Investor Attention and Mutual Fund Performance *

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Abstract

We extend Berk and Green's (2004) model by integrating Miller's (1977) insight on the effects of heterogeneous beliefs and restricted short sales, proposing that higher investor attention not only attracts optimistic inflows but also inflates assets under management and diminishes future fund performance. Using Abnormal View Share (AVS)—a novel measure of investor attention based on SEC EDGAR view data—we find that increased AVS predicts greater fund inflows in the following month but lower returns thereafter. This work underscores how limited attention and optimism impact fund valuations, advancing the intersection of investor attention and market dynamics theories.

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1 Introduction

Berk and Green (2004) show in a rational learning model that the response of investor capital flows to past mutual fund performance leads to a lack of persistence in future performance. A key assumption behind this conclusion are that fund managers have limited ability to find superior investments. Therefore, investors who use performance as a signal of managerial ability face decreasing returns to scale as the fund receives inflows, until the marginal value is equal to the cost of investment. We expand this logic to a model of attention by conjecturing that investors gather information to learn about the quality of mutual funds using past information. However, learning is costly and investors can only focus their limited attention on a subset of funds, in a market without provisions for short-selling. Moreover, in the spirit of Miller (1977), potential investors make different estimates about the ability of a fund's management. In that case, investors who are more optimistic about a fund's quality tend to purchase new shares in the fund while more pessimistic investors refrain from doing so. Consequently, funds that receive more attention, all else equal, experience higher inflows. In addition, the attention-driven demand from optimistic investors drives a fund's assets to excessive levels such that the marginal value of a fund's assets falls short of the cost of investment. As a result, greater investor attention predicts worse fund performance.

We explore this idea using the universe of U.S. mutual funds, investment vehicles that bundle stocks into diversified portfolios aligned with distinct strategic objectives. The advantages of these investment conglomerates for participants are manifold; they offer enhanced diversification by spanning and intertwining various asset classes, augment liquidity, and consolidate the number of transactions investors need to oversee. The mutual fund industry commands a considerable presence in the financial sector[1], playing a pivotal role in channeling capital toward

[1]As of 2021, the Investment Company Institute (ICI) reported that mutual funds managed about

the real economy. Predominantly, mutual fund investors are household entities[2], making a significant contribution to the aggregation of retirement savings. As open-ended investment firms, mutual funds are subject to regulation and registration with the U.S. Securities and Exchange Commission (SEC). The SEC mandates that all entities, both foreign and domestic, must submit registration statements, periodic reports, and other requisite documentation via the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR), which is publicly accessible and allows for the cost-free downloading of information.[3] The SEC also makes publicly available the so-called EDGAR Log Files – a data set that provides information on internet search traffic for EDGAR filings from January 2003 through June 2017, and from May 2020 through June 2023.

We measure investors' attention to specific mutual funds using the frequency of views of mutual fund disclosures, as reported in the EDGAR Log Files. Investor engagement with a fund's filings is interpreted as an index of attention to that fund. Additionally, the view count may be correlated with a latent variable responsible for the attention. For example the attention may be caused by recent posts on social media about the fund, while we observe the actions of some of these investors who search for additional information using SEC filings. We utilize the regulatory framework under which mutual funds operate and the availability of EDGAR system server logs from the SEC's Division of Economic and Risk Analysis to measure investor attention through interactions with mutual fund filings.

The EDGAR server logs provide granular data, including the exact times at

$24.4 trillion in U.S. assets. This represented a significant portion of all U.S. public equity. The growth from 2017 to 2021 reflected both the performance of the underlying assets and the net inflows from investors.

[2]Data from the ICI 2019 Factbook indicates that households were in possession of 89% of mutual fund assets at the culmination of 2018.

[3]In addition to mutual fund filings, the EDGAR system allows for the downloading of public company filings ranging from annual and quarterly reports (10-Ks and 10-Qs) to insider trading forms (Forms 3, 4, and 5), offering a window into the financial workings and regulatory compliance of publicly traded companies across the United States. See https://www.sec.gov/edgar.shtml for details on EDGAR's public accessibility and data retrieval provisions.

which individual filings were accessed by users, uniquely identifiable by their partially masked IP addresses. We also supplement this data with the MaxMind IP-Organization linking file, making it possible to identify the organizations associated with specific IP addresses. This process involves manually identifying financial organizations from a list of 38,000 that appear in the sample, allowing us to compare the impacts of attention from different types of investors. Using these data, we construct a fund-month level measure of abnormal attention, which we call Abnormal View Share (AVS).

To establish the context for our investigation, we examine aggregate patterns in viewership as well as in the filing activity of mutual funds. Our analysis reveals a marked decline in overall viewership subsequent to the year 2020. Conversely, the viewership of different categories of filings was relatively stable across the same period. We also observe that the viewership trends of mutual funds are in alignment with the general trends for views of all documents available on EDGAR, including those of publicly-traded corporations. Moreover, our findings suggest a pronounced preference towards the views of more contemporary filings among individuals, a trend which may be attributed to the anticipation that recent filings are more likely to encompass new information.

Findings from the analysis reveal that peaks in investor attention, as evidenced by an uptick in document views, foreshadow net inflows into mutual funds, only slightly lower than the average fund growth rate. Moreover, the positive and significant relation between AVS and future flows emerges despite the unit of our observation being the Central Index Key (CIK), not the individual fund. This could attenuate our estimates of the flow-to-AVS relation since multiple mutual funds of the same fund family often report together under the same CIK. In these cases, a CIK with a high measured AVS may include funds to which investors are paying little attention. Indeed, the predictive power of AVS for fund flows is stronger when we focus on the subsample of "single-fund CIKs" where we can directly match our attention measure to individual funds: a one standard deviation increase in investor attention predicts higher annualized flows of 0.62% over the following month.

Motivated by this, we explore several additional hypotheses. First, we distinguish between investor attention to relatively recent filings versus attention to older, more stale filings. The analysis reveals a preference for the most recent filings, capturing 15% of all views, which suggests that newer documents are more likely to draw investor attention. Our findings also indicate that the impact of AVS on flows is most pronounced for filings aged less than six months. For filings older than 12 months, we no longer find a significant relation between AVS and future flows.

Second, the relation between AVS and fund flows is also hypothesized to differ based on the type of investor, as financial organizations are typically considered to be more sophisticated. Consequently, this relationship is anticipated to be stronger for attention of non-financial viewers, rather than financial organizations if these flows are unsophisticated. Consistent with this hypotheses, we find that the impact on future flows is stronger for non-financial attention rather than that from financial organizations.

Third, our model predicts a stronger AVS-flow relationship when there is more disagreement about the fund quality. The reason is that higher disagreement increases the support of investors with extreme beliefs, thereby generating higher inflows from such optimistic investors. To test this prediction, we use fund age as a proxy for disagreement, as younger funds are likely to exhibit greater uncertainty regarding their quality, compared to older funds. In addition, due to the uncertainty about fund quality, the incremental benefit of conducting research on a younger fund is higher, meaning that investors gain more insight per hour of research on these funds. To investigate this idea, we examine the interaction between Abnormal View Share (AVS) and fund age to determine how the influence of abnormal attention varies with the level of disagreement about a fund. We find a significant negative coefficient on the interaction term, AVS*log(Age), indicating that the link between abnormal attention and net flows is strongest among funds about which there is more disagreement.

Fourth, we posit that fund inflows, and not outflows, should be sensitive to investor attention. This follows logically from Merton (1987) who points out that investors can not buy something of which they are not ex-ante aware, e.g. there must be attention paid to an investment opportunity before it is purchased, and from the short sale constraints present for mutual funds, which restrict pessimistic from responding to negative information. Therefore, we hypothesize that, because investor attention is associated with subsequent net buying, it must be associated with net inflows, rather than net outflows. In our empirical analysis, when we separate observations by whether net flows are positive or negative, this is exactly what we find.

Finally, having established that investor attention is strongly positively correlated with net fund flows, we find that these increased flows due to attention predict lower fund performance. This relationship is robust to multiple specifications of future return: at several horizons (1, 3, and 6 months), and adjusted for risk (FF5 + momentum alpha). Once again, we find stronger results for the subsample of single-fund CIKs for which AVS can be matched one-to-one with individual funds. Specifically, a one standard deviation increase in investor attention predicts lower annualized returns of 0.82% the month after. Overall, we interpret our results to mean that the presence of abnormal attention leads to increased flows from optimistic investors, and that these flows push a fund's assets under management to excessive levels, resulting in a larger decrease in future returns than we would expect with only the rational Berk and Green (2004) framework.

Our study relates to the theory of Miller (1977) that, in markets with heterogeneous beliefs and no short sales, optimistic investors will bid up asset values to excessive levels, especially in markets with greater investor attention. We bring this insight to mutual funds – a marketplace where fund investors plausibly have different opinions about a fund's quality, are unable to short sell, and face many available products on which to focus their limited attention. We conjecture that mutual funds with greater investor attention have higher capital flows and lower future returns, and that this relationship is stronger when investors disagree more about a fund's quality. This is exactly what we find in the data.

Furthermore, we show empirically that the predictive power of attention goes above and beyond a fund's past performance, suggesting that our findings are not driven by investors' reaction to past returns. These findings are consistent with recent work on investor beliefs by Roussanov, Ruan, and Wei (2020), who estimate the "efficient" fund size implied by the Berk and Green (2004) model, where flows rationally chase returns, and funds experience decreasing returns to scale. Their evidence suggests that investor beliefs are distorted by fund marketing, leading to a capital misallocation, where actual fund sizes differ from their "efficient" levels.

Our paper also contributes to prior studies of attention as a scarce cognitive resource (Kahneman (1973)). These studies examine the determinants of investor attention, whether limited attention generates price inefficiency, and often focus on underlying equity markets.[4] To our knowledge, we provide the first comprehensive study of investor attention to mutual funds using a direct measure based on investors' views of mutual fund disclosures. This contrasts with prior studies

[4]See, e.g., Kliger and Sarig (2000), Hirshleifer and Teoh (2003), Grullon, Kanatas, and Weston (2004), Tetlock, Saar-Tsechansky, and Macskassy (2008), Baker and Wurgler (2006), Peng and Xiong (2006), Barber and Odean (2008), Fang and Peress (2009), Hirshleifer, Lim, and Teoh (2009), Da, Engelberg, and Gao (2011), Da, Engelberg, and Gao (2015), Fisher, Martineau, and Sheng (2022), Sicherman, Loewenstein, Seppi, and Utkus (2016), Ben-Rephael, Da, and Israelsen (2017), Kim (2017), and Choi, Gao, and Jiang (2020).

that relate mutual fund flows to indirect measures of investor attention, such as mutual fund advertising or media coverage.[5] As we show, investor attention predicts greater fund flows and lower fund performance. In this way, we contribute to a large literature on the determinants of mutual fund flows.[6]

Finally, our empirical proxy for investor attention is based on the EDGAR Log Files – a dataset used in prior research. However, we focus on the filings of registered investment companies (i.e., mutual funds) whereas most studies focus on the filings of publicly-traded corporations.[7] Two exceptions, Cao, Du, Yang, and Zhang (2021) and Agarwal, Ruenzi, and Weigert (2024), use EDGAR Log Files to show that investors' attention to the portfolio disclosures of hedge funds affects investors' capital allocation decisions and the profitability of disclosure-based investment signals. We build on this work and use EDGAR Log Files to measure investor attention to mutual fund disclosures, and study the economic impact of greater investor attention on mutual fund flows and performance.

2 Model

In this section, we propose a simple framework to guide the empirical hypotheses. We assume that fund managers have different *alphas*, which represent their ability to generate excess returns through their investment portfolios. Investors learn about these alphas imperfectly by observing historical fund performance and forming their own heterogeneous opinions. Based on this information, they decide

[5] See, e.g., Sirri and Tufano (1998), Jain and Wu (2002), Solomon, Soltes, and Sosyura (2014), and Roussanov, Ruan, and Wei (2021).

[6] See, e.g., Barber and Odean (2000), Wermers (2000), Goyal and Wahal (2008), Pastor and Stambaugh (2003), Graham, Michaely, and Wang (2005), Schwert (1989), Wermers (2003), Hong, Kubik, and Stein (2004), Barber, Odean, and Zheng (2005), Choi, Kahraman, and Mukherjee (2016), Ben-David, Li, Rossi, and Song (2022).

[7] See, e.g., Bauguess, Cooney, and Hanley (2018), Drake, Roulstone, and Thornock (2015), Loughran and McDonald (2014), Loughran and McDonald (2017), Lee, Ma, and Wang (2015), Dyer (2017), Gibbons, Iliev, and Kalodimos (2020), Chen, Cohen, Gurun, Lou, and Malloy (2017), Drake, Johnson, Roulstone, and Thornock (2020), Li and Sun (2022), Crane, Crotty, and Umar (2023) Chen, Kelly, and Wu (2020) and Iliev, Kalodimos, and Lowry (2019).

whether to invest additional funds. In equilibrium, funds with higher alphas and those that attract more investors with diverse opinions achieve a larger final size.

Our model offers several contributions relative to Berk and Green's framework. First, we relax the assumption of perfectly elastic fund supply, allowing for the possibility that a limited number of "attentive" investors arrive stochastically and act on additional information. With this information, some investors become more optimistic, while others become more pessimistic. Second, we explore the implications of constraints on investors' actions: investors may face restrictions on selling based on negative information but can buy new fund holdings based on positive information. This asymmetry can lead to a scenario where optimistic investors push the fund size above its optimal level, and overpricing is not corrected by fund outflows. Third, we contrast the implications of rational learning from the fund's past performance and signals with cases where individual investors' opinions may be partially or completely unrelated to actual information.

2.1 Base Case

We begin with an equilibrium similar to that in Berk and Green (2004). Fund returns are modeled as the sum of true alpha and a noise term:

$$R = \alpha + \varepsilon_i,$$

where the noise term ε_i is normally distributed with mean zero and variance σ_i^2, implying that signal precision is $\omega_i = \frac{1}{\sigma_i^2}$.

The equilibrium size of assets under management, denoted q_i, determines the fund's cost and fee structures. We model a convex cost structure $C(q_i)$, where $C(q_i) > 0$, $C'(q_i) > 0$, and $C''(q_i) > 0$, assuming that costs are necessary for generating returns. Additionally, fund managers require positive compensation, $f > 0$, for managing the funds. The per-unit cost to investors is $c(q_i) = \frac{C(q_i)}{q_i} + f$, and returns net of costs are denoted as r_t.

