The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

Check for updates

THE JOURNAL OF FINANCE • VOL. LXXXI, NO. 2 • APRIL 2026

Institutional Investor Attention

ALAN KWAN, YUKUN LIU, and BEN MATTHIES*

ABSTRACT

Using data on Internet news reading, we measure fund-level attention to both aggregate and firm-specific news and relate it to fund portfolio allocation decisions. In the time series, we find that funds shift attention toward macroeconomic news during periods of high aggregate volatility. Those funds that exhibit stronger attention-reallocation patterns earn higher future returns. In the cross-section of fund portfolios, fund attention is positively related to stock holdings. Furthermore, fund attention to a stock increases the value-add of that position to the fund's performance. This relationship is stronger using fund attention to more value-relevant news articles.

THE DIFFICULTIES THE CANONICAL PORTFOLIO allocation model has faced in attempting to explain key empirical regularities in portfolio allocation decisions, such as underdiversification, home bias, and style investing, have sparked a large theoretical literature.[1] A potential mechanism proposed by the literature to address these puzzles is limited attention (e.g., Peng and Xiong (2006); Van Nieuwerburgh and Veldkamp (2009; 2010); Glode (2011), Kacperczyk et al. (2016), Maćkowiak et al. (2023)). Under limited attention, investors must decide how to allocate their scarce attention to acquire

*Alan Kwan is with the University of Hong Kong. Yukun Liu is with the University of Rochester. Ben Matthies is with the University of Notre Dame. We thank the Editor (Wei Xiong), an Associate Editor, and two anonymous referees for many helpful comments and suggestions. We also thank Nicholas Barberis, Azi Ben-Rephael (discussant), Alex Chinco, Zhi Da, Kent Daniel, Joseph Engelberg, Paul Gao, Stefano Giglio, Ben Golez, Ahmed Guecioueur (discussant), Ron Kaniel, Andrew Karolyi, Tim Loughran, Alan Moreira, Stefano Pegoraro, Lin Peng, Joel Peress (discussant), Paul Schultz, John Shim, Denis Sosyura, Yuehua Tang, Baolian Wang, Chen Wang, and seminar participants at Arizona State University, University of Cincinnati, University of Florida, University of Notre Dame, BFWG Conference, NBER Behavioral Finance Spring Meeting, and the Western Finance Association Annual Meeting for helpful comments. We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Alan Kwan, University of Hong Kong; e-mail: apkwan@hku.hk.

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

[1] For evidence of underdiversification, see, for example, Friend and Blume (1975) and Goetzmann and Kumar (2008). For evidence of home bias, see, for example, French and Poterba (1991) and Coval and Moskowitz (1999). For evidence of style investing, see, for example, Brown and Goetzmann (1997) and Chan et al. (2002).

DOI: 10.1111/jofi.70009

© 2026 The Author(s). *The Journal of Finance* published by Wiley Periodicals LLC on behalf of American Finance Association.

investment-relevant information. A major barrier in testing such theories, however, is that investor attention to different types of information is unobservable. In this paper, we leverage a new data set to directly measure fund-level attention to both aggregate and firm-specific news, which allows us to test existing theoretical predictions that link investor attention, portfolio allocation, and business cycles.

We conduct our study using a proprietary data set on Internet activity from a data analytics company. The data analytics company maintains a large publisher partnership network, comprising many major news organizations (e.g., general news sites that include broad coverage of financial news, retail-oriented financial news sites, and financial newswires), and it aggregates visitor activities on the websites of these publishers. These data allow us to observe the Internet activity of each institutional investor and in turn each fund's real-time reading of news articles across all covered publishers. We gather detailed information on the content of each article and identify whether the article corresponds to aggregate or firm-specific news, the latter of which we match to the relevant companies. For example, if an anonymized employee at a fund reads an article covering breaking news about a company on January 8, 2020 at 9:55 in the morning, we observe the user session, the article access time stamp, and the article data, including the uniform resource locator (URL) and headline, from which we extract information about the focal company.

Our final data set consists of the institutional investor, article access time, article source, and information about the article's content. For brevity, we refer to institutional investors as "funds" and to the companies the funds read about as "firms." We merge these data with investor holdings data from Factset and with CRSP and with stock characteristics from various databases. Our sample contains 481,820,400 fund-firm-quarters for 4,075 distinct funds. To the best of our knowledge, we are the first to study investor attention to news at the fund-stock level.

We start by studying how funds allocate attention to macroeconomic versus firm-specific news. Peng and Xiong (2006) and Kacperczyk et al. (2016) predict that attention-constrained investors allocate more attention toward macroeconomic news during times when aggregate volatility is high. To test this prediction, we first construct a measure of investor attention to macroeconomic news—the fraction of a fund's reading over the quarter of news articles about the aggregate stock market or macroeconomic conditions. We regress this measure on trailing aggregate volatility, which we capture using the Volatility Index (VIX) published by the Chicago Board Options Exchange. Consistent with theories of limited attention, we find that a one-standard-deviation increase in VIX [2] is associated with an increase of about 5% of the sample standard deviation of the fraction of a fund's attention toward macroeconomic news.

We next examine the sensitivity of funds' ability to reallocate attention to macroeconomic news during volatile times and their performance. High sensitivity may indicate that the fund is rationally allocating its limited attention (e.g., Kacperczyk et al. (2016))—such funds may be more efficient in utilizing their attention—and therefore should generate higher returns on average.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Alternatively, if funds have limited attention and if attention constraints are binding, these funds may exhibit bigger shifts in attention to macroeconomic news after an increase in aggregate uncertainty (see, for example, Peng and Xiong (2006), Kacperczyk et al. (2014)). In this case, funds with higher macroeconomic attention betas may have lower attention capacity and thus lower returns. Under this view, the sensitivity to macroeconomic news would predict lower fund performance on average.[2] Empirically, we construct a measure of a fund's attention reallocation by estimating the sensitivity of a fund's attention toward macroeconomic news to aggregate volatility.[3] We then regress future quarterly fund returns on the trailing attention sensitivity measure (macroeconomic attention beta). We document a positive and statistically significant relationship between future fund performance and the fund's macroeconomic attention beta. In the baseline specification, a one-standard-deviation increase in the fund's macroeconomic attention beta is associated with a 0.48% increase in quarterly fund returns (1.9% annualized). Moreover, consistent with the prediction of Kacperczyk et al. (2016), we find that the outperformance of high-attention-beta funds is concentrated in periods of high aggregate volatility. Additionally, consistent with the idea that high-beta funds are more efficient, these funds pay relatively less attention to salient stocks and have higher human capital compared to low-macroeconomic-beta funds. Moreover, the ability to reallocate attention according to aggregate volatility is a persistent characteristic, and hedge funds tend to have higher macroeconomic attention betas compared to other funds.

Turning to the properties of investor attention to firm-specific news, a common theoretical prediction of limited attention models is a positive association between attention and portfolio holdings. In equilibrium, investors prefer to hold assets they are more informed about, and they have incentives to acquire information about assets they expect to hold positions in. These forces generate a positive relationship between fund attention and holdings (e.g., Van Nieuwerburgh and Veldkamp (2010)). Indeed, we find that fund attention and portfolio holdings exhibit a positive relationship on both the extensive and intensive margins. On the extensive margin, we find that firms read about five times more articles per currently held stock than articles per nonheld stock among the U.S. stock universe. On the intensive margin, we restrict our sample to the set of held stocks, and regress the share of attention that an investor allocates to a stock in quarter t on the dollar share of the stock in the investor's portfolio in quarter $t-1$. We find a positive and significant relationship. We also conduct fixed effect analyses to decompose the variance of funds' stock-specific attention. We find that time fixed effects alone explain little of the variation in fund attention to firms, while fund and firm-investor fixed effects play a much larger role, consistent with the existence of attention habitats.

[2] Moreover, noninformation-based theories such as salience would predict a null or even negative relationship between attention reallocation and fund performance due to suboptimal trading (Barber and Odean (2008)).

[3] Specifically, for each fund-quarter, we estimate the beta of a firm's weekly attention to macroeconomic news on contemporaneous aggregate volatility over the trailing 52 weeks.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

In our next set of tests, we examine whether investor attention to firm-specific news generates value for the fund. In theories of rational attention, investors optimally allocate their attention across firms based on their priors, produce information about the firm, and invest accordingly (e.g., Van Nieuwerburgh and Veldkamp (2010)). We posit that fund attention to a stock position is positively associated with the value the position contributes to the fund's overall performance (which we term "position-level value-add"), as a fund's attention to a stock is increasing in its prior beliefs about the stock's future returns—learning about a stock becomes more valuable when the fund expects to hold a larger position (Van Nieuwerburgh and Veldkamp (2010)).

We test the relationship between attention to a stock and the position-level value-add, which we measure as $h_{ist-1} \times R_{st}$, where h_{ist-1} is fund i's dollar holdings of stock s as a fraction of its total dollar holdings at time $t-1$, and R_{st} is the future return of stock s in period t. The position-level value-add tests indicate not only whether a stock exhibits higher subsequent returns, but also whether the fund allocates more weight toward this outperforming stock. We document a positive and significant coefficient on fund attention to a stock.[4] A one-standard-deviation increase in attention to a position corresponds to a 5% standard deviation increase in the future value-add of the position. We also run specifications that interact attention with the size of the position at time $t-2$ as well as with the trade size measured as the magnitude of the change in position from $t-2$ to $t-1$. In both cases, the interaction terms are positive, indicating that investors generate greater value on their portfolio for stocks in which investors pay attention and hold large positions or make large trades.

We also implement a set of tests based on the fund's trading decisions. In theory, after allocating attention to a stock, the manager will receive a signal about the expected return of the stock that will influence the fund's trading decision. We test whether fund attention to a stock produces valuable information that the fund can trade profitably on. Specifically, we construct a trade-based value-add measure as the future return of stock s, R_{st}, times the change in dollar holdings of fund i in stock s from $t-2$ to $t-1$. In our regressions of trade-based value-add, we document a positive coefficient on attention that is significant at the 5% level. In additional specifications, we document that the coefficient on the interaction term between attention and trade size is positive and significant at the 5% level. Our baseline estimate reveals that a one-standard-deviation increase in attention corresponds to a 2.4% increase in trade-based value-add relative to its standard deviation. These results show that attention to a stock generates profitable trading by the fund and that this attention contributes more to fund value for larger trades.

In additional analyses, we study cross-sectional heterogeneity in this relationship across fund types and news types. First, across fund types, we

[4] In these specifications we incorporate firm-by-time fixed effects to test whether funds that pay more attention are better able to overweight (underweight) stocks that subsequently do well (poorly) compared to other funds holding the same stock, which provides an important empirical advantage over using simple stock returns, which would be subsumed by firm-by-time fixed effects.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

find that attention by hedge funds and mutual funds drives more fund value than attention by other types of investors. Index funds also seem to use attention less effectively than active funds. Second, we show that attention to firm-specific news from business and financial sites produces more value for a fund than attention to retail-oriented or general news sites. Third, motivated by Akepanidtaworn et al. (2023), who document that institutional investor buying adds value on average while selling does not, we measure the amount of attention to buys and sells, and we examine the trading performance of buys and sells with high and low attention. Overall, our results generally support the proposed mechanism of the paper. In particular, we find that investors pay more attention to buys relative to sells. In addition, attention is more important for buying decisions compared to selling decisions—attentive buys perform better than less attentive buys in the trade-based value-add specifications. We find mixed evidence, however, comparing the performance of attentive versus nonattentive sells.

