain supporting evidence. The results again suggest that when provided, investors use benchmark information to allocate funds.

The conclusion of this paper — that investors exhibit limited attention and therefore respond to salient and plausibly relevant information — has important policy implications. Mutual funds may want to provide additional relevant benchmark information to fund investors. This will reduce the cost of information acquisition for investors exhibiting limited attention and assist them to better allocate funds.

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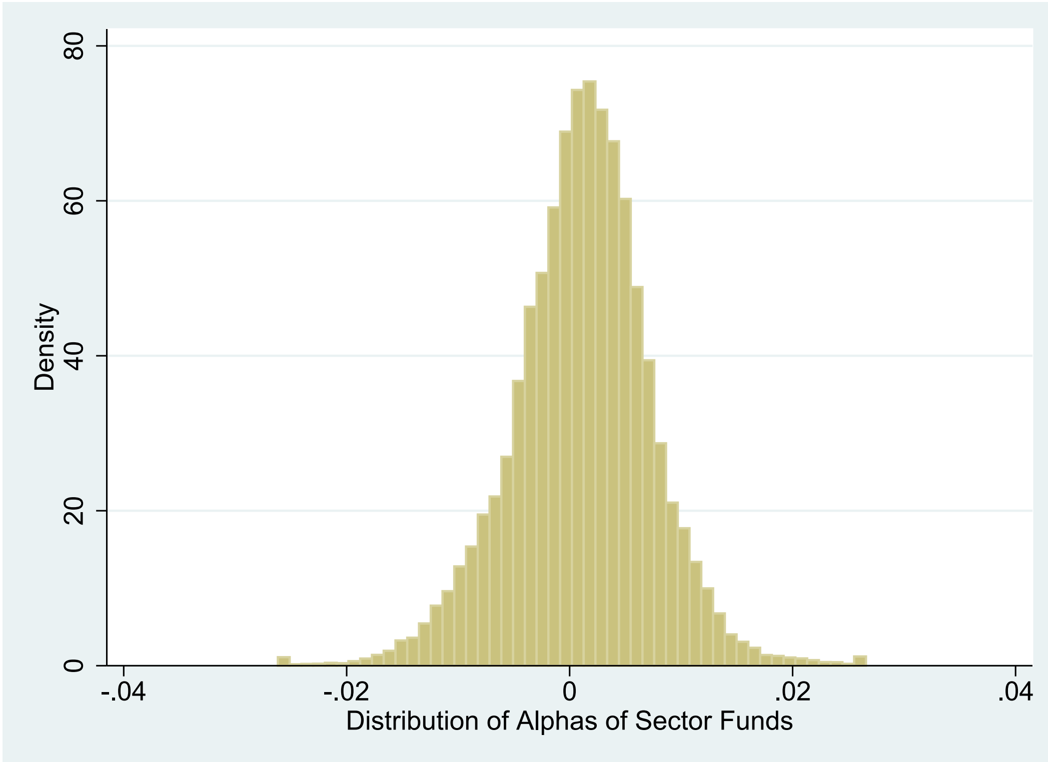


Figure 1: Risk-Adjusted Out-performance of Sector Funds

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 Jan 1999–Dec 2016.