Next, focus on a particular fund. All investors share the same prior belief about the manager's alpha, $N[\phi_0, \frac{1}{\gamma}]$. The posterior belief is denoted as $\phi_t = E(R_{t+1} \mid \mathcal{F}_t)$. In equilibrium, investors supply funds until they expect zero return in excess of the risk-free rate, i.e., $E_t(r_{t+1} \mid \mathcal{F}_t) = 0$. Therefore, the equilibrium condition is:

$$\phi_t = c(q_t) = \frac{C(q_t)}{q_t} + f,$$

indicating that with perfectly elastic fund supply, the expected payoff per unit of capital precisely covers the costs. Updating beliefs using Bayesian inference from ϕ_{t-1} to ϕ_t based on past performance is given by:

$$\phi_{t+1} = \frac{\gamma}{\gamma + \omega}\phi_t + \frac{\omega}{\gamma + \omega}R_{t+1}.$$

Using the equilibrium condition and the definition of r_t, we find that expected fund size after t iterations q_t is governed by:

$$c(q_t) = c(q_{t-1}) + \frac{\omega}{\gamma + t\omega}r_t,$$

which, using $\phi_t = c(q_t)$, gives:

$$\phi_t = \phi_{t-1} + \frac{\omega}{\gamma + t\omega}r_t.$$

Suppose, W.L.O.G, each investor has \$1 to contribute. Thus, in equilibrium, fund size q_t is worth \$$q_t$ and yields zero expected excess return.

2.2 Attentive Investors

Next, we model deviations from equilibrium by introducing attention. With probability $0 < \kappa < 1$, a fund gains "attention," and N new investors enter.[8] These N new investors, indexed "i", search for additional information and use it to form

[8] We treat the probability of a fund capturing attention as exogenous. The model can be extended by introducing costs to investors, limiting the number of funds they can investigate.

beliefs about the fund. Each investor obtains an additional signal or belief as follows:

$$S^i = \alpha + \varepsilon_S^i,$$

where ε_S^i is normally distributed with mean zero, and the perceived precision of the signal is $1/\mathrm{Var}(\varepsilon_S^i) = \omega_S$.[9]

The new investors are non-strategic: they cannot adjust their demand to account for other investors paying attention to the fund. They rely on their individual signals, while the summary or average signal from all attentive investors, $\overline{S} = \frac{1}{N}\sum_i (\alpha + \varepsilon_S^i)$, which can be inferred from changes in fund size, may be more precise.

We next describe how additional signals change attentive investors' beliefs and influence their investment decisions. Their subjective posterior belief is updated to $\phi_S^i = E(R_{t+1} \mid \mathcal{F}_t^i)$, where $\mathcal{F}_t^i$ is all information available to investor i.

This posterior is computed as a weighted combination of the previous posterior ϕ_t and the new signal:

$$\phi_S^i = \frac{\gamma + \omega}{\gamma + \omega + \omega_S}\phi_t + \frac{\omega_S}{\gamma + \omega + \omega_S}S^i. \tag{1}$$

Attentive investors observe the fund size q_t, compute the fund's costs $c(q)$, and estimate the expected net returns based on their beliefs:

$$E(R_{t+1} - c(q_t) \mid \mathcal{F}_t^i) = \phi_S^i - c(q_t). \tag{2}$$

2.3 Equilibrium with Attentive Investors

Optimistic investors may choose to invest in the fund, thus potentially increasing its size from q_t. The equilibrium size, denoted q^*, is determined by two conditions: (i) given the fund size q^*, optimistic investors ($\phi_S^i > c(q^*)$) each buy one unit of the fund, and (ii) the expected number of investors matches q^*.

[9] For simplicity, we assume that all individual signals have the same precision. The model can be extended to accommodate heterogeneity in precision.

For q_t rational investors already participating in the fund (see details in the base model) and N potential new investors, the equilibrium condition is:

$$q_t + N \cdot \text{Prob}[\phi_S^i > c(q^*)] = q^*. \tag{3}$$

Each of the N attentive investors invests one unit if they are "optimistic" ($\phi_S^i > c(q^*)$), and in expectation the number of such investors is N times that probability.

The size of the fund grows with more "attentive" investors N and as the probability of investor optimism increases. The investor becomes optimistic when:

$$\varepsilon_S^i > c(q^*)(\gamma + \omega + \omega_S)/\omega_S - (\gamma + \omega)\phi_t/\omega_S - \alpha, \tag{4}$$

The probability that an investor buys a fund share, given assumptions about signal distribution, can be expressed as:

$$1 - F\left[c(q^*)(\gamma + \omega + \omega_S)/\omega_S - (\gamma + \omega)c(q_t)/\omega_S - \alpha\right], \tag{5}$$

where $F(.)$ is the cumulative density function (CDF) of ε_S^i.

The equilibrium fund size q^* satisfies:

$$q_t + N\left(1 - F\left[c(q^*)(\gamma + \omega + \omega_S)/\omega_S - (\gamma + \omega)c(q_t)/\omega_S - \alpha\right]\right) = q^*. \tag{6}$$

This formula captures the fixed point of the equilibrium. For example, observe that an increase in q^* also increases $F(.)$, reducing the left-hand side until equilibrium is reached.

From the properties of the CDF function, note that $F(.)$ increases with volatility in the right tail of the distribution but decreases in the left tail. Therefore, if the parameters are such that the average-belief investor does not invest, the number of optimistic investors grows with the volatility of their beliefs as the distribution of beliefs widens.

Finally, observe that N, representing fund attention, positively influences fund size. When $N = 0$, the equilibrium size is $q^* = q_t$. As N grows, more optimistic investors enter, increasing the fund size—a relation that can be easily demonstrated by implicit differentiation.

2.4 Original Investors' Strategies

Anticipation that the arrival of attentive investors may distort fund size influences the strategies of original investors. When a fund attracts attention, its size may become excessive, leading to underperformance. Original investors can preemptively reduce their initial demand q_t to mitigate this risk. Does this mean that the effect of attentive investors can be completely undone by strategic demand trimming?

If, with probability κ, a fund gains "attention" and N new investors enter, the equilibrium is defined by two conditions. As before, new investors choose the optimal size, which we call q^*_{t+1}, given the initial size q^*_t:

$$q^*_t + N\left(1 - F\left[(\gamma + \omega + \omega_S)c(q^*_{t+1}) - (\gamma + \omega_S)\phi_t\right]\right) = q^*_{t+1}. \tag{7}$$

Additionally, the initial size q^*_t aligns with the expected fund size $(1-\kappa)q^*_t + \kappa q^*_{t+1}$:

$$\phi_t = c((1-\kappa)q^*_t + \kappa q^*_{t+1}), \tag{8}$$

implying $q^*_t < q_t$. Note that q^*_t decreases with κ, showing that original demand is optimally trimmed in anticipation of new investors.

The trimming has only a partial effect and does not offset the future negative performance of funds affected by attention. Intuitively, investors cannot anticipate which funds will attract attention, and their strategic actions offset only the average effect. Funds that capture attention and receive additional inflows will perform worse than expected at $t = 2$. Meanwhile, funds that do not capture attention will perform relatively better.

2.5 Model Illustration

We use a numerical example to illustrate the model. We assume that a fund is endowed with $N = 50$ potential fund investors. Each investor i holds a subjective belief about the fund manager's ability. We assume the beliefs are drawn from the distribution $\phi_i \sim N(2\%, 1\%)$. The top panel of Figure 1 shows the distribution of beliefs. The shaded grey region represents the set of optimistic investors who hold beliefs larger than the mean (i.e. $\phi_i \geq 2\%$). Given that $N = 50$, 25 investors are optimistic in expectation.

We also assume that the fund's costs are expressed as $c(q) = 0.01 + 0.001q + 0.0001q^2$. The bottom panel of Figure 1 plots the fund's cost as a function of its size. For example, suppose that all optimistic investors allocate their \$1 to the fund. In that case, the fund size would be \$25 and its cost would be 10%. This cannot be an equilibrium because, to satisfy investor rationality, all 25 investors must have $\phi_i \geq 10\%$. But this is not the case since the beliefs of optimistic investors only satisfy $\phi_i \geq 2\%$.

The bottom panel of Figure 2 shows the equilibrium as an intersection of two curves. The first (solid blue curve) plots the fund's cost and the second (dotted yellow curve) plots the required belief of the marginal investor for different levels of fund size. The marginal investor is the least optimistic among all fund investors. In equilibrium, the marginal investor in a fund of size q has $\phi_i = c(q)$ and is just indifferent between investing in the fund or not. The point x identifies the equilibrium fund size ($q = \$10$) and marginal belief ($\phi = 3\%$). It occurs when the two curves intersect. The top panel shows the distribution of investor beliefs where the shaded grey region corresponds to fund investors in equilibrium, when $\phi_i \geq 3\%$ for all i. When $N = 50$, fund investors are expected to be the ten most optimistic.

Finally, the top panel of Figure 3 shows that the equilibrium fund cost increases with the level of attention (N). This is because, as N increases, so does the number of optimistic investors who can invest in the fund. For example, at $N = 100$, there are now 20 investors with beliefs $\phi_i \geq 3\%$, twice as many as when $N = 50$. However, this is not an equilibrium because a fund size of \$20 would generate a cost greater than 3% and violate investor rationality for some investors. Hence, in equilibrium, the marginal investor is more optimistic for higher N, leading to a greater fund size and cost. The bottom panel compares two cases of investor beliefs. The first is the baseline case ($\phi_i \sim N(2\%, 1\%)$) and a High disagreement case ($\phi_i \sim N(2\%, 2\%)$ featuring a greater dispersion in beliefs. We see that a greater dispersion generates a larger equilibrium level of fund size, and a a steeper relation between fund size and attention.

2.6 Informative vs. Uninformative Beliefs

We have so far worked under the assumption that attentive investors follow a strategy dictated by their belief or signal, which could potentially be completely uninformative about the true type of the fund. The intuition becomes more nuanced if attentive investors arrive with informed opinions or signals.

Conceptually, the restrictions on selling the fund imposed on investors play a key role in how they respond to information. Suppose we have a group of *attentive* investors learning precisely and homogeneously about a fund's alpha. If their information relative to the prior is positive, they invest, increasing the fund size and reducing future returns. If their information is negative, they take no action. In expectation, funds receiving attention will have smaller returns in the future compared to other funds because positive information is partially offset by the new investment, while negative information is not acted upon.

Suppose, in addition to an informative average opinion, there is heterogeneity in opinions such that, all else equal, some investors are more optimistic than others.

In this case, we observe an *incremental* effect. Due to opinion differences, inflows can occur even with marginally positive signals, although inflows are larger when the information is more positive. Funds receiving *attention* tend to perform worse than other funds, with lower performance being more pronounced when opinion spreads are wider.

Although we assume that their beliefs are informative about the true state, we continue to assume that investors have bounded rationality when focusing on their beliefs. Potentially, they can learn better by observing the fund size. Rational investors may also act strategically by reducing their demand when other investors pay attention to the fund. Heterogeneous opinions, however, are difficult to reconcile with rationality (see, e.g., Huang and Thakor (2013) RFS). Formally, we assume that each investor receives an informative signal:

$$S^i = \alpha + \varepsilon_S^i,$$

where ε_S^i is normally distributed with mean zero, and the precision of the signal is $1/\mathrm{Var}(\varepsilon_S^i) = \omega_S$. This setup implies that each investor's signal provides some degree of accurate information about the true alpha of the fund manager. Define the summary or average signal from all attentive investors:

$$\overline{S} = \frac{1}{N}\sum_i (\alpha + \varepsilon_S^i) = \alpha + \frac{1}{N}\sum_i \varepsilon_S^i,$$

which grows in precision with the number of attentive investors. To determine the equilibrium fund size q^* in the presence of informative signals, we consider the conditions under which investors decide to buy fund shares. An investor i chooses to invest if their posterior expectation of net returns exceeds the costs, i.e.,

$$E(R_{t+1} - c(q) \mid \mathcal{F}_t^i) = \phi_S^i - c(q) > 0. \tag{9}$$

The probability that an investor i decides to invest based on their signal S^i can be derived similarly to previous cases. The equilibrium condition becomes:

$$q_t + N\left(1 - F\left(\frac{(\gamma + \omega + \omega_S)c(q^*) - (\gamma + \omega_S)\phi_t}{\omega_S}\right)\right) = q^*. \tag{10}$$

We assess how informative signals influence the expected returns to the original investors, using our previous result:

$$E(R_{t+1} - c(q_t) \mid R_t) = \phi_t - c(q_t), \tag{11}$$

compared to $\phi_t - c(q_t) = 0$ in equilibrium in the base model. By applying the unconditional expectation at $t = 0$, we infer:

$$E_0(E_t(R_{t+1} - c(q_t) \mid \mathcal{F}_t) \mid \mathcal{F}_0) = E_0(R_{t+1} - c(q_t) \mid \mathcal{F}_0), \tag{12}$$

with $c(q_t)$ increasing in $\overline{S}$. As an example, consider the situation where many attentive investors aggregate their signals such that $\overline{S} \to \alpha$. If they respond sufficiently to positive news ($\overline{S} > c(q_t)$) but remain inactive for $\overline{S} < c(q_t)$, we find that, in expectation:

$$E_0(R_{t+1} - c(q_t) \mid \overline{S} < c(q_t)) + E_0(R_{t+1} - c(q_t) \mid \overline{S} > c(q_t)) < 0. \tag{13}$$

Responding with inflows only to positive information creates an asymmetry, so that the unconditional returns are expected to be negative even if the dispersion of beliefs is small.

2.7 Model Extension with Additional Signal Period

We also extend the model by introducing an additional time period before attentive investors act on their investment decisions. In accord with the intuition in Miller (1977), the extended time allows to reduce the volatility of the individual beliefs, thereby reducing the effect on fund size and performance.

In this second period, each attentive investor receives a second uncorrelated signal about the fund's true alpha, denoted as $S_2^i = \alpha + \varepsilon_2^i$, where ε_2^i represents noise with mean zero and precision ω_S. This additional signal, independent of the initial signal $S^i = \alpha + \varepsilon_S^i$, provides each investor with more information about the fund's expected return.

