Attention Allocation and Fund Flows: Evidence from Institutional Investors

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Abstract

With more than $40 trillion dollars under management, institutional investors of funds play an important role in the financial market. Using novel data on fund viewership, we are the first to examine how these investors allocate attention to specific institutional funds. Exploiting quasi-random variation in screen display features on a prominent institutional asset management platform as instruments, we provide causal evidence that their direct attention drives flows to institutional funds and exerts positive price pressure on their underlying stocks. Overall, our evidence suggests that even sophisticated institutional fund investors suffer from attention constraints, which have important asset pricing implications.

JEL Classification: G11, G12, G14, G4, G23

Keywords: Institutional fund investors; limited attention; fund flow; price pressure

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1 Introduction

By the end of 2023, U.S. institutional asset owners, including pension funds, endowments, and foundations, held combined assets exceeding $40 trillion, surpassing the total assets under management of U.S. mutual funds by $15 trillion.[1] These institutional investors allocate capital across a range of institutional products (i.e., funds). While prior research has examined both the performance of these products and the role of consultants, a crucial aspect has been overlooked: how institutional fund investors allocate their attention across funds, a necessary precursor to investment decisions.[2] Understanding this behavior is important because their investment choices directly affect the welfare of ultimate beneficiaries such as pension fund members and, given the scale of their assets, may also influence asset prices.

We develop a novel measure of institutional investors' direct attention to specific equity products using viewership data from Nasdaq eVestment, a leading institutional investment platform that tracks over $13 trillion in institutional assets annually. The platform monitors user interactions with thousands of institutional equity funds across 479 fund families, recording daily product-level viewership as well as the intensity of those views.[3] Unlike traditional proxies for fund investor attention that rely on equilibrium outcomes such as fund flows, our data enable us to observe direct attention allocation by investors to individual funds.

Our analysis focuses on the attention allocation of institutional fund investors, the ultimate decision-makers in capital allocation, rather than their consultants. This distinction is economically meaningful, as it reflects the active role institutional asset owners play in manager selection. While prior research examines consultant viewership patterns

[1] See Goyal, Wahal, and Yavuz (2024) for sources to calculate these figures.

[2] For example, Jones, Martinez, and Montag (2023); Goyal, Wahal, and Yavuz (2024); Jones and Martinez (2017); Chaudhuri, Ivković, and Trzcinka (2018); Cookson, Jenkinson, Jones, and Martinez (2022a); Andonov, Bonetti, and Stefanescu (2023).

[3] Most major institutional investors, such as CalPERS, use this platform to search for equity funds. While Morningstar is a widely used platform for *retail-oriented* mutual fund searches, Nasdaq eVestment is the dominant platform in *institutional* asset management.

in a different context (Chava, Kim, and Weagley, 2022), institutional investors constitute the dominant user group on the platform, averaging 1,064 active accounts per month compared with 187 consultants. To the best of our knowledge, we are the first to analyze institutional investors' viewership of individual funds. By isolating the behavior of institutional investors from that of consultants, we provide a more direct lens into the drivers of institutional attention allocation decisions and their implications for asset prices.

To quantify attention, we begin by aggregating daily viewership data to the monthly level. We construct this measure separately for institutional investors and consultants. As expected, for both groups, attention levels are lower during weekends and December holidays, and are positively correlated with fund size and the experience of the fund's marketing team. We then construct and focus on an abnormal attention (AA) metric by comparing the current-month views tp the median monthly views over the prior six months. We again compute this measure separately for institutional investors ($Investor\_AA$) and for consultants ($Consultant\_AA$).

When examining the determinants of future abnormal attention from institutional investors and consultants, we uncover both similarities and meaningful differences between $Investor\_AA$ and $Consultant\_AA$ in their responses to fund performance and fees. For example, both measures increase with past fund returns and decline with return volatility, indicating that investors and consultants tend to direct greater abnormal attention toward funds that have exhibited strong and stable recent performance. The two groups diverge, however, in their sensitivity to fund fees. While $Consultant\_AA$ is negatively associated with posted fund fees, $Investor\_AA$ shows no significant relationship. This difference reflects institutional practice: investors typically negotiate fee arrangements directly with fund managers at later stages of the selection process, rendering posted fees less relevant when determining which funds to examine initially. Differences also emerge with respect to fund age. $Investor\_AA$ is positively associated with fund age, consistent with a preference for fund managers with longer track records and established reputations. Consultants, by contrast, exhibit no such sensitivity to fund age, likely reflecting their mandate to present clients with a diverse range of options, including both seasoned and younger funds.

Barber and Odean (2008) posit that under attention constraints, investors' attention determines their investment choice sets. When coupled with short-sale constraints, investor attention systematically predicts purchase decisions. Applying this intuition to the institutional fund setting, we expect that higher $Investor\_AA$ is associated with greater subsequent institutional inflows. We confirm this prediction in regressions controlling for many fund characteristics that may be correlated with both abnormal attention and fund flows, including $Consultant\_AA$. The economic magnitude is substantial: a one-standard-deviation increase in $Investor\_AA$ is associated with a 0.43% increase in net inflows, which translates to approximately $14.4 million in additional capital. In contrast, after controlling for $Investor\_AA$, $Consultant\_AA$ does not predict higher institutional flows to the fund, consistent with the idea that institutional fund investors themselves are the ultimate decision makers. In addition, as a placebo test, we do not find $Investor\_AA$ to predict retail flows to that fund.

Among investors, spikes in viewership do not uniformly translate into subsequent fund flows. Analyzing viewer activity using the unique investor identifiers on the Nasdaq eVestment platform, we find that the relation between Investor AA and subsequent fund flows depends on viewer type. First, abnormal attention from first-time viewers is strongly associated with future flows, whereas attention from repeat viewers is weaker and generally insignificant. This finding is consistent with the notion of the short-sale constraint. First-time viewers are more likely to be buyers than repeat viewers, as they are less likely to be existing investors and therefore cannot sell the fund. Second, we expect that investors who focus on a small subset of funds are more likely to invest than those who view many funds simultaneously. We find empirical support for this prediction.

To identify the causal impact of institutional fund investor attention on fund flows, we conduct two complementary instrumental variable (IV) tests that exploit variation in user search behavior on the Nasdaq eVestment platform. In the first test, we leverage a screen display feature of the Nasdaq eVestment platform that presents funds in alphabetical order, regardless how investors conduct their searches. This design feature gives rise to attention spillovers from one fund to its close neighbors in the alphabetical order. Consequently, $Investor\_AA$ of these name-based neighboring funds can serve as a valid instrument for the focal fund's $Investor\_AA$.

We confirm the instrument's relevance: in the first-stage regression, the focal fund's $Investor\_AA$ is positively and significantly related to the $Investor\_AA$ of its close alphabetical neighbors, but not to that of distant neighbors. In the second stage, the instrumented $Investor\_AA$ remains a positive and significant predictor of the focal fund's subsequent-period flow. While Chen, An, Wang, and Yu (2023) document attention spillovers among retail investors trading individual stocks on Chinese online platforms, our findings indicate that even sophisticated U.S. institutional fund investors are subject to similar attention constraints.

In the second test, we exploit the fact that past performance is among the most frequently used search criteria on the Nasdaq eVestment platform and past one-year is the most common lookback horizon.[4] Specifically, using a rolling one-year performance window, as time passes, the most recent month's fund return enters the rolling average fund performance calculation, while the return from 13 months ago (Ret_{t-13}) drops out. If institutional fund investors rationally use past performance as a fund selection criterion, we expect a positive relationship between Ret_{t-13} and subsequent investor attention. In contrast, if institutional investors are subject to limited attention, this relationship can be negative. When a poor Ret_{t-13} exits the rolling window, reported recent performance mechanically improves, potentially causing the fund to newly satisfy investors' screening criteria and leading to an increase in abnormal investor attention.

Empirically, $Investor\_AA$ positively loads on monthly fund returns from $t-1$ to

[4]Fund AUM is the most common search criterion, followed by past performance. However, AUM is arguably not a suitable instrument, as it may reflect institutional investors' size-related constraints. For instance, some institutions only consider funds with at least $500 million, while others require fund AUM to be greater than $1 billion in AUM to be considered.

$t-12$, consistent with the earlier evidence that past fund performance is a major driver of $Investor\_AA$. In sharp contrast, $Investor\_AA$ negatively and significantly loads on Ret_{t-13}, consistent with the attention channel. A large positive Ret_{t-13}, when dropped out of the rolling window, reduces the past one-year fund performance variable, and therefore institutional fund attention. Using Ret_{t-13} as an instrument for $Investor\_AA$, we again document the causal impact of fund investor attention on the fund flow, consistent with the evidence documented for mutual funds by Phillips, Pukthuanthong, and Rau (2016).

By design, exogenous variation in attention is unlikely to reflect rational attention allocation decision. Collectively, the IV results suggest that institutional fund investors do not allocate their attention in a fully rational manner. The observed attention spillovers from alphabetically neighboring funds provide compelling evidence supporting this behavioral interpretation based on limited attention. Furthermore, the opposite impact of returns from 12 versus 13 months prior indicates systematic departures from optimal information processing. The rational attention hypothesis would have a hard time explaining why AA responds negatively to returns from 13 months ago, but positively to fund returns in other past horizons. Having established a causal relationship between institutional fund investors' "non-fundamental" attention and their investment behavior, we next examine whether these attention-driven trading patterns have broader implications for asset prices.

When institutional funds receive attention-induced inflows, they typically scale up their existing portfolios (Pollet and Wilson, 2008; Li, 2022b), creating positive price pressure on underlying stocks. This pressure subsequently dissipates as market forces restore equilibrium (Coval and Stafford, 2007; Lou, 2012; Ben-David, Li, Rossi, and Song, 2022a), resulting in only a temporary boost to fund performance. Consistent with this mechanism, we find that while $Investor\_AA$ positively and significantly predicts fund performance in the subsequent quarter, this effect reverses and becomes negative over the following two quarters.

Fund performance is also influenced by many factors such as portfolio constraints and managerial skill. To more directly assess the asset pricing implications of institutional investors' attention, we examine whether attention-induced trading by institutional funds exerts price pressure on underlying stocks. We construct a stock-level measure of abnormal attention (SAA) by aggregating the fund-level AAs across funds holding the stock, in the spirit of Lou (2012). Our results indicate that SAA forecasts higher stock returns in the next quarter, but this effect gradually fades and becomes statistically insignificant over a one-year horizon.

To further isolate price impact attributable specifically to the "non-fundamental" attention channel, we replace $Investor\_AA$ with its instrumented version in the construction of SAA. Using either Ret_{t-13} or the $Investor\_AA$ of name-based neighboring funds as instruments for AA, we obtain consistent results. The instrumented SAA continues to predict stock returns over the next two quarters, with the predictive effect diminishing over time and becoming statistically insignificant by the end of the first year.

Taken together, these findings support the interpretation that institutional investor attention leads to capital flows, which in turn creates temporary price pressure on underlying stocks. This pressure fades as markets adjust, consistent with the transitory nature of attention-driven trading effects.

Our paper contributes to the literature on institutional investors of funds—a relatively underexplored yet influential investor group—by examining a novel factor that acts as a critical precursor to their capital allocation decisions. In doing so, we provide new insights into the underlying mechanisms that drive institutional investment behavior. Prior research has primarily focused on institutional investors' manager selection capabilities (Brown, Gredil, and Kantak, 2023; Jones, Martinez, and Montag, 2023; Goyal, Wahal, and Yavuz, 2024), conflicts of interest arising from advisory consultants (Jones and Martinez, 2017; Chaudhuri, Ivković, and Trzcinka, 2018; Dyck, Manoel, and Morse, 2022; Cookson, Jenkinson, Jones, and Martinez, 2022a; Andonov, Bonetti, and Stefanescu, 2023), scale-related inefficiencies (Evans, Rohleder, Tentesch, and Wilkens, 2023; Huang, Lu, Song, and Xiang, 2025), portfolio performance outcomes (Ferson and Khang, 2002; Busse, Goyal, and Wahal, 2010; Elton, Gruber, and Blake, 2014; Gerakos, Linnainmaa, and Morse, 2021; Dyck, Lins, and Pomorski, 2013; Busse, Goyal, and Wahal, 2014; Goyal, Wahal, and Yavuz, 2024), and flow–performance dynamics (Del Guercio and Tkac, 2002; Evans and Fahlenbrach, 2012; Jiang and Yuksel, 2017).

A fundamental gap remains in understanding the cognitive constraints underlying these investment choices. Such insights have profound policy implications: if institutional investors such as pension funds make suboptimal asset-manager selection decisions, the costs will ultimately flow through to retail beneficiaries and plan members (Dyck, Manoel, and Morse, 2022). We address this gap by demonstrating that attention constraints represent a first-order determinant of institutional capital allocation. Our findings suggest that even sophisticated institutional investors operate under binding cognitive limitations that systematically influence their investment choices, with measurable consequences for asset prices.

We also advance the literature on investor attention by providing the first empirical evidence on attention allocation by institutional fund investors. The attention literature has demonstrated that attention constraints shape investor behavior and market dynamics in other asset classes—spanning equities, fixed income, and alternative investments (e.g., Hirshleifer, Lim, and Teoh, 2009; Andrei and Hasler, 2015; Drake and Thornock, 2016; Li, 2022a; Lu, Ray, and Teo, 2016). Earlier studies by Barber and Odean (2008), Da, Engelberg, and Gao (2011), and Ben-Rephael, Da, and Israelsen (2017) have highlighted distinctions in attention allocation patterns between individual and institutional market participants.[5] Other studies leverage the SEC's EDGAR system to infer investor attention via access patterns to corporate filings (e.g., Lee, Ma, and Wang, 2015; Lu, Ray, and Teo, 2016; Cao, Du, Yang, and Zhang, 2021; Agarwal, Ruenzi, and Weigert,

[5]For recent developments in stock market attention, see Madsen and Niessner (2019), Choi, Gao, and Jiang (2020), Chen, Tang, Yao, and Zhou (2022), Cronqvist, Ladika, Pazaj, and Sautner (2024), Fedyk (2024), Da, Hua, Hung, and Peng (2024), Li (2022a), and Barber, Huang, Odean, and Schwarz (2022), among others.