Finally, we present results linking investor attention and future returns at the stock level. These tests extend the intuition of the trade-based value-add tests by studying whether attentive trading, aggregated across funds, predicts future stock returns. We construct stock-level measures of attention to a stock by buying funds (and similar measures for holding and selling funds). We find that attention by buying funds significantly positively predicts future stock returns, in both Fama-MacBeth tests and portfolio tests. A one-standard-deviation increase in attention by buying funds corresponds to around a 0.35% increase in monthly returns (4% annualized). Moreover, this relationship is stronger for buying hedge funds compared to other types of funds. Finally, attention by holding and selling funds has weaker predictive power for future stock returns. Overall, the results are consistent with our trade-based value-add evidence.

Our paper relates to the literature on limited attention and information processing capacity. Many theoretical studies focus on rational inattention in macroeconomics.[5] Prior work proposes limited attention to explain various puzzles in finance, such as underdiversification (e.g., Van Nieuwerburgh and Veldkamp (2010); Kacperczyk et al. (2016)) and style investing (e.g., Barberis and Shleifer (2003); Peng and Xiong (2006)), as well as in the study of portfolio allocation (e.g., Peng and Xiong (2006); Van Nieuwerburgh and Veldkamp (2010); Abel et al. (2013); Kacperczyk et al. (2016)). Our contribution is to test the assumptions and predictions of these theories regarding attention allocation between macro news and firm-specific news and attention allocation across firm-specific news. Our results highlight the importance of limited attention, as theories with unlimited attention capacity and full information face difficulty reconciling our findings.

Prior literature has used proxies for investor attention such as Google searches and aggregate news attention on Bloomberg (Da et al. (2011); Ben-Rephael et al. (2017); Liu et al. (2023); Da et al. (2025)). Gargano and

[5] See, for example, Sims (2003), Moscarini (2004), and Mackowiak and Wiederholt (2009; 2015).

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Rossi (2018) and Sicherman et al. (2016) measure investor attention of retail investors with respect to brokerage accounts. In addition, some recent studies examine institutional investors' readings of companies' filings via EDGAR (Chen et al. (2020); Dyer (2021); Crane et al. (2023)). Our key advantage is to relate specific investors' holdings to their news attention. This allows us to test theories that these prior studies could not address because they do not have a measure of both firm and macro news that is connected to investor holdings.

This paper also relates to the literature on news media and the stock market. Tetlock (2007) and Fang and Peress (2009) study the relationship between media coverage and stock returns. Peress (2014) identifies a causal impact of the media on the stock market using newspaper strikes. Some studies posit that news coverage can be used to infer investors' attention to macroeconomic variables (Manela and Moreira 2017; Fisher et al. 2022; Liu and Matthies 2022). Kwan et al. (2022) use company attention to news to study managerial learning from stock prices. We provide direct evidence of how investors process the news to complement their trading decisions.

The paper is organized as follows. Section I discusses the data. Section II develops our hypotheses and introduces our empirical design. Sections III and IV present the main empirical results. Finally, Section V concludes.

I. Data

A. Financial News

Our measures of investor attention are based on news reading activity by institutional investors. We work with a data analytics company from the marketing technology space that we refer to as the "Data Partner." The Data Partner maintains a large network of partnerships with online publishers focused primarily (but not exclusively) on business content and news. As part of the partnership, participating publishers contribute to the Data Partner's pooled data set via a mechanism that shares information about web content consumption, including the external IP address of the network originating the HTTP request and the URL of content accessed. Overall, the platform aggregates around 1 billion content consumption events per day. From this large data set, the Data Partner (i) associates visitors with companies and (ii) quantifies the "topics" that visitors read about. The Data Partner then produces an indicator that aims to quantify the business topics that companies are reading about. These analytics are sold to companies primarily to facilitate sales and marketing, by identifying companies with heightened research interest in a specific business topic. Participating publishers receive some of the Data Partner's analytics in return. The Data Partner does not sell these analytics products to financial institutions for the purpose of financial trading.

To start, we obtain event-level data from the Data Partner for the period November 2017 to June 2022. Event-level data describe an instance of an article being consumed, including the time stamp, the company associated with the visitor, and the URL accessed. The Data Partner does not sell this

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

event-level data commercially and made it specially available for academic research. The data have been cleaned of personally identifiable information and were accessed remotely.

From the event data set, we focus on over a dozen financial publishers whose names cannot be disclosed but are among some of the largest financial publishers in the world. The publishers that we use in this study total over 100 million content interactions per day. Although not exclusively, these platforms are offered primarily in the English language.

We merge our event-level data with news data from Ravenpack to identify the topic, subject, and sentiment of articles in our data set.[6] Ravenpack is a leading data analytics provider widely used in academic studies as well as in practice by high-frequency trading firms, hedge funds, banks, and asset managers. Historically, the Data Partner has primarily tracked content in terms of broad business topics. While some companies are themselves topics, due to the design of its algorithm, the Data Partner has not been able to comprehensively record companies referenced in articles. Moreover, its topic taxonomy consists of broad business topics and does not consist of certain topics that might be useful to financial economists such as corporate events (for example, capital raising, mergers, or payout announcements) and textual sentiment. We, therefore, obtain these features from Ravenpack.

We describe our merge process in the Internet Appendix.[7] Joining our data to Ravenpack allows us to obtain the stock tickers associated with each article. For conciseness, we refer to financial institutions as "funds" and the assets they read about (or hold) as "firms." The final data set consists of the count of articles read by a fund on a specific date about a specific stock or macroeconomic topic defined by Ravenpack.

Table I presents statistics describing the publishers in the data set. Panel A presents a breakdown of the types of websites in our data. We segment sites into retail-oriented investor websites, business websites (including premium, paywalled financial newswires, and financial news sites that have no paywall), and general news sites that include financial content. This classification gives us some sense of where the data come from. About 16% comes from retail-oriented financial websites, about 13% from general news, and the rest comes from business or financial newswires.[8]

In Panel B, we present a summary based on the type of article (full article, filing, press release, or tabular). Relative to RavenPack, we tend to have a

[6] We access data from Ravenpack 1.0, which includes Ravenpack's most detailed offering, inclusive of major financial publishers it licenses content from, as well as open-access content across blogs, social media posts, news sites, and regulatory filings.

[7] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[8] We also considered other classifications, such as the Internet Advertising Bureau classifications, but these classifications do not sharply distinguish the different sites in our sample. For example, the Webshrinker API classifies everything as IAB 12 (news), 13 (financial site), or 13-3 (financial news). This motivates us to create our own classification.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table I
Data

In Panel A, we report the breakdown of publisher types by the amount read in our data set, the first row corresponds to business and financial newswire publishers, the second row to retail-oriented financial news sites, and the third row to general news sites that also contain financial news. In Panel B, we report the breakdown of articles in our data set according to RavenPack-provided article classifications. “Full Article” refers to a full-length news or op-ed article. “Filing” refers to a redistribution of a corporate filing. “Press Release” refers to a short corporate press release without a full article associated. “Tabular Material” refers to data. Column (1) refers to the frequency distribution over our sample period in the RavenPack data set, column (2) reports the corresponding number in our sample, and column (3) weights the frequency distribution by reading frequency.

Panel A: Statistics by Publisher Type

Publisher Type	% Read
Financial or Business-Oriented Newswire	71.34
Retail-Oriented Financial Websites	15.99
General News	12.67

Panel B: Reads by Article Type

Article Type	% Ravenpack (1)	% Data (2)	% Read (3)
Full Article	90.832	94.754	95.381
Filing	0.098	4.221	4.114
Press Release	5.807	0.613	0.047
Tabular Material	1.493	0.411	0.458

higher proportion of “full articles,” although the vast majority of articles in both RavenPack and our data set fall within this type.

To map reading events to investors consuming information, we rely on the Data Partner’s proprietary methodology. For each visitor to a Data Partner website, the Data Partner creates a profile through the use of first- and third-party cookies. This enables the publisher, and in turn the Data Partner, to observe when a visitor returns to a website. Over time, the Data Partner infers the association between the profile and a firm through a wide ensemble of industry-accepted methods. For example, user profiles are associated with a company when visitors use a work email to log into a member’s website. Similarly, if a profile consistently logs onto a publisher website from a work-associated IP address, this gives a strong indication that the profile belongs to a particular company. The Data Partner also receives data from third-party sources that also perform visitor identity resolution.[9] Crucially, the Data Partner assembles these data sources and constructs an association between the user profile and a firm, where a profile can be longitudinally observed even

[9] Other methods include verification of an IP address or profile through the clicking of an email sent to a work address, logging into a site with a work email, information shared on social profiles, or other methods.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

though the visitor may traverse different IP addresses. This allows the data to remain effective even when a visitor is working remotely. We note that we aggregate funds to the web domain, equivalent to the fund family level.[10]

B. Sample and Metrics of Investor Attention

We construct two basic measures of investor attention: attention to the macroeconomy and attention to the firm. In addition to the supplementary data from RavenPack 1.0, we collect a number of additional data sets. Holdings information for mutual funds comes from CRSP. We focus on actively managed equity funds following papers such as Cremers et al. (2016).[11] Beyond mutual funds, we collect 13-F holdings from Factset LionShares. In addition to those institutional descriptions provided by Factset LionShares, which classify institutions into several broad categories,[12] we use Form ADV, Factset, and Securities and Exchange Commission Form N-1 to collect fund descriptions to help us further classify funds using their textual descriptions. Finally, we collect standard data from CRSP and Compustat.

To compare the merged data set to the original RavenPack data set, Table II presents statistics on the proportions of article observations in each data set broken down by stock characteristic quartiles for: the number of years listed, book-to-market, advertising expenditure relative to sales, and analyst coverage. The last section of the table includes a breakdown by industry. We also include the column "% Read," which reports the breakdown within each category based on total reading. In general, our sample composition is similar to that of RavenPack, but the percentage of articles read—which reflects the preference of investors to read given the composition of articles written—shows interesting (although minor) tilts in our data. For example, we see a large over-representation of tech firms in reading proportions, despite an underrepresentation of this sector by article counts in our data set. Also, despite the number of news articles written, construction and manufacturing firms are read relatively less by investors. We also see that investors are drawn to stocks that have been around longer and to stocks with higher advertising, and moderate tilts toward stocks with high book-to-market ratios.

[10] There are many more mutual funds than hedge funds, but they are usually one of around 600 to 800 mutual fund families, which is our level of granularity. For instance, according to the Morningstar report (https://morningstardirect.morningstar.com/clientcomm/DueDiligenceReports/FundFamily150.pdf), retrieved October 2024, they make reference to 800 fund families.

[11] We examine the sensitivity of our analysis to this choice in Internet Appendix Table IA.XVII. As we expect, the results are stronger for active equity funds than other types of funds.