By incorporating this second signal, attentive investors now average the two signals they receive, forming a combined signal $\bar{S}^i = \frac{1}{2}(S^i + S_2^i)$. Because both signals are noisy but centered on the true alpha, averaging them reduces the noise variance, effectively increasing the precision of the combined signal to $\omega_{\bar{S}} = 2\omega_S$. Consequently, investors base their posterior beliefs on this more precise average signal, which reduces the dispersion of opinions about the fund's expected return among attentive investors.

This reduction in opinion dispersion has direct implications for the equilibrium fund size. In the original model, investors formed opinions based on a single noisy signal, resulting in broader differences in beliefs about the fund's quality. With reduced dispersion due to averaging two signals, investors' updated posterior beliefs are more closely aligned, meaning fewer investors hold the strongly optimistic views necessary to push the fund size beyond its optimal level.

As a result, the fund size q^* in equilibrium is expected to be smaller with the introduction of this second signal period. With narrower belief dispersion, fewer investors exceed the threshold of optimism needed to invest, leading to reduced inflows. This outcome aligns with economic intuition: as investors access more information, the tendency to overreact to individual signals diminishes, stabilizing fund growth around a more moderate level.

3 Data Description

Following a Freedom of Information Act (FOIA) request, the SEC has made the server log files of the EDGAR website available to the public. The log files provide daily records of all document requests to EDGAR from January 01, 2003 through

June 30, 2017 and from June 1, 2020 through June 30, 2023[10]. We have a break in our sample because the log files are not available from July 2017 to May 2020. From these log files, we extract all views of mutual fund which are of Central Index Keys (CIKs) that can be mapped to the CRSP Mutual Fund Universe through CRSP's fundno in the CRSP/Compustat linking table provided on the Wharton Research Data Services (WRDS) website.

The unit of observation at the filing level is the CIK, though throughout we use the terms "CIK" and "fund" interchangeably. The CIK is a required piece of logon information for EDGAR for any filer to the SEC, individuals or companies. There is a lack of standardization in how mutual fund management companies group their mutual funds within CIKs. For most fund companies, the CRSP MGMT_CD maps one to one with the CIK (1015 maps); however, some management companies have grouped funds together under separate trusts. For example, the Fidelity Concord Street Trust contains distinct funds and a different CIK than the Fidelity Aberdeen Street Trust. Some fund companies, like American Funds or Oppenheimerfunds, have separate CIK entries for different funds. Ultimately, the filer has discretion in its choices to set up multiple CIKs or not, to satisfy the SEC's disclosure requirements. In our sample of 2,134 CIKs, 334 correspond to only one CRSP fund, with the average CIK being the SEC identifier for 25 funds.

The log files from January 2003 through June 2017 contain the unique identifier for the filing requested, the time and date of the request, the associated CIK of the filer, and the IP address displayed in IPv4 format, with the fourth number masked, e.g. 199.67.131.jag. This masking is done in such a way as to maintain the uniqueness of the IPs throughout the sample. The files from June 2020 through June 2023 do not contain IP information. In the earlier sample where individual

[10] The description for the log files (found at https://www.sec.gov/data-research/sec-markets-data/edgar-log-file-data-sets) states that document views by internal SEC IP addresses are not included in the data, meaning that we are not truly capturing **every** view. However, given that we are interested in the viewership of prospective buyers, not views by regulators, this should not impact our tests.

IPs can be distinguished, we find that the average IP Accesses EDGAR 2.15 days per month, and views about 100 files. However the median IP views only one file per month, suggesting that a significant portion of total viewership is concentrated in a subset of IP addresses.

We supplement the log files with monthly and daily net-of-fees return data as well as monthly data on total assets and 12b-1 fees downloaded from the CRSP mutual fund database, removing all observations with missing total assets data. For the cases where many funds file under the same CIK, we value-weight all measures according to total assets and aggregate them at the CIK level. We begin by measuring net fund flows as the difference between a funds change in assets and return for a given month, and creating an indicator variable, $Inflows$, which is equal to 1 if net flows for a fund-month are positive, and 0 otherwise. 47.8% of fund-months in the sample experienced inflows, increasing fund value in those months by an average of 2.22%. To control for known impacts on fund flows, we use the standard deviation of daily fund returns within each month as a measure of volatility, and the age of each fund as the number of months it has appeared in the entire CRSP mutual fund universe. The average fund is 13.5 years old, and has returns of 0.58% per month with a standard deviation of 2.9%. Table 1 outlines these and other summary statistics for the sample.

[*INSERT TABLE 1 HERE*]

Table 2 ranks the 10 largest funds, in terms of mean total net assets (TNA) over the sample, and reports the average proportion of total EDGAR views that are of each fund's filings (Viewership Share). The viewership share for these funds ranks 95th percentile and above, suggesting that there may be unobserved correlation between levels of attention and fund size. When estimating a causal relationship between investor attention and fund flows, this needs to be considered, as larger funds may attract more attention due to this unobserved variable rather than the flows being a result of the attention. We address this through the construction of our key variable: Abnormal View Share.

[*INSERT TABLE 2 HERE*]

To address the above concerns about omitted variables, we focus on *shocks* to attention rather than levels. To construct Abnormal View Share (AVS), we begin by removing duplicate observations of the same IP address viewing the same filing on the same day. Then, as an intermediate step, we calculate another variable, EDGAR View Share (EVS), as the monthly proportion of total viewership attributable to each CIK (the same as Viewership Share in Table 2):

$$EDGARViewShare_{i,t} = \frac{FilingsViewed_{i,t}}{\sum_{i=1}^{n} FilingsViewed_{i,t}} \tag{14}$$

where $FilingsViewed_{i,t}$ is the total number of views of fund i's filings in month t. Abnormal View Share is then calculated as:

$$AVS_{i,t} = EVS_{i,t} - median\left(EVS_{i,\tau\in(t-1,t-5)}\right) \tag{15}$$

This will allow us to avoid the concerns above and provides us with a clean measure of fluctuations in investor attention across time.

To understand what fund characteristics attract investor attention, we can regress the two measures of attention (EVS in (1)-(3) and AVS in (4)-(6)) onto the vector of 1-period lagged control variables with month fixed effects and standard errors clustered at the CIK level. The results of this regression are presented in Table 3. The results are similar for both levels and shocks to attention. On average, larger, younger, and less volatile funds have higher EVS/AVS. Interestingly, 1 month and 12 month past returns have opposite signs, suggesting that funds who performed worse recently, or better over the past year have higher EVS/AVS. The fact that the filings of younger funds attract more views is consistent with investors using EDGAR filings to learn about mutual funds. Such information would be particularly useful to investors when considering younger funds that are presumably less-established.

We continue with some additional facts about the data to better understand viewership activity in Section 4, and conduct a series of OLS regressions in Section 5 to explore the relationships between investor attention, mutual fund flows, and future performance.

4 Types of Filings

To understand what filings are generally available for viewing and which are of interest to investors, we provide a brief summary of the broad trends in viewership below. We start with the supply-side of EDGAR filings, and examine aggregate filing activity by funds for different categories of filings.

Some of the specific form types are standard and are present in most years of observation. Over the sample period, however, there have also been introductions of new types of filings (for example, form NPORT was introduced in 2019 as a replacement for form N-Q). This would normally complicate a study of attention to information by filing type, as an investor could be paying attention to the same information, but would appear to be changing the form type they are viewing. To address this, we manually assign each form type to one of seven classes: prospectuses, proxy statements, reports, legal disclosures, registrations, withdrawals, and other forms. This mapping is summarized in Table 4.

[*INSERT TABLE 4 HERE*]

With this mapping of form type to category, we are able to detect shifts in both the filing activity by funds, and viewership by investors. The mapping treats form types that contain similar information as one, avoiding concerns about shifts in the universe of filing types. Figure 4 charts each of the filing categories, as a percentage of all forms submitted by funds each year. Prospectuses have become more prominent over time, while registrations and legal disclosures have become less prevalent.

[*INSERT FIGURE 4 HERE*]

Next, we turn our attention to aggregate trends in viewership (the demand-side of filings). Beginning with trends in total viewership, Figure 5 plots the total number of views, both for all EDGAR filings and for only mutual fund filings.

[*INSERT FIGURE 5 HERE*]

The red dotted line on Figure 5 indicates the time gap between the two samples. There is a large decrease in the absolute number of mutual fund filing views in between the two sub-periods. A similar discontinuity is present in the number of total views, meaning that the decrease in mutual fund viewership is not due to a movement of attention away from mutual funds, but rather a decrease in the overall usage of EDGAR filings as a way to gather information. The correlation between mutual fund views and total views is 0.97.

Exploring trends in the demand for filings further, Figure 6 charts the views of each of the filing categories in Table 4 as a percentage of total views across time. The relative demand for the different types has remained fairly consistent throughout the sample. Prospectuses attract the majority of views, with legal disclosures becoming much more prominent in the final two years of the sample.

[*INSERT FIGURE 6 HERE*]

Filings can also differ in ways other than just SEC form type. For example, we would expect that viewers should be more interested in newer filings, if they believe them to contain the most recent information. We explore this dimension of viewership in Figure 7, which plots the cumulative proportion of all views in the sample which are of filings of different ages, up to 2 years old.

[*INSERT FIGURE 7 HERE*]

The relationship between viewership and filing age is concave, meaning that viewers exhibit a preference for more recent filings, and that marginal interest in filings decreases with the age of the filing. Next, we present the results from our series of OLS regressions to shed light on the relationship between attention and mutual fund flows.

5 Regression Results

In this section, we explore the relationship between abnormal attention and future fund flows and returns.

5.1 Does Investor Attention Predict Fund Flows?

We run the following pooled regression:

$$NetFlow_{i,t+1} = \alpha + \beta AVS_{it} + controls + \epsilon_{i,t+1}$$

where $NetFlow_{i,t+1}$ is the net fund flow of fund i in month $t+1$, defined as the change in total assets of fund i from month t to $t+1$ minus fund i's return during month $t+1$. The key variable, $AVS_{i,t}$, is fund i's abnormal view share during month t. A finding $\beta > 0$ would indicate that greater attention to fund i in month t is associated with higher net flows in the following month. Control variables are measured at time t and include the fund's return over the past month and year, the log of total fund assets (in millions of dollars), volatility of a fund's daily returns, the log of fund age (measured in months), 12b-1 fees (measured in percentage points), and year-month fixed effects. We cluster standard errors at the CIK level. All independent and dependent variables in the regression are standardized to have a zero mean and unit variance.

Panel A of Table 5 presents the results for the full sample of CIKs. The coefficient on AVS in Column (4) is 0.0084 (t-statistic= 4.37), which means that a one standard deviation increase in AVS is associated with a 0.0084 standard deviation increase in fund flows the following month. On an annualized basis, this works out to an increase in flows of 0.26% ($= 12 \times 0.0084 \times 2.57\%$). Also, consistent with prior research, we find that funds with better recent returns attract more flows, while higher fee funds attract less (Del Guercio and Tkac (2008)).

[*INSERT TABLE 5 HERE*]

The coefficient on AVS is significant but its magnitude is modest. One possible reason has to do with the fact that our measures of investor attention and fund flows are measured at the CIK level, rather than at the level of the individual mutual fund. As noted, many funds report under the same CIK. This could attenuate the flow-AVS relation as some CIKs may have a high overall AVS while including many funds to which investors are not paying much attention. Therefore, we repeat our analysis for the subsample of CIK's for which there is a single fund and our measure of investor attention can be matched to individual funds.

Panel B of Table 5 shows the results for single-fund CIKs. Again, the coefficient on AVS is positive and significant, but now more than twice as large as that for the full sample of CIKs in Panel A. In economic terms, a one standard deviation increase in AVS is associated with higher annualized flows of 0.66% over the following month ($= 0.0190 \times 2.73\%$). Overall, the evidence shows that greater investor attention precedes greater fund flows.

5.2 Attention to New vs. Old Filings

Information in filings becomes stale over time, with recent filings likely containing more valuable information. This conjecture aligns with Figure 7, where we see that viewers generally prefer more recent filings, with 15% of all views being of filings less than 1 month old. For fully rational, information-seeking investors, we would expect the AVS-Flow relationship to be stronger for more recent filings. To understand if filing age has an impact on the relationship between abnormal attention and flows, we divide the log files based on the age of the filings at time of viewing, and construct AVS within each sample.

Table 6 gives the regression results for each of the different age groups. The relation between AVS and fund flows appears monotonic in the age of the filings being viewed. For relatively recent filings with an age of less than six months, a one standard deviation increase in AVS is associated with significantly higher future flows (coef.=0.0060; t-statistic=2.98). The coefficient is also significant but smaller for filings between 6 and 12 months old; for filings older than 12 months, the coefficient is not significant.

[*INSERT TABLE 6 HERE*]

These results suggest that abnormal investor attention to recent information positively predicts flows. This is consistent with the behavior of rational investors with an understanding of efficient markets who would expect such information to be stale. Even so, the fact that attention to filings between 6 and 12 months old also predicts flows might reflect the investment behavior of unsophisticated investors who think such filings are recent enough to contain valuable information (i.e. a few months old).

5.3 Attention to Passive vs. Active Funds

Under the rational framework of Berk and Green (2004), investors chase past returns, which are interpreted as a signal of managerial skill. Our setting allows us to test this assumption, to see if the AVS-flow relationship is indeed due to investor learning about managerial skill. We can do this by comparing the strength of the relationship for index funds and ETFs (passive: where managerial skill is not an issue), and non-index funds (active).

Under rational learning, we would expect abnormal attention's impact on fund flows to be greater for active funds. To test this, we interact AVS with an indicator, *Passive*, that takes on a value of 1 for all CIKs which are of the indicated type (index fund in (1) & (2), and ETF/ETN in (3) & (4)). To keep the identification clear, we restrict the sample to those CIKs for which all funds have the same *Passive* value (90% of the total sample). This removes potential concerns about CIKs with both types confounding our estimation.