2024; Aragon, Tserlukevich, Keen, and Wymbs, 2024). Kwan, Liu, and Matthies (2024) measure institutional investor attention to individual stocks using their web browsing history of news related to specific firms or the macroeconomy. Unlike the existing literature, we are the first to measure the *direct* attention to specific funds by institutional fund investors, who manage 60% more assets than mutual funds.

Most relevant to our paper is the study by Chava, Kim, and Weagley (2022), who examine the search behavior of investment consultants using similar eVestment data. Our study differs from theirs in two important ways. First, we isolate the attention allocation of institutional asset owners—the ultimate decision-makers in capital allocation—from that of consultants. Our data are more granular, allowing us to demonstrate that direct institutional investors account for the majority of search activity and that, conditional on $Investor\_AA$, consultants' abnormal attention exhibits no incremental explanatory power for capital flows. Goyal and Wahal (2008) document that not all public plan sponsors use the services of investment consultants, and about 50% of corporate sponsors do not hire investment consultants. Crucially, Cookson, Jenkinson, Jones, and Martinez (2022b) find that investment consultants do not tend to add value.[6]

Second, and more importantly, we provide novel causal evidence that even sophisticated institutional investors face binding attention constraints. Owing to limited data availability on these fund investors, the academic literature has relatively less insight into their behavior. Using exogenous variation in these investors' attention allocation, we show that their attention constraints materially affect their capital allocation decisions across funds, with significant implications for stock prices. This finding challenges the conventional view that institutional sophistication mitigates attention-driven market inefficiencies, as well as the belief that such inefficiencies are primarily driven by retail in-

[6]Our private conversation with an institutional investor reveals that the limited value-added of listed-equity consultants is argubaly a common perception in the industry. Although this institutional investor also engages an investment consultant, the consultant's recommendations rarely diverge from the investor's internal views. Decisions regarding the hiring or termination of asset managers, and the allocation of capital, are determined by the investor. The continued retention of consultant services is therefore puzzling. Perhaps, it may reflect institutional inertia, fiduciary requirements, or other institutional frictions.

vestors. Examining these causal mechanisms underlying institutional attention and asset pricing consequences lie beyond the scope of Chava, Kim, and Weagley (2022).[7]

The remainder of the paper is organized as follows. Section 2 describes our data and the construction of main variables. In section 3, we examine the determinants of abnormal fund investor attention and provides three pieces of causal evidence that such attention drives future fund flows. Section 4 then studies the impact of abnormal fund investor attention on future fund returns and the prices of their underlying stocks. Finally, Section 5 concludes.

2 Data and variable construction

Our primary data source is Nasdaq eVestment. Below, we describe the dataset and outline the process of constructing our sample.

2.1 Viewership data for institutional funds and measure of abnormal attention

We collect data on U.S. actively managed domestic institutional equity products (i.e., funds) from Nasdaq eVestment, a leading institutional investment platform widely used by institutional investors such as pension funds, funds of funds, and investment consultants. An institutional product refers to an investment strategy managed by an asset management firm. Institutional investors typically invest in these products through separate accounts, which give them direct ownership of the underlying stocks.[8] For ease of exposition, we follow prior research on institutional funds and use the terms "products" and "funds" interchangeably. Notably, the eVestment database retains information on all

[7]Chava, Kim, and Weagley (2022) identify $500 million as a common screening threshold among consultants. Such AUM thresholds do not necessarily reflect attention constraints, as consultants may rationally exclude smaller funds due to mandate limitations. This is particularly relevant because institutional investors, given their large mandates, are often unable to invest in small funds.

[8]Busse, Goyal, and Wahal (2014, p. 561) note that "institutional products are not the same as (and should not be confused with) the institutional class of traditional retail mutual funds."

funds, including those that have ceased operations, thus helping to eliminate survivorship bias (Jones, Martinez, and Montag, 2023; Goyal, Wahal, and Yavuz, 2024).

Institutional users of the Nasdaq eVestment platform typically search for funds using one of two common methods: by directly entering a fund name or by applying search criteria. The first method, shown in Figure 2, involves typing a fund name into the search box. As the user types, the platform suggests funds that closely match the search term, including those that are alphabetically adjacent. We will leverage these platform features to help isolate and identify the effect of abnormal attention on fund-level outcomes. The second method, illustrated in Figure 1, allows users to apply systematic screens such as all funds with AUM exceeding a certain threshold. According to Nasdaq eVestment, they do not feature any specific funds on the platform, as their objective is to provide institutional investors and consultants with a neutral environment for independent research and monitoring. This platform does not serve retail investors.

The platform tracks user activity, recording which products are viewed and the frequency of those views daily. For each viewing instance, we observe a unique anonymous viewer identifier, the number of views, view date, and viewer type (either an investment consultant or a direct investor of funds). Nasdaq eVestment also provides us data on characteristics of viewed funds such as returns, fees, AUM, etc, which are also observable to viewers at the time of their view. Users from the same organization share a unique viewer ID assigned at the organizational level. Beyond researching new funds, Nasdaq eVestment's clients could also use the platform to monitor their existing investments and compare them with potential alternatives. Even after an institutional investor invests in a fund, they continue to monitor a group of "bench" fund managers, who can potentially replace the chosen fund at any point in time. The dataset spans from January 2018 to December 2023.

To construct the abnormal attention measure, we begin by aggregating the daily view count from all viewers for each fund into monthly totals. We then compute fund abnormal attention, AA, as the difference between the natural logarithm of one plus the current month's view count and the natural logarithm of one plus the median view count over the preceding six months.[9] This approach allows us to capture unusual spikes or dips in investor interest, providing insight into shifts in attention that diverge from the product's normal viewing patterns. We compute AA separately for direct investors such as pension funds ($Investor\_AA$) and investment consultants ($Consultant\_AA$). Our results do not qualitatively change if we use either one-year historical average or three-year historical average as the benchmark.

While recent literature has used Nasdaq eVestment data to examine institutional fund performance (Jenkinson, Jones, and Martinez, 2016; Jones and Martinez, 2017; Jones, Martinez, and Montag, 2023; Huang, Lu, Song, and Xiang, 2025; Goyal, Wahal, and Yavuz, 2024), the platform's rich viewership data remain under-explored. To the best of our knowledge, Chava, Kim, and Weagley (2022) represent the sole exception, which analyzes investment consultants' search data. However, our analyses differ from theirs along several critical dimensions.

First, Chava, Kim, and Weagley (2022) observe only consultant viewership, but not the search activities of direct institutional investors, who are the ultimate decision-makers in capital allocation. Our study period captures the recent trend toward investment internalization, during which pension funds and other institutional investors have substantially enhanced their internal capabilities and reduced consultant dependence. As Brown, Gredil, and Kantak (2023) document, consultants increasingly view clients' internal teams as "their major competition" (p. 3077).

Second, our dataset is more comprehensive, revealing that focusing exclusively on consultants would significantly understate the attention that a fund has on the investment platform. As Figure 3 demonstrates, direct institutional investors (2,926 unique users)

[9] Zero view count occurs for about 5% of the final sample. Our results do not qualitatively change when we exclude them and define AA as the difference between the natural logarithm of the current month's view count and the natural logarithm of the median view count for the remaining 88% our observations.

outnumber consultants (340 unique users) by nearly nine-to-one on the Nasdaq eVestment platform. This disparity is even more pronounced in usage intensity: monthly research activity averages 1,064 investors versus only 187 consultants. Consequently, consultant-only studies capture merely 15% of total search activity in a given month, overlooking the vast majority of attention-driven capital allocation decisions from direct investors. This comprehensive coverage proves essential for understanding the relationship between investor attention, fund outcomes, and asset pricing implications, which represent the distinct focus of our investigation. Third, unlike prior work, we focus on abnormal attention rather than the attention level, enabling us to identify periods when investor focus deviates from historical norms. Using this measure, we uncover previously undocumented phenomena such as attention spillover effects and the asset pricing implications of institutional investors' cognitive constraints.[10]

Nasdaq eVestment obtains their data on fund characteristics and holdings directly from asset managers. While the data are self-reported, several mechanisms exist to ensure the accuracy of the data. First, asset managers have strong incentives to report accurately and be included in the database, because it enhances their funds' visibility, enabling them to tap into Nasdaq eVestment's significant institutional client base.

Nasdaq eVestment is the dominant platform in the institutional asset management sector. For example, the Government Pension Investment Fund (GPIF) of Japan, one of the world's largest pension funds with approximately $1.5 trillion in total AUM, discloses that they access asset managers' investing strategies via Nasdaq eVestment platform.[11] Appendix Table A.1 presents a partial list of Nasdaq eVestment clients' names, spanning from major public pension funds such as CalPERS (the largest public pension in the U.S. with over $469 billion in AUM) and major pension funds in Australia with trillions of

[10]Chava, Kim, and Weagley (2022) exclude funds with AUM greater than $2.5 billion, whereas we retain these funds, as institutional investors typically manage large mandates. Given that institutional investors are typically large, this filter likely excludes funds that are of direct interest.

[11]In a public document issued to global asset managers, GPIF advises that "GPIF can access the applicant's strategy if it is registered in the eVestment database, and thus applicants will not be required to update performance data if their strategy is registered therein."

dollars in AUM to corporate pensions (AT&T, Google, Shell, etc.). Several large asset managers such as BlackRock and AQR Capital Management also disclose their use of Nasdaq eVestment data in their in-house research (BlackRock, 2023; AQR, 2017). Given that institutional investors rely on this database to oversee trillions of dollars in assets, it is likely that they trust the database to be of investment quality.[12]

Second, Nasdaq eVestment data undergo cross-checking and verification by the clients themselves. Investors and investment consultants leverage Nasdaq eVestment data for routine comparisons between their current fund managers and prospective ones. Through this process, they could evaluate and verify the accuracy of the data, especially for products in which they have invested (Jones and Martinez, 2017).[13] Third, all funds in our sample comply with GIPS reporting requirements, further enhancing the accuracy of reported data (Goyal, Wahal, and Yavuz, 2024).

2.2 Institutional fund characteristics

Nasdaq provides data on all institutional fund (i.e., product) characteristics, which are also observable to actual users on their platform. Specifically, we collect fund-level data on net-of-fee returns measured monthly, fees, AUM, fund managers' disclosed investment styles (i.e., value, growth, or core), and whether the fund has an ESG mandate. In addition, as funds with more marketing staff are likely to invest more in marketing strategies to attract investor attention (Lou, 2014; Roussanov, Ruan, and Wei, 2021; Chen, Jiang, and Xiaolan, 2024), we control for the percentage of marketing employees (scaled by the

[12] We talked to a fund manager and asked why they choose to voluntarily report data to Nasdaq eVestment. They explained that disclosure on the platform has become a necessary condition for any fund seeking to be considered by institutional investors.

[13] During our discussion with a pension fund, an asset owner, regarding their use of Nasdaq eVestment data, we learned that their search for potential fund managers typically begins with research on the Nasdaq eVestment platform, alongside input from an investment consultant. Based on the client's investment objectives, the consultant provides a list of potential products along with their corresponding Nasdaq eVestment identifiers. Since the final investment decisions lie with the pension fund's internal team, these product identifiers allow the managers to conduct independent research on the platform as needed. Conversely, the pension fund's managers also identify products of interest by their eVestment IDs and seek the consultant's assessment of those options.

total number of employees dedicated to the fund), as well as the average experience (in years) of marketing employees.

Following the vast majority of the literature, we compute net flows into fund f in quarter t, $Flow_{f,t}$, as the percentage growth of new assets: $Flow_{f,t} = \frac{TNA_{f,t}}{TNA_{f,t-1}} - (1+R_{f,t})$, where $TNA_{f,t}$ is the total net assets under management of fund p at the end of quarter t, and $R_{f,t}$ is the fund return over the quarter t. Although monthly returns are available, AUM data are only available at the quarterly frequency and thus, tests that use the flow measure are conducted using quarterly data.

To proxy for the activeness of a product, we use the adjusted R^2 from the market-model regression of monthly excess returns on a product on the excess return on the market. In addition, we control for fund age, computed as the natural logarithm of the number of months since product inception. We further include the volatility of fund returns, computed as the standard deviation of monthly fund returns over the past 18 months.

To control for media attention, we follow prior research (e.g., Solomon, Soltes, and Sosyura, 2014; Ben-David, Franzoni, Kim, and Moussawi, 2023) and obtain news coverage data for individual stock holdings, which we source from RavenPack. Funds' quarterly stock holdings are obtained from Nasdaq eVestment. We construct a dummy variable, *High Media Coverage*, which equals 1 if a fund's weighted-average media coverage of its underlying stocks falls within the top 20%, and 0 otherwise.

For each fund, Nasdaq eVestment supplies a strategy indicator, which we use to identify and focus on actively managed equity funds, excluding passive and index funds. Following prior research, we remove funds with less than \$10 million in AUM or those holding fewer than 10 stocks (Elton, Gruber, and Blake, 2001). Additionally, we do not include funds that are younger than 24 months to minimize the potential influence of incubator bias (Evans, 2010).