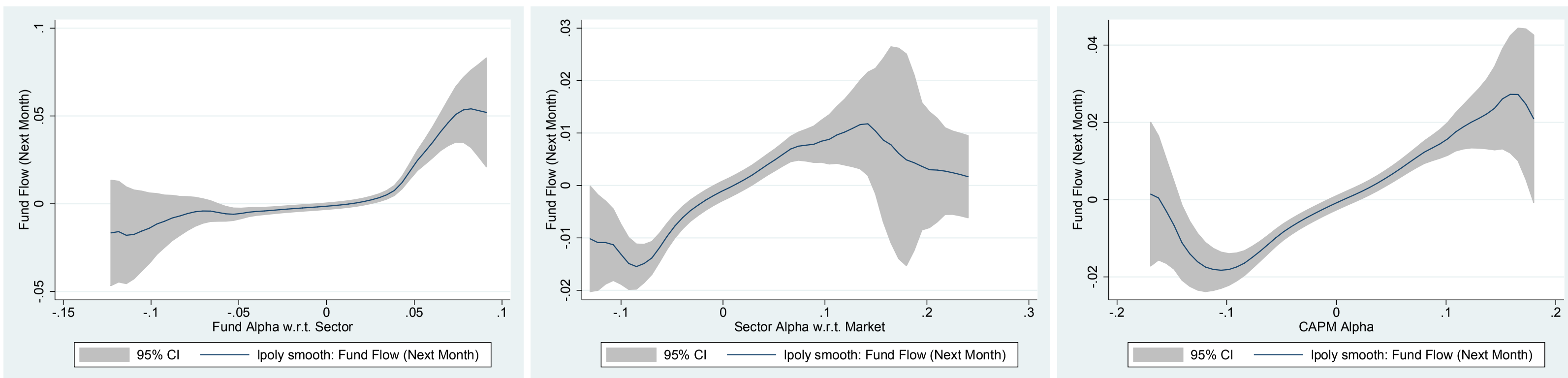


Figure 2: Flow Performance Sensitivity

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.

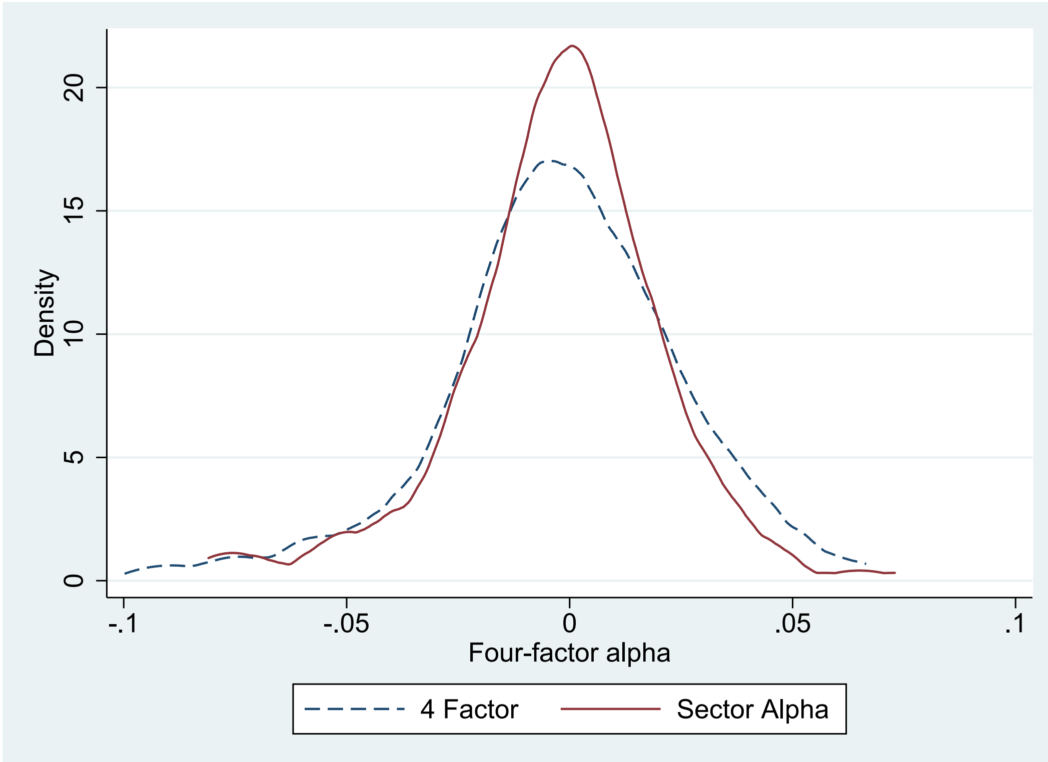


Figure 3: Horse race between the four factor model and sector benchmark model

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. The unit of observation is fund-month and the sample period is from Jan 1999–Dec 2016, all sector funds.

Table I: Summary Statistics

Panel A: 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. The data sample period is 1999–2016.