[*INSERT TABLE 7 HERE*]

The results are reported in TABLE 7. The coefficient on the interaction variable $AVS \times Passive$ is not significant, indicating that abnormal attention to both passive and active funds have a similar relationship to future flows. This suggests that the abnormal attention captured by our measure is not simply learning about managerial skill, but rather has an unsophisticated component, where some investors believe they are gaining valuable information by researching passive funds.

It is also possible that rational investors use regulatory filings to verify the costs of investing in different passive funds. In this case, greater attention to both passive and active funds could generate a higher flow response.

5.4 Attention from sophisticated vs. unsophisticated investors

We expect the AVS-flow relationship to vary with viewer type. For example, attention from financial organizations is usually considered more sophisticated. Thus, when comparing financial attention to less sophisticated, retail attention, we would expect to find a stronger relationship between AVS and flows under the rational hypothesis, as financial organizations should be able to learn more efficiently.

We can extract information about the type of investor for the sample period ending in 2017, during which the EDGAR Log Files provide the IP address for each site visit; after 2017, IP information is not available. Specifically, we use the MaxMind IP-Organization linking file to identify the organizations corresponding to different IP addresses. We manually identify which organizations of the ∼38,000 which appear in the sample are financial, and which are not. Finally, any IP address that does not link to an organization is included in the non-financial sample. With this mapping, we construct Abnormal View Share and test its relationship to future flows for each type of viewer.

[*INSERT TABLE 8 HERE*]

Table 8 reports the results. Column (3) shows that attention from individuals and non-financial organizations (Non-Financial AVS) is significantly related to future flows; in contrast, attention from financial organizations (Financial AVS) is not. This supports the idea that the flow-to-AVS relation is not purely driven by the information-gathering of rational investors, but may also have an unsophisticated component. We recognize that some viewers may use VPNs to anonymize their IP addresses, leading our classification method to falsely identify some financial organizations as non-financial. However, this misidentification means that our estimate of the relationship between non-financial attention and fund flows is attenuated, so the interpretation of the results unaffected.

5.5 Attention to young vs. old funds

There is more disagreement about younger funds, since there are fewer signals about fund quality relative to older funds. A wider range of investor beliefs means that there is more support for extremely optimistic views. In this case, we would expect greater inflows due to the presence of such optimistic investors. In addition, for younger funds, the marginal value of research is expected to be higher (e.g. for each hour spent researching, an investor may learn more valuable information about the younger fund than the older). Similarly, we may expect the relation between abnormal attention and fund flows to be stronger for younger funds. This is because investors perceive their learning about these funds to be more fruitful, and thus will allocate more flows to these funds. To explore this idea, we interact the AVS variable with fund age to understand how the impact of abnormal attention on fund flows depends on the level of disagreement about the fund.

[*INSERT TABLE 9 HERE*]

The results are reported in Table 9. The negative significant coefficient on the interaction term, AVS*log(Age), suggests that the relationship between abnormal attention and flows is stronger for younger funds. This aligns with the model prediction that in the presence of higher disagreement about fund quality, attention will have a greater impact on fund flows. It also suggests that investors will focus attention, and therefore allocate capital to those funds for which they believe their attention will be most productive.

5.6 Inflows vs. Outflows

In the context of mutual funds, which cannot be short sold, abnormal investor attention is expected to have a positive impact on future purchase decisions. Investors who already hold a fund tend to make a sell decision purely based on past performance and change in fund fees. However, deciding on a purchase of a new fund requires exploration. This idea is explored in Table 10, where we introduce an indicator, $NetInflows$, which is equal to 1 for all fund-months for which net flows are positive, and 0 otherwise.

[*INSERT TABLE 10 HERE*]

Table 10 shows the results. In Column (4), the coefficient on AVS is insignificant, and the interaction term is positive and significant, with coefficients of -0.0009 (t=-0.68) and 0.0093 (t = 3.48), respectively. This suggests that for fund-months which experienced net outflows ($NetInflows = 0$), these flows were not impacted by AVS, but for those which experienced net inflows, abnormal attention positively predicts future flows. While AVS shows a positive correlation with subsequent new inflows into funds, it does not have a significant association with outflows.

We are aware that the sign of net flows is not a perfect measure of inflows, only that the fund received more inflows than outflows in a given period. To clarify this measure, we gather data from Morningstar on separated inflows and outflows, as measured by sales and redemptions of fund shares. Morningstar sources these data from form NSAR, where issuances and redemptions are reported to the SEC, and available in monthly quantities. In Table 11 we test our asymmetric predictions about the impact of AVS on inflows and outflows using these measures. $Inflows$ ($Outflows$) is measured as the amount of flows into the fund, as a percentage of assets. Similar to the conclusions in Table 10, we find that AVS positively predicts inflows, but not outflows. This aligns with our expectations about investors' ability to incorporate positive information more easily than negative information, due to short sale constraints present in the mutual fund market.

[*INSERT TABLE 11 HERE*]

5.7 Does Investor Attention Predict Fund Returns?

In the Berk and Green (2004) framework, increased flows can lead to decreased future returns due to decreasing returns to scale. They argue that mangers experience inflows following good performance, up to the point where the marginal return on another dollar of AUM is equal to marginal cost. We connect this idea to our results on abnormal attention and flows, and argue that the component of the flows driven by unsophisticated attention pushes firm size past the optimal point, resulting in even lower future returns than would be expected otherwise.

We run the following pooled regression:

$$NetReturn_{i,t\to t+k} = \alpha + \beta AVS_{i,t-1} + controls + \epsilon_{i,t+1}$$

where $NetReturn_{i,t\to t+k}$ is the compounded net-of-fees fund return of fund i from month t to month $t+k$. As in our flow regression, the key variable, $AVS_{i,t-1}$ is fund i's abnormal view share during month t. A finding $\beta < 0$ would indicate that greater attention to fund i in month $t-1$ is associated with subsequently lower net returns. Control variables are measured at time t and include the fund's return over the past month and year, the log of total fund assets (in millions of dollars), volatility of a fund's daily returns, the log of fund age (measured in months), 12b-1 fees (measured in percentage points), and year-month fixed effects. We cluster standard errors at the CIK level, and future fund returns at 4 different horizons: 1, 3, 6, and 12 months.

The results are reported in Table 12. We find that abnormal attention significantly and negatively predicts future returns at one, three, and six-month horizons. For the full sample of CIKs in Panel A, the coefficient at the one-month horizon is -0.0070 (t-statistic=3.70). This suggests that a one standard deviation increase in AVS during month $t-1$ predicts 24 basis points per year lower returns in month $t+1$ ($= -0.007 \times 0.0291 \times 12$) there is a delay between the fund growth and the impact of decreasing returns to scale. Once, again, the results are stronger for the subsample of single-fund CIKs. Panel B shows a coefficient of -0.0235 at the one-month horizon. This means that a one standard deviation increase in AVS predicts 82 basis points per year lower returns ($= -0.0235 \times 0.0291 \times 12$). This is consistent with the idea that limits to a fund's quality investment opportunities manifest when new inflows are incorporated into a fund's holdings.

[*INSERT TABLE 12 HERE*]

Consistent with the short sale constraints in the mutual fund market, the coefficient on AVS becomes insignificant for the 12-month horizon, suggesting the value-eroding fund growth can be reversed gradually, but not immediately. Motivated by this idea, we exploit another institutional detail: the fact that ETF mutual funds can be short sold.[11] We repeat the tests in Table 12, this time including an indicator, $ETFFund$, which is equal to 1 when all CRSP funds in a

[11] Todorov, Yegen, and Chau (2024) argue that short-selling activity is a disciplinary tool for investors to remove managers of underperforming ETFs.

given CIK are ETFs, and 0 when they are all not ETFs. The results are given in Table 13. The total impact of AVS on returns for ETFs is given by the sum of the coefficients on AVS and its interaction with the indicator. For the 1 month horizon, the coefficient on AVS is -0.0105 (t = -5.63), and that on the indicator is 0.0400 (t = 3.94). The sum of these is insignificantly different from zero, so the short term ETF returns appear to be unaffected by attention, on average. This is consistent with the over-growth from attention being more quickly correctable for these types of funds.

The heterogeneous beliefs, resulting from disagreement about the fund's quality (in the model, each investor receives their own signal, S^i), also interact with limited attention. In the model, this disagreement means some fixed proportion of the attentive investors will be overoptimistic, while the number of these optimistic investors increases with the amount of attention on the fund. To investigate this implication, we interact AVS with the intra-month volatility of daily returns as a proxy for disagreement. The results of these tests are given in Table 14. The coefficients on AVS for the 1, 3 and 6 month horizons are similar to those in the previous tests. The coefficient on the interaction at the 1-month horizon is significantly negative, suggesting that the negative impact of attention on future return is increased when there is more dispersion in investor beliefs about fund quality.

A negative relation between investor attention and future fund performance also holds for risk-adjusted returns. Specifically, we estimate fund-month level alphas by regressing each fund's return on the Fama-French 5 factors along with momentum, downloaded from Ken French's Data Library [12]. With the estimated coefficients from these regressions for each fund (βs), we calculate the expected returns in each month by multiplying the matrix of βs by the factor values for

[12] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

that period. Alpha is then defined to be the difference between the realized fund return and the factor model expected return. We then regress alpha at the four different horizons in period t+1 on AVS in period t-1, and controls in period t.

[*INSERT TABLE 15 HERE*]

Panel A of Table 15 shows the results for the full sample of CIKs. AVS is only significantly negatively related to future three-month horizon alpha, with a coefficient of -0.0048 (t=-2.40). Panel B shows that, for the sample containing only single fund CIKs, the coefficient for 1-month returns is -0.136 (t = -1.93), more than four times larger in magnitude than that for the full sample, and now significant. Specifically, a 1 sd increase in attention in a given month predicts a 23 basis point decrease in annualized alpha. Generally, attention impacts short-term alphas, rather than those at longer horizons.

In summary, we document a relationship between current abnormal attention and future fund flows. We provide evidence that this attention is unsophisticated, including that investors focus their attention on stale information, and that the relationship exists even for passive funds. Finally, we argue that the flows due to abnormal attention push the fund beyond optimal size, resulting in larger decreases in future returns than that which could be explained in the existing rational framework[13].

6 Conclusion

Mutual fund investors have limited attention, hold different views about a fund's quality, and are unable to sell short. We incorporate these features into an extended model of Berk and Green (2004) in which a fund with greater attention

[13]We also find that the negative return-attention relationship in Table 12 is driven by the unsophisticated attention we study in Table 8.

from investors subsequently realizes higher capital flows as more optimistic investors purchase its shares. This attention-driven demand can generate excessive levels of assets under management, harming future performance. Additionally, the model predicts a stronger effect when there is more disagreement about fund quality.

We empirically test these predictions using a new measure of investor attention to mutual funds – Abnormal View Share (AVS) – that is based on internet search traffic for funds' regulatory filings through the SEC's EDGAR database. We find that AVS is a significant and positive predictor of future flows, while also uncovering other features of the flow-attention relationship. It appears to be driven by unsophisticated attention, is stronger for newer filings, and scales with the level of uncertainty about fund quality.

Finally, we find evidence that the flows from attention predict lower future fund performance, as the fund is pushed beyond the optimal size implied by Berk and Green (2004). Overall, while our findings are consistent with an extension of the idea of Berk and Green (2004), we argue that attention-driven flows from unsophisticated investors may exacerbate the flow-performance relationship that they model, leading to larger decreases in future returns.

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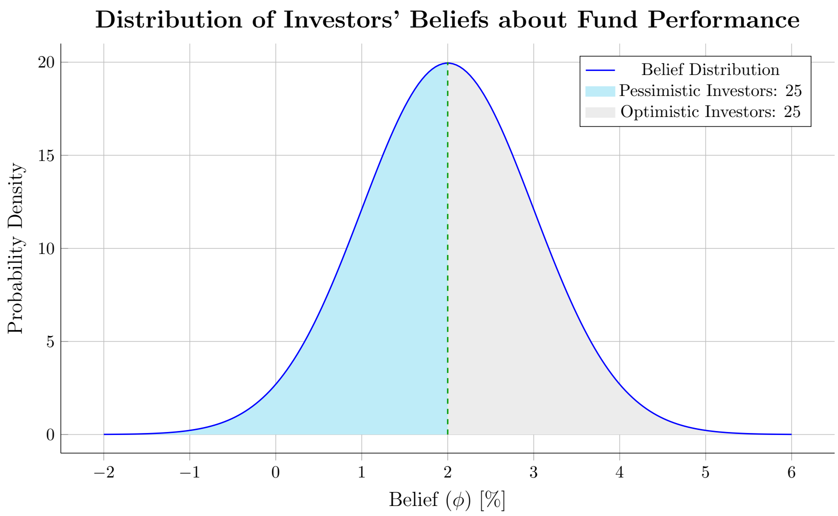
Figure 1: **Illustration of Model Assumptions**

The top panel shows a hypothetical distribution of beliefs across investors about fund manager ability ϕ. The distribution is assumed to be normal with a mean of 2% and standard deviation of 1%. The grey shaded region represent the proportion of optimistic investors (i.e., $\phi \geq 2\%$); the blue shaded region shows the proportion of pessimistic investors (i.e., $\phi < 2\%$). Each investor group is expected to contain 25 investors when there are 100 total attentive investors (i.e., $N = 50$). The bottom panel illustrates the increase in fund cost (c) for different levels of fund size (q). The cost function is $c = .01 + .001q + .0001q^2$. The point x denotes when each of the 25 optimistic investors provides $1 of capital. This is not an equilibrium because, given the 10% cost at $q = 25$, only investors with $\phi \geq 10\%$ would choose to invest.