[12] These categories include hedge fund, broker-dealer, investment adviser, mutual fund, pension fund, and other unclassified.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table II

Comparison of Sample Publishers versus All Publishers

This table summarizes the proportions of observations within stock characteristic categories in terms of the number of articles in the RavenPack sample, the number of articles in our merged sample, and the amount of reading in our merged sample. Classification of each stock is done prior to the sample period. In Panel A, stocks are sorted into quartiles of the four characteristics listed. In Panel B, stocks are sorted into industries using the North American Industrial Classification System. For brevity, we combine two-digit industries into the sectors shown below. Finance, Real Estate aggregates two-digit industries 52 and 53; Information, Scientific and Technical Services aggregates industries 51 and 54; Retail/Wholesale Trade and Transportation combine 42, 44, 45, 48 and 49; Construction/Manuf combine 23, 31, 32, and 33; Mining, Energy and Utilities combine 21 and 22; and Accommodation, Food, Entertainment, and Recreation combine 71 and 72.

Panel A: By Characteristics

Number of Years Listed				Value (B/M)			
Category	% Ravenpack	% Data Set	% Read	Category	% Ravenpack	% Data Set	% Read
Bin 1 (Low)	4.640	4.610	4.650	Bin 1 (Low)	36.020	36.590	36.110
Bin 2	31.430	21.260	19.420	Bin 2	35.530	28.050	25.790
Bin 3	23.310	26.740	24.930	Bin 3	13.710	13.010	12.680
Bin 4 (High)	40.620	47.390	51.010	Bin 4 (High)	14.740	22.350	25.420

Advertising Relative to Sales				Analyst Coverage			
Category	% Ravenpack	% Data Set	% Read	Category	% Ravenpack	% Data Set	% Read
Bin 1 (Low)	5.700	5.460	6.580	Bin 1 (Low)	3.660	2.740	2.130
Bin 2	15.620	18.230	16.590	Bin 2	5.380	3.660	1.880
Bin 3	47.290	44.770	35.750	Bin 3	8.490	7.360	8.400
Bin 4 (High)	31.390	31.540	41.080	Bin 4 (High)	82.470	86.240	87.580

Panel B: By Sector (Aggregated Across NAICS2)

Category	% Ravenpack	% Data Set	% Read
Accommodation, Food, Entertainment, Recreation	1.780	2.180	1.300
Agriculture	0.050	0.040	0.010
Construction/Manuf	20.550	21.210	15.300
Finance, Real Estate	13.850	15.870	17.530
Information, Scientific Technical Services	51.050	45.100	54.750
Mining, Energy, Utilities	1.620	2.040	0.770
Other	2.630	2.550	2.210
Retail/Wholesale Trade, Transportation	8.460	11.030	8.130

II. Hypothesis Development and Empirical Design

A. Attention Allocation to Macroeconomic News

We first discuss predictions about fund attention to macroeconomic news made by models featuring limited attention. A number of papers (e.g., Peng and Xiong (2006), Glode (2011), Kacperczyk et al. (2016)) imply that fund attention to macroeconomic news should vary across the business cycle. In particular,

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

attention-constrained investors are expected to allocate relatively more attention toward macroeconomic news during times when aggregate volatility is high (e.g., Peng and Xiong (2006), Kacperczyk et al. (2016)). Consistent with this prediction, Peng et al. (2007) document that co-movement in asset prices increases with market-wide uncertainty. Similarly, salience-related channels (e.g., Barber and Odean (2008), Bordalo et al. (2012)) may predict that investor attention to macroeconomic news increases during periods of high aggregate volatility, if investors consider high-volatility events more salient.

While these theories make similar predictions about the relationship between attention to macroeconomic news and aggregate volatility, they generate different predictions about fund performance. On the one hand, a fund's ability to shift attention according to the business cycle may indicate that the fund is rationally allocating its limited attention to the most value-relevant information (e.g., Kacperczyk et al. (2016)). Under this view, funds whose attention to macroeconomic news responds more strongly to aggregate volatility are the funds that are more efficient in utilizing their attention and vice versa. In this case, the former funds should generate higher returns on average. Furthermore, this superior performance should be more pronounced during times of high aggregate volatility, when information production about macroeconomic conditions is most valuable. On the other hand, investors with lower attention capacity may be more responsive in shifting attention to macro news after an increase in aggregate uncertainty (see Peng and Xiong (2006), Kacperczyk et al. (2014)). Under this view, the sensitivity between fund attention to macroeconomic news and aggregate volatility may capture funds with more binding attention constraints, in which case funds with high sensitivity would have lower fund performance on average. Moreover, noninformation-based theories such as salience would predict no relationship or even a negative relationship between this attention reallocation and fund performance: if a fund's attention is distracted by salient, high-volatility events, this may lead to suboptimal trading (Barber and Odean (2008)).

Our data allow us to measure investor attention to both macroeconomic and firm-specific news. This permits us to directly test the hypothesis that investors reallocate their attention toward macroeconomic news during times of high aggregate volatility. Furthermore, combining our measures of fund attention with data on fund performance, we can test the hypothesis that funds whose attention to macroeconomic news exhibits the strongest relationship with aggregate volatility deliver superior returns.

B. Attention Allocation to Firm-Specific News

In classic models of portfolio allocation (e.g., Markowitz (1952), Sharpe (1964)), investors have unlimited attention and learn all publicly available information, which implies no systematic relationship between attention and portfolio holdings. However, if funds face attention capacity constraints, fund managers must allocate their attention efficiently across assets (e.g., Peng and Xiong (2006), Van Nieuwerburgh and Veldkamp (2009), Kacperczyk et al.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

(2016)). These attention constraints generate different predictions than the unconstrained benchmark about the relationship between attention, portfolio holdings, and fund performance.

One key prediction common to many models of limited attention is a positive association between attention and portfolio holdings. This prediction arises since, in equilibrium, investors prefer to hold assets they are more informed about and have incentives to acquire information about assets they expect to hold positions in. Both of these forces generate a positive feedback effect between attention and holdings, resulting in a positive relationship (e.g., Van Nieuwerburgh and Veldkamp (2010)). Using our data on investor attention to firm-specific news alongside holdings data, we test the hypothesis that fund attention and portfolio holdings should exhibit a positive relationship on average.

Theories of limited attention also generate predictions about attention to firm-specific news and performance. In models such as Van Nieuwerburgh and Veldkamp (2010), a fund's attention to a stock is increasing in its prior beliefs about the stock's future returns, since learning about a stock becomes more valuable when the fund expects to hold a larger position. Accordingly, fund attention to a stock position should be positively associated with the future value the position contributes to the fund's overall performance. This "value-add" is driven by the stock's higher expected return and by the fund allocating greater weight to the position.

To test this hypothesis, we use our data on fund attention to firm-specific news alongside data on fund positions to examine whether investor attention allocation to a stock adds value to fund performance. In these tests, since we are able to observe each fund's attention to each firm as well as the portfolio holdings, we can directly link fund attention to firm-specific news to the value-add of the position to the fund's future performance.

We next study the relationship between attention to firm-specific news and trading performance. After the fund allocates attention to a stock, the fund manager will receive a signal about the expected return of the stock. This signal can be positive or negative, centered around the prior, and as such will not affect the unconditional positive relationship between value-add and attention discussed above. However, if fund attention does produce a valuable signal, we should expect a positive relationship between attention-driven trading and future stock returns. For example, we would expect higher returns for a stock if in aggregate funds pay attention to the stock while increasing their positions.

Testing this positive relationship allows us differentiate from other theories of attention, such as salience, where fund attention to a firm may or may not produce value-relevant information (e.g., Barber and Odean (2008)). In this case, we would not expect to see a relationship between attention-driven trading decisions and performance. Moreover, Peng and Xiong (2006) show that the interaction between rational attention allocation and overconfidence makes the relationship between attention and fund performance unclear.

Empirically, we test this prediction in two ways. First, we implement a set of trade-based value-add tests where the dependent variable is given as a stock's

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

future period t return multiplied by the change in dollars held by a fund from $t-2$ to $t-1$. We expect to find a positive relationship between this trade-based value-add measure and attention to the stock in period $t-1$.

Second, we implement a set of stock-level return predictability tests using the Fama-MacBeth procedure and portfolio tests. In these tests, we construct signals based on aggregate fund attention to buys (and separate signals based on aggregate attention to holds and to sells). These signals incorporate news received by the fund after allocating attention to a stock, which then informs the fund's buy/sell decision.

III. Investor Attention to Macroeconomic News

A. Attention to Macroeconomic News and Aggregate Volatility

We first test the prediction that attention-constrained investors reallocate their attention toward macroeconomic news when aggregate volatility is high (e.g., Peng and Xiong (2006), Kacperczyk et al. (2016)). We capture investor attention to macroeconomic news using the fraction of a fund's reading of news articles covering the aggregate stock market or the economy throughout a month.[13] Our baseline measure of aggregate market volatility is the VIX^2, which is commonly used in the literature (e.g., Bekaert and Hoerova (2014); Manela and Moreira (2017)). As Bekaert and Hoerova (2014) discuss, VIX^2 is a risk-neutral probability measure that has a nice additive property. In robustness tests, we employ two alternative measures of aggregate market volatility—the square root of VIX^2, or VIX, and a realized volatility measure that does not require option prices. The VIX index is published by the Chicago Board of Exchange. The realized volatility measure is the daily volatility of the S&P 500 index over the month. We run the following specification:

$$InstAttn_{it}^{macro} = \beta VIX_{t-1}^2 + \mu_i + Controls + \epsilon_{it}, \tag{1}$$

where $InstAttn_{it}^{macro}$ is the fraction of fund i's reading of macroeconomic news articles in month t, VIX_{t-1}^2 is the average level of VIX^2 in month $t-1$, and μ_i is a vector of fund fixed effects.[14] Table III reports the regression results. Column (1) reports results using VIX^2 as the independent variable. Column (2) reports a similar specification controlling for aggregate market returns and including fund fixed effects. The coefficient on VIX_{t-1}^2 is positive and significant at the 5% level in both specifications. Column (3) uses VIX as the dependent variable and column (4) uses the realized daily volatility of the S&P 500 index ($Volatility_{t-1}$) as an alternative aggregate volatility measure. The coefficients on both VIX_{t-1} and $Volatility_{t-1}$ are positive and significant at the 5% level in their respective specifications. A one-standard-deviation increase in VIX ^{2} is associated with a 5% increase of the sample standard deviation of

[13] We list all of the macroeconomic topics in Internet Appendix Table IA.II.

[14] The choice of using VIX^2 to proxy for aggregate volatility follows other research such as Manela and Moreira (2017).

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table III

Macro versus Firm-Specific Attention

This table reports results for the specification:

$$InstAttn_{it}^{macro} = \beta VIX_{t-1}^2 + \mu_i + \epsilon_{it},$$

where $InstAttn_{it}^{macro}$ is the attention of fund i in month t to macroeconomic news (fraction of reading about macroeconomic news), and VIX is the Chicago Board Options Exchange (CBOE) Volatility Index. To facilitate comparison, both VIX_{t-1} and VIX_{t-1}^2 have been normalized to have a mean of 0 and a standard deviation of 1. Standard errors in parentheses are clustered by fund and time. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	InstAttn $_{it}^{macro}$			
	(1)	(2)	(3)	(4)
VIX $_{t-1}^2$	0.2502**	0.2314**		
	(0.1043)	(0.1098)		
VIX $_{t-1}$			0.2409**	
			(0.1196)	
Volatility $_{t-1}$(× 100)				0.4437**
				(0.2133)
Return $_{t-1}$(× 100)		−0.0031	−0.0041	0.0168
		(0.0453)	(0.0437)	(0.0491)
Observations	234,934	234,934	234,934	234,934
R^2	0.00235	0.21436	0.21450	0.21636
Fund FE		✓	✓	✓

$InstAttn_{it}^{macro}$. The significant and positive relationship between fund attention to macroeconomic news and aggregate volatility indicates that funds allocate their attention consistent with limited attention (e.g., Peng and Xiong (2006), Kacperczyk et al. (2016)).