2.3 Sample and summary statistics

After applying the aforementioned data filters to fund characteristics, the final sample comprises 89,217 fund-month observations for the period spanning 2018 through 2023, covering 1,667 unique U.S. domestic actively managed equity funds from 479 unique fund families. Table 1 Panel A presents the summary statistics for key variables used in the empirical analysis.

At the monthly frequency, the average institutional fund receives 4.64 views from institutional investors and 4 views from consultants. The mean value of abnormal investor attention ($Investor\_AA$) is 0.009, with a median of zero. The standard deviation of $Investor\_AA$ (0.62) suggests substantial heterogeneity in institutional investor attention across the sample. $Consultant\_AA$ exhibits a similar distribution.

While funds generate an average net-of-fee return of 0.90% per month, the average four-factor alpha (net of fees and adjusted for the Fama and French's (1993) three factors and Carhart's (1997) momentum factor) is −0.10%. The average posted fee is 0.63%, and only 4.5% of the funds have stock holdings that receive high media coverage in a given month. The average net flow in a given quarter is 2.0%, with the standard deviation of 18.5%.

Institutional funds in our sample are generally well-established, with an average age of 265.8 months since inception and an AUM of \$3.32 billion with a median AUM of \$1.1 billion. The average adjusted R^2 from the market model is 0.83, consistent with active management. The average marketing team has 1.1 years of experience. Approximately 2.9% of funds are dedicated to ESG strategies, 29.6% follow value-oriented strategies, 27.1% adopt growth styles, and the remainder pursue core investment strategies.

3 Empirical analyses

We first examine the relation between attention allocation and institutional fund characteristics. We then establish the causal relationship between $Investor\_AA$ and subsequent capital flows, demonstrating that abnormal attention serves as a leading indicator of investment decisions.

3.1 Attention and institutional fund characteristics

We begin the empirical analysis by studying the correlations between fund characteristics and both levels and abnormal measures of attention. The correlations reported in Table 1 Panel B reveal several noteworthy patterns. First, both investor and consultant attention levels are positively correlated with fund AUM, with correlation coefficients of approximately 0.32 for both groups. This relatively strong relationship indicates that larger institutional funds generally attract greater attention than smaller ones.

Second, attention levels for both groups are positively associated with the experience of funds' marketing teams, suggesting that funds investing in marketing expertise tend to attract greater attention levels from potential investors. Third, attention levels are positively correlated with the fund age, likely driven by the fund size as well. The correlations among other explanatory variables are relatively low, suggesting that multicollinearity is unlikely to pose a concern in subsequent regressions.

Given our primary interest in abnormal attention (AA), we explore its empirical properties by first documenting its distribution across daily and monthly horizons to identify potential seasonality. We then turn to a multivariate framework to isolate the fund-level determinants that drive idiosyncratic shifts in institutional attention.

In Figure 4 Panel A, we examine investor and consultant AA across days of the week. Investors and consultants exhibit distinct patterns in their viewing behavior. Consultant AA is low on Monday, rises to a peak on Wednesday, and then declines toward the end of the workweek. In contrast, investor AA is lowest on Monday and increases throughout the week, reaching its peak on Friday. As expected, both investor AA and consultant AA are lower on the weekend.[14]

Figure 4 Panel B plots the average AA in each month of the year. As before, we observe both similarities and differences across the two groups. First, both investors and consultants exhibit the lowest AA in December. Second, investor AA is highest in January, declines toward the middle of the year, and increases again in October. In contrast, consultant AA peaks in February and gradually declines until the middle of the year.

In the next analysis, we regress one-month-ahead abnormal attention (AA)—estimated separately for investors and consultants—on lagged fund performance, fees, and other fund characteristics. All model specifications include time fixed effects to control for systematic time-varying influences on attention and style fixed effects to capture unobserved, time-invariant differences across fund styles.

Table 2 reports the results. The first block (Columns 1 through 3) presents the regression estimates for consultants, while the second block (Columns 4 through 6) focuses on direct institutional investors. The first two columns of each block include time and fund style fixed effects, while the last column further controls for fund family fixed effects, which capture time-invariant unobservable characteristics of the fund family, such as reputation. Both groups allocate significantly more abnormal attention to funds with stronger past returns. In contrast, only consultants' AA exhibits (weak) sensitivity to posted fees, whereas investors' AA shows no such relationship. This finding is consistent with institutional practice: institutional investors typically negotiate fees directly with fund managers after the initial selection stage, making posted fees less relevant during early screening. Prior research similarly documents limited cross-sectional variation and temporal stability in institutional fees (Jones and Martinez, 2017; Busse, Goyal, and Wa-

[14] Some of the weekend activity may reflect Nasdaq's recording convention, whereby activity by global investors is timestamped based on U.S. time.

hal, 2010), as well as comparable after-fee performance across funds with different fee structures (Sheng, Simutin, and Zhang, 2023).[15]

Although attention levels and fund size are positively correlated, the relationship between AA and fund size is negative, implying that smaller funds are more likely to attract disproportionately higher spikes in AA. Interestingly, the coefficient on marketing experience is also negative in the regressions with style and time fixed effects, suggesting that greater marketing experience does not necessarily sustain elevated abnormal attention among investors or consultants. However, once we include fund family fixed effects, which capture fund family reputation, the coefficient on marketing team experience becomes positive in the regression for consultant AA and insignificant in the regression for investor AA.

The coefficient on high media coverage is close to zero and statistically insignificant, indicating that neither consultants nor investors allocate abnormal attention based on media exposure. Both groups, however, display a strong preference for performance stability: fund volatility is negatively and significantly related to abnormal attention across all specifications.

Historical fund flows are not predictive of abnormal attention for either group, as evidenced by the insignificant coefficients on past flows in all models. In contrast, both groups respond strongly to fund R^2, a proxy for managerial activeness.

Institutional attention toward ESG designations diverges across the two groups. Consultant abnormal attention exhibits no statistically significant difference between ESG and non-ESG funds; however, institutional investors allocate significantly less abnormal attention to ESG-labeled funds. A similar divergence occurs regarding fund age. Consultant AA does not vary with age in baseline specifications and remains negatively correlated with age after controlling for fund family fixed effects. This result is consistent with the

[15] Dannhauser and Pontiff (2024) also find that performance chasing is prevalent among active retail mutual funds, index mutual funds, and ETFs. Fees tend to play a larger role for retail investors in 401(k) plans (Kronlund, Pool, Sialm, and Stefanescu, 2021; Pool, Sialm, Stefanescu, and Zhang, 2024).

idea that consultants prioritize younger funds to expand their coverage universe. In contrast, investor AA shows no correlation with fund age once fund family fixed effects are included. This finding implies that for direct investors, fund family reputation is a more salient determinant of attention than individual fund tenure.

Both types of abnormal attention are persistent. Consistent with industry practice in which consultants and investors collaborate during fund evaluation, lagged $Investor\_AA$ significantly predicts consultants' abnormal attention, and vice versa.

Finally, the adjusted R^2 across all regressions is modest, ranging from 2.7% to 4.1%, indicating that conventional fund-level characteristics explain only a limited portion of the variation in institutional abnormal attention. This result reinforces the importance of directly measuring institutional investors' attention, as observable fund characteristics are unlikely to fully account for it.[16]

3.2 Abnormal attention and future fund flows

This section examines whether abnormal attention serves as a leading indicator of capital allocation decisions, as measured by subsequent fund flows. If abnormal attention serves as a precursor to investment decisions (as opposed to casual browsing), it should positively predict future fund flows. Table 3 presents regression results with future fund flows as the dependent variable and investor and consultant AA as key explanatory variables.

Column 1 focuses on one-quarter-ahead fund flow as the dependent variable. The coefficient on $Investor\_AA$ is 0.007 with an associated t-statistic of 2.73, which is statistically significant at the 1% level. This effect is also economically meaningful: a one-standard-deviation increase in $Investor\_AA$ is associated with a 0.43% rise in net inflows, representing approximately 21.7% of the sample mean.[17] Given the average fund size of

[16] The conclusions remain unchanged when we apply the Fama–MacBeth cross-sectional regression approach.

[17] This is computed as $\frac{0.007 \times 0.621}{0.020} \times 100$, where 0.621 is the standard deviation of $Investor\_AA$, and 0.020 is the mean fund flows.

\$3.32 billion in AUM, this translates to an estimated \$14.4 million in additional net inflows. In contrast, the coefficient on $Consultant\_AA$ is 0.002 (t-statistic = 1.04), which is small and statistically insignificant. These findings suggest that investor attention, rather than consultant attention, is the precursor to actual investment flows. This divergence aligns with institutional decision-making hierarchies. While many investors employ the services of consultants, institutional investors conduct their own independent search of institutional funds and ultimately retain discretionary authority over capital allocation decisions.

The temporal dynamics of attention effects are equally revealing. Column 2 shows that the coefficient on $Investor\_AA$ remains positive in the second quarter, at 0.008 (t-statistic = 2.68), which is statistically significant at the 1% level. However, Columns 3 and 4 indicate that the predictive power of $Investor\_AA$ dissipates starting from quarter 3 in which the coefficient becomes statistically insignificant. This pattern suggests that attention-driven capital allocation is primarily short-term in nature.[18]

In Column 5, we employ a placebo test by focusing on institutional funds that also serve retail investors. Specifically, we replace the dependent variable with retail flows to the same fund. If $Investor\_AA$ genuinely captures institutional investors' abnormal attention, it should not predict retail investors' flows since only institutional investors have access the Nasdaq eVestment platform. Indeed, we find that the coefficient on $Investor\_AA$ is small and statistically insignificant. While this null result is expected, it provides reassurance that our findings are not spurious.

Effects of Morningstar ratings: Evans and Sun (2021) and Ben-David, Li, Rossi, and Song (2022b) find that U.S. mutual fund flows follow Morningstar ratings. Given that our focus is on the behavior of institutional investors and consultants on the Nasdaq eVestment platform, which does not display Morningstar ratings, our results are unlikely to be driven by these ratings. Nevertheless, to formally assess this possibility, we collect

[18]Our results do not qualitatively change under the Fama-MacBeth regression approach.

data on Morningstar ratings for the institutional products in our sample. Only 24% of the total number of unique products in our sample receive a Morningstar rating at any point during the sample period. This limited coverage reflects the relatively low relevance of Morningstar ratings for institutional investors compared with their widespread use in the retail mutual fund space. We then repeat the analysis in Table 3 using a subsample of funds without Morningstar ratings. The results, available upon request, remain qualitatively unchanged.

3.3 Cross-sectional heterogeneity of investors

The previous section shows that investor AA, as opposed to consultant AA, leads to fund flows. In this section, we conduct further tests to examine the potential heterogeneity in investor viewership. Although we do not observe investor identities or characteristics, the unique viewer identifiers allow us to study their viewing activity on the platform.

Our first cross-sectional analysis focuses on whether an investor is a first-time viewer of a fund. Since investors cannot short sell funds, attention is more likely to be associated with buying activity. Compared to repeat viewers, first-time viewers of fund are more likely to be potential buyers, as they are unlikely to be existing investors. As such, their abnormal attention should be more likely to increase fund flows than repeat viewers' AA. To examine this prediction, for each fund we classify viewers into two groups. First-time viewers are those who access a fund for the first time within the past two years, while repeat viewers are all others. On average, a fund receives 1.9 new viewers and 1.6 repeat viewers per month. We then construct separate AA measures for each group and replicate the analysis in Table 3.

Table 4 Panel A reports the estimation results. The coefficient on first-time investor AA is positive and statistically significant over the subsequent three quarters, whereas the coefficient on repeat investor AA is weaker and statistically insignificant across most horizons, except for quarter 2, where it is significant at the 10% level. The estimates imply that a one standard deviation increase in first-time investor AA is associated with an 18 basis point increase in one-quarter-ahead fund flows, which corresponds to approximately 9% of the average quarterly fund flow over the subsequent three quarters. These results are consistent with our prediction that AA from first-time viewers, who are unlikely to be existing investors, is more strongly associated with future flows than AA from repeat viewers.

Our second cross-sectional analysis examines investors' viewing breadth. In each month, we rank and sort viewers into terciles based on the number of funds they view concurrently, where the top tercile consists of viewers with the highest viewing breadth. We classify these viewers as the High Viewing Breadth group, while the remaining viewers form the Low Viewing Breadth group. On average, High Viewing Breadth investors view 24 funds per month, compared with 4.5 funds for the middle tercile and 1.4 funds for the bottom tercile. We then construct separate Investor AA measures for each group and repeat the regressions above.

Table 4 Panel B reports the estimation results. In the regression predicting one-quarter-ahead flows, the coefficient on Low Viewing Breadth AA is 0.008 (t-statistic = 2.3), which is twice larger than the coefficient on High Viewing Breadth AA (0.004 with an associated t-statistic of 0.9). These results suggest that investors who view many funds concurrently are less likely to allocate capital to any given fund than those who focus on a smaller set of funds. The coefficient on Low Viewing Breadth AA implies that a one standard deviation increase is associated with a 22 basis point increase in subsequent fund flows, which corresponds to approximately 11% of the sample mean.

3.4 Instrumental variable regressions: Attention spillovers and lagged 13-month returns

To more precisely identify the causal impact of abnormal investor attention on subsequent fund flows, we use instrumental variable (IV) regressions. We employ two complementary instruments: name-based neighboring funds' AA and the lagged fund return measured in month $t - 13$.

3.4.1 Neighboring funds' AA as instrument for focal funds' AA

Our first instrument leverages on a screen display feature of Nasdaq eVestment that presents funds in alphabetical order. Specifically, users searching for a specific fund can enter its name in the search box. When they do so, the platform not only displays the fund that matches the search term but also includes other funds that are alphabetically adjacent to it. Figure 2 provides an example of eVestment's results window. As the user types a fund name, the list dynamically updates to include nearby funds in alphabetical order. Under this search mode, the result window displays only limited additional information—specifically, the investment focus and geographic focus, without showing any additional fund characteristics.