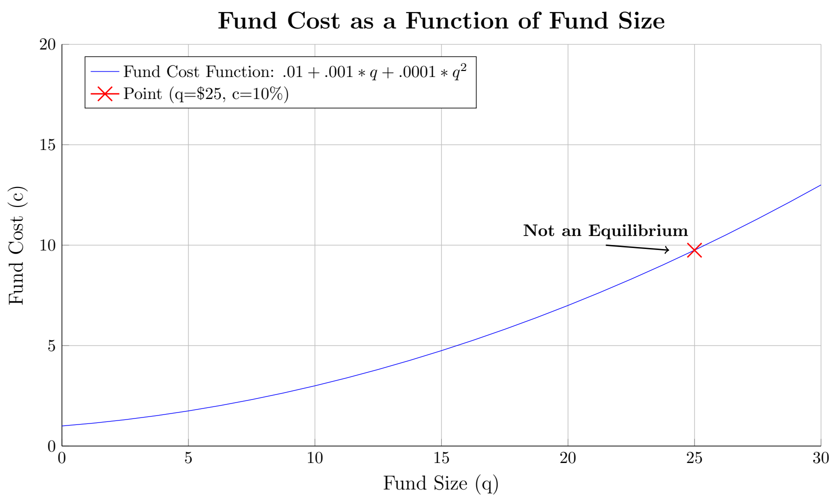
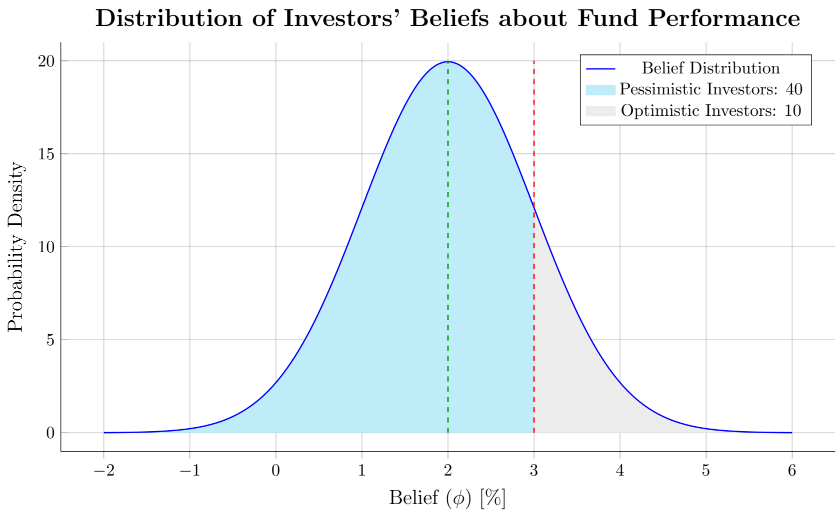


Figure 2: **Illustration of Model Equilibrium**

The top panel shows the distribution of investor beliefs from the top panel of Figure 1. The shaded grey region corresponds to fund investors in equilibrium, when $\phi_i \geq 3\%$ for all i. When $N = 50$, fund investors are expected to be the ten most optimistic. The bottom panel shows the cost function from the bottom panel in Figure 2 (in blue). The dotted yellow curve plots the required belief of the marginal investor for different levels of fund size. The marginal investor is the least optimistic among all fund investors. In equilibrium, the marginal investor in a fund of size q has $\phi_i = c(q)$ and is just indifferent between investing in the fund or not. The point x identifies the equilibrium fund size ($q = 10$) and marginal belief ($\phi = 3\%$). It occurs when the two curves intersect.



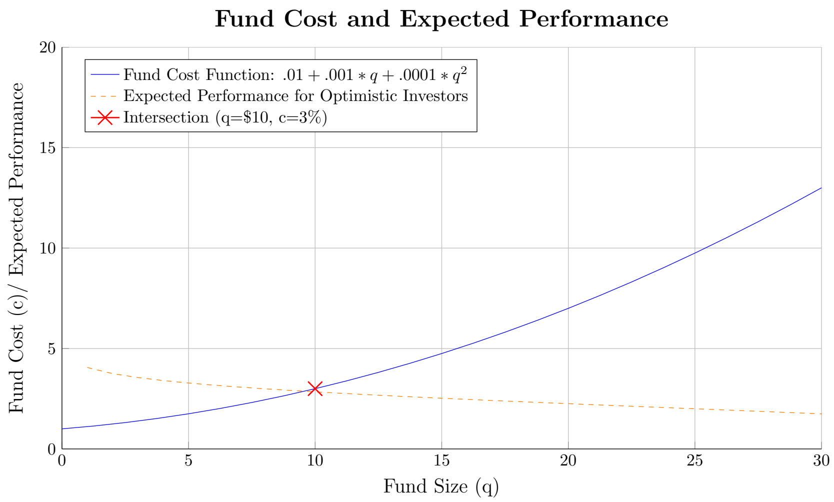
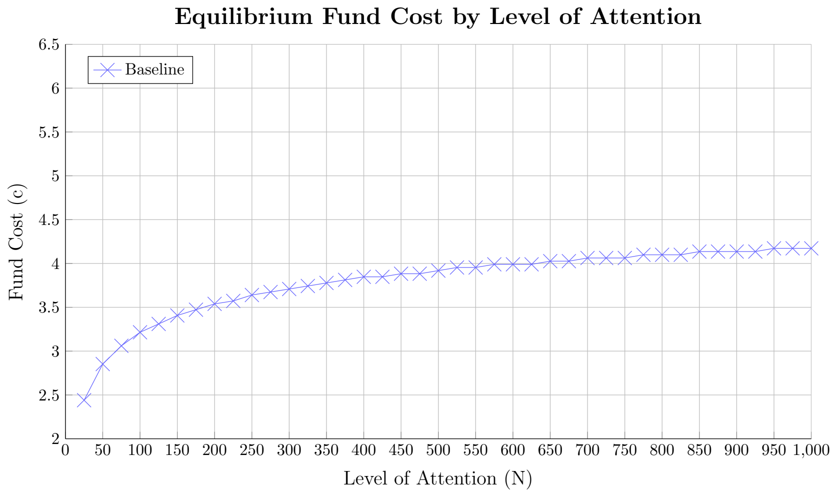


Figure 3: **Illustration of Model Comparative Statics**

The top panel shows how the equilibrium level of fund cost varies with the number of attentive investors (N). The bottom panel shows how the equilibrium level of fund cost varies with N for two different levels of investor disagreement: the baseline level is 1% and the High disagreement level is 2%. Investor disagreement is measured as the standard deviation of the distribution of beliefs



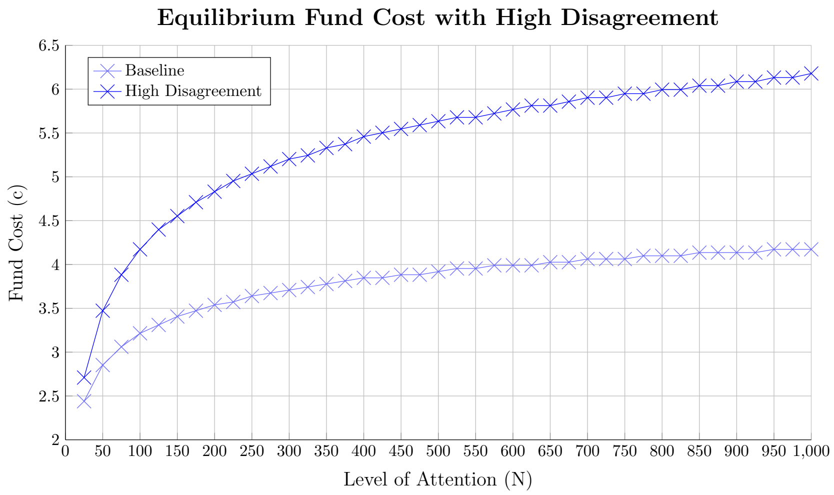


Figure 4: **Filings by Class**

This figure shows the overall proportion of mutual fund filings of different categories across time. Classification is provided in Table 4. We use the number of documents of each filing type submitted to the SEC each year by all mutual funds. Note that this chart does not provide information about viewership. This data are from: https://www.sec.gov/Archives/edgar/full-index/.

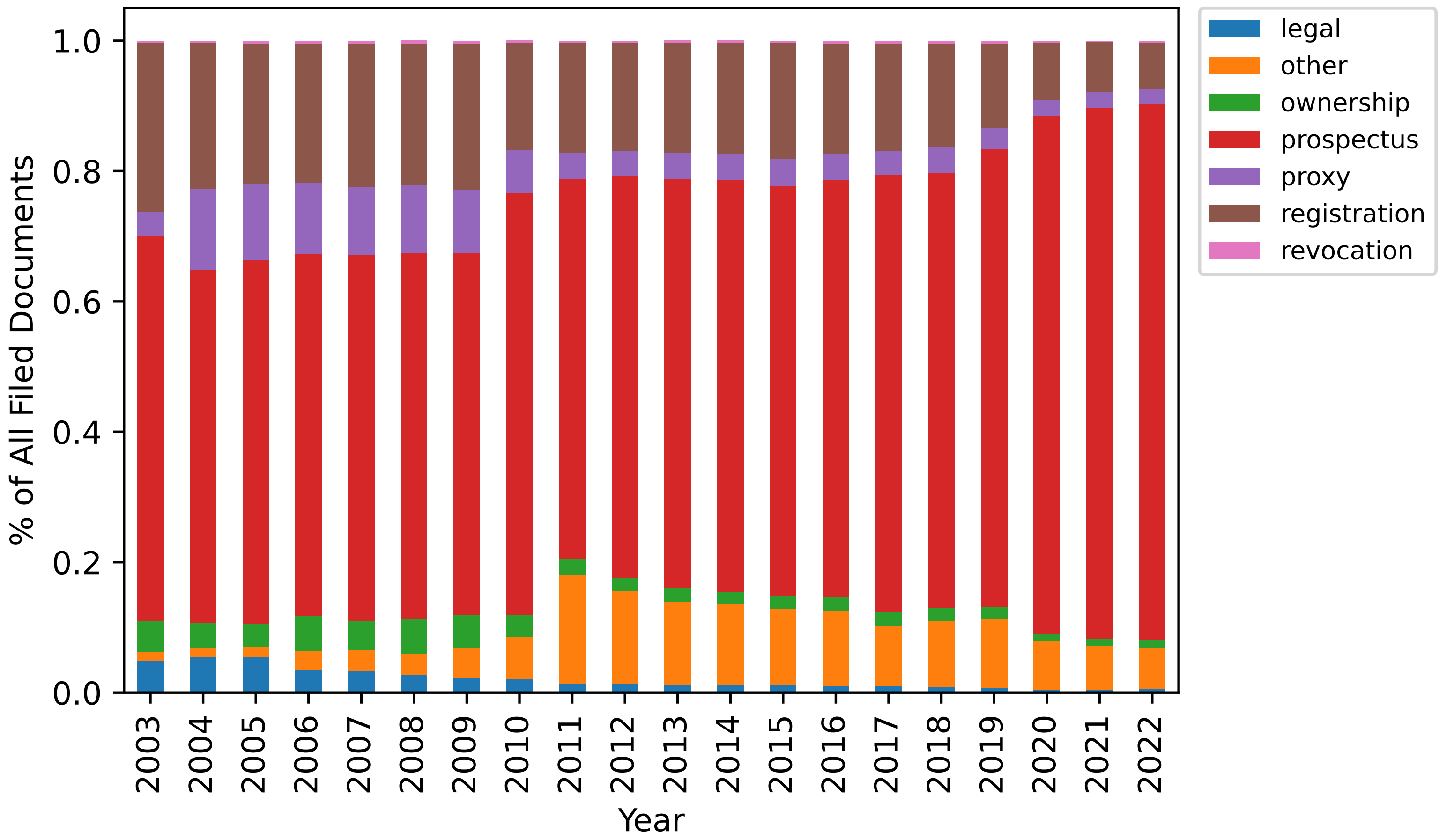


Figure 5: **Mutual Fund Views and Total Views Over Time**

This figure plots total viewership activity by month. The orange line showing lower values is for mutual fund views, while the blue line is for all views. The red dotted line shows the break in the data between 2017 and 2020. We track viewership by counting the total number of views on EDGAR each month. The correlation between total viewership and mutual fund viewership is 0.97.

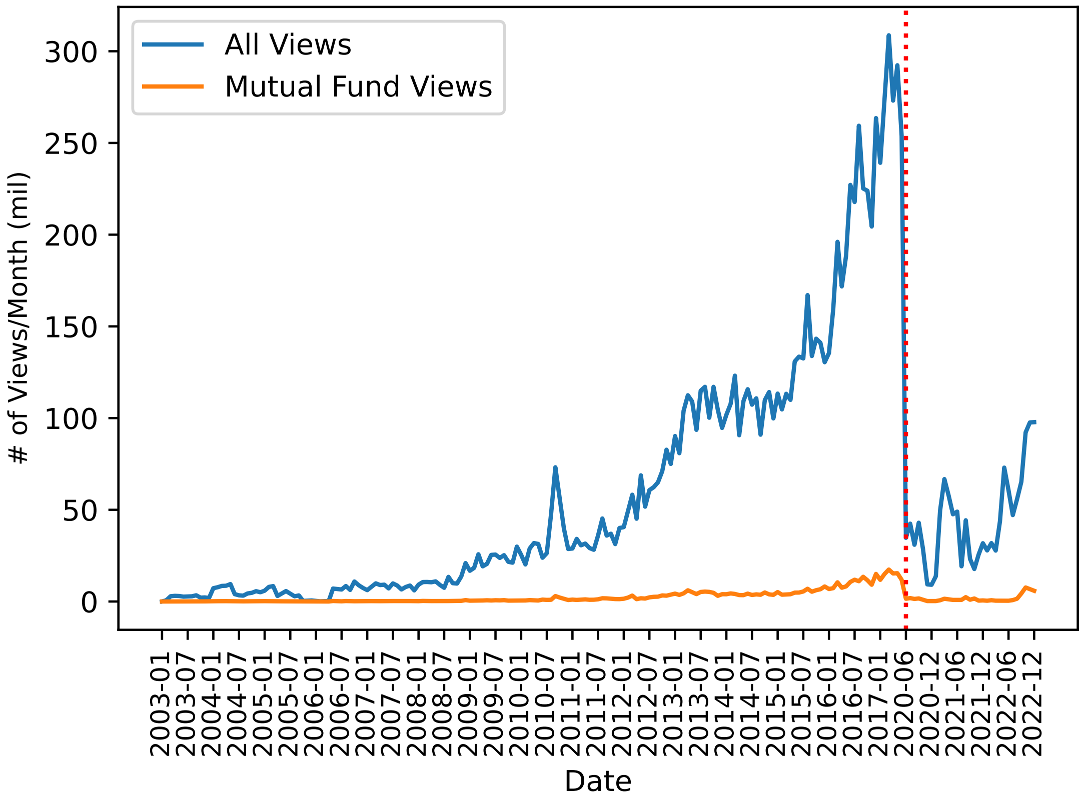


Figure 6: **Views by Class**

The figure charts the annual viewership share of the different filing categories. Classification of filings is provided in Table 4. The filing-level data for this graph are described in text. We tally the yearly views of each category, and examine their relative prominence throughout the sample.