	Mean	Stdev	1st Quartile	Median	3rd Quartile
Sector Health and Biotechnology: 104 unique portfolios.					
Number of Funds	44.9	26.94	15	51	68
Equity Net Asset Value ($ Millions)	808.1	2,445	32.51	177.7	630.2
Number of Unique Securities Held	61.92	40.86	37	52	74
Number of Unique S&P 500 Securities Held	20.51	13.46	9	18	27
Number of Securities in Sector Universe	232.2	66.31	212.8	250	276
Number of S&P 500 Securities in Sector Universe	42.32	12.3	28.25	47	52
Sector Natural Resources: 97 unique portfolios.					
Number of Funds	47.31	29.06	22	41	81
Equity Net Asset Value ($ Millions)	576.7	1,326	39.27	129.6	576.6
Number of Unique Securities Held	50.58	27.17	31	45	65
Number of Unique S&P 500 Securities Held	20.26	12.45	10	19	29
Number of Securities in Sector Universe	218.7	61.53	198.8	235.5	259.5
Number of S&P 500 Securities in Sector Universe	69.18	10.63	65	72.5	76.5
Sector Real Estate: 162 unique portfolios.					
Number of Funds	70.97	46.11	25	79	111
Equity Net Asset Value ($ Millions)	575.2	2,474	27.56	104.7	442.7
Number of Unique Securities Held	46.38	27.5	33	41	53
Number of Unique S&P 500 Securities Held	10.46	10.3	6	11	14
Number of Securities in Sector Universe	121.5	49.23	117.2	137	153.5
Number of S&P 500 Securities in Sector Universe	10.92	7.918	3	10.5	18.25
Sector Science and Technology: 205 unique portfolios.					
Number of Funds	82.14	52.49	25	83	128
Equity Net Asset Value ($ Millions)	450	1,115	23.29	89	358.1
Number of Unique Securities Held	64.4	49.19	38	52	75
Number of Unique S&P 500 Securities Held	25.8	18.56	13	21	33
Number of Securities in Sector Universe	279.5	79.82	250.2	309.5	325
Number of S&P 500 Securities in Sector Universe	78.32	21.76	60.75	91	95.25
Sector Telecommunications: 32 unique portfolios.					
Number of Funds	13.79	6.56	9	14	18
Equity Net Asset Value ($ Millions)	243.1	440.7	12.57	79.3	269.2
Number of Unique Securities Held	38.8	26.36	20	34	50
Number of Unique S&P 500 Securities Held	12.87	7.57	8	11	17
Number of Securities in Sector Universe	94.11	48.45	72	89.5	122.5
Number of S&P 500 Securities in Sector Universe	26.86	13.42	21	25	32
Sector Utilities: 64 unique portfolios.					
Number of Funds	36.34	10.97	38	39	42
Equity Net Asset Value ($ Millions)	654.4	1,648	40.55	158.4	585.9
Number of Unique Securities Held	53.06	28.73	34	48	66
Number of Unique S&P 500 Securities Held	29.12	16.42	19	26	34
Number of Securities in Sector Universe	211.3	45.43	184.2	221	235.8
Number of S&P 500 Securities in Sector Universe	97.29	36.92	65.5	96	132
Generalist Funds: 1337 unique portfolios.					
Number of Funds	653.4	298.4	439	743	859
Equity Net Asset Value ($ Millions)	1,621	5,941	59.21	227.1	908.2
Number of Unique Securities Held	153.4	238.8	55	83	143
Number of Unique S&P 500 Securities Held	95.9	99.33	42	64	102
Number of Securities in Sector Universe	4,139	741.8	3,998	4,344	4,643
Number of S&P 500 Securities in Sector Universe	516	11.99	507	515	523

Panel B: Descriptive Statistics of Mutual Fund Performance Data

This table reports summary statistics of mutual fund performance data for the sample period (years 1999 to 2016). Data are at monthly frequency and returns are in decimal points. α 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 $fundsec$ the subject returns are the returns to a fund, and benchmarks are the fund's sector benchmark and the S&P 500. For $secS\&P$ the subject returns are the return to the fund's sector benchmark, and the benchmark is the S&P 500. Fund size represents the size of the fund in logarithm of Total Net Assets.

	mean	sd	min	max	N
Fund Flow (Next Month)	-0.0007	0.3094	-9.9958	9.8027	119,304
S&P$_t$	0.0059	0.0410	-0.1674	0.1096	121,631
Sector Benchmark Return	0.0141	0.0589	-0.2863	0.4067	121,631
Fund Return	0.0068	0.0612	-0.7502	2.9521	121,489
α(fund - sec)$_t$	-0.0063	0.0219	-0.6679	2.9024	120,707
α(sec - S&P)$_t$	0.0077	0.0367	-0.1303	0.2404	121,631
4 factor α_t	0.0002	0.0341	-0.4128	2.8031	120,707
(S&P - Risk-free)$_t$	0.0047	0.0411	-0.1679	0.1096	121,631
Sign of Index-Adjusted Fund Flow	-0.2706	0.9626	-1.0000	1.0000	121,107
Difference of Signs	-0.5051	1.2764	-6.1310	4.6453	120,443
Fund Size (log TNA)	3.7517	2.2835	-2.3026	10.5039	119,738