To the extent that abnormal attention to neighboring assets can spill over to another asset when they are displayed together (Chen, An, Wang, and Yu, 2023), the AA of neighboring funds can serve as a valid instrument for a focal fund's AA. Exploiting the default display settings of the Nasdaq eVestment platform, we follow Chen, An, Wang, and Yu (2023) and construct the instrument as follows.

First, we sort funds alphabetically based on fund names within each investment style in a given month.[19] For each focal fund, we select the five funds listed immediately before and the five listed immediately after it. We then compute the weighted-average abnormal attention of these neighboring funds, using the inverse distance between the focal fund and its neighbors as weights. This weighted-average AA, denoted as $NeighborFunds\_AA$, serves as the instrument for the focal fund's AA.

The validity of this instrument relies on a key identification assumption: the AA of

[19] A fund name typically begins with the name of the family company (e.g., Aberdeen US Equity Small Cap).

name-based neighboring funds affects the focal fund's flows only through its impact on the focal fund's AA. We argue that this exclusion restriction is likely to hold because fund names are unlikely to be systematically related to differences in fundamentals between the focal fund and its neighboring funds.

To examine whether focal funds and neighboring funds are fundamentally similar, we regress a focal fund's characteristics on the corresponding characteristics of its neighboring funds. Panel A of Table 5 reports the estimation results. We find that none of the coefficients are statistically significant, with the exception of fees, which are significant at the 10% level. These results indicate that spillover in abnormal attention to a focal fund is unlikely to be driven by similarities in fund characteristics.[20] Using the instrument, we next estimate the following 2SLS model.

First-stage regression:

$$AA_{f,t} = \beta_0 + \beta_1 NeighborFunds\_AA_{f,t-1} + \delta' X_{f,t-1} + \theta_f + \omega_f + \tau_t + \epsilon_{f,t} \tag{1}$$

Second-stage regression:

$$Flow_{f,t+1} = a_0 + a_1 \widehat{AA_{f,t}} + \gamma' X_{f,t} + \theta_f + \omega_f + \tau_t + \epsilon_{f,t} \tag{2}$$

where $AA_{f,t+1}$ represents $Investor\_AA$ to fund f in month $t+1$. $NeighborFunds\_AA$ denotes the distance-weighted average AA of neighboring funds, defined as the five funds preceding and the five funds following the focal fund f in the alphabetical ordering of fund names within a given style in month t. $\widehat{AA_{f,t}}$ is the predicted abnormal attention

[20] In untabulated analyses, we further test whether attention spillover is driven by proximity in fund characteristics by regressing the difference between focal fund's abnormal attention (AA) and neighboring funds' AA on the absolute differences in lagged characteristics between these funds. If investors' abnormal attention to neighboring funds spills over to the focal fund due to similarities in characteristics, we would expect these differences to be significant predictors of the focal fund's AA. Consistent with our main results, we find that none of the coefficients on the absolute differences in fund characteristics are statistically significant, except for historical fund flows, which are significant at the 10% level. These findings reinforce the conclusion that attention spillover is unlikely to be driven by similarities in fund characteristics.

obtained from the first-stage regression. $X_{f,t}$ represents the set of control variables, while θ_f, ω_f, and τ_t denote fund family, fund style, and time fixed effects, respectively. Fund family fixed effects are particularly relevant for this test because investors' attention to a fund could be driven by fund family reputation.[21]

Table 5 Panel B presents the estimation results. Column 1 reports the first-stage regression, while Column 2 displays the second-stage results. In Column 1, the coefficient on $NeighborFunds\_AA_t$ is 0.03, which is statistically significant at the 5% level. This confirms the instrument's relevance, indicating that abnormal attention to neighboring funds positively affects the focal fund's abnormal attention (AA). The result is also consistent with evidence of attention spillover in the Chinese stock market documented by Chen, An, Wang, and Yu (2023). The coefficient estimate indicates that a one-standard-deviation increase in $NeighborFunds\_AA_t$ is associated with an increase in $Investor\_AA$ by 0.57%, which is economically large given the mean $Investor\_AA$ of 0.90% in our sample.[22]

In Column 2, the coefficient on the instrumented AA is 0.48 (t-statistic = 3.2), statistically significant at the 1% level. This suggests that instrumented AA, using $NeighborFunds\_AA_t$ as the instrument, has a strong positive effect on future fund flows. The coefficient estimate indicates that a one-standard-deviation increase in $NeighborFunds\_AA_t$ is associated with a 1.6% increase in fund flows, representing approximately \$51.7 million in inflows.[23]

In this test and the other subsequent IV test, the coefficient on predicted AA is larger than that of uninstrumented abnormal attention reported in Table 3, a common feature of IV regressions (Jiang, 2017). A possible explanation is that our instrument captures the additional spillover attention from name-based neighboring funds that experience

[21] We confirm that our results in other tables remain qualitatively unchanged when we include fund family fixed effects.

[22] This is computed as 0.03×0.189, where 0.189 is the standard deviation of $NeighborFunds\_AA_t$.

[23] This is computed as $0.48 \times 0.033 \times \$3.32 billion$, where 0.033 is the standard deviation of predicted AA, and \$3.32 billion is the average AUM.

unusually high attention shocks. The IV estimate, therefore, reflects a stronger local average treatment effect among IV funds, whose attention is elevated in response to their neighbors' heightened visibility.

To assess whether the effect of $NeighborFunds\_AA$ could be spurious, we construct a placebo instrument, $Distant\_NeighborFunds\_AA$, based on abnormal attention to funds alphabetically ranked between the 6^{th} and 20^{th} positions away from the focal fund. Since these funds are more distant in the alphabetical ordering, their attention levels are unlikely to spill over. However, if investors apply additional filtering criteria that correlate with alphabetical proximity, we might still observe a positive association.

Panel C of Table 5 reports the placebo test results. In the first-stage regression (Column 1), the coefficient on $Distant\_NeighborFunds\_AA_t$ is 0.01 (t-statistic = 0.32), which is statistically insignificant at conventional levels. This indicates that abnormal attention to distant neighboring funds does not affect the focal fund's AA. In the second-stage regression (Column 2), the coefficient on the instrumented AA is -0.02 (t-statistic = -0.85), which is also statistically insignificant. Together, these results suggest that the placebo instrument does not influence future fund flows, thereby reinforcing the validity of our identification strategy.

3.4.2 Ret_{t-13} as instrument for abnormal attention

Our second instrument is motivated by the observed screening behavior of institutional investors on the Nasdaq eVestment platform. Figure 5 Panel A reports the criteria investors employ when filtering funds. Among fund characteristics, AUM and historical performance emerge as the primary screening metrics, followed by static fund attributes.[24]

The platform provides pre-calculated performance metrics across horizons ranging

[24]While we observe the categories selected by users, the specific parameter thresholds, such as whether a search is restricted to funds with AUM exceeding $500 million, are not available to us. Furthermore, while AUM is the most frequent criterion, its use may reflect institutional mandates rather than attention constraints.

from one to ten years. Panel B examines the distribution of these performance windows to identify the most salient horizons for institutional oversight. One-year performance is the dominant screening variable, used in 52.4% of searches, followed by five-year (19.4%) and three-year (18.5%) horizons. This pronounced preference for recent performance motivates our second instrument: the lagged fund return from month $t-13$. As the rolling one-year performance window advances, the return from month $t-1$ enters the investor's primary screen while the return from 13 months prior, Ret_{t-13}, is mechanically excluded. This exogenous shift in the information set available to investors provides a natural setting to identify the impact of performance-based screening on capital allocation.

If institutional investors interpret past performance as evidence of managerial skill, we should observe a positive relation between Ret_{t-13} and abnormal attention. Conversely, if investors are driven by salience and cognitive biases, we expect a negative relation, as a data point mechanically exits the performance window (Phillips, Pukthuanthong, and Rau, 2016).[25] For example, consider two funds A and B that have the same 10% past one-year return. Fund B's performance decreases from 20% down to 10%, while Fund A's performance increases from 5% to 10%. Due to a feature of eVestment that allows users to screen funds based on 12-month returns, Fund A would not have entered the screen until the poor month-13 return drops out of the return calculation. This in turn causes the abnormal attention to Fund A to increase. The exclusion restriction is plausibly satisfied because returns from 13 months ago do not enter the calculation of 12-month performance.

To examine whether investors' abnormal attention is negatively associated with Ret_{t-13}, we estimate a regression of $Investor\_AA$ on $Ret_{t-1,t-12}$, Ret_{t-13}, $Ret_{t-14,t-36}$, and control variables. Table 6 Column 1 reports the results. The coefficients on $Ret_{t-1,t-12}$ and $Ret_{t-14,t-36}$ are positive and statistically significant at the 1% level. In contrast, the coefficient on Ret_{t-13} is negative and significant at the 1% level, consistent with the notion

[25] Phillips, Pukthuanthong, and Rau (2016) find that mutual fund investors fail to recognize the influence of the 13^{th}-month return lag on reported performance, and instead direct flows toward funds that benefit from this "expired" return.

that returns exiting the calculation window reduce investors' attention to past fund performance. The magnitude implies that a 1% decrease in Ret_{t-13} is associated with an increase in $Investor\_AA$ of 0.3, corresponding to 18.6% of its standard deviation. These results suggest that Ret_{t-13} is a relevant instrument for abnormal attention.[26]

Given the relevance of Ret_{t-13} as an instrument, we estimate a first-stage regression of $Investor\_AA$ on Ret_{t-13}, the set of standard control variables, and style and time fixed effects (Column 2, Table 6). In the second stage, reported in Column 3, we regress future fund flows on the predicted $Investor\_AA$ from the first stage, along with the same set of control variables, and style and time fixed effects. (Our results do not qualitatively change if we control for $Ret_{t-1,t-12}$ and $Ret_{t-14,t-36}$ in both stages.) The coefficient on predicted $Investor\_AA$ is positive and significant at the 1% level, indicating that instrumented abnormal attention has a positive effect on future fund flows. The estimated coefficient of 0.44 implies that a one standard deviation increase in predicted AA is associated with a 1.8% increase in fund flows, which corresponds to 9.9% of the standard deviation of fund flows.[27]

As discussed in the previous section, it is common for the marginal effect of instrumented AA to exceed that from the ordinary least squares estimates (Jiang, 2017). This difference likely arises because our instrument captures episodes in which a large Ret_{t-13} drops out of investors' performance calculations, making recent performance changes more salient to investors and thereby triggering a spike in AA. These sharp increases, in turn, cause the estimated local average treatment effect to be larger.

[26]In untabulated analysis, we do not find a significant relation between abnormal attention and returns measured in month $t-37$, suggesting that 36-month historical average returns may not be a commonly used performance metric among institutional investors in our sample.

[27]This is computed as $\frac{0.44 \times 0.0418}{0.185} \times 100$, where 0.0418 is the standard deviation of predicted AA and 0.185 is the standard deviation of fund flows.

4 Abnormal attention, fund returns, and stock prices

This section examines the asset pricing implications of abnormal fund investor attention, investigating its impact on both fund-level performance and the prices of underlying portfolio securities.

4.1 Abnormal attention and future fund returns

We first analyze how abnormal attention predicts subsequent fund performance, a relationship that provides additional insights into the impact of institutional attention allocation.

Under rational attention theories, sophisticated investors optimally allocate their limited cognitive resources to identify skilled managers and superior investment opportunities (van Nieuwerburgh and Veldkamp, 2010; Kacperczyk, van Nieuwerburgh, and Veldkamp, 2016). If institutional investors successfully direct attention toward skilled asset managers, funds receiving heightened attention should subsequently outperform, reflecting the information content embedded in attention allocation decisions. Such outperformance will disappear eventually under the decreasing return to scale as pointed out by (Berk and Green, 2004).[28] In this case, abnormal attention should positively predict fund performance in the short run, and such predictive power should converge to zero in the long run.

If attention allocation is driven by salience rather than fundamental analysis, it may cause temporary price appreciation as attention-driven capital flows push asset values above fundamental levels, followed by subsequent reversals (Barber and Odean, 2008; Kwan, Liu, and Matthies, 2024). Under this interpretation, abnormal attention should also positively predict fund performance in the short run, but such predictive power should

[28] Recent research suggests that concerns about diminishing returns to scale may be less pronounced than previously thought. Huang, Lu, Song, and Xiang (2025), for example, find that the magnitude of diminishing returns to scale in equity fund performance has been overestimated by up to 90%.

switch to become negative in the long run.

We examine the relationship between abnormal attention and future fund returns across multiple horizons. Table 7 presents the regression results, with future net-of-fee returns as the dependent variable in Panel A and future net-of-fee alphas in Panel B. At the end of each month t, we estimate each fund's betas with respect to the four factors using net-of-fee return data from the preceding 36 months. We then use these estimated betas to compute fund alpha from $t+1$ through $t+12$.

The results reveal a temporal pattern that is not consistent with rational attention theories. For example, Panel A Column 1 shows that $Investor\_AA$ positively predicts monthly future returns in the quarter ahead, with a coefficient of 0.032% (t-statistic = 3.57). The effect is economically meaningful: a one-standard-deviation increase in $Investor\_AA$ is associated with a 2 basis point increase per month in fund returns, translating into an estimated $663,000 in additional gains per month to investors in the first quarter.[29]

However, this effect reverses rapidly within one year. Beginning in month $t+4$ (Column 2), the coefficient turns negative and becomes statistically significant between months $t+7$ and $t+9$, with an estimated value of -0.03% (t-statistic = -3.99), significant at the 1% level. The magnitude of this reversal closely offsets the gains observed in the first quarter, suggesting that the initial benefits to fund investors are effectively erased by the third quarter. Beyond month $t+10$, the relationship weakens and becomes statistically insignificant. This pattern of reversal is more consistent with attention-induced price pressure than with rational inattention models. Specifically, the temporary outperformance driven by investor attention is followed by significant underperformance as the transitory price pressure fades and prices gradually revert to their fundamental values.