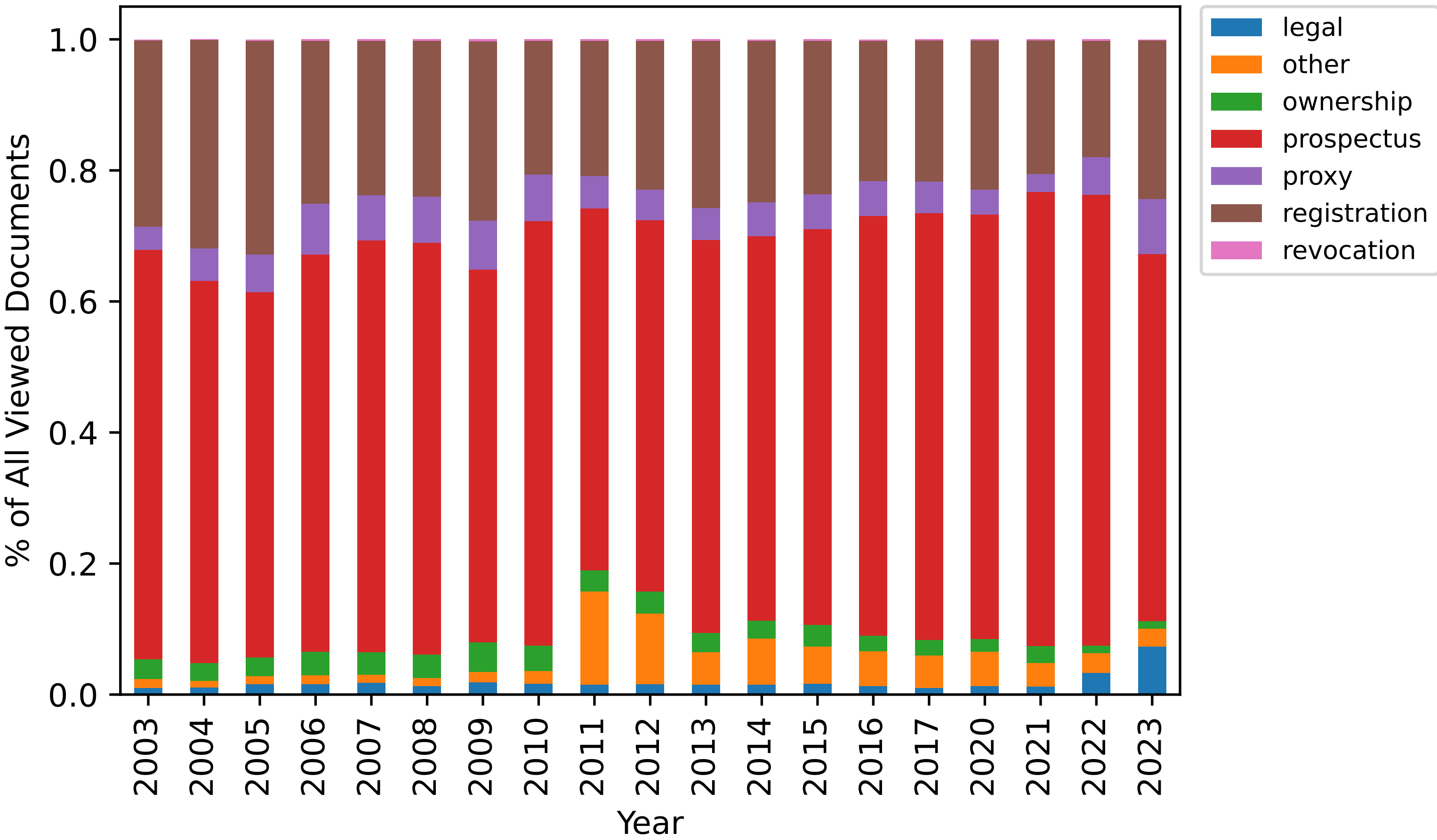


Figure 7: **Views by Horizon**

The figure charts aggregate *cumulative* viewership by age of the viewed filing. We count the total number of views, across the entire sample period, which are of filings less than x days old, where x $\in$ (1, 730). We then scale the measure by total number of views in the sample.

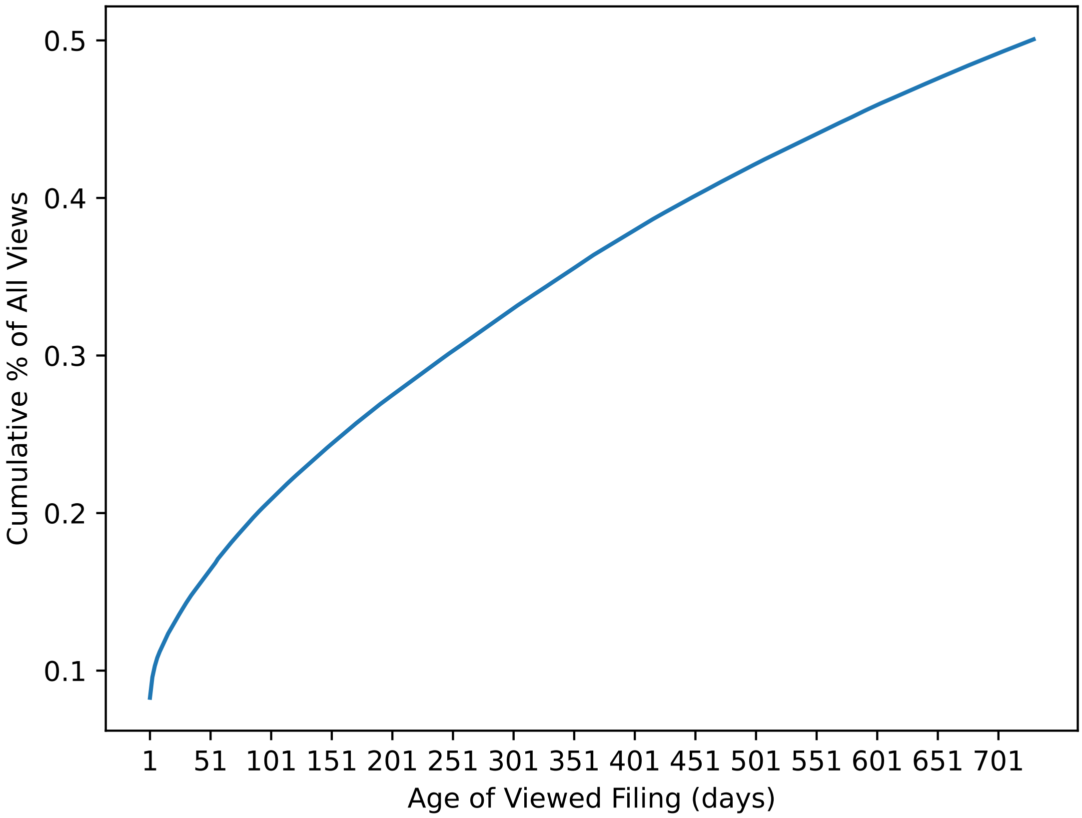


Table 1: **Summary Statistics**

This table provides summary statistics for all major variables. Panel A provides IP-level statistics on viewership. Frequency of Activity is how many days per month IPs view documents on EDGAR, and Filing Age is the age of the filing when it is viewed, in days. Panel B summarizes the fund-month level measures used in the regression analyses. Net flows, monthly and annual returns, alpha, 12b-1 fees, as well as viewership share and AVS are measured in percentage points, and Inflows is an indicator variable for whether or not net flows in a given period were positive.

Panel A: IP-Level Trends

Variable	N	Mean	SD	1%	50%	99%
Filings Viewed/ Month	4,588,555	98.69	3625.08	1	1	784
Frequency of Activity	4,588,555	2.15	3.78	1	1	22
Filing Age	4,588,555	1039.36	1376.63	0	405	5843

Panel B: Fund-Level Measures

Variable	N	Mean	SD	1%	50%	99%
Net Flows	279,884	0.32%	2.57%	-4.33%	-0.07%	7.25%
Inflows	279,884	0.478	0.500	0	0	1
Monthly Return	279,884	0.58%	2.91%	-5.94%	0.39%	6.39%
Annual Return	279,884	6.10%	11.49%	-17.90%	4.89%	30.13%
Age (months)	279,884	162.1	1.9	29.0	180.8	426.2
Total Assets (m)	279,884	1341.3	8.0	18.7	1416.3	47069.0
Intra-month Return SD	279,884	0.58%	0.71%	0.01%	0.32%	1.40%
Monthly Alpha	279,884	0.06%	1.41%	-3.29%	0.11%	2.77%
12b-1 Fees	279,884	0.13%	0.15%	0.00%	0.05%	0.48%
Viewership Share	279,884	0.05%	0.05%	0.01%	0.04%	0.18%
Abnormal View Share	279,884	0.002%	0.02%	-0.04%	0.00%	0.05%

Table 2: **Top 10 Largest Funds by Mean Total Assets**

This Table ranks the 10 largest Central Index Keys (CIKs) in terms of mean Total Assets, measured in billions of dollars, throughout the sample, which consists of all mutual funds with non-missing Total Assets data in the CRSP mutual fund universe from 1/2003-6/2017, and 6/2020-6/2023. EDGAR View Share is calculated as described in Eq (9), and reported in this Table as the average value across the sample.

Rank	**Fund Name**	**Total Net Assets (B)**	**Viewership Share**
1	Vanguard Index Funds	530.38	0.16%
2	iShares Trust	366.49	0.18%
3	PIMCO Funds	304.44	0.18%
4	J.P. Morgan Trust I	221.75	0.16%
5	Goldman Sachs Trust	208.58	0.18%
6	Allspring Funds Trust	195.00	0.18%
7	Federated Hermes Money Market Obligations Trust	185.54	0.16%
8	Vanguard Bond Index Funds	179.02	0.08%
9	J.P. Morgan Trust II	164.79	0.17%
10	Charles Schwab Family of Funds	151.31	0.13%

Table 3: **Predictors of Attention**

The dependent variables in this table are two different measures of attention, EDGAR View Share (EVS), and Abnormal View Share (AVS), constructed according to Eqs (9) and (10), respectively. The control variables are returns over the past month and year, Volatility of Daily Return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of Total Assets (measured in millions of dollars) and Age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

	EDGAR View Share			**Abnormal View Share**		
Dep. Var: Attention	(1)	(2)	(3)	(4)	(5)	(6)
Last Month Return	-0.0061***		-0.0086***	-0.0133***		-0.0141***
	(-2.66)		(-3.31)	(-4.81)		(-5.08)
Last Year Return	0.0250***		0.0231***	0.0047**		0.0053**
	(2.90)		(2.95)	(1.99)		(2.26)
log(Total Assets)	0.4911***		0.5144***	0.0265***		0.0273***
	(27.53)		(28.66)	(15.54)		(15.45)
Daily Return Volatility		-0.2011***	-0.0537***		-0.0190***	-0.0118***
		(-14.85)	(-4.89)		(-12.04)	(-7.41)
log(Age)		-0.0841***	-0.1873***		-0.0141***	-0.0195***
		(-5.37)	(-13.16)		(-8.16)	(-11.33)
12b-1 Fees		-0.0733***	-0.0253**		-0.0063***	-0.0037***
		(-4.48)	(-1.95)		(-4.12)	(-2.55)
Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SEs (CIK)	Yes	Yes	Yes	Yes	Yes	Yes
N	279,884	279,884	279,884	279,884	279,884	279,884
R-Squared	0.2485	0.0571	0.2846	0.0246	0.0243	0.0251

Table 4: **SEC Mutual Fund Reporting Forms**

We manually assign each form type into 1 of 7 classes: prospectuses, reports, proxy statements, registration documents, withdrawals, legal disclosures, or other. This mapping treats form types that contain similar information as one, avoiding concerns about shifts in the universe of filing types. This mapping is used in Figures 4 and 6.