B. Fund Return Predictability

We next examine the relationship between investor attention to macroeconomic news and fund-level returns. We construct a measure of attention reallocation by estimating the sensitivity of a fund's attention toward macroeconomic news to aggregate volatility. Specifically, for each fund in each quarter, we regress the fraction of that fund's attention to macroeconomic news on the contemporaneous average level of aggregate volatility, measured by VIX^2. We use weekly data over a trailing 52-week period. We denote this measure by $\beta_{it-1}^{VIX^2}$. In Table III, we aim to show that funds' attention to macroeconomic news is heightened after high aggregate market volatility. Accordingly, we regress funds' attention to macroeconomic news on prior-period volatility measures. Here, our goal is to measure the sensitivity of a fund's attention to macroeconomic news when aggregate uncertainty is high. We, therefore, construct β^{VIX^2} by regressing funds' attention to macroeconomic news on the contemporaneous VIX^2. In robustness checks, we repeat Table III with contemporaneous

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

aggregate market volatility and find that funds also tend to pay more attention to macroeconomic news when aggregate market volatility is high.

As we discuss in Section II.A, on the one hand, a high β^{VIX^2} may indicate that the fund is rationally allocating its limited attention (e.g., Kacperczyk et al. (2016)). In other words, funds with high β^{VIX^2} are the funds that are more efficient in allocating their attention and thus generate higher returns on average. On the other hand, investors with lower attention capacity may be more responsive in shifting attention to macro news after an increase in aggregate uncertainty (see Peng and Xiong (2006), Kacperczyk et al. (2014)). Under this view, a high β^{VIX^2} would indicate a more binding attention constraint and hence predict lower average performance. Moreover, noninformation-based theories such as salience would predict no relationship, or even a negative relationship, between attention reallocation and fund performance due to suboptimal trading (Barber and Odean (2008)).

Table IV reports results from fund-level return predictability specifications using $\beta_{it-1}^{VIX^2}$. Column (1) reports the baseline specification of next-quarter fund return on $\beta_{it-1}^{VIX^2}$ including only time fixed effects. The coefficient estimate on $\beta_{it-1}^{VIX^2}$ is positive and significant at the 5% level, indicating that funds with higher attention sensitivity to aggregate volatility earn higher returns on average. Column (2) reports results including fund fixed effects, to control for time-invariant fund characteristics, in addition to the time fixed effects. The coefficient estimate on $\beta_{it-1}^{VIX^2}$ increases from 0.31 to 0.34 and is significant at the 5% level. Column (3) further includes log assets under management and the log number of articles read by the fund as control variables. The coefficient estimate on $\beta_{it-1}^{VIX^2}$ is stable at 0.36 and significant at the 1% level. In terms of economic magnitudes, the estimate of 0.36 indicates that a one-standard-deviation increase in $\beta_{it-1}^{VIX^2}$ is associated with a 0.36% increase in quarterly fund returns (1.4% annualized).[15] Column (4) includes the interaction between $\beta_{it-1}^{VIX^2}$ and the VIX level itself. We find that the interaction is positive and significant at the 5% level, suggesting that the return predictability of $\beta_{it-1}^{VIX^2}$ is more pronounced during times of high aggregate volatility. In our final specification, we test the strength of the relationship between fund returns and $\beta_{it-1}^{VIX^2}$ for different levels of aggregate volatility. We define $VIX_{t-1}Q2$, $VIX_{t-1}Q3$, and $VIX_{t-1}Q4$ as dummy variables indicating when VIX is in the second, third, and fourth quartile of its sample value, respectively. We regress future fund returns on $\beta_{it-1}^{VIX^2}$ interacted with each dummy variable and report the coefficient estimates in column (5). The coefficient on the interaction between $\beta_{it-1}^{VIX^2}$ and $VIX_{t-1}Q4$ is 0.73 and significant at the 5% level, indicating that the relationship between fund returns and $\beta_{it-1}^{VIX^2}$ is about two times stronger during periods of high volatility in our sample.

[15] This magnitude is sizeable in light of prior literature, which has found that, based on various signals, the top quintile of funds can outperform the bottom quintile by around 2% to 5% depending on the study (e.g., Bai et al. (2022)).

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table IV

Fund-Level Return and Macro Attention

This table reports results on the fund-level relationship between returns (i.e., returns at time t weighted by holdings at $t-1$) and the ability to reallocate attention from firm-specific to macroeconomic news, denoted by $\beta_{t-1}^{VIX^2}$, where $\beta_{t-1}^{VIX^2}$ is the regression coefficient of a fund's attention to macroeconomic news (fraction of reading about macroeconomic news) on the aggregate volatility measure over the 52 weeks prior to the quarter, and where $\beta_{t-1}^{VIX^2}$ and its variants are normalized to have a mean of 0 and a standard deviation of 1. We define $VIX_{t-1}Q2$, $VIX_{t-1}Q3$, and $VIX_{t-1}Q4$ as dummy variables indicating when the VIX is in the second, third, and fourth quartile of its sample value, respectively. Controls include the log assets under management and the log number of articles read. We report the coefficients, the standard errors clustered by fund and time in parentheses, the R^2, and the number of observations. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	Fund Ret $_{it}$				
	(1)	(2)	(3)	(4)	(5)
$\beta_{it-1}^{VIX^2}$	0.3059**	0.3433**	0.3636***	−0.4333	−0.1384
	(0.1391)	(0.1333)	(0.1198)	(0.3404)	(0.1172)
$\beta_{it-1}^{VIX^2}$ × VIX(t-1)				0.0390**	
				(0.0168)	
$\beta_{it-1}^{VIX^2}$ × VIX(t-1) Q2					0.4405***
					(0.1080)
$\beta_{it-1}^{VIX^2}$ × VIX(t-1) Q3					0.6109**
					(0.2255)
$\beta_{it-1}^{VIX^2}$ × VIX(t-1) Q4					0.7322**
					(0.3013)
Controls?	No	No	Yes	Yes	Yes
Observations	51,207	51,207	51,207	51,207	51,207
R^2	0.85065	0.86033	0.86258	0.86259	0.86260
Time FE	✓	✓	✓	✓	✓
Fund FE		✓	✓	✓	✓

Overall, we find that funds with the ability to reallocate attention toward macroeconomic news according to aggregate volatility deliver superior fund returns on average and that this superior performance arises primarily during times of high aggregate volatility. Taken together, the results are consistent with the view that β^{VIX^2} captures the extent to which funds rationally allocate their limited attention (e.g., Kacperczyk et al. (2016)). In other words, funds with high β^{VIX^2} are the funds that are more efficient in allocating their attention relative to other funds.

We conduct three sets of tests to assess robustness of these results. First, we calculate macroeconomic betas using VIX instead of VIX^2. The results, reported in Internet Appendix Table IA.V, are significant but slightly reduced relative to those results based on VIX^2, which implies that relatively extreme states of uncertainty matter. Next, we change the parametric form of VIX to the inverse hyperbolic sine of VIX. The results, reported in Table IA.VI, are similar. Finally, in Table IA.VII, we examine the relationship between return

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

and macroeconomic attention betas by fund type. We find that the hedge fund subsample displays a sharper relationship between fund return and macroeconomic attention betas compared with other fund types.

C. Tests of Efficiency of High-Beta VIX Funds

The analysis above indicates that funds with high β^{VIX^2} tend to generate superior returns, consistent with the view that they are more efficient in allocating their attention between macroeconomic news and firm-specific news. To further support this interpretation, we examine differences in characteristics between high-β^{VIX^2} funds and low-β^{VIX^2} funds.

First, we expect high-β^{VIX^2} funds to respond less to salient events, consistent with these funds being more efficient in allocating their attention. We follow Barber and Odean (2008) to define salient events using abnormal trading volume and past extreme one-day returns.[16] For each investor-quarter, we compute the attention-weighted average of each of the salience characteristics according to $Char_{it}^{j} = \sum_{s} InstAttn_{ist} \times StockChar_{st}^{j}$, where $InstAttn_{ist}$ is fund i's reading of about stock s in quarter t divided by the fund's total reading about all stocks in the quarter, and $StockChar_{st}^{j}$ is the max return, the max absolute return, abnormal trading volume, or abnormal trading volume squared during quarter t. We compute the average of these numbers across high and low β^{VIX^2}.

Table IA.VIII in the Internet Appendix presents the results. In Panel A, we start by reporting the average attention-weighted saliency of stocks read by high- and low-β^{VIX^2} funds. We find that above-median β^{VIX^2} funds pay less attention to salient stocks than below-median β^{VIX^2} funds for all of the measures considered. In terms of economic magnitudes, the average attention-weighted salient characteristics are 0.78% to 1.74% lower for the above-median β^{VIX^2} funds relative to the below-median β^{VIX^2} funds, with the differences statistically significant at the 5% level.

One might be concerned that high-β^{VIX^2} funds may hold less salient stocks, which could mechanically generate the differences in reading patterns. To address this concern, in Panel B, we report holding-weighted salient characteristics separately for high-β^{VIX^2} funds and low-β^{VIX^2} funds, while Panel C reports the difference in reading- versus holding-weighted characteristics. Panel B shows no statistically important difference in holdings characteristics (although the coefficients are somewhat negative). Panel C, however, shows that the net-of-holdings difference in reading patterns is even stronger, with the average holding-adjusted characteristics about 10% lower for funds with high β^{VIX^2}. This result is consistent with the view that the attention of these funds is less affected by stock-level salience. In additional specifications that further test robustness of these results, we find that differences in reading orientation

[16] In particular, for each stock-quarter, we obtain the maximum daily return and the maximum absolute daily return. We compute abnormal trading volume and abnormal trading volume squared for each stock as the trading volume and trading volume squared in the quarter, versus in the prior 252 trading days.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

are more stark if we divide funds into the top 20% versus the bottom 80% of β^{VIX^2}. We also find similar results if we examine static fund-level characteristics (e.g., do not permit funds to be time-varying).

Second, we expect funds with high β^{VIX^2} to have high human capital. Using LinkedIn data obtained from Revelio Labs, we measure funds' human capital based on the fraction of fund employees that have advanced degrees, including an MBA, Masters, and Ph.D. As Internet Appendix Table IA.IX shows, funds with higher β^{VIX^2} also tend to have a 17% larger proportion of employees with advanced degrees. Given that prior studies find that fund managers with advanced degrees tend to generate superior performance (see, for example, Chevalier and Ellison (1999)), this evidence supports the interpretation that high-β^{VIX^2} funds are more efficient.