The coefficient on $Consultant\_AA$ is small and statistically insignificant across all prediction horizons, indicating that consultants' abnormal attention does not predict fu-

[29]This is computed as \$3.315 billion$\times$0.02%, where \$3.315 billion is the average fund size.

ture fund returns. This result aligns with mounting evidence that questions the value-added of investment consultants in institutional asset management (Jenkinson, Jones, and Martinez, 2016; Cookson, Jenkinson, Jones, and Martinez, 2022a). Cookson, Jenkinson, Jones, and Martinez (2022a), for example, demonstrate that consultants systematically manipulate performance calculations to overstate their track records, while their actual recommendations fail to generate superior risk-adjusted returns.

4.1.1 Asset pricing implications of fund investors' attention allocation

The previous sections demonstrate that abnormal attention precedes fund flows. We now examine whether attention-induced trading by institutional funds ultimately affects stock returns. For this analysis, we obtain fund holdings data from Nasdaq eVestment, available at the quarterly frequency. For each fund, we observe stock identifiers, share quantities, and total holding values at quarter-end. Using these data, we construct a monthly measure of stock-level abnormal attention ($SAA_{j,t}$) for each stock j in quarter t as follows:[30]

$$SAA_{j,t} = \frac{\sum_f shares_{f,j,t-1} \times \widehat{AA}_{f,t}}{shrout_{j,t-1}} \tag{3}$$

where $shares_{f,j,t}$ is the number of shares of stock j held by fund f at the end of quarter t, and $\widehat{AA}_{f,t}$ is the predicted value from a model of abnormal attention.

We construct $\widehat{AA}_{f,t}$ using four approaches. First, we use the raw AA for each fund (without any model). Second, we use predicted AA from a regression of AA on Ret_{t-13} as an instrument and style fixed effects. Third, we use predicted AA obtained from a regression of AA on lagged name-based neighboring funds' AA as an instrument and style fixed effects. Fourth, we use residual consultant AA from a regression of consultant AA on investor AA, which serves as a placebo. This residual measure isolates variation

[30]This measure is similar in spirit to the stock-level rating-induced trading pressure of Ben-David, Li, Rossi, and Song (2022b), which is based on the flow-induced trading measure of Lou (2012).

in consultant attention that is orthogonal to investor attention, allowing us to address potential confounding effects of investor-driven trading activity. We estimate these models using the Fama–MacBeth approach, obtaining fitted values each month to avoid look-ahead bias. Our earlier results suggest that stocks with positive (negative) SAAs are likely to be brought (sold).

At the end of each quarter, we rank stocks into quintiles based on the lagged value of each SAA measure. We then compute value-weighted returns for each quintile over holding periods ranging from one to four quarters ahead. In Table 8, we report the differentials (spread) between the top portfolio, containing the most heavily purchased stocks, and the bottom portfolio, which consists of the most heavily sold stocks. We present both the portfolio return spreads and the average spread of the sorting variable SAA during the formation quarter and subsequent prediction periods. We estimate alphas on these portfolios using the four-factor model including the market, size, book-to-market, and momentum factors.

Panel A presents results using the raw (uninstrumented) investor AA. The average difference in SAA between the top and bottom portfolios in the first quarter is 2.04%, indicating that stocks in the top portfolio continue to experience substantially higher SAA than those in the bottom portfolio. The average SAA declines over time to 1.16% by the fourth quarter.[31]

Examining the return differentials, we find significant short-term price effects from attention-induced trading. Over one-quarter holding periods, the SAA spread portfolio generates an average four-factor alpha of 0.23% per month with a t-statistic of 2.32, which is statistically significant at the 5% level. These results indicate that stocks experiencing higher SAA exhibit superior short-term performance relative to those experiencing attention-induced sales. The economic magnitude of our findings is both meaningful and plausible.

[31] These dynamics parallel the findings of Lou (2012), who documents that his flow-induced trading measure decreases from 7.86% in the first quarter and to 3.02% by the fourth quarter.

To assess the economic magnitude, we compute a "return-per-unit-SAA" slope, which indicates that every additional percentage point of SAA is associated with approximately 11.2 basis points (bps) of additional return in the subsequent quarter.[32] This magnitude of the alpha estimate is both economically meaningful and consistent with prior literature. Studies examining flow-induced trading effects report monthly spread alphas ranging from 0.05% to 2.31% across different market contexts (Lou, 2012; Ben-David, Li, Rossi, and Song, 2022a), with our findings falling comfortably within this established range.

As holding periods extend, the SAA spread systematically diminishes. Over the 12-month horizon, the alpha declines to a statistically insignificant 0.007% per month (t-statistic = 0.15). This pattern is consistent with the hypothesis that attention-induced price effects are transitory, generating initial price pressure that subsequently dissipates as attention wanes and prices revert toward fundamental values.[33]

To isolate the price pressure attributable specifically to the attention channel, we replace $Investor\_AA$ with its instrumented version in the SAA construction. Specifically, panels B and C employ instrumental variable approaches, using Ret_{t-13} and name-based neighboring funds' AA as instruments, respectively. Both panels corroborate the main findings: spread portfolios generate positive and significant returns during the initial periods, with effects becoming statistically insignificant by the end of the year. This consistency across different identification strategies strengthens confidence in our causal interpretation.

To address the concern that *any* attention measure used to construct SAA may mechanically generate price pressure, we conduct a placebo analysis in Panel D using residual consultant AA, which is orthogonal to investor AA, to compute stock-level SAA. Under this specification, the resulting spread alpha is negative, though economically small and statistically insignificant. This placebo evidence suggests that the price effects observed

[32]This is computed as $\frac{0.23\%}{2.05\%}$, where 2.05% represents the average difference in SAA between top and bottom portfolios in the first quarter, and 0.23% is the corresponding average spread alpha.

[33]Significant return reversals may emerge beyond 12 months, but the limited time span of our sample period constrains our ability to detect such longer-term patterns with statistical precision.

in Panel A are not spurious and are unlikely to be driven by mechanical effects alone.

5 Conclusion

Despite overseeing trillions of dollars in assets, the cognitive processes governing institutional investors' attention allocation across fund alternatives remain poorly understood. This study addresses this gap by leveraging comprehensive attention data from a prominent institutional asset management platform to examine how sophisticated fund investors navigate complex fund selection decisions.

Our findings reveal that even highly sophisticated institutional fund investors operate under limited attention when evaluating thousands of fund alternatives. Our analysis of alphabetically neighboring funds uncovers novel spillover effects, where attention directed toward one fund is systematically influenced by adjacent alternatives. Moreover, institutional investors focus on fixed historical performance measurement windows, suggesting that salience rather than comprehensive analysis of fund managers' performance records drives attention allocation. Taken together, these attention patterns are difficult to reconcile with purely rational search behavior.

Institutional investors' attention constraints have profound economic consequences. Abnormal investor attention translates into substantial fund inflows, creating temporary price pressure on underlying portfolio holdings. Our results also carry important implications for asset pricing theory. The findings challenge the widely held assumption in theories that institutional investors operate as purely rational actors and highlight the significant role of attention constraints in professional asset management.

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Figure 1. The Nasdaq eVestment platform

This figure illustrates the screening capabilities of the Nasdaq eVestment platform, which allows institutional users to filter funds based on various criteria such as returns, fees, and assets under management (AUM). The platform also records the view date and frequency of each user. Nasdaq eVestment provides unique, anonymous viewer identifiers, along with their classification (e.g., asset consultants or direct investors). According to Nasdaq eVestment, the platform does not display fund names or feature specific funds. Instead, users must search for funds by name or characteristics.

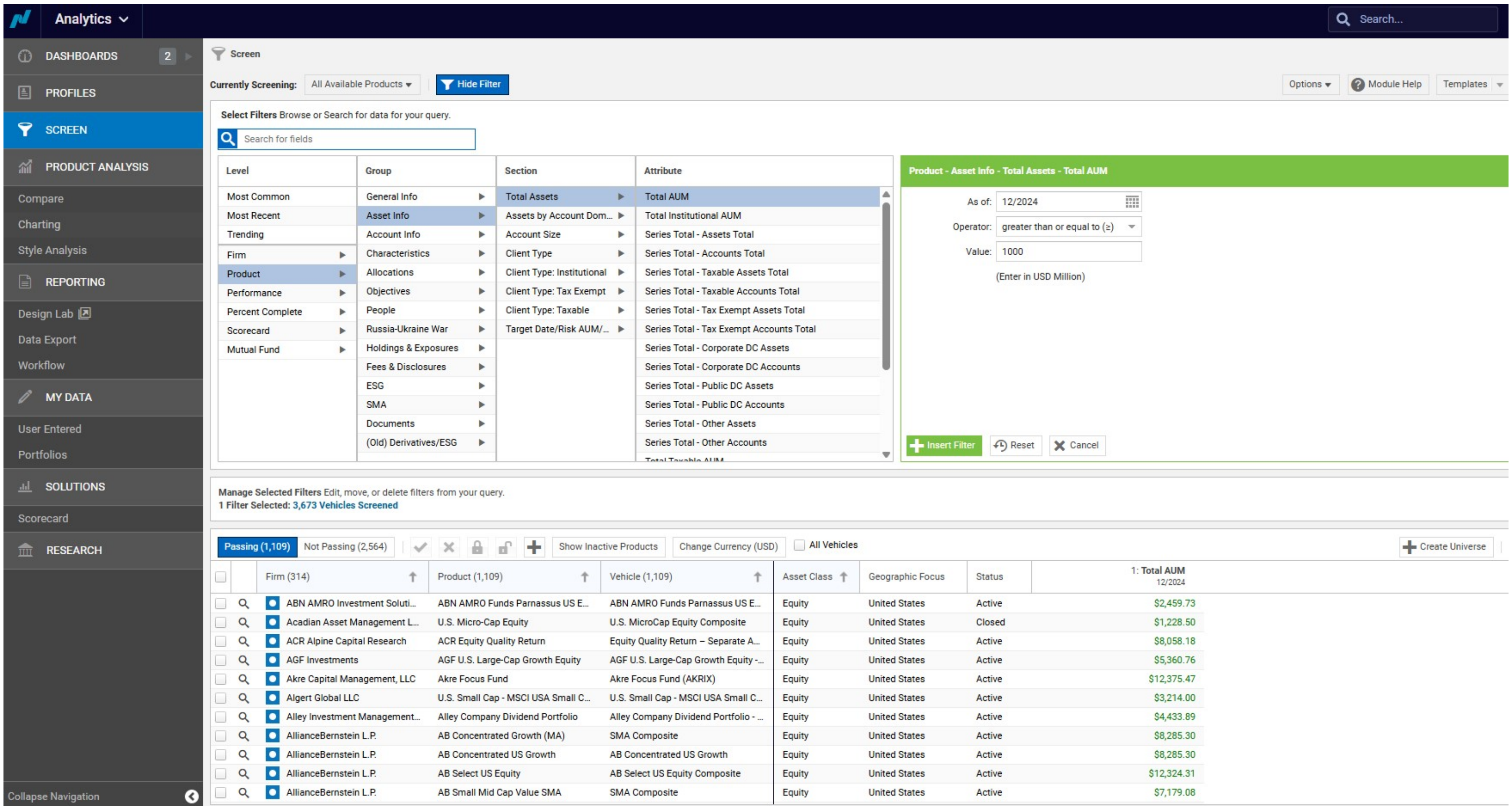


Figure 2. Searching for a fund on Nasdaq eVestment platform: Example

This figure illustrates the default display feature of the Nasdaq eVestment platform. As users type a search term for a fund name, the platform updates in real time, displaying funds with similar names in the results window. By default, funds are listed alphabetically.