	Category	**List**
A	Prospectus: Summary information about fund performance, distributions, portfolio holdings, or other fund attributes.	10-D 10-D/A 10-K 10-K/A 10-Q 10-Q/A 424B1 424B2 424B3 424B4 424B5 424B8 424I 425 497 497AD 497H2 497J 497K 497K1 497K2 497K3A 497K3B 8-K 8-K/A ARS D D/A FWP N-30D N-30D/A N-CSR N-CSR/A N-CSRS N-CSRS/A NPORT-EX NPORT-EX/A NPORT-P NPORT-P/A N-Q N-Q/A NSAR-A NSAR-A/A NSAR-AT NSAR-AT/A NSAR-B NSAR-B/A NSAR-BT NSAR-BT/A NSAR-U NSAR-U/A
B	Reports: Disclosures about external block ownership, as well as insider holdings.	11-K 11-K/A 13FCONP 13F-E 13F-E/A 13F-HR 13F-HR/A 13F-NT 13F-NT/A 3 3/A 4 4/A 40-17F1 40-17F1/A 40-17F2 40-17F2/A 5 CB N-18F1 N-18F1/A N-23C3A N-23C3A/A N-23C3C N-23C3C/A SC 13D SC 13D/A SC 13G SC 13G/A SC 14D9 SC 14D9/A SC TO-I SC TO-I/A SC TO-T SC TO-T/A
C	Proxy Statements: Filings related to shareholder proxy voting.	DEF 14A DEF 14C DEF13E3 DEFA14A DEFA14C DEFC14A DEFM14A DEFM14C DEFN14A DEFR14A DEFR14C DEFS14A DEFS14C N-PX N-PX/A PRE 14A PRE 14C PREA14A PREC14A PREC14C PREM14A PREM14C PREN14A PRER14A PRER14C PRES14A PRES14C PX14A6G

SEC Mutual Fund Reporting Forms-CONTINUED

	Category	List
D	Registrations: Initial filings for registration with the SEC to be able to operate as a mutual fund.	1 144 144/A 20-F 20-F/A 24F-1 24F-2EL 24F-2EL/A 24F-2NT 24F-2NT/A 24F-2TM 305B2 40-24B2 40-24B2/A 40-6B 40-6B/A 40-8B25 40-APP 40-APP/A 40-F 40-F/A 40-OIP 40-OIP/A 485A24E 485A24F 485APOS 485BPOS 485BXT 486APOS 486BPOS 6-K 6-K/A 8-A12B 8-A12B/A 8A12BT 8-A12G DEL AM F-1 F-1/A F-3 F-3/A F-3ASR F-3MEF F-4 F-4/A F-8/A F-9 F-9 POS F-9/A F-N F-N/A F-X F-X/A N-1 N-1/A N-14 N-14/A N-14AE N-14AE/A N14AE24 N14AE24/A N14EL24 N14EL24/A N-1A N-1A EL N-1A EL/A N-1A/A N-2 N-2/A N-8A N-8A/A N-8B-2 N-8B-2/A POS 8C POS AM POS AMI POS EX POS462B POSASR RW WD S-1 S-1/A S-11 S-11/A S-3 S-3/A S-3ASR S-6 S-6/A S-6EL24 S-6EL24/A S-8 S-8 POS
E	Withdrawals: Filings for revocation of previously submitted documents.	15-12B 15-12G 15-15D 25 25/A 25-NSE 25-NSE/A 40-8F-2 40-8F-2/A APP WD APP WD/A AW AW WD N-8F N-8F/A RW
F	Legal Disclosures: Disclosures about legal claims or settlements which the fund was involved in.	40-17G 40-17G/A 40-17GCS 40-33 40-33/A
G	Other	40-206A 40-206A/A 40-6C 40-6C/A 40-8F-A 40-8F-A/A 40-8F-L 40-8F-L/A 40-8F-M 40-8F-M/A 485B24E 485B24F 485BXTF 486A24E 486B24E 6B NTC 6B ORDR ABS-15G ADN-MTL APP NTC APP ORDR APP WDG CERT CERTAMX CERTARCA CERTBATS CERTCBO CERTNAS CERTNYS CERTPAC CORRESP CT ORDER DFAN14A DRS DRS/A DRSLTR EFFECT IRANNOTICE N-30B-2 N-8F NTC N-8F ORDR N-CEN N-CEN/A N-CR N-CR/A N-MFP N-MFP/A N-MFP1 N-MFP1/A N-MFP2 N-MFP2/A NO ACT NT 10-K NT 10-Q NT 11-K NT N-CEN NT N-MFP NT N-MFP1 NT N-MFP2 NT NPORT-EX NT NPORT-P NTFNCEN NTFNCSR NTFNSAR NTN 10Q NT-NCEN NT-NCEN/A NT-NCSR NT-NCSR/A NT-NSAR NT-NSAR/A OIP NTC OIP ORDR REGDEX SBSE-A SBSE-A/A SBSE-C SUPPL TH UNDER UPLOAD

Table 5: **AVS-Flow Relationship**

The dependent variable in this table is net fund flows, measured in percentage points, calculated as the percentage change in total assets minus return for a given fund-month. The independent variable of interest is Abnormal View Share (AVS), calculated as described in Eq (10). The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. Panel A is the full sample of CIKs, Panel B is just those CIKs which correspond to a single CRSP fund, and 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

	Panel A: All CIKs			
Dep. Var: Net Flows	(1)	(2)	(3)	(4)
Abnormal View Share	0.0130***	0.0127***	0.0095***	0.0084***
	(6.44)	(6.32)	(4.88)	(4.37)
Last Month Return		0.0852***		0.0847***
		(19.21)		(19.26)
Last Year Return		0.1733***		0.1695***
		(24.57)		(24.29)
log(Total Assets)		0.0176***		0.0470***
		(2.87)		(8.63)
Daily Return Volatility			-0.0430***	-0.0349***
			(-7.74)	(-6.44)
log(Age)			-0.1942***	-0.2005***
			(-27.79)	(-29.67)
12b-1 Fees			-0.0395***	-0.0421***
			(-5.56)	(-6.07)
Constant	0.0000	0.0000	0.0000	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)
N	279,884	279,884	279,884	279,884
R-Squared	0.0329	0.0551	0.0724	0.0960

Panel B: Unique CIKs				
Dep. Var: Net Flows	(1)	(2)	(3)	(4)
Abnormal View Share	0.0197***	0.0209***	0.0178**	0.0190***
	(1.97)	(2.10)	(1.79)	(1.92)
Last Month Return		0.1026***		0.1011***
		(9.12)		(8.83)
Last Year Return		0.1204***		0.1121***
		(5.94)		(5.50)
log(Total Assets)		-0.0376***		0.0081
		(-2.33)		(0.54)
Daily Return Volatility			-0.0105	-0.0125
			(-1.05)	(-1.22)
log(Age)			-0.1409***	-0.1385***
			(-10.22)	(-10.09)
12b-1 Fees			-0.0592***	-0.0567***
			(-2.87)	(-2.70)
Constant	-0.0923***	-0.1134***	-0.0959***	-0.0744***
	(-5.71)	(-5.11)	(-4.80)	(-2.67)
N	31,382	31,382	31,382	31,382
R-Squared	0.0318	0.0507	0.0559	0.0722

Table 6: **AVS-Flow Relationship, by Filing Age**

This table divides the EDGAR viewership sample into five groups, based on the age of the filings at time of viewership (0-6, 6-12, and >12 months). The dependent variable is net fund flows, measured in percentage points, calculated as the percentage change in total assets minus return for a given fund-month. The independent variable of interest is Abnormal View Share (AVS), which is calculated for each subsample. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

Dep. Var: Net Flows		(1)	(2)	(3)	(4)
Filing Age:					
	0-6m	0.0060***			0.0059***
		(2.98)			(2.94)
	6-12m		0.0052***		0.0049***
			(2.67)		(2.45)
	>12m			0.0038***	0.0020
				(2.15)	(1.12)
Controls		YES	YES	YES	YES
Month Fes		YES	YES	YES	YES
Clustered SEs (CIK)		YES	YES	YES	YES
N		279,789	279,789	279,789	279,789
R-Squared		0.0960	0.0960	0.0960	0.0960

Table 7: **AVS-Flow Relationship by Fund Type**

This table divides the sample by type of fund. *Passive* is an indicator which takes on a value of 1 if all of the CRSP funds filing under a given CIK are of the indicated type, and 0 if all are not of the indicated type (index funds or ETFs). The dependent variable in this table is net fund flows, measured in percentage points, calculated as the percentage change in total assets minus return for a given fund-month. The independent variables of interest are Abnormal View Share (AVS), *Passive*, and their interaction. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

	Index Fund		**ETF/ETN**	
Dep. Var: Net Flows	(1)	(2)	(3)	(4)
Abnormal View Share	0.0121***	0.0090***	0.0112***	0.0082***
	(5.40)	(4.12)	(5.43)	(4.07)
Passive	0.2273***	0.0322	0.4174***	0.1315***
	(6.34)	(1.13)	(10.99)	(4.17)
AVS*Passive	0.0017	-0.0028	0.0060	0.0027
	(0.17)	(-0.30)	(0.59)	(0.28)
Last Month Return	0.0881***	0.0862***	0.0868***	0.0849***
	(19.38)	(19.03)	(19.47)	(19.19)
Last Year Return	0.1736***	0.1724***	0.1716***	0.1693***
	(24.07)	(24.03)	(24.24)	(24.06)
log(Total Assets)	0.0092	0.0503***	0.0128**	0.0418***
	(1.42)	(8.70)	(2.05)	(7.57)
Daily Return Volatility		-0.0404***		-0.0392***
		(-7.14)		(-7.14)
log(Age)		-0.1974***		-0.1895***
		(-27.55)		(-26.78)
12b-1 Fees		-0.0438***		-0.0383***
		(-6.14)		(-5.50)
Constant	-0.0200***	0.0054	-0.0209***	-0.0066
	(-2.76)	(0.84)	(-3.05)	(-1.09)
Month FEs	Yes	Yes	Yes	Yes
Clustered SEs (CIK)	Yes	Yes	Yes	Yes
N	252,425	252,425	273,693	273,693
R-Squared	0.0590	0.0959	0.0613	0.0948

Table 8: **Flow-AVS Relationship by Viewer Type**

This table divides the sample by type of viewer at the IP-level. IPs are linked to organizations through the MaxMind linking file, and organizations are manually identified as either financial or non-financial. The dependent variable in this table is net fund flows, measured in percentage points, calculated as the percentage change in total assets minus return for a given fund-month. The independent variable of interest is Abnormal View Share (AVS), constructed for views from each type. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

Dep. Var: Net Flows	(1)	(2)	(3)
Financial AVS	0.0032		0.0010
	(1.56)		(0.52)
Non-Financial AVS		0.0090***	0.0087***
		(4.39)	(4.29)
Last Month Return	0.0872***	0.0873***	0.0873***
	(19.41)	(19.45)	(19.44)
Last Year Return	0.1738***	0.1738***	0.1738***
	(23.26)	(23.26)	(23.26)
log(Total Assets)	0.0493***	0.0491***	0.0491***
	(8.19)	(8.16)	(8.15)
Daily Return Volatility	-0.0374***	-0.0373***	-0.0372***
	(-5.96)	(-5.95)	(-5.95)
log(Age)	-0.2106***	-0.2105***	-0.2105***
	(-28.91)	(-28.90)	(-28.90)
12b-1 Fees	-0.0461***	-0.0461***	-0.0461***
	(-6.27)	(-6.27)	(-6.27)
Constant	0.0000	0.0000	0.0000
	(0.00)	(0.00)	(0.00)
N	234,764	234,765	234,766
R-Squared	0.0959	0.0960	0.0960

Table 9: **Flow-AVS Relationship Interacted with Fund Age**

This table interacts Abnormal View Share (AVS) with fund age. The dependent variable in this table is net fund flows, measured in percentage points, calculated as the percentage change in total assets minus return for a given fund-month. The independent variables of interest are AVS, fund age, and their interaction. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

Dep. Var: Net Flows	(1)	(2)	(3)	(4)
Abnormal View Share	0.0093***	0.0096***	0.0070***	0.0074***
	(5.04)	(5.23)	(3.79)	(4.05)
log(Age)	-0.1947***	-0.1917***	-0.2060***	-0.2005***
	(-27.94)	(-27.70)	(-30.09)	(-29.69)
AVS*log(Age)	-0.0081***	-0.0079***	-0.0079***	-0.0078***
	(-3.30)	(-3.26)	(-3.24)	(-3.21)
Last Month Return		0.0867***		0.0848***
		(19.88)		(19.28)
Last Year Return		0.1677***		0.1695***
		(24.21)		(24.28)
log(Total Assets)			0.0585***	0.0470***
			(10.84)	(8.63)
Daily Return Volatility			-0.0261***	-0.0349***
			(-4.79)	(-6.45)
12b-1 Fees			-0.0340***	-0.0421***
			(-4.90)	(-6.07)
Constant	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.02)	(-0.02)	(-0.02)	(-0.02)
Month FEs	Yes	Yes	Yes	Yes
Clustered SEs (CIK)	Yes	Yes	Yes	Yes
N	279,884	279,884	279,884	279,884
R-Squared	0.0695	0.0904	0.0753	0.0961

Table 10: **Flow-AVS Relation by Net Flow Sign**

This table divides the sample based on the sign of net flows in a given month. $Inflows$ is an indicator variable which is equal to 1 if net flows are positive in a given month, and zero otherwise. The dependent variable in this table is net fund flows, measured in percentage points, calculated as the percentage change in total assets minus return for a given fund-month. The independent variables of interest are AVS, $Inflows$, and their interaction. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

Dep. Var: Net Flows	(1)	(2)	(3)	(4)
Abnormal View Share	-0.0010	0.0002	-0.0015	-0.0009
	(-0.76)	(0.13)	(-1.09)	(-0.68)
NetInflows	1.4057***	1.3950***	1.3835***	1.3696***
	(91.64)	(90.64)	(90.38)	(88.78)
AVS*NetInflows	0.0095***	0.0093***	0.0094***	0.0093***
	(3.52)	(3.45)	(3.49)	(3.48)
Last Month Return		0.0381***		0.0406***
		(13.75)		(14.47)
Last Year Return		0.0778***		0.0742***
		(18.47)		(17.51)
log(Total Assets)		-0.0350***		-0.0165***
		(-9.59)		(-4.55)
Daily Return Volatility			0.0176***	0.0100***
			(5.37)	(2.98)
log(Age)			-0.0753***	-0.0717***
			(-16.49)	(-15.85)
12b-1 Fees			0.0080**	0.0029***
			(2.18)	(0.79)
Constant	-0.6726***	-0.6675***	-0.6620***	-0.6553***
	(-100.52)	(-100.25)	(-91.43)	(-91.54)
Month FEs	Yes	Yes	Yes	Yes
Clustered SEs (CIK)	Yes	Yes	Yes	Yes
N	279,884	279,884	279,884	279,884
R-Squared	0.5146	0.5199	0.5203	0.5245

Table 11: **Flow-AVS Relation by Flow Sign, Separated**

This table supplements Table 10 by separating inflows from outflows, and testing for the expected asymmetric impact of AVS. The dependent variable is flow as a percentage of total assets, with Columns (1) and (2) being for inflows, and (3) and (4) being for outflows. The data on separated flows are sourced from Morningstar Direct, which gets them from form NSAR sales and redemptions. The independent variable of interest is AVS. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

	Inflows		**Outflows**	
Dep. Var: Flows	(1)	(2)	(3)	(4)
Abnormal View Share	0.0071***	0.0041**	0.0014	0.0016
	(3.38)	(2.11)	(0.70)	(0.85)
Last Month Return	0.0049**	0.0014	-0.0412***	-0.0435***
	(2.44)	(0.46)	(-19.19)	(-13.93)
Last Year Return	0.0533***	0.0517***	-0.0541***	-0.0512***
	(5.50)	(5.67)	(-5.76)	(-5.66)
log(Total Assets)	0.1776***	0.2172***	0.1656***	0.1888***
	(8.85)	(12.03)	(7.80)	(9.98)
Daily Return Volatility		-0.0397**		-0.0194
		(-2.51)		(-1.19)
log(Age)		-0.1849***		-0.0508***
		(-10.35)		(-2.83)
12b-1 Fees		0.2632***		0.3283***
		(14.04)		(17.48)
Constant	0.0026	-0.0096	-0.0011	-0.0161
	(0.12)	(-0.51)	(-0.05)	(-0.84)
Month FEs	Yes	Yes	Yes	Yes
Clustered SEs (CIK)	Yes	Yes	Yes	Yes
N	182,062	182,062	182,062	182,064
R-Squared	0.0511	0.1581	0.0441	0.1502