Third, if β^{VIX^2} captures the efficiency of funds in allocating attention between macroeconomic news and firm-specific news, then β^{VIX^2} should be a persistent fund characteristic. To test for such persistence, each period, we sort funds into quartiles based on β^{VIX^2} (from low to high). We find that for funds with the lowest β^{VIX^2}, the probability of being in the same quartile one year later is 62%, which is much higher than random assignment (25%). The probability of shifting from the first to the second quartile is 18%, and from the first to the third or fourth quartile is only about 10%. For funds with the highest β^{VIX^2}, the probability of staying in the same quartile a year later is 66%. Overall, the results indicate that the reallocation of attention according to aggregate volatility is a persistent fund characteristic.

Fourth, we find that hedge funds tend to have higher β^{VIX^2}, compared to mutual funds or other institutional investors. As Table IA.XI in the Internet Appendix shows, the average β^{VIX^2} of hedge funds is markedly higher than those of mutual funds and non-hedge funds or mutual funds. For example, the average β^{VIX^2} of hedge funds is more than twice that of mutual funds. The differences are statistically significant at the 1% level. If we view hedge funds as more sophisticated, this evidence suggests that β^{VIX^2} proxies for the efficiency of funds' ability to use attention efficiently.

IV. Firm-Specific Attention

A. Attention and Holding

Extensive Margin. Panel A of Table V compares the attention a fund allocates to stocks held in its portfolio against the fund's attention to stocks it does not currently hold. We construct a fund-quarter level measure of reading about held stocks, *Articles/Held*, where *Articles* is the total number of articles a fund reads regarding the stocks it held at the end of the previous quarter, and *Held* is the total number of stocks the fund held at the end of the previous quarter. Similarly, we construct *Articles/NotHeld* as the per-stock reading of stocks it did not hold in the previous quarter about which it read at least one article.[17] We average these observations by different groupings: "All" for all

[17] If the universe were all stocks not held, the ratio would be over 20 times lower.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table V

Investor Attention: Held versus Not Held

Panel A reports the number of articles read about held stocks versus nonheld stocks. Reading occurs at time t, whereas the holding decision is observed at the end of quarter $t-1$. *Held* stocks are based on an investor's 13-F filings. $Articles/Held$ is constructed at the fund-by-quarter level as the total number of articles the fund read about stocks it held at the end of the previous quarter divided by the total number of stocks held at the end of the previous quarter. $Articles/NotHeld$ is analogously defined for the stocks it did not hold but read at least once in the previous quarter. We present the following groupings: "All" for all funds, "Hedge Funds," "Mutual Funds," and "Not HF/MF." The final column presents t-statistics from a test of differences in means between the average reading of held stocks versus nonheld stocks. Panel B reports the relationship between investor attention and lagged holdings. $InstAttn_{ist}$ is the fraction of fund i's reading about firm s in quarter t compared to the fund's total reading activity about all firms in the quarter, and h_{ist-1} is the fraction that firm s comprises fund i's portfolio at the end of quarter $t-1$. Columns vary by fixed effects as indicated. We report the coefficients, the standard errors clustered by fund, firm, and time in parentheses, the R^2, and the number of observations. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Extensive Margin

Group	$\frac{Articles}{Held}$	$\frac{Articles}{NotHeld}$	t-Stat
	(1)	(2)	(1) − (2)
All	23.182	3.860	79.124
Hedge funds	11.382	4.120	23.005
Mutual Funds	30.303	7.359	28.579
Not HF/MF	25.966	3.615	73.062

Panel B: Intensive Margin

	InstAttn $_{ist}$			
	(1)	(2)	(3)	(4)
h $_{ist-1}$	13.09***	14.27***	0.6556***	0.6466***
	(2.882)	(3.357)	(0.1026)	(0.0893)
Observations	11,910,288	11,910,288	11,910,288	11,910,288
R^2	0.07008	0.10655	0.71172	0.72031
Time FE	✓			
Fund × Time FE		✓		✓
Firm × Time FE			✓	✓

funds, "Hedge Funds," "Mutual Funds," and "Not HF/MF."[18] Funds tilt their attention strongly toward stocks they hold, with hedge fund (mutual fund) $Articles/Held$ at 11.4 (30.3) compared with an $Articles/NotHeld$ of 4.1 (7.4). The final column in the table presents t-statistics from a test of differences in means between the average reading of held stocks versus nonheld stocks. The t-statistics of the difference are positive and statistically significant at the 1% level for all fund-type groupings.

[18] The "Not HF/MF" category contains all funds that are not hedge funds and also not mutual funds (e.g., pension funds, private equity, and broker-dealers.)

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Intensive Margin. In Panel B of Table V, we study the relationship between attention and the relative share of a stock in a fund's portfolio. To study the intensive margin, we restrict our sample to the set of held stocks, or $h_{ist-1} > 0$, resulting in approximately 11.9 million fund-stock-quarter observations. We then run the following regression of fund reading on holdings:

$$InstAttn_{ist} = \alpha + \beta h_{ist-1} + \epsilon_{ist}, \tag{2}$$

where $InstAttn_{ist}$ and h_{ist-1} are the investor attention measure (share of fund i's attention on stock s at time t) and holdings measures (share of dollar value held in stock s at time $t-1$), and α denotes fixed effects.

Columns (1) to (4) present results where we vary the fixed effects. The coefficient estimate on h_{ist-1} is positive and significant across all four specifications. When we include firm-by-time fixed effects, the point estimate on h_{ist-1} decreases substantially, suggesting that funds tend to pay attention to and hold large positions in certain firms at the same time. In column (3), which controls for firm-by-time fixed effects, a one-standard-deviation increase in h_{ist-1} is associated with an approximately 1.02 standard-deviation increase in $Inst_{ist}$. These results confirm a strong positive relationship between attention to a stock and the size of the fund's portfolio holding.

The extensive and intensive margin results consistently indicate a strong positive relationship between investor attention to firm-specific news and fund holdings of the firm. These results are consistent with and provide the first direct evidence in support of theories of limited attention (e.g., Van Nieuwerburgh and Veldkamp (2010)).

Fixed Effects Analysis. We next explore patterns in attention by decomposing the variance in fund attention into several components: fixed fund characteristics, fixed firm characteristics, common variation in investor attention over time, and a residual component. We discuss the empirical specification in detail in Section II.C of the Internet Appendix and present the results in Table IA.XII.[19] The key findings are that time fixed effects alone explain almost none of the variation in fund attention to firms. Fund and firm fixed effects together play a much larger role, and the fund-by-firm fixed effects explain the majority of the overall variation in investor attention to firm-specific news. Overall, these results suggest that funds have attention habitats: funds allocate attention to the same set of firms with limited time-series variation in attention. This result echoes empirical patterns of underdiversification in fund portfolios documented and studied in Friend and Blume (1975) and Goetzmann and Kumar (2008).

Cross-Sectional Relationship. We also study stock characteristics related to fund attention and their relationship to aggregate volatility. In particular, we run the regression specification $InstAttn_{ist} = \alpha + \beta_1 characteristic_{st} + \beta_2 characteristic_{st} \times 1\{VIX_t \geq threshold\}$, where $InstAttn_{ist}$ is fund i's attention allocated to firm s in quarter t, $characteristic_{st}$ is a firm characteristic, and

[19] Giglio et al. (2021) use the fixed effects approach to study variation in investor beliefs.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

$1\{VIX_t \geq threshold\}$ is a dummy variable equal to 1 if the VIX crosses one of three possible thresholds (25, 30, and 35).[20] The firm characteristics include: trailing CAPM beta, market capitalization, Amihud illiquidity, idiosyncratic volatility of the firm's returns, book-to-market, and gross profitability. We control for portfolio shares in each of the specifications.

Table IA.XIII in the Internet Appendix presents the results using VIX cutoffs of 25, 30, and 35 in columns (1), (2), and (3), respectively. The coefficient estimates on market capitalization, Amihud illiquidity, idiosyncratic volatility, and book-to-market are positive and significant at the 5% level. The coefficients on the interaction term between VIX and β are positive and significant at the 1% level using the VIX cutoffs of 30 and 35. In contrast, the coefficient on the interaction term between VIX and idiosyncratic volatility is negative and significant at the 1% level for the VIX cutoffs of 30 and 35. Thus, funds pay more attention to high-β firms but less attention to high-idiosyncratic-volatility firms during times of high aggregate volatility. These results indicate that when aggregate volatility increases, attention to stocks shifts toward high-beta stocks and away from stocks with high idiosyncratic volatility, consistent with the model predictions put forth by Kacperczyk et al. (2016). We also find that during periods of high aggregate volatility, investor attention tilts toward value stocks and away from high-profitability stocks.

B. Value-Add Tests

In this section, we first test the predictions outlined in Section II.B that there should be a positive relationship between attention to a stock and the value this position adds to the fund. Specifically, we measure the position-level value-add of stock s as $h_{ist-1} \times R_{st}$, where h_{ist-1} is fund i's dollar holdings of stock s as a fraction of its total dollar holdings at time $t-1$, and R_{st} is the return of stock s in period t. The position-level value-add tests indicate not only whether the stocks exhibit higher subsequent returns, but also whether the fund allocates more weight toward these outperforming stocks. The position-level value-add measure is similar in spirit to Berk and Van Binsbergen (2015), who measure the "value-add" of a mutual fund manager as the fund's abnormal return multiplied by assets under management. Berk and Van Binsbergen (2015) argue that value-add represents a theoretically sound measure compared to pure return-based measures, since value-add measures weight return performance by the size of investments.[21]

[20] The 75th percentile of the sample VIX is 25.

[21] The intuition follows the stylized example of Berk and Van Binsbergen (2015), who note that "a manager who adds a gross alpha of 1% on a \$10 billion fund adds more value than a manager who adds a gross alpha of 10% on a \$1 million fund." In our setting, our measure captures the value-add of a stock position based on the stock return, and the portfolio weight is analogous to the fund's size in Berk and Van Binsbergen (2015).

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

We implement our analysis at the fund-stock-quarter level.[22] Specifically, we run the following regression of position-level value-add on attention:

$$h_{ist-1} \times R_{st} = \alpha + \beta InstAttn_{ist-1} + \delta h_{ist-2} + \epsilon_{ist}, \quad (3)$$

where α denotes fixed effects, $InstAttn_{ist-1}$ is the fraction of fund i's reading about firm s in quarter $t-1$ compared to fund i's total reading activity about all firms in the quarter, and h_{ist-2} controls for the fund's holdings in time $t-2$. Controlling for prior holdings, h_{ist-2}, addresses the concern that the positive relationship between value-add and attention may arise due to the positive relationship between attention and holdings documented above. Moreover, we run the position-level value-add analysis on the sample of held stocks ($h_{ist-1} > 0$) to ensure that the dependent variable is not mechanically 0.[23] These specifications allow us to incorporate stock-by-time fixed effects to test whether funds that pay more attention are better able to overweight (underweight) stocks that subsequently do well (poorly) compared to other funds holding the same stock. This analysis provides an important empirical advantage over using simple stock returns, which would be subsumed by stock-by-time fixed effects.