Table II: 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)
$\text{Sec}_t - \text{S\&P}_t$	0.202***	0.202***	0.192***	0.205***
	(10.69)	(10.67)	(10.45)	(8.80)
$\text{Fund}_t - \text{Sec}_t$	0.357***	0.369***	0.341***	0.340***
	(5.78)	(5.80)	(5.82)	(5.78)
$\text{S\&P}_t$	-0.00313	-0.00357	0.00971	
	(-0.16)	(-0.18)	(0.49)	
Fund Size	-0.00707***	-0.00666***	-0.0267***	-0.0277***
	(-6.43)	(-6.65)	(-7.91)	(-7.71)
Constant	0.0322***	0.0263***	0.106***	0.131***
	(5.67)	(5.07)	(8.26)	(7.76)
Sector FE	No	Yes	No	No
Fund FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	118049	118049	118049	118049
Adjusted R^2	0.005	0.006	0.008	0.014

t statistics in parentheses

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

Table III: 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, two risk-adjusted outperformance measures (α), 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 ($S\&P$). α 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 $fund - sec$ the subject returns are the returns to a fund, and benchmarks are the fund's sector benchmark and the S&P 500. For $sec - S\&P$ 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)
α(fund - sec)$_t$	0.315***	0.330***	0.325***	0.342***
	(5.59)	(5.55)	(5.39)	(5.41)
α(sec - S&P)$_t$	0.194***	0.192***	0.180***	0.202***
	(9.61)	(9.78)	(9.68)	(7.95)
(S&P - Risk-free)$_t$	0.00320	0.00233	0.0137	
	(0.17)	(0.12)	(0.70)	
Fund Size	-0.00698***	-0.00658***	-0.0267***	-0.0276***
	(-6.34)	(-6.56)	(-7.91)	(-7.71)
Constant	0.0313***	0.0253***	0.106***	0.127***
	(5.57)	(4.91)	(8.24)	(7.53)
Sector FE	No	Yes	No	No
Fund FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	117933	117933	117933	117933
Adjusted R^2	0.004	0.005	0.008	0.014

t statistics in parentheses

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

Table IV: 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)
Difference of Signs	0.0670***	0.0625***	0.0521***	0.0576***
	(16.66)	(16.26)	(15.52)	(17.20)
Fund Size	0.0150***	0.0125***	0.0304***	0.0328***
	(4.26)	(3.52)	(3.97)	(3.91)
Constant	-0.294***	-0.334***	-0.360***	-0.121
	(-19.69)	(-12.49)	(-12.39)	(-1.87)
Sector FE	No	Yes	No	No
Fund FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	118658	118658	118658	118658
Adjusted R^2	0.009	0.016	0.006	0.036

t statistics in parentheses

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

Table V: Impact of Risk Adjusted Outperformance on Fund Flows

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 indicator variable that captures fund outperformance measured by the two-factor sector-plus-market model compared to the one-factor market (CAPM) model. The first two columns have fund performance ranked into deciles as in Barber, Huang, and Odean (2016) and the next two have fund performance ranked into terciles. The odd columns show regressions with fund fixed effects, and the even columns show regressions with both fund- and time-period fixed effects. We use monthly data.