Table 12: **Attention Driven Flows and Future Returns**

This table regresses future returns at different horizons onto the portion of flows that is driven by Abnormal View Share (AVS). The dependent variable in this table is future fund returns, measured in percentage points, compounded over the indicated horizon. The independent variable of interest is AVS, calculated as described in Eq (10). The control variables are flows in period t, returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. Panel A is the full sample of CIKs, Panel B is just those CIKs which correspond to a single CRSP fund. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

Panel A: All CIKs

	Return Horizon			
Dep. Var: Future Return	**1m**	**3m**	**6m**	**12m**
Abnormal View Share	-0.0070***	-0.0073***	-0.0065***	0.0004
	(-3.72)	(-3.86)	(-3.75)	(0.25)
Current Flows	0.0028	0.0058***	0.0065***	-0.0038
	(1.43)	(2.38)	(2.20)	(-1.16)
Last Month Return	-0.0242***	0.0065***	0.0278***	-0.0029
	(-10.51)	(2.80)	(12.01)	(-1.16)
Last Year Return	-0.0538***	-0.0729***	-0.1112***	-0.0275***
	(-14.74)	(-15.36)	(-19.58)	(-5.25)
log(Total Assets)	0.0112***	0.0298***	0.0528***	0.0627***
	(3.75)	(6.59)	(8.87)	(9.25)
Daily Return Volatility	0.0445***	0.1146***	0.1998***	0.2200***
	(14.12)	(22.30)	(27.59)	(24.71)
log(Age)	-0.0075***	-0.0114***	-0.0166***	-0.0100
	(-2.68)	(-2.71)	(-3.01)	(-1.57)
12b-1 Fees	0.0198***	0.0314***	0.0426***	0.0404***
	(7.43)	(7.97)	(8.33)	(6.90)
Constant	-0.0051	-0.0057	-0.0051	-0.0060
	(-1.84)	(-1.39)	(-0.96)	(-1.01)
N	277,750	277,750	277,750	277,750
R-Squared	0.0949	0.2166	0.2978	0.3386

Panel B: Unique CIKs				
	Return Horizon			
Dep. Var: Future Return	**1m**	**3m**	**6m**	**12m**
Abnormal View Share	-0.0236***	-0.0142*	-0.0134	-0.0057
	(-3.26)	(-1.73)	(-1.40)	(-0.74)
Current Flows	0.0038	0.0161***	0.0177	0.0174
	(0.62)	(2.13)	(1.89)	(1.84)
Last Month Return	0.0011	0.0188***	0.0391***	0.0193***
	(0.14)	(2.49)	(5.47)	(2.83)
Last Year Return	-0.0117	-0.0205	-0.0399***	0.0451***
	(-1.27)	(-1.67)	(-2.48)	(2.69)
log(Total Assets)	-0.0029	-0.0037	-0.0046	0.0048
	(-0.28)	(-0.22)	(-0.20)	(0.17)
Daily Return Volatility	0.0665***	0.1165***	0.1540***	0.1561***
	(9.65)	(10.43)	(10.16)	(8.34)
log(Age)	0.0064	0.0159	0.0289	0.0527***
	(0.78)	(1.21)	(1.65)	(2.49)
12b-1 Fees	-0.0051	-0.0079	-0.0109	-0.0128
	(-0.42)	(-0.38)	(-0.40)	(-0.39)
Constant	-0.0760***	-0.1218***	-0.1661***	-0.1821***
	(-5.18)	(-5.09)	(-5.25)	(-4.74)
N	31,048	31,048	31,048	31,048
R-Squared	0.0683	0.1597	0.2142	0.2290

Table 13: **Attention Driven Flows and ETF Returns**

This table regresses future returns at different horizons onto Abnormal View Share (AVS). The dependent variable in this table is future fund returns, measured in percentage points, compounded over the indicated horizon. The independent variable of interest is AVS, calculated as described in Eq (10), interacted with an ETF indicator, equal to 1 if all CRSP funds under a given CIK are ETFs. The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

	Return Horizon			
Dep. Var: Future Return	**1m**	**3m**	**6m**	**12m**
Abnormal View Share	-0.0105***	-0.0081***	-0.0058***	0.0018
	(-5.63)	(-4.21)	(-3.38)	(1.23)
ETF Indicator	-0.0583***	-0.1173***	-0.1776***	-0.2025***
	(-2.95)	(-3.49)	(-3.90)	(-3.80)
AVS * ETF	0.0400***	0.0040	-0.0106	-0.0185*
	(3.94)	(0.38)	(-0.95)	(-1.92)
Current Flows	0.0031	0.0063***	0.0072***	-0.0029
	(1.56)	(2.53)	(2.43)	(-0.87)
Last Month Return	-0.0227***	0.0076***	0.0285***	-0.0019
	(-9.70)	(3.23)	(12.17)	(-0.75)
Last Year Return	-0.0533***	-0.0723***	-0.1106***	-0.0267***
	(-14.56)	(-15.17)	(-19.40)	(-5.05)
log(Total Assets)	0.0120***	0.0316***	0.0556***	0.0662***
	(4.11)	(7.16)	(9.61)	(10.03)
Daily Return Volatility	0.0473***	0.1189***	0.2053***	0.2260***
	(16.20)	(25.72)	(31.79)	(27.86)
log(Age)	-0.0109***	-0.0186***	-0.0274***	-0.0224***
	(-3.96)	(-4.57)	(-5.25)	(-3.72)
12b-1 Fees	0.0192***	0.0298***	0.0398***	0.0370***
	(7.25)	(7.60)	(7.85)	(6.40)
Constant	-0.0033	-0.0017	0.0010	0.0011
	(-1.21)	(-0.42)	(0.19)	(0.18)
N	271,574	271,574	271,574	271,574
R-Squared	0.0943	0.2161	0.2972	0.3377

Table 14: **Attention Driven Flows, Disagreement, and Returns**

This table regresses future returns at different horizons onto Abnormal View Share (AVS). The dependent variable in this table is future fund returns, measured in percentage points, compounded over the indicated horizon. The independent variable of interest is AVS, calculated as described in Eq (10), interacted with the volatility of daily returns as a proxy for disagreement about a fund. The control variables are returns over the past month and year, and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

	Return Horizon			
Dep. Var: Future Return	**1m**	**3m**	**6m**	**12m**
Abnormal View Share	-0.0079***	-0.0071***	-0.0065***	-0.0003
	(-3.89)	(-3.46)	(-3.50)	(-0.16)
Daily Return Volatility	0.0443***	0.1147***	0.1998***	0.2198***
	(14.11)	(22.32)	(27.60)	(24.70)
AVS * Daily Volatility	-0.0076***	0.0020	0.0000	-0.0050***
	(-2.56)	(0.69)	(0.01)	(-2.05)
Current Flows	0.0028	0.0058***	0.0065***	-0.0038
	(1.44)	(2.38)	(2.19)	(-1.15)
Last Month Return	-0.0241***	0.0065***	0.0278***	-0.0028
	(-10.50)	(2.80)	(12.01)	(-1.15)
Last Year Return	-0.0537***	-0.0729***	-0.1112***	-0.0275***
	(-14.74)	(-15.36)	(-19.58)	(-5.25)
log(Total Assets)	0.0111***	0.0298***	0.0528***	0.0627***
	(3.75)	(6.59)	(8.87)	(9.24)
log(Age)	-0.0074***	-0.0114***	-0.0166***	-0.0100
	(-2.67)	(-2.71)	(-3.01)	(-1.56)
12b-1 Fees	0.0198***	0.0314***	0.0426***	0.0404***
	(7.43)	(7.97)	(8.33)	(6.90)
Constant	-0.0052	-0.0057	-0.0051	-0.0061
	(-1.88)	(-1.38)	(-0.96)	(-1.02)
N	277,750	277,750	277,750	277,750
R-Squared	0.0950	0.2166	0.2978	0.3387

Table 15: **Attention Driven Flows and Future Alpha**

This table regresses future FF5 alpha onto Abnormal View Share (AVS). The dependent variable is one month-ahead fund alpha, measured in percentage points, estimated using the FF5 factors, plus momentum, downloaded from Ken French's website. The independent variable of interest is AVS, calculated as described in Eq (10). The control variables are returns over the past month and year, volatility of daily return (s.d. of intra-month daily return), and 12b-1 fees, all measured in percentage points, along with the natural logarithms of total assets (measured in millions of dollars) and age (measured in months). All variables are demeaned and scaled by their standard deviations. Standard errors are clustered at the fund level, and month fixed effects are included in all columns. Panel A is the full sample of CIKs, Panel B is just those CIKs which correspond to a single CRSP fund. 10, 5, and 1% significance levels are indicated with *, **, ***, respectively, and t-statistics are reported in parentheses.

Panel A: All CIKs

	Alpha Horizon			
Dep. Var: Future Alpha	**1m**	**3m**	**6m**	**12m**
Abnormal View Share	-0.0029	-0.0048***	-0.0006	-0.0021
	(-1.60)	(-2.40)	(-0.30)	(-1.29)
Current Flows	0.0160***	0.0253***	0.0370***	0.0160***
	(7.21)	(8.60)	(10.45)	(3.61)
Last Month Return	0.0238***	0.0106***	0.0084***	0.0482***
	(6.80)	(2.85)	(2.35)	(13.31)
Last Year Return	-0.0032	-0.0047	-0.0042	0.0011
	(-1.24)	(-1.25)	(-0.87)	(0.18)
log(Total Assets)	-0.0004	-0.0036	-0.0061	-0.0047
	(-0.09)	(-0.68)	(-0.98)	(-0.65)
Daily Return Volatility	0.0101***	0.0033	0.0102	0.0133
	(1.96)	(0.57)	(1.50)	(1.64)
log(Age)	0.0034	-0.0028	-0.0054	-0.0135
	(0.81)	(-0.50)	(-0.82)	(-1.71)
12b-1 Fees	0.0130***	0.0159***	0.0160***	0.0082
	(3.79)	(3.43)	(2.94)	(1.27)
Constant	0.0007	-0.0007	-0.0018	-0.0033
	(0.19)	(-0.16)	(-0.33)	(-0.54)
N	267,343	265,754	263,568	259,413
R-Squared	0.1671	0.1796	0.1770	0.1697

Panel B: Unique CIKs				
	Alpha Horizon			
Dep. Var: Future Alpha	**1m**	**3m**	**6m**	**12m**
Abnormal View Share	-0.0136**	-0.0065	-0.0065	-0.0100
	(-1.93)	(-0.68)	(-0.58)	(-1.16)
Current Flows	0.0128**	0.0079	0.0117	-0.0026
	(2.01)	(1.00)	(1.27)	(-0.26)
Last Month Return	0.0194**	-0.0127	-0.0036	0.0345***
	(1.92)	(-1.19)	(-0.36)	(3.28)
log(Total Assets)	-0.0377***	-0.0419***	-0.0515***	-0.0577***
	(-3.24)	(-2.87)	(-2.86)	(-2.59)
Daily Return Volatility	0.0173**	0.0141	0.0176	0.0254
	(2.22)	(1.36)	(1.42)	(1.68)
log(Age)	0.0181**	0.0062	-0.0002	-0.0050
	(1.95)	(0.54)	(-0.02)	(-0.27)
12b-1 Fees	-0.0255	-0.0306	-0.0314	-0.0466
	(-1.67)	(-1.62)	(-1.47)	(-1.69)
Constant	-0.0767***	-0.0782***	-0.0785***	-0.0926***
	(-4.53)	(-3.80)	(-3.18)	(-2.93)
N	27,118	27,111	27,099	27,074
R-Squared	0.0886	0.0976	0.0983	0.0968

Appendix: Modeling Background and Specifications

Notation Shorthand

Summary of Notation

- φ: Prior belief about the manager's alpha.
- S_t: Signal received by investors, $S_t = \alpha + \epsilon_S$, where $\epsilon_S \sim N(0, \frac{1}{\omega_S})$.
- q_S: Fund size based on the additional signal S_t.
- q: Fund size based solely on past performance.
- q^*: Combined fund size.
- δ: Fraction of investors receiving the signal S_t.

Bayesian updating with sequential signals

We provide the solution method for the two-signal updating. Suppose the prior distribution of α is given by:

$$N(\phi_0, \frac{1}{\gamma})$$

The observed signals are received sequentially, they are linear and have precisions of ω_i and ω_X:

$$\begin{aligned} R &= \alpha + \varepsilon_i, & \varepsilon_i &\sim N(0, \frac{1}{\omega_i}) \\ R' &= \alpha + \varepsilon_{Xi}, & \varepsilon_{Xi} &\sim N(0, \frac{1}{\omega_X}) \end{aligned}$$

A Primer on Bayesian Updating with Two Independent Signals

Given the independence of ε_i and ε_{Xi}, the posterior precision and mean after observing both signals are updated as follows. First, the posterior precision, combining information from the prior and both independent signals, is:

$$\gamma_i = \gamma + \omega_i,$$

$$\gamma_X = \gamma + \omega_i + \omega_X,$$

To incorporate the information from both signals into the posterior mean, we first calculate individual contributions and then combine them, weighted by their respective precisions. The updated posterior mean is:

$$\phi_i = \frac{\gamma\phi_0 + \omega_i R}{\gamma + \omega_i}$$

$$\phi_X = \frac{\gamma\phi_0 + \omega_i R + \omega_X R'}{\gamma + \omega_i + \omega_X}$$

This formula represents a weighted average, where the weights are the precisions of the prior and the signals. We have:

$$\phi_X = \frac{\phi_i(\gamma + \omega_i) + \omega_X R'}{\gamma + \omega_i + \omega_X}$$

or

$$\phi_X = \frac{\phi_i(\gamma + \omega_i)}{\gamma + \omega_i + \omega_X} + \frac{\omega_X R'}{\gamma + \omega_i + \omega_X}$$