Table VI, Panel A, presents the results. The coefficient on attention is positive and significant at the 10% level in column (1). A one-standard-deviation increase in attention to a position corresponds to a 3.3% standard deviation increase in the future value-add of the position. Column (2) includes the interaction term between attention and the size of the prior position, h_{ist-2}, as well as firm-by-quarter fixed effects, to mitigate the concern that attention is allocated specifically to stocks that may be salient because they are in the news. We document a positive coefficient on the interaction term that is significant at the 5% level. This positive interaction term indicates that stocks that investors pay attention to and hold large positions in deliver higher position-level value-add.[24] In column (3), we further control for trade size, defined as $|ihs(shares_{ist-1} \times P_{st-1}) - ihs(shares_{ist-2} \times P_{st-1})|$,[25] its interaction with attention. We find that the coefficient on the interaction with prior holdings remains positive and significant, suggesting that the result is not driven by the size of the trade alone. The coefficient estimate on the interaction between attention and trade size is positive but not significant, suggestive that fund attention to the positions in which the fund makes larger trades has a stronger association with future value-add.

[22] For each fund in our fund-by-firm-by-time "value-add" analyses, we require 500 nonzero stock-quarters for the fund to be included, and at least 100 nonzero fund-quarters for the stock to be included. A fund also has to read 50 articles in a quarter and the fund needs to read at least 500 articles over the full sample. While modulating these thresholds increases or decreases our sample, our results are not sensitive to variations in these thresholds.

[23] Our results are qualitatively similar when we use the full sample.

[24] We find similar results after controlling for h_{ist-1}, which suggests that the results are not driven by funds mechanically holding larger positions in assets after they have allocated more attention to them. The results are presented in Internet Appendix Table IA.XV.

[25] We normalize trade size to take a mean of 0 and a standard deviation of 1.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table VI

Attention and "Value-Add" Regressions

This table presents results of analysis at the fund-firm-time (quarterly) level. Panel A corresponds to the position-level value-add specifications and Panel B to the trade-based value-add regressions. In Panel A, the outcome variable is defined as $h_{ist-1} \times R_{st} \times 100$, where h_{ist-1} is the fraction that firm s comprises fund i's portfolio at the end of quarter $t-1$ and R_{st} is the return of stock s in quarter t. In Panel B, the dependent variable is defined as the change in dollars held from $t-2$ to $t-1$ (denoted by $\Delta Position$) times the return of the stock at time t. We regress the outcome variable on $InstAttn_{ist-1}$, the fraction of the fund i's reading about firm s in quarter $t-1$ compared to the fund's total reading activity about all firms in the quarter. Additional variable definitions are in Section I.A in the Internet Appendix. We report standard errors clustered by fund, firm, and time in parentheses. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Position-Level Value-Add

	$h_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $_{ist-1}$	0.0022*	−0.0008*	−0.0008*
	(0.0011)	(0.0004)	(0.0004)
h $_{ist-2}$	1.548	1.437	1.461
	(1.237)	(1.117)	(1.133)
InstAttn $_{ist-1}$ × h $_{ist-2}$		0.0893**	0.0918**
		(0.0414)	(0.0430)
Trade Size			0.0006
			(0.0005)
InstAttn $_{ist-1}$ × Trade Size			0.0003
			(0.0003)
Observations	11,935,182	11,935,182	11,934,715
R^2	0.27603	0.47951	0.47955
Fund × Time FE	✓	✓	✓
Firm × Time FE		✓	✓

Panel B: Trade-Based Value-Add

	$\Delta Position_{ist-1} \times R_{st} \times 100$			
	(1)	(2)	(3)	(4)
InstAttn $_{ist-1}$	0.0739**	0.0736***	−0.1308*	−0.0742
	(0.0301)	(0.0243)	(0.0743)	(0.0902)
Trade Size		−0.0613	0.0007	−0.2735
		(1.739)	(1.443)	(1.482)
InstAttn $_{ist-1}$ × Trade Size			0.5822***	0.4921**
			(0.1687)	(0.1746)
h $_{ist-2}$				−387.4
				(410.3)
Sample	Trade	Trade	Trade	Trade
Observations	11,081,586	11,081,586	11,081,586	11,081,586
R^2	0.06453	0.06453	0.11662	0.11677
Firm × Time FE	✓	✓	✓	✓
Fund × Time FE			✓	✓

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

We next test the predictions in Section II.B, that attention to a stock should produce valuable information that a fund can trade profitably on. To do so, we define trade-based value-add as the future return of stock s, R_{st}, times $\Delta Position_{ist-1}$, the dollar change in fund i's holdings in stock s from $t-2$ to $t-1$, which is given by $ihs(shares_{ist-1} \times P_{st-1}) - ihs(shares_{ist-2} \times P_{st-1})$.[26] This trade-based value-add measure aligns closely with prior research, which typically considers the relationship between trading and returns.

Analogous to equation (3), we run the regression

$$\Delta Position_{ist-1} \times R_{st} = \alpha + \beta InstAttn_{ist-1} + \delta h_{ist-2} + \epsilon_{ist}, \tag{4}$$

Panel B of Table VI presents the results of the trade-based value-add specifications. All four specifications are run on the "Trade" sample, which restricts the sample to positions that were traded from $t-2$ to $t-1$.[27] The specifications include firm-by-time fixed effects, which absorb time-series variation in the amount of news produced about each firm. The fixed effects permit the interpretation that across investors in the same stock, the investors who allocate more of their attention generate more value from the trade.

Column (1) presents the results of trade-based value-add on attention. The coefficient on attention is positive and significant at the 5% level. Column (2) includes trade size as a control. The coefficient on attention remains positive and significant at the 5% level, indicating that the result is not simply driven by a positive association between fund attention and larger trade size. The coefficient implies that one-standard-deviation increase in attention corresponds to a 0.06% increase in the outcome variable relative to its standard deviation. Column (3) reports results from the specification that includes an interaction term between attention and trade size. The coefficient on the interaction term is positive and significant at the 1% level, suggesting that fund attention to a position contributes more to fund value for larger trades. The last column shows similar results when we further control for prior holdings, h_{ist-2}. Overall, these findings are consistent with the second prediction of limited attention theories as discussed in Section II.B.

We conduct additional robustness tests in the Internet Appendix. For example, Table IA.XVI shows that the results are robust to using log attention (specifically, the inverse hyperbolic sine). When we collapse a fund's attention to its portfolio to the overall fund level, and interact attention to firm-specific

[26] Converting shares to dollars by multiplying both $shares_{ist-1}$ and $shares_{ist-2}$ by P_{st-1} ensures that $\Delta Position$ will equal 0 when shares do not change. For robustness, we also examine $R_{st} \times (ihs(shares_{ist-1}) - ihs(shares_{ist-2}))$ and find similar results.

[27] The traded sample comprises over 11 million observations and is similar in size to the 12 million observations in the held sample. This is comparable to the unconditional relationship between holdings and trading from Factset data. A passive fund that receives inflows will increase its position in every stock in its portfolio. Our trade-based value-add results are not driven by flow-based trades. We show that these results are robust to fund-by-time fixed effects, which absorb variation in fund flows, and to controlling for prior-period holdings, h_{ist-2}. In the Internet Appendix, we show that the results are qualitatively similar when we use the full sample, including positions not traded from $t-2$ to $t-1$.

news with aggregate volatility, we find that firm-specific news matters more during periods of low aggregate volatility. This test provides a logical complement to our previous analysis showing that macroeconomic beta VIX matters more during periods of high uncertainty.

C. Heterogeneity in Value-Add and Attention

In this section, we test whether attention by more sophisticated investors and attention to more value-relevant content add more value to fund performance. First, we examine heterogeneity across hedge funds, mutual funds, and other types of investors. We implement the position-level and trade-based value-add tests subsampled by hedge funds, mutual funds, and other types of investors and present these results in Table VII. Various studies focus on the investment skill of hedge funds over other investors. For both the position-level value-add tests and the trade-based value-add tests, our results indicate that hedge fund attention and mutual fund attention contribute more to fund value than the attention of other types of investors. However, we do not see a clear difference in the effectiveness of attention between hedge funds and mutual funds.

Second, we test whether attention to more value-relevant news contributes more to fund performance. Based on the news content of each site, we segment the sites in our data set into business/financial websites (including premium, paywalled financial newswires and financial news sites that have no paywall), retail-oriented investor websites, and general news sites that also cover some financial news. We implement the position-level and trade-based value-add tests where we divide our attention measure based on the type of websites.

Table VIII presents the results. We define $InstAttn_{ist-1}^{BizNews,FinNewswire}$ as fund i's total reading about stock s in quarter $t-1$ on business/financial websites divided by the fund i's total reading about all stocks in quarter $t-1$. Attention to retail websites and general news sites are defined similarly. Panel A reports results of the position-level value-add tests and Panel B the results for the trade-based value-add tests. In both sets of analyses, we find that attention to business and financial news is the primary driver of value-add, suggesting that reading about more value-relevant information adds more value to fund performance.

Additional Tests. To supplement our earlier analysis, we explore classifications among mutual funds. In Internet Appendix Table IA.XVII, we split them into active, index, and nonequity funds. We find suggestive evidence that the relationship between attention and value-add is stronger for active funds than for other funds. We discuss these results in detail in Section II.D of the Internet Appendix.

D. Buying versus Selling

We next examine differences in institutional investor attention for buys and sells. This analysis is motivated by Akepanidtaworn et al. (2023), who

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table VII

Value-Add Tests Across Fund Types

This table reports results from value-add tests across three subsamples: hedge funds, mutual funds, and other funds. In Panel A, the outcome variable is defined as $h_{ist-1} \times R_{st} \times 100$ where h_{ist-1}, is the fraction that firm s comprises fund i's portfolio at the end of quarter $t-1$, and R_{st} is the return of stock s in quarter t. In Panel B, the dependent variable is defined as the change in dollars held from $t-2$ to $t-1$ (denoted by $\Delta Position$) times the return of the stock at time t. We regress the outcome variable on $InstAttn_{ist-1}$, the fraction of fund i's reading about firm s in quarter $t-1$ compared to the fund's total reading activity about all firms in the quarter. In both panels, columns (1), (2), and (3) present results for the hedge fund, mutual fund, and other subsamples, respectively. For the position-level value-add specifications, we focus on the held sample (with $h_{ist-1} > 0$), and for the trade-based value-add tests, we restrict the sample to traded positions (shares changed from $t-2$ to $t-1$). Additional variable definitions are included in Section I.A of the Internet Appendix. We report the coefficients, the standard errors clustered by fund, firm, and time in parentheses, the R^2, and the number of observations. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Position-Level Value-Add

	$h_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $_{ist-1}$	−0.0012*	−0.0021**	−0.0006
	(0.0006)	(0.0007)	(0.0004)
h $_{ist-2}$	1.260	1.611	1.518
	(0.8095)	(1.175)	(1.256)
InstAttn $_{ist-1}$ × h $_{ist-2}$	0.1152**	0.1366**	0.0767
	(0.0487)	(0.0562)	(0.0451)
Trade Size	0.0008**	0.0007	0.0005
	(0.0003)	(0.0005)	(0.0005)
InstAttn $_{ist-1}$ × Trade Size	0.0005*	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0002)
Fund Type	HF	MF	Other
Observations	1,979,998	1,311,328	8,643,389
R^2	0.47369	0.50979	0.50472
Fund × Time FE	✓	✓	✓
Firm × Time FE	✓	✓	✓

Panel B: Trade-Based Value-Add

	$\Delta Position_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $_{ist-1}$	−0.9717**	−0.0974	−0.0440
	(0.4148)	(0.1777)	(0.0624)
Trade Size	0.1961	0.7197	−0.2804
	(0.9758)	(0.6378)	(1.883)
InstAttn $_{ist-1}$ × Trade Size	0.6565**	0.7802**	0.5398**
	(0.2574)	(0.3027)	(0.1968)
Fund Type	HF	MF	Other
Observations	2,155,764	1,150,886	7,774,936
R^2	0.11220	0.19557	0.14597
Firm × Time FE	✓	✓	✓
Fund × Time FE	✓	✓	✓

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table VIII

Information Content and Attention

This table reports results from value-add tests split by news content. Panel A reports results from position-level value-add specifications and Panel B reports results from trade-based value-add regressions. We classify our sample of publishers into three types: business/financial newswires, retail, and general news. Attention measures are normalized to have 0 mean and a standard deviation of 1. For the position-level value-add specifications, we focus on the held sample (with $h_{ist-1} > 0$), and for the trade-based value-add tests we restrict the sample to traded positions (shares changed from $t-2$ to $t-1$). We report the coefficients, the standard errors clustered by fund, firm, and time in parentheses, the R^2, and the number of observations. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. For brevity, we suppress the individual noninteraction terms (h_{ist-2}, trade size, and attention terms).