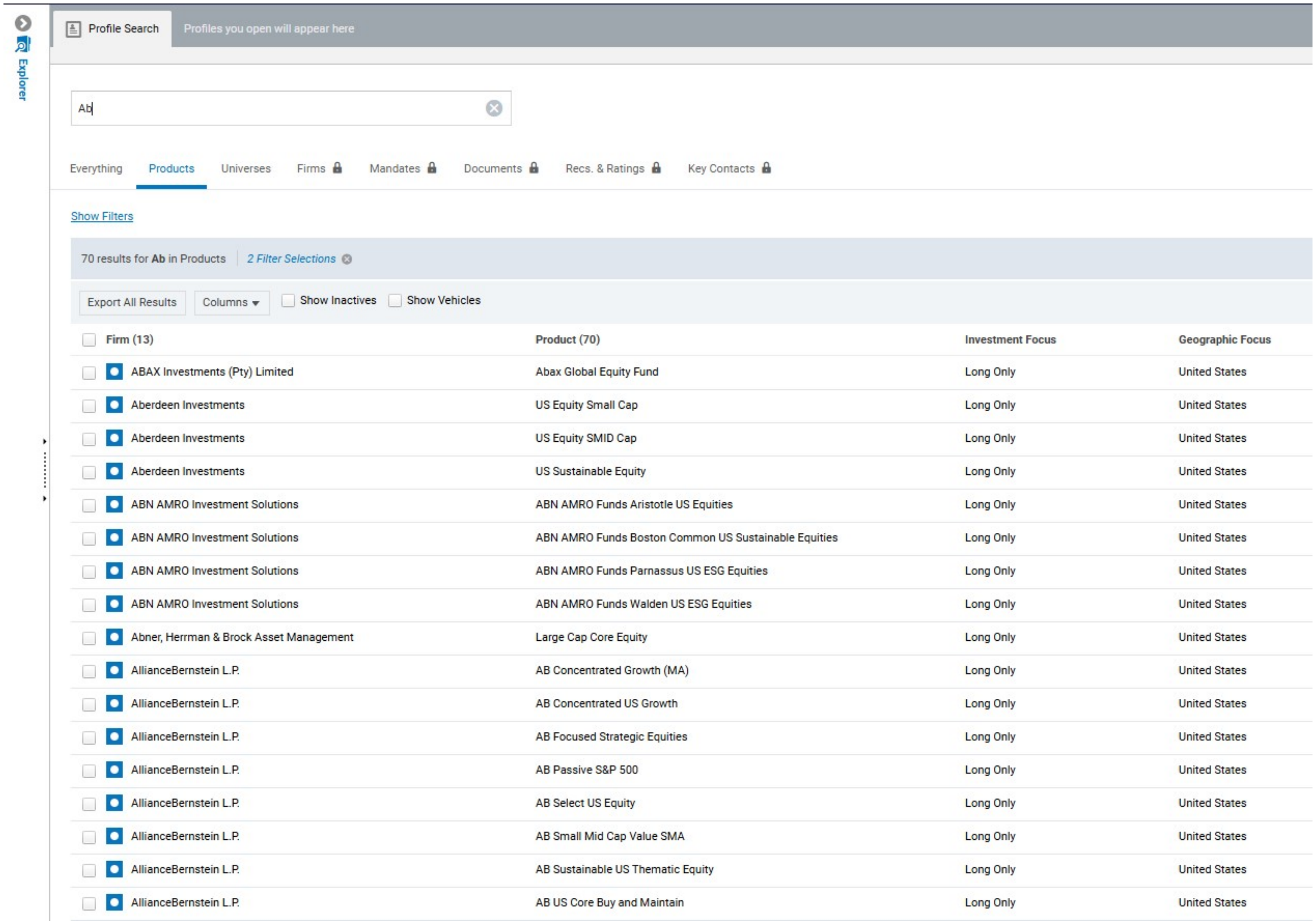


Figure 3. Users of Nasdaq eVestment platform by types

The figure shows the distribution of user types on the platform. The left-hand-side bar of each group displays number of unique users, while the right-hand-side bar of each group shows the average number of unique active users, classified by user types, i.e., asset consultants (the left-hand-side group) or direct institutional investors (the right-hand-side group). Examples of direct institutional investors include pension plans, insurance companies, funds of funds, and endowments. The sample period is from January 2018 through December 2023.

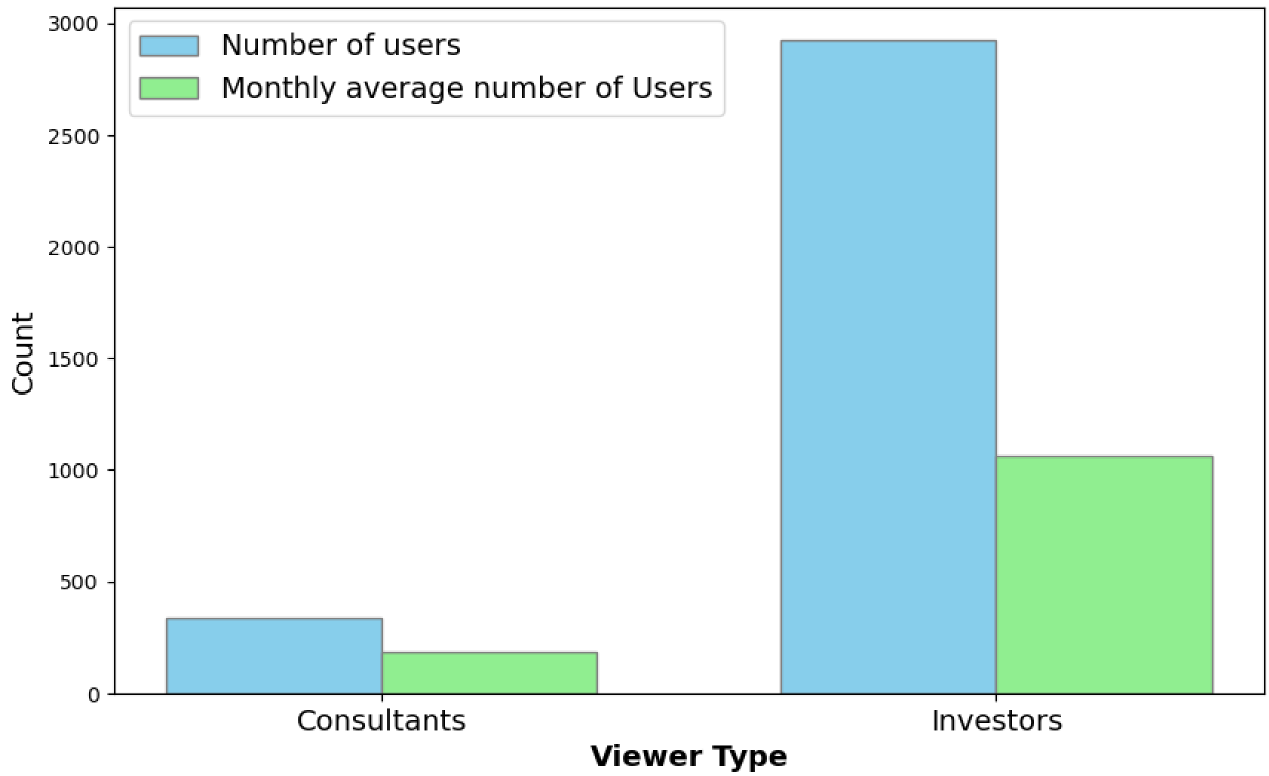
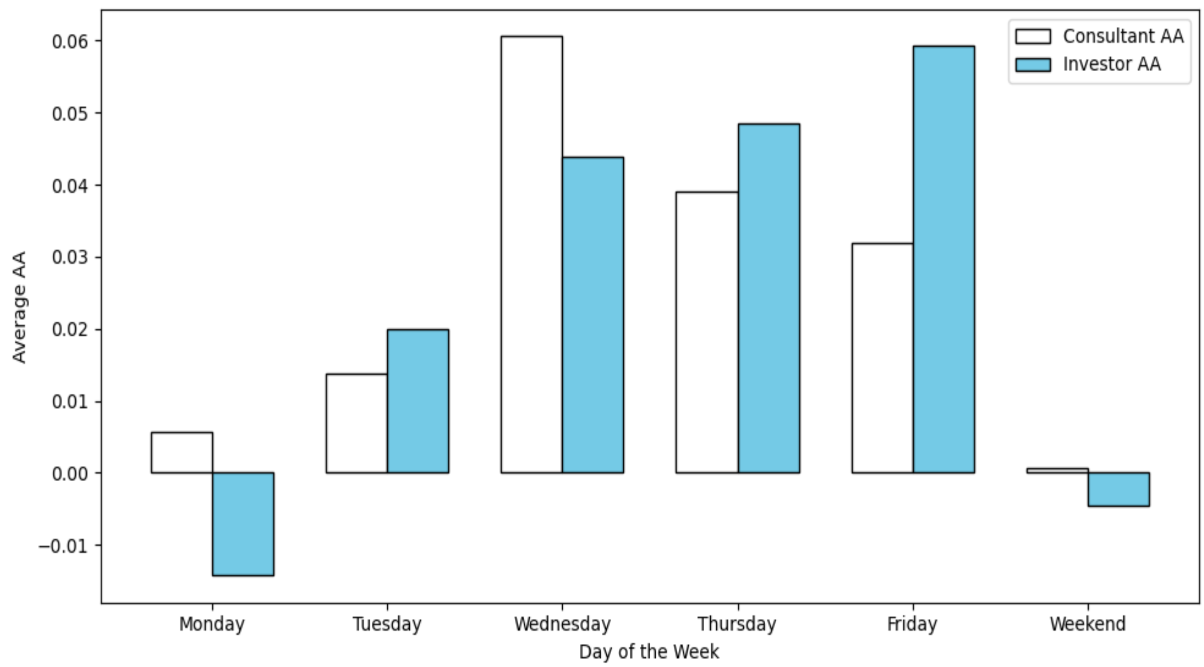


Figure 4. Seasonality of Abnormal Attention

This figure presents the seasonality of abnormal attention (AA) among institutional investors and consultants. Panel A reports AA by day of the week, while Panel B reports the average AA for each month of the year.

Panel A: AA on each day of the week



Panel B: AA in each month of the year

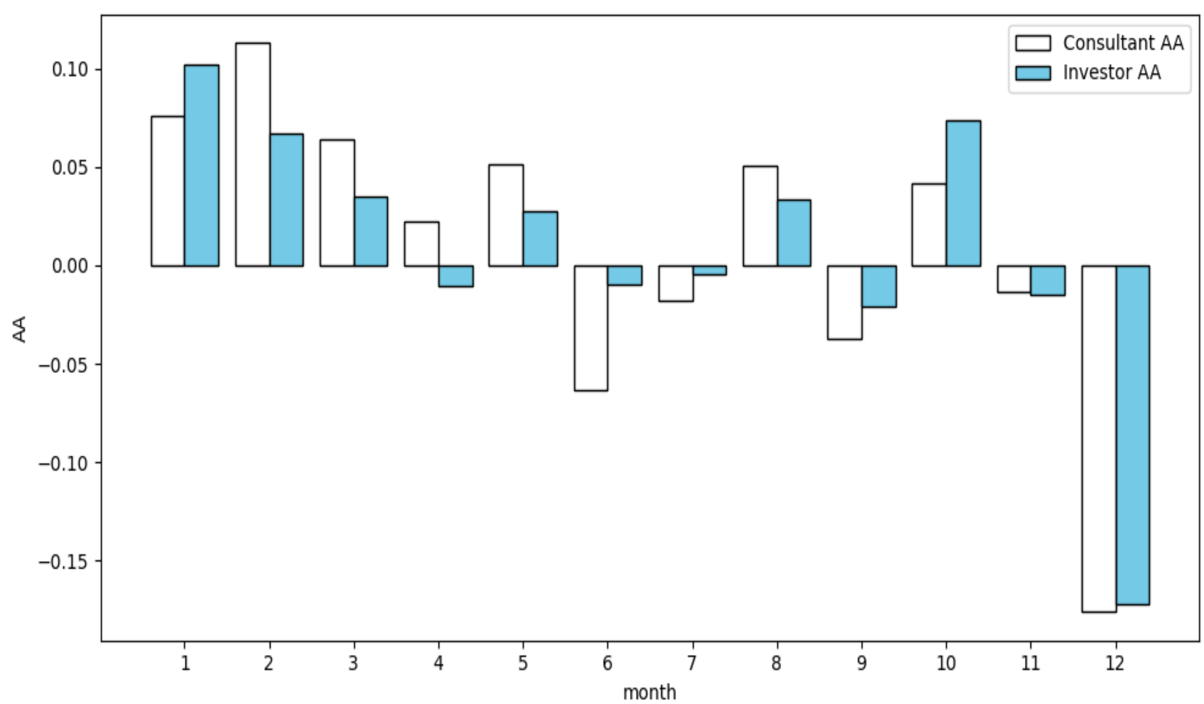
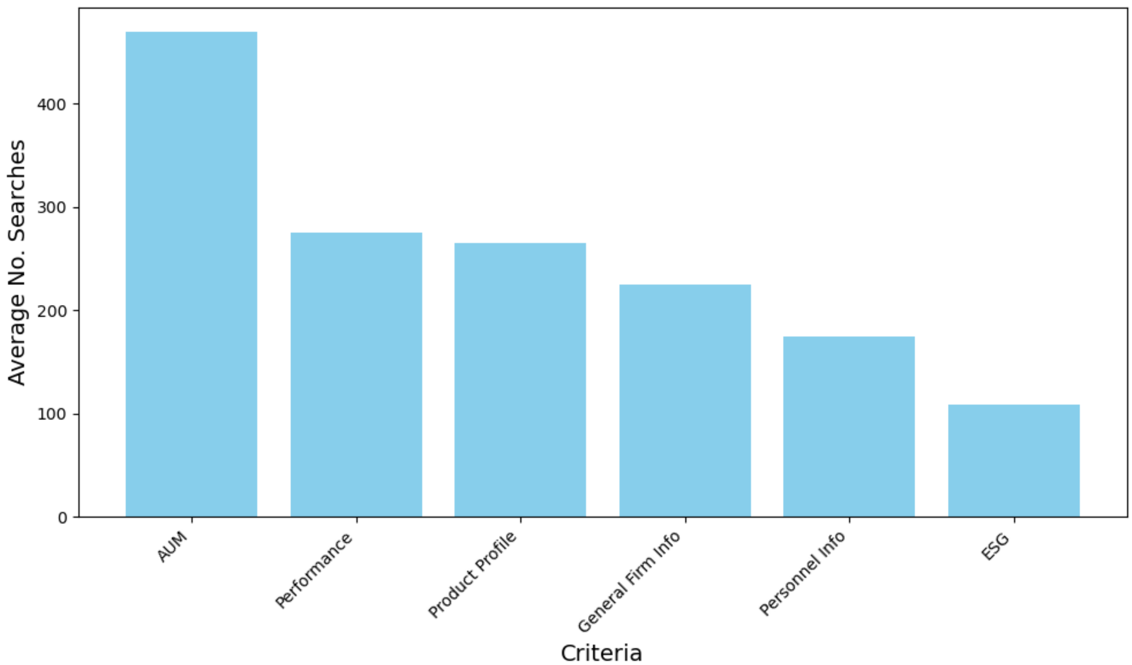


Figure 5. Frequency of Search Criteria

This figure illustrates the frequency of search criteria employed by users on the Nasdaq eVestment platform from January 2018 to December 2023. **Panel A** displays searches by fund characteristics, categorized into time-series criteria (AUM and Performance) and static criteria (Product Profile, General Firm Information, Personnel Information, and ESG indicators). **Panel B** provides a granular breakdown of searches within the Performance category, specifically focusing on 1-year, 3-year, 5-year, and 10-year return windows.