	Next Month Fund Flows			
	Decile		Tercile	
	(1)	(2)	(3)	(4)
Rank(α_m)$\leq$ Rank(α_s)	0.175***	0.195***	0.183***	0.180***
	(14.24)	(16.58)	(13.92)	(13.43)
Fund Size	0.0333***	0.0382***	0.0246**	0.0351***
	(4.15)	(4.36)	(2.93)	(3.97)
Constant	-0.481***	-0.242**	-0.451***	-0.218*
	(-15.43)	(-3.21)	(-13.94)	(-2.32)
Fund FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	Yes
Observations	96440	96440	59298	59298
Adjusted R^2	0.010	0.040	0.010	0.045

t statistics in parentheses

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

Table VI: Comparison of CAPM and Sector models on Fund Flows

Dependent variable: sign of Index-Adjusted Fund Flow. Panel A shows results for a fund-level panel regression of the sign of the index-adjusted flow of funds to a mutual fund, on the standardized alpha of CAPM and the standardized alpha with respect to a sector benchmark model which is orthogonal to the CAPM alpha. Panel B shows results for a fund-level panel regression of the sign of the index-adjusted flow of funds to a mutual fund, on the standardized alpha of the 4-factor model and the standardized alpha with respect to a sector benchmark model which is orthogonal to the 4-factor alpha. The first two columns compare the explanatory power of the two estimated alphas in a pooled setting. In the last two columns, we include funds and time-period fixed effects. We use monthly data.

	Panel A: CAPM			
	Sign of Index-Adjusted Fund Flow			
	(1)	(2)	(3)	(4)
CAPM α_t	0.178***	0.181***	0.189***	0.181***
	(14.95)	(6.95)	(13.13)	(6.91)
Orthog. α(fund - sec)$_t$		0.162***		0.142***
		(4.09)		(3.52)
Fund Size	0.0147***	0.0135***	0.0329***	0.0391***
	(4.17)	(3.87)	(4.10)	(4.68)
Constant	-0.327***	-0.323***	-0.429***	-0.309***
	(-21.83)	(-21.44)	(-6.35)	(-4.81)
Fund FE	No	No	Yes	Yes
Month FE	No	No	Yes	Yes
Observations	118921	118921	118921	118921
Adjusted R^2	0.035	0.063	0.066	0.087

	Panel B: 4-factor model			
	Sign of Index-Adjusted Fund Flow			
	(1)	(2)	(3)	(4)
4-factor α_t	0.162***	0.164***	0.173***	0.164***
	(12.43)	(5.65)	(10.86)	(5.55)
Orthog. w.r.t. 4-factor α_t		0.172***		0.152***
		(4.49)		(3.90)
Fund Size	0.0147***	0.0135***	0.0318***	0.0391***
	(4.19)	(3.87)	(3.91)	(4.65)
Constant	-0.328***	-0.323***	-0.340***	-0.251***
	(-21.87)	(-21.44)	(-4.99)	(-3.89)
Fund FE	No	No	Yes	Yes
Month FE	No	No	Yes	Yes
Observations	118921	118921	118921	118921
Adjusted R^2	0.029	0.060	0.060	0.084

t statistics in parentheses

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

Table VII: 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)
$\text{Sec}_t - \text{S\&P}_t$	0.154***	0.155***		
	(14.97)	(12.20)		
$\text{Sec}_t \geq \text{S\&P}_t$			0.0126**	0.0128**
			(5.14)	(4.88)
Constant	0.0116	0.0113	0.00638	0.00558
	(0.60)	(0.57)	(0.33)	(0.28)
Sector FE	No	Yes	No	Yes
Month FE	No	Yes	No	Yes
Observations	1356	1356	1356	1356
Adjusted R^2	0.377	0.379	0.373	0.375

t statistics in parentheses

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

Table VIII: Experimental Evidence

Panel A: Descriptive Statistics of Allocation Experiment

The table reports summary statistics of fund and index performance data for the experiment. The table also reports summary statistics of demographic and financial experience information collected during the survey. Risk Aversion is measured using the approach of Weber, Blais, and Betz (2002), who provide the survey questions in their Appendix C, Questions I and G. The Domain-Specific Risk-Taking (DOSPERT) scale is a psychometric scale that assesses risk taking in five content domains, one of which is financial decisions.

	mean	sd	min	max	N
Sector Fund Allocation	0.35	0.26	0.00	1.00	745
Market Fund Allocation	0.45	0.28	0.00	1.00	745
Treatment	0.41	0.49	0.00	1.00	745
Sector Fund Return	0.10	0.06	0.00	0.20	745
Market Fund Return	0.10	0.06	0.00	0.20	745
Government Fund Return	0.02	0.014	0.00	0.04	745
Market Index Return	0.10	0.06	0.00	0.20	745
Sector Index Return	0.10	0.06	0.00	0.20	305
Government Index Return	0.02	0.014	0.00	0.04	745
Age	31–35	N/A	18–20	61–65	745
Income ('000s)	43.83	31.21	0.00	190.00	745
Gender	0.50	0.50	0.00	1.00	745
Investor	0.60	0.49	0.00	1.00	730
Investor Mutual Fund	0.47	0.50	0.00	1.00	690
Risk Aversion	3.84	0.52	2.13	4.75	745