Panel A: Position-Level Value-Add

	$h_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $_{ist-1}{}^{BizNews,FinNewswire}$ × h $_{ist-2}$	0.1070**	0.1097**	0.1229***
	(0.0462)	(0.0440)	(0.0408)
InstAttn $_{ist-1}{}^{RetailWebsite}$ × h $_{ist-2}$		−0.0122	−0.0058
		(0.0206)	(0.0183)
InstAttn $_{ist-1}{}^{GeneralNews}$ × h $_{ist-2}$			−0.0498
			(0.0414)
InstAttn $_{ist-1}{}^{BizNews,FinNewswire}$ × Trade Size	0.0006*	0.0006*	0.0006*
	(0.0003)	(0.0003)	(0.0003)
InstAttn $_{ist-1}{}^{RetailWebsite}$ × Trade Size		3.23e−5	4.61e−5
		(0.0001)	(0.0001)
InstAttn $_{ist-1}{}^{GeneralNews}$ × Trade Size			−0.0001
			(0.0001)
Observations	11,893,425	11,893,425	11,893,425
R^2	0.48062	0.48063	0.48067
Fund × Time FE	✓	✓	✓
Firm × Time FE	✓	✓	✓

Panel B: Trade-Based Value-Add

	$\Delta Position_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $^{BizNews,FinNewswire}_{ist-1}$	−0.1289*	−0.1153*	−0.1005*
	(0.0692)	(0.0589)	(0.0554)
Trade Size	-7.50×10^{-5}	-2.63×10^{-6}	0.0020
	(1.4430)	(1.4430)	(1.4430)
InstAttn $^{BizNews,FinNewswire}_{ist-1}$ × Trade Size	0.5489***	0.5058***	0.4471**
	(0.1782)	(0.1534)	(0.1675)
InstAttn $^{RetailFin.News}_{ist-1}$		−0.0784	−0.0711
		(0.0452)	(0.0447)
InstAttn $^{RetailFin.News}_{ist-1}$ × Trade Size		0.1379	0.1191
		(0.1344)	(0.1337)
InstAttn $^{GeneralNews}_{ist-1}$			−0.0471
			(0.0416)

(*Continued*)

Table VIII—*Continued*

Panel B: Trade-Based Value-Add			
	$\Delta Position_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $^{GeneralNews}_{ist-1}$ × Trade Size			0.1628
			(0.1075)
Observations	11,081,586	11,081,586	11,081,586
R^2	0.11662	0.11662	0.11662
Fund × Time FE	✓	✓	✓
Firm × Time FE	✓	✓	✓

document that institutional investor buying adds value on average while selling does not. Moreover, Barardehi et al. (2024) argue that institutional investors may buy and sell stocks for different reasons. They examine within-industry long-short trading and document a pattern whereby sell trades are executed to raise cash for buy trades or to maintain sector exposure. We build on these findings by conducting two analyses. First, we examine the amount of attention to buys and sells. Second, we examine the trading performance of buys and sells with high and low attention. The results generally support the mechanisms proposed in these papers. In particular, we find that investors pay more attention to buys relative to sells. Moreover, attention is more important, from a trade-based value-add perspective, for buying decisions compared to selling decisions. Attentive buys perform better than less attentive buys in the trade-based value-add specifications. However, we find mixed evidence comparing the performance of attentive versus nonattentive sells. We discuss these tests below.

Table IX, Panel A, compares average attention to buys and sells. Specifically, we compare the average of a fund's attention to buy positions with its average attention to sell positions, where attention is residualized on firm-by-quarter fixed effects to mitigate the effect of news coverage on attention. Consistent with the idea of buying slow and selling fast in Akepanidtaworn et al. (2023), we find that the average *buy* trade commands more attention than the average *sell* trade, controlling for the stock and the amount held or traded. This difference is significant at the 1% level. We obtain similar results if we residualize attention on the size of holdings at $t-2$ and the absolute amount traded from $t-2$ to $t-1$, which controls for potential confounding effects of amount held of trade size on attention.

Next, Table IX, Panel B, examines the trading performance of buys and sells using the trade-based return specification. Specifically, we regress the trade-based value-add on attention, trade size, and the interaction between the two. Columns (1) and (2) present split-sample specifications (for the buy subsample and the sell subsample, respectively), while column (3) stacks both samples and interacts all terms with *Buy*, a dummy variable equal to 1 if $shares_{ist-1} > shares_{ist-2}$ and 0 otherwise. The results indicate that attention improves

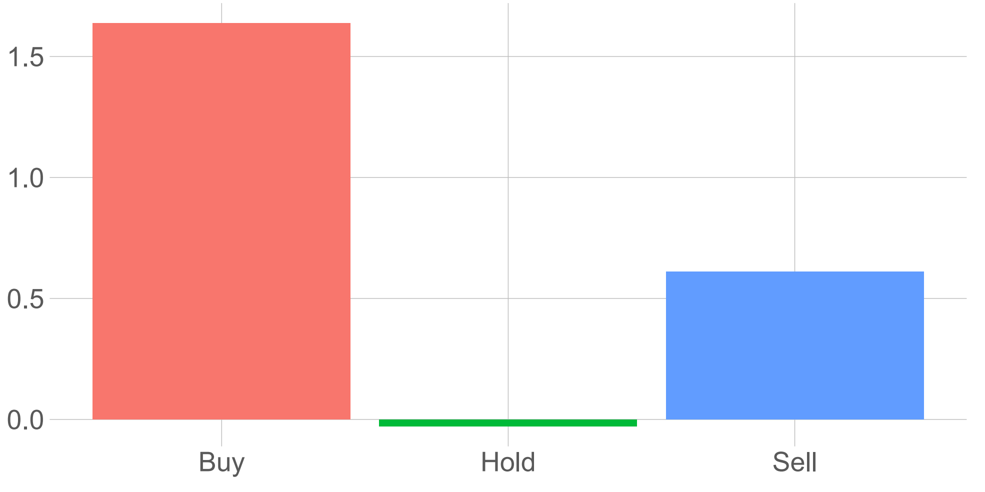
15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table IX

Buys versus Sells

Panel A shows fund attention to buy, hold, and sell positions. We regress attention ($InstAttn_{ist-1}$) on firm by quarter fixed effects and extract the residuals from the regression. We compute the average residualized attention for buys, holds, and sells. In Panel B, we present the regression analysis used in Panel B of Table VI, segmenting the sample by buy or sell actions or pooling trades and interacting with an indicator variable for buys. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Average Residualized Attention by Trading Action



Panel B: Performance of Buys versus Sells

	$\Delta Position_{ist-1} \times R_{st} \times 100$		
	(1)	(2)	(3)
InstAttn $_{ist-1}$	−0.4034*	0.0715	−0.4899
	(0.1996)	(0.1080)	(0.3567)
Trade Size	9.968	−12.02	−10.04
	(11.70)	(12.83)	(13.42)
InstAttn $_{ist-1}$ × Trade Size	1.198**	−0.6869	−0.7631
	(0.4988)	(0.5777)	(0.6271)
Buy			8.285
			(10.86)
InstAttn $_{ist-1}$ × Buy			0.5581
			(0.5636)
Trade Size × Buy			18.54
			(25.01)
InstAttn $_{ist-1}$ × Trade Size × Buy			2.146*
			(1.157)
Sample	Buy	Sell	Trade
Observations	5,671,872	5,409,714	11,081,586
R^2	0.49262	0.45122	0.12589
Firm × Time FE	✓	✓	✓
Fund × Time FE	✓	✓	✓

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

value-add for buys but not for sells.[28] Overall, the results support the underlying mechanisms of Akepanidtaworn et al. (2023). Funds pay more attention to buys than to sells, and attentive buys outperform less-attentive buys.

We note that an alternative interpretation of these results arises from the fact that many funds in our sample are not allowed to short-sell. Given this constraint, buys are more likely to reflect new position openings while sells are more likely to reflect existing position exits. If there is alpha decay, as in Mascio et al. (2022), then position openings as indicated by buys will earn higher returns than exits as indicated by sells. This difference may be even more pronounced if funds exit out of existing positions and forgo the remaining expected return of these positions in order to reallocate scarce capital into even more attractive new trading ideas (e.g., Von Beschwitz et al. (2022)). Moreover, if funds pay more attention before opening new positions, which we find support for, then attentive buys would perform better than other (follow-up) buys, whereas this may not hold for sells.

E. Stock-Level Return Predictability

E.1. Fama-MacBeth Regressions

In this section, we implement firm-level return predictability tests using the Fama-MacBeth regression method. The results in the previous section show that attention to a stock is associated with trade-based value-add to fund performance. Here, we extend this intuition to test whether attentive trading aggregated across funds predicts future stock returns. We construct stock-level measures of fund attention associated with a fund's buying, holding, and selling decisions. Specifically, attention by buying funds is the inverse hyperbolic sine of the sum of all reading by funds that increased their position in a stock from $t-2$ to $t-1$, deflated by the total reading about the stock by funds that pay attention to the stock at $t-1$. Attention by holding funds and attention by selling funds are constructed similarly.