Panel A: Frequency of Search Criteria



Panel B: Percentage of Performance-Based Searches by Time Window

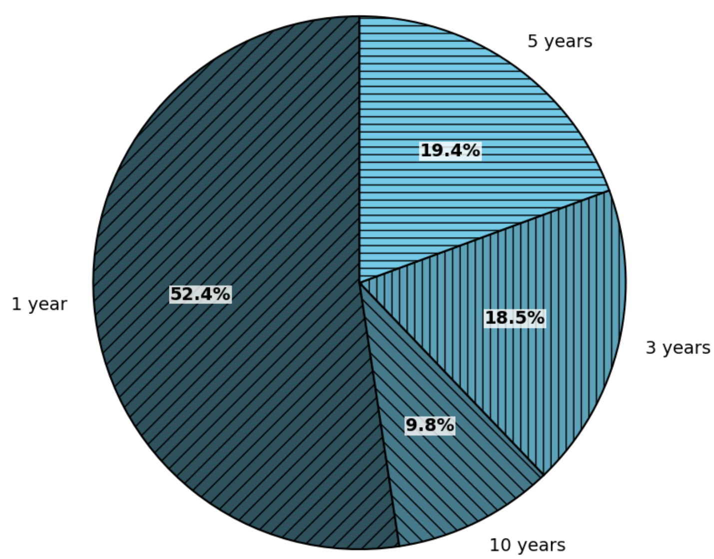


Table 1. Summary Statistics and Univariate Correlations

This table reports (Panel A) the descriptive statistics of funds in the sample and (Panel B) the correlations between attention measures and fund characteristics. All funds are U.S. domestic actively managed equity funds obtained from Nasdaq eVestment for the period 2018–2023. *AA* denotes the monthly abnormal attention of either consultants or institutional investors, measured as the difference between the natural logarithm of the current month's view count and the natural logarithm of its median view count over the preceding 180 days. Investor *AA* and Consultant *AA* refer to abnormal attention paid by direct investors and consultants, respectively. All other variables are defined in Appendix Table A.1.

Panel A: Summary Statistics

Variable	Mean	SD	25th	50th	75th
Investor Attn (level)	4.640	7.547	0	2.000	6.000
Consultant Attn (level)	4.025	5.852	0	2.000	5.000
Investor AA	0.009	0.621	-0.405	0	0.322
Consultant AA	0.009	0.612	-0.318	0	0.288
AUM	3315.41	5332.57	300.60	1109.56	3413.33
Fund Size (log(AUM in $m))	6.814	2.074	5.703	7.010	8.134
Marketing Team Experience	1.106	1.417	0	0	2.833
Fund Return (net of fees)	0.009	0.061	-0.028	0.014	0.047
Four-factor alpha	-0.001	0.003	-0.002	-0.001	0.001
Fees (in %)	0.631	0.072	0.598	0.627	0.662
High Media Coverage	0.045	0.000	0.000	0.000	0.000
Fund Volatility	0.055	0.019	0.043	0.056	0.066
Flow (time t)	0.020	0.185	-0.042	-0.016	0.003
Past Flow	-0.010	0.117	-0.046	-0.020	0.002
Age in months	265.76	128.91	187.00	255.00	332.00
Fund Age (log(Age in months))	5.434	0.654	5.236	5.545	5.808
Adj R^2	0.832	0.118	0.777	0.859	0.914
ESG Fund	0.029	0.167	0	0	0
Value style	0.296	0.457	0	0	1
Growth style	0.271	0.445	0	0	1

Panel B: Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Investor Attn	(1)	1														
Consultant Attn	(2)	0.5158	1													
Investor AA	(3)	0.3071	-0.014	1												
Consultant AA	(4)	-0.0054	0.3843	0.0564	1											
lnAUM	(5)	0.3164	0.3176	-0.0438	-0.0395	1										
Marketing Exper	(6)	0.0839	0.0555	-0.010	-0.0057	-0.1096	1									
Fund Return	(7)	-0.0064	-0.014	-0.0011	-0.0069	0.0131	0.0036	1								
Fees	(8)	0.0416	0.0059	-0.0148	-0.0056	-0.0027	0.0166	0.0033	1							
High Media Coverage	(9)	-0.0169	-0.019	-0.0021	-0.0038	-0.0085	0.0264	0.0012	0.0079	1						
Fund Volatility	(10)	-0.0258	-0.024	0.012	-0.0043	-0.0609	0.0048	0.1192	0.0225	-0.0112	1					
Past Flow	(11)	0.0289	0.0484	0.003	0.0002	0.0837	0.0074	-0.0033	-0.0124	-0.003	-0.0116	1				
Adj. R2	(12)	-0.0616	-0.013	0.0183	0.0066	0.1213	-0.0259	0.0608	-0.1449	-0.0191	0.1072	-0.0025	1			
Fund Age	(13)	0.0859	0.0684	-0.0096	-0.0028	0.2316	-0.0346	-0.0009	-0.0089	0.0063	0.0449	-0.0984	0.0791	1		
ESG Fund	(14)	-0.027	-0.017	-0.0005	-0.0034	-0.0295	-0.0324	0.0011	0.0077	-0.0026	-0.0136	0.017	0.0712	-0.0821	1	
Value style	(15)	0.0128	-0.022	-0.0031	-0.0008	-0.0235	0.0291	-0.0145	0.1235	0.0246	0.0187	-0.0362	-0.1381	0.0273	-0.0761	1
Growth style	(16)	0.0498	0.0762	-0.0061	0.0005	0.1148	-0.0279	0.0173	0.296	-0.0114	0.0846	0.0144	-0.0367	0.027	0.0049	-0.4038

Table 2. Abnormal attention and institutional fund characteristics

This table presents the estimation results from fund-month–level regressions examining institutional investors' abnormal attention. Institutional investors' abnormal attention, $Investor\_AA_{t+1}$, and consultants' abnormal attention, $Consultant\_AA_{t+1}$, are defined as the difference between the natural logarithm of the current month's view count and the natural logarithm of the median view count over the preceding six months, for direct institutional investors and consultants, respectively. The dependent variable is measured in month $t+1$, while all fund characteristics are measured in month t. Standard errors are clustered at the fund level, and the results are robust to alternative clustering schemes such as fund-month or style-month clustering. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix Table A.1.

Dep. Var =	$Consultant\_AA_{t+1}$	$Consultant\_AA\_t+1$	$Consultant\_AA_{t+1}$	$Investor\_AA\_t+1$	$Investor\_AA\_t+1$	$Investor\_AA\_t+1$
	(1)	(2)	(3)	(4)	(5)	(6)
Fund Return	0.510***	0.465***	0.472***	0.575***	0.548***	0.545***
	(5.013)	(4.633)	(4.675)	(5.716)	(5.557)	(5.490)
Fees	-0.060*	-0.054*	-0.022	0.007	0.009	0.011
	(-1.665)	(-1.672)	(-0.631)	(0.268)	(0.360)	(0.380)
Fund Size	-0.015***	-0.013***	-0.014***	-0.013***	-0.012***	-0.013***
	(-15.092)	(-14.743)	(-12.187)	(-13.445)	(-13.015)	(-11.626)
Marketing Expr	-0.007***	-0.006***	0.005*	-0.005***	-0.004***	-0.002
	(-4.783)	(-4.785)	(1.779)	(-3.656)	(-3.585)	(-0.849)
High Media Coverage	-0.011	-0.011	-0.005	-0.010	-0.009	-0.002
	(-1.150)	(-1.217)	(-0.588)	(-0.987)	(-0.952)	(-0.208)
Fund Volatility	-1.000***	-0.872***	-0.376**	-0.753***	-0.640***	-0.538***
	(-4.853)	(-4.753)	(-2.057)	(-4.410)	(-4.179)	(-3.061)
Past Flow	0.032	0.027	0.019	0.025	0.021	0.015
	(1.561)	(1.444)	(0.951)	(1.464)	(1.343)	(0.902)
Adj R2	0.085***	0.076***	0.083***	0.038**	0.034**	0.036*
	(4.034)	(4.067)	(4.056)	(2.053)	(1.985)	(1.877)
ESG Fund	-0.017	-0.015	-0.022	-0.025**	-0.022**	-0.021
	(-1.283)	(-1.241)	(-1.536)	(-2.365)	(-2.344)	(-1.590)
Fund Age	-0.004	-0.003	-0.013***	0.007	0.006*	-0.004
	(-0.780)	(-0.789)	(-3.109)	(1.606)	(1.651)	(-0.890)
$Investor\_AA_{t+1}$		0.012***	0.009**		0.097***	0.092***
		(3.206)	(2.511)		(26.775)	(25.167)
$Consultant\_AA_t$		0.113***	0.106***		0.021***	0.018***
		(30.561)	(28.283)		(5.486)	(4.783)
N	89217	89217	89215	89217	89217	89215
Adj R2	0.027	0.039	0.041	0.026	0.036	0.041
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Family FE	No	No	Yes	No	No	Yes

Table 3. Abnormal attention and future fund flows

This table reports the estimation results of the regression of future net fund flows on Investor AA and Consultant AA, controlling for fund characteristics. In Columns 1–4, the dependent variable is a fund's net institutional flows (i.e., flows coming from institutional investors) measured over various future periods, ranging from one to 12 months ahead. In Column 5, the dependent variable is a fund's retail flows, which are typically the twin mutual fund of the same institutional product. All regressions control for the standard set of control variables used in Table 2 but are not tabulated for brevity. Standard errors are clustered at the fund and date level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Institutional flows				Placebo Flow
	$Flow_{t+1,t+3}$ (1)	$Flow_{t+4,t+6}$ (2)	$Flow_{t+7,t+9}$ (3)	$Flow_{t+10,t+12}$ (4)	$Retail_{t+1,t+3}$ (5)
Investor AA	0.007**	0.008**	0.003	-0.001	0.002
	(2.730)	(2.676)	(0.769)	(-0.207)	(0.384)
Consultant AA	0.002	0.005	0.005	0.001	-0.001
	(1.037)	(1.517)	(1.660)	(0.205)	(-0.045)
N	29850	29464	29160	28876	10244
adj. R-sq	0.043	0.018	0.014	0.013	0.003
Controls	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes

Table 4. Abnormal attention and future fund flows: Cross-sectional heterogeneity of viewers

This table reports the estimation results from regressions of future net fund flows on Investor AA measures constructed from different cross-sections of viewers. In Panel A, we construct two measures of Investor AA based on whether a viewer accesses a fund for the first time within the past two years. Specifically, for each fund–viewer pair, we classify viewers as either "first-time" viewers, those who view the fund for the first time within the past two years, or "repeat" viewers, all others. We then construct abnormal attention (AA) measures for each group and re-estimate the baseline regressions in Table 3. In Panel B, we rank and sort viewer IDs into terciles based on the number of funds viewed concurrently in a given month, referred to as viewing breadth. Viewers in the top tercile have the highest viewing breadth, meaning they view the largest number of funds concurrently. We construct two Investor AA measures for each group, where High Viewing Breadth AA is based on viewers in the top tercile and Low Viewing Breadth AA is based on all other viewers. All regressions include the standard set of control variables used in Table 2, which are omitted for brevity. Standard errors are clustered at the fund and date levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First-time vs repeat viewers

	(1) $Flow_{t+1,t+3}$	(2) $Flow_{t+4,t+6}$	(3) $Flow_{t+7,t+9}$	(4) $Flow_{t+10,t+12}$
First Time Investor AA	0.004*	0.005**	0.005**	0.001
	(1.821)	(2.063)	(2.114)	(0.292)
Repeat Investor AA	0.001	0.005*	-0.001	0.005
	(0.447)	(1.654)	(-0.358)	(1.352)
N	21509	21333	21188	21046
adj. R-sq	0.055	0.026	0.017	0.019
Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes

Panel B: Number of funds viewed concurrently

	(1) $Flow_{t+1,t+3}$	(2) $Flow_{t+4,t+6}$	(3) $Flow_{t+7,t+9}$	(4) $Flow_{t+10,t+12}$
Low Viewing Breadth AA	0.008**	-0.001	-0.001	0.001
	(2.296)	(-0.157)	(-0.287)	(0.172)
High Viewing Breadth AA	0.004	0.007	-0.003	0.010
	(0.882)	(1.170)	(-0.405)	(1.618)
N	27886	27607	27355	26010
adj. R-sq	0.019	0.014	0.014	0.012
Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes

Table 5. Name-based neighboring funds' *AA* as instrument for focal funds' *AA*
This table presents the results of the 2SLS estimation of the effect of abnormal attention (AA) on quarterly flows, using the AA of neighboring funds as an instrument. The rationale behind this instrument is based on the default display settings of the eVestment platform. When a user searches for a fund, the platform automatically shows other funds that are alphabetically related to the search term. As a result, while funds that match the search criterion appear earlier in the search results, the display also includes alphabetically adjacent funds. Motivated by this default display, we construct the instrument by first sorting funds alphabetically within each investment style. For each focal fund, we identify the five funds listed before and the five funds listed after it in alphabetical order. We then compute the weighted average AA of these neighboring funds, using the inverse distance between the focal fund and each neighboring fund as weights. This weighted average AA serves as the instrument in our analysis. Panel A presents the results of the regression of a characteristic of the focal fund on the corresponding characteristic of its neighboring funds, controlling for style and time fixed effects. Panel B reports the 2SLS results in which the nearest neighboring funds' AA is used as an instrument for the focal funds' AA. Since flows are measured at the quarterly frequency, the regressions are estimated at the quarterly frequency. Panel C provides a placebo test for the 2SLS results in which the weighted-average AA of more distant neighboring funds–those ranked 6 to 20 places away from the focal fund in alphabetical order–is used as an instrument. All regressions control for style and time fixed effects. In Panel B, the Cragg-Donald F-statistic for the first-stage regression is 46.72. Standard errors are clustered at the fund level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Correlations between characteristics of focal funds and their neighbors

	Estimate	p-value
Fund Returns	0.123	(0.557)
High Media Coverage	-0.126	(0.361)
Fund Volatility	0.175	(0.197)
Past Flow	0.039	(0.913)
Adj R2	0.033	(0.443)
Fees	0.140*	(0.090)
Fund Age	-0.121	(0.515)
Fund Size	-0.000	(0.651)
Marketing Expr.	0.109	(0.298)
Marketing Ratio	-0.286	(0.220)

Table 5 – continued: Name-based neighboring funds' *AA* as instrument

Panel B: 2SLS–Nearest neighbors' AA as instrument

	1^{st} stage	2^{nd} stage
	(1)	(2)
	AA	*Flow*
NeighborFunds_AA	0.028**	
	(2.009)	
Predicted AA		0.483***
		(3.172)
N	29846	29461
adj. R-sq	0.025	0.026
Focal Fund's Controls	Yes	Yes
Date FE	Yes	Yes
Style FE	Yes	Yes
Fund Family FE	Yes	Yes

Panel C: 2SLS–Placebo using distant neighbors' AA as instrument

	1^{st} stage	2^{nd} stage
	(1)	(2)
	AA	*Flow*
Distant_NeighborFunds_AA	0.010	
	(0.316)	
Predicted AA		-0.015
		(-0.854)
N	29717	29461
adj. R-sq	0.032	0.025
Focal Fund's Controls	Yes	Yes
Date FE	Yes	Yes
Style FE	Yes	Yes
Fund Family FE	Yes	Yes

Table 6. IV regressions using Ret_{t-13} as an instrument for abnormal attention
This table reports estimation results examining the effect of distant past returns (Ret_{t-13}) on abnormal attention and subsequent fund flows. Column 1 presents first-stage results from regressing institutional investors' abnormal attention (AA_t) on Ret_{t-13} and control variables. Column 2 displays the second-stage estimation results, where fund flows ($Flow_{t+1}$) constitute the dependent variable. We control for the standard set of variables, including recent past returns in both stages, but these are not tabulated for brevity. All regressions include investment style and time fixed effects. Standard errors are clustered at the fund level to account for within-fund correlation. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The Cragg-Donald F-statistic for the first-stage regression is 24.29. Variable definitions are provided in Appendix Table A.1.

		1^{st} stage	2^{nd} stage
	(1)	(2)	(3)
	AA	AA	$Flow$
$Ret_{t-1,t-12}$	0.133***		
	(5.760)		
Ret_{t-13}	-0.436***	-0.304***	
	(-3.898)	(-3.074)	
$Ret_{t-14,t-36}$	0.047***		
	(3.436)		
Predicted AA			0.435***
			(4.131)
N	15400	24405	24174
adj. R-sq	0.037	0.033	0.018
Controls	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes

Table 7. Abnormal attention and future fund returns

This table reports the estimation results for regressions of monthly future net-of-fee fund returns, in percent, on monthly Investor AA and Consultant AA, controlling for fund characteristics. In Panel A, the dependent variable is the monthly average net-of-fee return measured over various future horizons, from $t+1$ to $t+12$. In Panel B, the dependent variable is the fund net-of-fee alpha measured over the same horizons. At the end of each month t, we estimate each fund's exposures to the Fama-French-Carhart four factors using the fund's net-of-fee returns data from the preceding 36 months. We then use these estimated betas to compute future fund alpha from $t+1$ to $t+12$. All right-hand-side variables are measured in month t. All regressions include the standard set of control variables used in Table 2, which are omitted for brevity. Standard errors are clustered at the fund level. *, **, and *** indicate statistical significance at the 10

Panel A: Fund net-of-fee returns

	$Ret_{t+1,t+3}$ (in %) (1)	$Ret_{t+4,t+6}$ (in %) (2)	$Ret_{t+7,t+9}$ (in %) (3)	$Ret_{t+10,t+12}$ (in %) (4)
Investor AA	0.032***	-0.001	-0.034***	0.008
	(3.566)	(-0.030)	(-3.985)	(0.797)
Consultant AA	0.001	-0.006	-0.005	0.006
	(0.109)	(-0.666)	(-0.578)	(0.677)
N	89224	88554	87815	86778
adj. R-sq	0.778	0.775	0.775	0.754
Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes

Panel B: Fund alphas

	$Alpha_{t+1,t+3}$ (in %) (1)	$Alpha_{t+4,t+6}$ (in %) (2)	$Alpha_{t+7,t+9}$ (in %) (3)	$Alpha_{t+10,t+12}$ (in %) (4)
Investor AA	0.031***	-0.008	-0.039***	0.006
	(3.523)	(-0.922)	(-4.671)	(0.626)
Consultant AA	0.005	-0.004	-0.007	0.012
	(0.568)	(-0.506)	(-0.773)	(1.305)
N	85507	84878	84181	83236
adj. R-sq	0.188	0.170	0.173	0.171
Controls	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes

Table 8. Asset pricing implications of abnormal attention

This table presents the results of portfolio tests examining the impact of flow-induced trading on stock prices. Attention-induced trading (SAA) for each stock each month is estimated using Equation (3). In Panel A, the formula uses raw investor AA without instrumentation. Alpha is estimated using the four-factor model, including the market, size, book-to-market, and momentum factors. In Panel B, $\widehat{AA}_{f,t}$ is the fitted value obtained from the regression of investor AA on R_{t-13}. In Panel C, $\widehat{AA}_{f,t}$ is the fitted value obtained from the regression of investor AA on name-based neighboring funds' Investor AA. Panel D presents the results of a placebo test using consultant AA to predict fund flows. To construct the portfolios, at the end of month t, stocks are ranked and sorted into quintiles based on each of the SAA measures, computed at the end of month $t-1$. Portfolios are held for 1 to 4 quarters. The spread is the return difference between quintile 5 and quintile 1 stocks. Alphas are from the four-factor model (Fama-French + momentum). All figures are in percent. t-statistics use Newey-West standard errors with 12 lags.

	3	6	9	12
Panel A: Raw (un-instrumented) attention				
Spread alpha	0.230	0.135	0.038	0.007
	(2.32)	(1.84)	(0.66)	(0.15)
Mean SAA spread (in %)	2.046	1.409	1.223	1.160
Panel B: Using month t–13 returns as instrument				
Spread alpha	0.237	0.114	0.008	0.009
	(3.16)	(1.47)	(0.13)	(0.17)
Mean SAA spread	4.124	2.271	2.378	2.279
Panel C: Using name-based neighboring funds' AA as instrument				
Spread alpha	0.240	0.123	0.067	0.059
	(2.01)	(1.36)	(0.81)	(0.71)
Mean SAA spread	3.576	1.446	1.216	1.198
Panel D: Placebo using consultant AA				
Spread alpha	-0.114	-0.093	-0.107	-0.073
	(-1.14)	(-1.26)	(-1.62)	(-1.21)
Mean SAA spread	1.054	0.959	0.626	0.494

Figure A.1. Nasdaq eVestment Partial List of Clients

This figure presents a partial list of clients of Nasdaq eVestment as of 2023, obtained from Nasdaq eVestment.

166 public pensions
169 corporate pensions
17 superannuations
85 endowments
57 foundations
136 family offices
77 insurers
48 sovereign wealth funds
59 hedge fund of funds

Australia
Bahrain
Belgium
Bermuda
Brazil
Canada
China
Denmark
Finland
Germany
Guernsey
Hong Kong
India
Indonesia
Ireland
Italy
Japan
Kuwait
Lichtenstein
Luxembourg
Malaysia
Mauritius
Mexico
Monaco
Netherlands
New Zealand
Norway
Oman
Peru
Poland
Portugal
Qatar
Saudi Arabia
Singapore
South Africa
South Korea
Spain
Sweden
Switzerland
Thailand
United Arab Emirates
United Kingdom
United States
Uruguay

Last updated 04 October 2023

Partial Client List

Public Plans

Alaska Permanent Fund
Alberta Investment Management Company
CalPERS
CalSTRS
First Swedish National Pension Fund (AP1)
LGPS Central Pool
London Pensions Fund Authority
Massachusetts PRIM
National Pension Service of Korea
New York State Common Retirement Fund
Pension Fund Association of Japan
Public Institute for Social Security Kuwait

Financial Advisors

CapTrust
Jeffries Wealth Management
Lincoln Investment Advisors Group
Raymond James Alternative Investments
St. James' Place Wealth Management
UBS Financial Services

Family Offices

Bessemer Trust Company
Capricorn Investment Group
Potenza Capital
Strenta Investment Management

Corporate Pensions

AT&T
Bayerische Versorgungskammer
Boeing Company
Google
Kaiser Permanente
PGGM Investment Management
Shell Asset Management Company
UPS Group Trust

Endowments

Baylor University
Cambridge Investment Management Limited
Haverford College
University of California Board of Regents
Vanderbilt University

Insurers

Allstate Insurance Company
American Family Insurance
CIGNA
Dai-ichi Life Insurance Company
Hartford Life Insurance Company
Northwestern Investment Management Company
Zurich Financial Services

Sovereign Wealth Funds

Future Fund Board of Guardians
Korea Investment Corporation
Kuwait Investment Authority
Mumtalakat Investing for Bahrain
State Administration of Foreign Exchange (China)

Hedge Fund of Funds

Ashburton Investments
Double Eagle Capital
Hatteras Funds
SCS Financial Holdings

Foundations

Alfred P Sloan Foundation
Harry & Jeanette Weinberg Foundation
Rotary International Foundation
VELUX Foundations
W K Kellogg Foundation

Superannuations

AustralianSuper
CBUS
New Zealand Superannuation Fund

nasdaq.com/solutions/asset-owners

Table A.1. Variable definitions

Variable	Definition
$Investor\_Attn$	Monthly institutional fund investors' attention levels, representing the view count by direct investors that the fund received in a given month.
$Consultant\_Attn$	Monthly institutional consultants' attention levels, representing the view count by direct investment consultants that the fund received in a given month.
$Consultant\_AA$	Consultants' abnormal attention to a fund calculated as the difference between the natural logarithm of one plus the current month's view count by consultants that the fund received and the natural logarithm of one plus the median consultants' view count over the preceding six months, measured for each fund in a given month.
$Investor\_AA$	Institutional fund investors' abnormal attention to a fund calculated as the difference between the natural logarithm of one plus the current month's view count by direct investors that the fund received and the natural logarithm of one plus the median investors' view count over the preceding six months, measured for each fund in a given month.
$Consultant\_AA$	Consultants' abnormal attention to a fund (i.e., institutional product) calculated as the difference between the natural logarithm of one plus the current month's view count by consultants that the fund received and the natural logarithm of one plus the median consultants' view count over the preceding six months, measured for each fund in a given month.
Fund Return (net of fees)	monthly net-of-fee returns on a fund.
Fund alpha	four-factor alpha of each fund. To estimate alpha, in a given month t we estimate the beta loadings of each fund's excess net-of-fee returns on the Fama-French three factors and the momentum factor using 36-month rolling windows. We then calculate fund alphas from $t+1$ to $t+12$ using the beta estimates obtained at time t and fund returns over the same period.
Fees (in %)	annual fund fees.
High Media Coverage	a dummy variable that is equal to one if the weighted average media news counts of stocks held by a fund is above the median value, and zero otherwise. The media coverage of individual stocks is obtained from Ravenpack, while fund holdings data are obtained from Nasdaq eVestment.
Fund Volatility	the monthly standard deviation of fund returns, estimated using 18-month rolling windows of data for each fund.
Flow (time t)	net fund flow computed as $Flow_{pt} = \frac{TNA_{pt}}{TNA_{p,t-1}} - (1 + R_{pt})$, where TNA_{pt} is the total net assets under management of fund p at the end of quarter t, and R_{pt} is the fund return in quarter t.
Past Flow	the average net fund flows, computed using 18-month rolling windows of flows for each fund.
Age in months	the number of months since a fund's inception date.
Fund Age (log(Age in months))	the natural logarithm of fund age.
AUM	asset under management measured in \$ million.
Fund Size (log(AUM in \$m))	the natural logarithm of fund AUM.
Adj R2	the adjusted R-squared obtained from the 36-month rolling-window regressions of a fund's net-of-fee returns on the excess return on the market.
Marketing Team Ratio	the ratio of marketing personnel to the total number of employees in a fund.
Marketing Expr	the natural logarithm of the average experience (years) of the marketing team in a fund.
ESG Fund	a dummy variable that is equal to one if a fund is an ESG dedicated fund, and zero otherwise.
Value style	a dummy variable that is equal to one if a fund identifies itself as a value fund, and zero otherwise.
Growth style	a dummy variable that is equal to one if a fund identifies itself as a growth fund, and zero otherwise.