Panel B: Sector Fund Allocation with or without Benchmark Information

Dependent variable: Sector Fund Allocation, next period. This table shows regressions of sector allocation decision, on an intercept, returns to the market fund, sector fund, market index, and the random treatment which is information regarding the benchmark index performance. The table utilizes allocation data from a panel of survey respondents.

	Sector Fund Allocation			
	(1)	(2)	(3)	(4)
Treatment	0.0630***	0.0629***	0.0669***	0.0511*
	(3.33)	(3.59)	(3.80)	(2.37)
Sector Fund		1.442***	1.426***	1.422***
		(9.81)	(9.54)	(7.85)
Market Fund		-0.972***	-0.957***	-0.816***
		(-6.54)	(-6.45)	(-4.55)
Market Index		-0.230	-0.176	-0.211
		(-1.56)	(-1.19)	(-1.12)
Constant	0.328***	0.307***	0.285***	0.281*
	(26.10)	(10.39)	(5.74)	(2.14)
Demographic Controls	No	No	Yes	Yes
Financial Controls	No	No	No	Yes
Observations	745	745	735	545
Adjusted R^2	0.013	0.175	0.183	0.152

t statistics in parentheses, standard errors are robust to heteroscedasticity.

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

Panel C: Experimental Evidence regarding Information Availability

Dependent variable: Sector Fund Allocation, next period. This table shows regressions of sector allocation decision, on an intercept, returns to the market index, the difference between returns to the sector benchmark and returns to the market index (Sec − Mkt), and the difference between returns to the fund and returns to the sector benchmark ($Fund - Sec$). The table utilizes allocation data from a panel of survey respondents to mimic Table II that utilizes panel data for sector mutual funds.

	Sector Fund Allocation			
	(1)	(2)	(3)	(4)
Mkt	1.652***	1.602***	1.732***	1.674***
	(4.64)	(4.49)	(3.78)	(3.86)
Sec − Mkt	1.719***	1.691***	1.903***	1.816***
	(5.97)	(6.03)	(5.49)	(5.41)
Fund − Sec	1.144***	1.134***	1.281***	1.201***
	(5.10)	(5.23)	(5.17)	(4.51)
Constant	0.227***	0.197**	0.396	0.215***
	(6.42)	(2.88)	(1.77)	(4.81)
Demographic Controls	No	Yes	Yes	No
Financial Controls	No	No	Yes	No
Individual FE	No	No	No	Yes
Observations	305	305	240	240
Adjusted R^2	0.092	0.125	0.160	0.311

t statistics in parentheses, standard errors are robust to heteroscedasticity.

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

Table IX: Benchmark Returns and Fund Flows

This table shows versions of the Risk-Adjusted Outperformance model (Table III) and the Difference-of-Signs model (Table IV), 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 noted. 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)$_t$	0.243***	5.506***		
	(33.69)	(12.67)		
α(sec - S&P)$_t$	0.164***	3.401***		
	(48.88)	(16.32)		
Fund Size	0.0000920	-0.0541***	0.0281*	0.0447***
	(0.68)	(-7.52)	(2.40)	(3.76)
Difference of Signs			0.0679***	0.0198**
			(9.44)	(3.18)
Constant	0.00445*	0.153*	-0.0835	-0.0687
	(2.18)	(2.48)	(-0.56)	(-0.44)
Sector FE	No	Yes	No	No
Fund FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	21748	21399	21714	21351
Adjusted R^2	0.486	0.100	0.069	0.036

t statistics in parentheses

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

Table X: 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 $Sec_t \geq S\&P_t$ 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 $Fund_t \geq Sec_t$ 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)
$\text{Sec}_t \geq \text{S\&P}_t$	0.0153***	0.0152***	0.0152***	0.0185***
	(7.98)	(8.21)	(8.20)	(7.97)
$\text{Fund}_t \geq \text{Sec}_t$	0.0158***	0.0156***	0.0128***	0.0121***
	(6.40)	(6.42)	(5.99)	(5.67)
$\text{S\&P}_t$	0.0101	0.00913	0.0205	
	(0.53)	(0.48)	(1.07)	
Fund Size	-0.00706***	-0.00668***	-0.0268***	-0.0277***
	(-6.43)	(-6.67)	(-7.95)	(-7.74)
Constant	0.0171***	0.0108*	0.0928***	0.118***
	(3.43)	(2.35)	(7.61)	(7.32)
Sector FE	No	Yes	No	No
Fund FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	118052	118052	118052	118052
Adjusted R^2	0.005	0.005	0.008	0.014

t statistics in parentheses

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

Table XI: 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 (α), 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 ($S\&P$). α 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 $fund-sec$ the subject returns are the returns to a fund, and benchmarks are the fund's sector benchmark and the S&P 500. For $sec-S\&P$ the subject returns are the return to the fund's sector benchmark, and the benchmark is the S&P 500. For 4 factor α, 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)
α(fund - sec)$_t$	0.186**	0.187**	0.178**	0.270***
	(2.93)	(2.95)	(2.92)	(4.03)
α(sec - S&P)$_t$	0.102**	0.0911**	0.0765*	0.151***
	(2.93)	(2.60)	(2.35)	(3.72)
4 factor α_t	0.156**	0.174**	0.176***	0.0868
	(2.78)	(3.13)	(3.41)	(1.49)
(S&P - Risk-free)$_t$	0.000997	-0.0000774	0.0117	
	(0.05)	(-0.00)	(0.60)	
Fund Size	-0.00699***	-0.00659***	-0.0268***	-0.0276***
	(-6.35)	(-6.57)	(-7.92)	(-7.72)
Constant	0.0312***	0.0249***	0.106***	0.127***
	(5.56)	(4.86)	(8.24)	(7.56)
Sector FE	No	Yes	No	No
Fund FE	No	No	Yes	Yes
Month FE	No	No	No	Yes
Observations	117933	117933	117933	117933
Adjusted R^2	0.005	0.005	0.008	0.014

t statistics in parentheses

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

Appendix

A Experiment Methodology and Data

We conduct the experiment using Mechanical Turk (MTurk), an Internet platform by Amazon, which provides researchers relatively low-cost access to online experiment participants. MTurk has been used in research in economics (examples include Montiel Olea and Strzalecki, 2014; Kuziemko, Norton, Saez, and Stantcheva, 2015) and finance (see, for example Duarte, Siegel, and Young, 2012; Kumar, Niessen-Ruenzi, and Spalt, 2015).

The MTurk platform enables Requesters, e.g., researchers, to post Human Intelligence Tasks (HITs) to Workers, i.e., registered MTurk participants. MTurk participants are required to register, i.e., receive a WorkerID, and provide taxpayer information, including Social Security Number and a permanent residence address in the U.S. As a result, all MTurk participants in our experiment are U.S. residents. As is standard practice among researchers using MTurk, we do not disclose the nature and objectives of our experiments to the participants.

We now discuss two important concerns about using MTurk for experiments. One concern is regarding the effects of small compensation on MTurk experiment participants on the quality of data collected. Amir, Rand, and Gal (2012) show that experiments implemented on the MTurk platform result in comparable evidence to those implemented in standard laboratories, even when using small compensation amounts. In our experiment, we compensate each participant a market-based amount of compensation on the MTurk platform, i.e., about 15 cents per minute (the equivalent of $9 per hour).

Another concern is that not monitoring experiment participants directly may result in moral hazard, and thus reduce the data quality. However, in contrast with laboratory participants, the MTurk platform has an incentive structure that is conducive to conscientious behavior. When a Worker submits a HIT, a Requester can choose to reject it. As a result, experiment participants have incentive to follow instructions and pay attention to the experiment, e.g., carefully consider a stimulus prior to answering questions. In addition, researchers commonly require participants to have a high approval rate, implying that more rejections will make fewer HITs available. That is, sub-standard data quality affects participants' immediate as well as future compensation. Because of these incentives, MTurk data have consistently been found to be of high quality.

Following literature, we use quality filters and measure ex-post attrition. Specifically, we restrict our experiments to participants with MTurk ratings of 95% or above. We also restrict participants from repeat participation. Further, we use various attention checks at certain points of the experiments, and we exclude participants who do not pass these checks. The attrition rate for the experiment was 0%. Overall, we believe that the quality of data compiled from the MTurk platform is comparable to the quality of standard laboratory samples.

Vignette

You have saved $100 and have decided to invest the money in order to fund your lifestyle in the future.

The following screens will provide information about various investment options which are available to you. After reviewing the information, you will allocate your money into the investments as you prefer.

>>

(a) A brief description viewed by respondents before the task.

The below information reports the returns of the funds and benchmark indices from the last period. Please allocate your $100.

Fund	Return (%)
Stock Market Fund	4
Sector Fund	6
Risk-free Government Securities Fund	4

Benchmark Index	Return (%)
Stock Market Index	1
Sector Index	0
Risk-free Government Securities Index	3

Please allocate your funds into the investments as you desire.

Stock Market Fund	0
Sector Stock Fund	0
Risk-free Government Securities Fund	0
Total	0

(b) An allocation example for the treatment group.

The below information reports the returns of the funds and benchmark indices from the last period. Please allocate your $100.

Fund	Return (%)
Stock Market Fund	19
Sector Fund	18
Risk-free Government Securities Fund	3

Benchmark Index	Return (%)
Stock Market Index	7
Risk-free Government Securities Index	2

Please allocate your funds into the investments as you desire.

Stock Market Fund	0
Sector Stock Fund	0
Risk-free Government Securities Fund	0
Total	0

(c) An allocation example for the control group.

Figure A.1: Experiment Screens

The figure reports the description respondents view before the task, and allocation examples for the treatment and control group. The control group does not receive a benchmark index return.

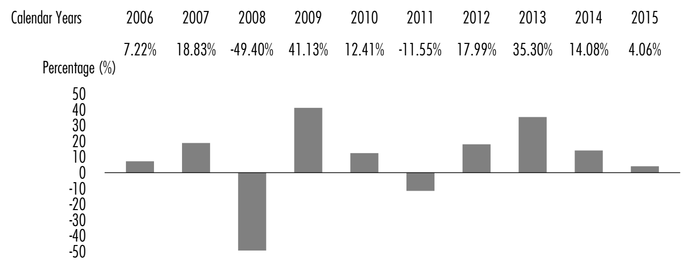
B Additional Tables and Figures

Table B.1: Cross-correlation table

The table reports correlations between monthly value weighted sector returns in our sample with monthly returns of the market index. Sample period is from 1999 to 2016.

Variables	S&P 500 Index	Health and Biotech	Natural Resources	Real Estate	Science and Tech.	Telecom	Utilities
S&P 500 Index	1.000						
Health and Biotech	0.753	1.000					
Natural Resources	0.675	0.477	1.000				
Real Estate	0.605	0.522	0.426	1.000			
Science and Tech.	0.848	0.613	0.571	0.441	1.000		
Telecom	0.885	0.633	0.589	0.502	0.908	1.000	
Utilities	0.823	0.659	0.728	0.545	0.623	0.736	1.000

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 **(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.

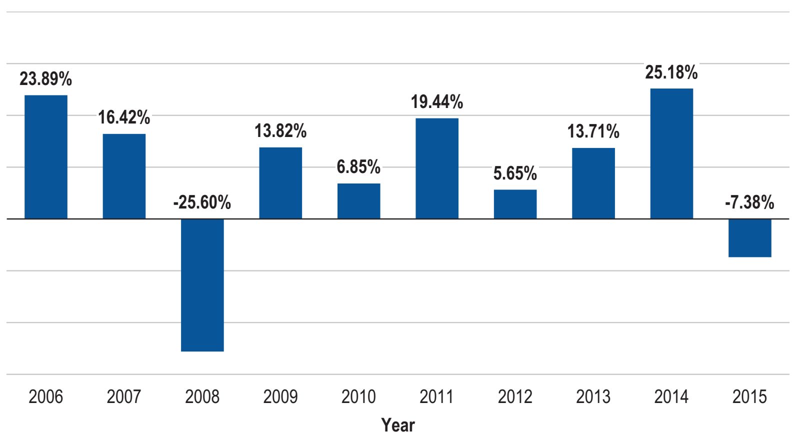
5 ***Prospectus***

Figure B.2: 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 B.3: 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).