Table X summarizes the results. We first examine the relationship between attention by buying funds of a stock and its future returns. Column (1) shows that attention by all buying funds positively predicts future stock returns. To facilitate interpretation, we normalize the independent variables to have a mean of 0 and a standard deviation of 1. The results indicate that a one-standard-deviation increase in fund attention to buys corresponds to around a 0.35% increase in monthly returns (around 4% annualized), controlling for

[28] The results of these tests suggest an asymmetry between buying and selling. We note that this could be because funds generally do not pay enough attention to sells compared to buys (as discussed in Akepanidtaworn et al. (2023), a fund may sell a stock for a number of reasons beyond return maximization). Asymmetry may also arise due to data limitations since we do not observe short positions. A fund buying a stock unequivocally represents favorable views of future performance. This generates clear, testable predictions: fund attention to a stock that it buys should be positively related to trade-based value-add. The ideal comparison to our buying specifications would be to test whether stocks that a fund shorted had subsequent poor performance. Such tests cannot be run, however, given the lack of visibility of short positions in our holdings data.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table X
Fama-MacBeth Regressions

In this table, we present Fama-MacBeth regressions at the monthly level. The dependent variable is the stock return times 100. The main variable is the total readership of the stock by buying (or selling / unchanged position) funds in the category (e.g., hedge funds, mutual funds) divided by total reading about the stock by fund as indicated. For ease of interpretation, these coefficients are normalized to have a standard deviation of 1. We control for return predictors such as size, book-to-market, gross profitability, and investment, as well as the logged number of news coverage. In addition, we control for the number of funds engaging in the corresponding actions (e.g., ihs(# Buying HF)). Standard errors are adjusted by Newey-West standard errors with two lags. Additional definitions are available in Section I.A of the Internet Appendix. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1)	(2)	(3)	(4)
(Intercept)	−2.983	−14.668***	−5.912*	−7.714**
	(3.198)	(3.375)	(3.344)	(3.348)
Attention by Buying Funds	0.352			
	(0.236)			
Attention by Buying Funds ^{HedgeFund}		0.513*	0.561***	
		(0.277)	(0.183)	
Attention by Buying Funds ^{MutualFund}		−0.290		
		(0.279)		
Attention by Buying Funds ^{OtherFund}		−0.443**		
		(0.173)		
Attention by Holding Hedge Funds			0.366	
			(0.294)	
Attention by Selling Hedge Funds			0.260	
			(0.195)	
Per Fund Attn.^{BuyingHF}				−2.833**
				(1.170)
ihs(# Buying HF $_{t-1}$) × Per Fund Attn.^{BuyingHF}				0.930***
				(0.355)
Controls	✓	✓	✓	✓
R^2	0.052	0.058	0.061	0.055
N	54	54	54	54

return predictors such as size, book-to-market, gross profitability, investment, and overall firm news coverage (the log total number of news articles that discuss the firm in the period). Importantly, we also control for the number of funds buying the stock.[29] Column (2) separates attention by buying funds by fund type (hedge funds, mutual funds, and non-HF/MFs). Attention by buying hedge funds significantly positively predicts future stock returns. A one-standard-deviation increase in attention by buying hedge funds is associated with a sizable 6% annualized increase in returns. Controlling for attention by buying hedge funds, the coefficient on attention by buying mutual funds is negative and insignificant and the coefficient on attention by buying non-HF/MFs is negative and significant. Column (3) focuses on attention by buying hedge

[29] We similarly control for the number of funds selling or holding when testing those measures.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

funds, controlling for attention by holding hedge funds and attention by selling hedge funds. Only attention by buying hedge funds is significant. Finally, in column (4) we interact the per-fund attention by buying hedge funds with the number of buying hedge funds. The coefficient on the interaction term is positive and significant at the 1% level, indicating that return predictability is stronger for stocks with attentive buying from many funds. This again confirms that the result is not driven solely by the positive relationship between the number of buying funds and future returns. While these are ordinary least squares (OLS) results, Table IA.XX in the Internet Appendix shows that the results are generally similar or stronger under weighted least squares (WLS) estimations. For example, some of the results for sold positions become significantly negative.

Our main measure of investor attention in Table X is scaled by the total reading of funds. Although we include news coverage about the stock in the regressions to control for news production, to further mitigate the concern that our measure is simply capturing the amount of news, we conduct split-sample tests in Table IA.XXIII in the Internet Appendix. For each period, we split the sample into two groups based on the news coverage of the firm (measured as the log total number of news articles that a firm has in the period). The odd-numbered columns are based on normal OLS Fama-MacBeth, while the even-numbered columns are based on WLS regressions weighted by market capitalization in the previous month. The coefficient estimates on the interaction terms between the per-fund attention by buying hedge funds and the number of buying hedge funds are positive in all of the specifications, suggesting that the results are unlikely to be driven solely by news production. The coefficient estimates tend to be larger for the above-median subsample, suggesting that the results are stronger for firms with more news coverage.

E.2. Portfolio Tests

In our final set of analyses, we conduct return predictability tests based on portfolio sorts. Our empirical choices are motivated by findings for the Fama-MacBeth analyses above. We first show the predictability result for each investor type (hedge funds, mutual funds, and other types of funds). We, then, rank firms into five quintiles based on the amount of investor attention received among bought stocks. Specifically, stocks are ranked following the measure from the Fama-MacBeth specifications above based on the attention by buying funds for each investor type.

Table XI presents the results. Panel A shows the average returns to each portfolio for both the equal- and value-weighted portfolios by investor type. Panel B shows factor alphas for the long-short strategy. Attention by buying hedge funds delivers significantly stronger predictability results compared with attention from other types of funds. The magnitudes from this portfolio analysis are comparable to those from the Fama-MacBeth exercise, with the long-short strategy producing an average excess return of 0.53% (0.80%) per month for the equal-weighted (value-weighted) result.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table XI

Investor Attention to Buy and Portfolio Returns

In this table, we test the relationship between returns in quarter t and investor attention by each set of investors (hedge funds, mutual funds, and other funds) at $t-1$ on stocks bought during that quarter. For each set of investors, every quarter we rank firms into five quintiles based on the amount of investor attention received among bought stocks, defined as the percentage of investor reads of the stock by buying funds, relative to all articles read about the stock by those funds. We track the performance of each bin in the next three months. In particular, the coefficients and t-statistics that correspond to the difference between the highest and lowest attention and are reported in the second-last and last rows, respectively, and we apply Newey-West adjustment with two lags. Panel A shows raw returns for each portfolio, with equal-weighted portfolios labeled "EW" and value-weighted portfolios labeled "VW." Panel B shows factor alphas and standard errors, for which we apply the Newey-West adjustment with two lags. Additional definitions are available in Internet Appendix I.A. Statistical significance is represented by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Portfolio Returns

Bin	HF EW	HF VW	MF EW	MF VW	Other EW	Other VW
1	0.587	0.625	0.735	0.913	0.763	0.901
2	0.793	0.664	0.977	0.975	0.952	0.923
3	0.793	0.570	0.884	0.876	0.965	0.914
4	0.910	0.705	0.881	1.107	0.807	0.839
5	1.122	1.420	0.894	0.859	0.647	0.971
H-L	0.534	0.795	0.160	−0.054	−0.116	0.070
t-Stat	2.748	2.225	0.474	−0.110	−0.329	0.162

Panel B: Long-Short Strategy Alphas

Factor Model	HF EW	HF VW	MF EW	MF VW	Other EW	Other VW
CAPM	0.56***	0.852*	0.359	0.138	0.04	0.218
	(0.186)	(0.436)	(0.276)	(0.444)	(0.339)	(0.506)
FF3	0.468***	0.667**	0.21	−0.03	−0.157	−0.077
	(0.133)	(0.296)	(0.2)	(0.351)	(0.168)	(0.213)
FF3+MOM	0.47***	0.679**	0.209	0.019	−0.15	−0.067
	(0.137)	(0.309)	(0.194)	(0.334)	(0.175)	(0.221)
FF5	0.446***	0.462	0.271	0.095	−0.099	−0.212
	(0.159)	(0.318)	(0.182)	(0.312)	(0.184)	(0.205)

We conduct two sets of robustness tests, which we present in Table IA.XXV in the Internet Appendix. First, to mitigate the concern that the results are driven by news production instead of fund attention, we conduct portfolio sorts conditional on the news coverage of each stock in each period. Each quarter, we first rank firms into two bins based on the news coverage of the firm, measured as the log total number of news articles about the firm in the period.[30] Then, within each news coverage bin, we perform the same sorting exercise. The

[30] We also conducted the same analysis using an alternative news coverage measure—the number of news articles divided by market capitalization—which mitigates size effects. We obtain qualitatively similar results using this news coverage definition.

results, reported in Panel A, suggest that the return predictability is somewhat stronger in the subsample of firms that receive more news coverage, consistent with the Fama-MacBeth results.

Next, we conduct subsample analysis based on the number of buying funds. We split the sample into two groups based on the number of funds buying a given stock in the portfolio sorting period. The results reported in Panel B, show that the long-short strategy factor alphas are positive across all specifications and significant at the 5% level in the sample for high-buying funds in a majority of the specifications.[31] Thus, similar to the Fama-MacBeth analysis, our results highlight the importance of the interaction between attention and buying for the predictability results. In particular, the return predictability is stronger for the high-funds-buying sample.[32]

V. Conclusion

We study investor attention to macroeconomic and firm-specific news using proprietary data on the daily Internet news reading of over 4,000 funds from November 2017 to June 2022. Combining investor attention information with data on portfolio holdings, we test predictions from models of limited attention (e.g., Peng and Xiong (2006), Van Nieuwerburgh and Veldkamp (2010), Glode (2011), Kacperczyk et al. (2016)).

Consistent with predictions of these models, we find that funds reallocate attention toward macroeconomic news during periods of high aggregate volatility. Moreover, funds that reallocate attention in this way outperform those that do not, especially during times when aggregate volatility is high. In terms of fund attention to firm-specific news, investor attention is positively associated with portfolio holdings. Importantly, fund attention to firm-specific news informs investments and creates value for the fund. This value creation is more pronounced when funds focus on more value-relevant information such as articles from business and financial newswires. In addition, we find heterogeneity across different investor types. For example, we present strong evidence that hedge funds outperform nonmutual/hedge funds, and weaker but still suggestive evidence that hedge funds outperform mutual funds. Finally, we complement these value-add results with Fama-MacBeth and portfolio sorting exercises and show that attention by buying hedge funds positively predicts stock future returns. Taken together, the results suggest that attention is an important resource used by funds to contribute to their performance.

Initial submission: April 25, 2022; Accepted: June 15, 2024
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

[31] We can also split based on the total market value of the dollars purchased (e.g., shares bought at $t-1$ times the price variable at $t-1$) and reach similar conclusions.

[32] In Internet Appendix Table IA.XXIV, consistent with the trade-based value-add results, we find no significant results for attention to stocks held or sold, even by hedge funds.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

REFERENCES

Abel, Andrew B., Janice C. Eberly, and Stavros Panageas, 2013, Optimal inattention to the stock market with information costs and transactions costs, *Econometrica* 81, 1455–1481.

Akepanidtaworn, Klakow, Rick Di Mascio, Alex Imas, and Lawrence DW Schmidt, 2023, Selling fast and buying slow: Heuristics and trading performance of institutional investors, *The Journal of Finance* 78, 3055–3098.

Bai, John Jianqiu, Yuehua Tang, Chi Wan, and H. Zafer Yuksel, 2022, Thematic investing in mutual funds, University of Florida Working Paper Series.

Barardehi, Yashar H., Zhi Da, and Mitch Warachka, 2024, The information in industry-neutral self-financed trades, *Journal of Financial and Quantitative Analysis* 59, 796–829.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

Bekaert, Geert, and Marie Hoerova, 2014, The VIX, the variance premium and stock market volatility, *Journal of Econometrics* 183, 181–192.

Ben-Rephael, Azi, Zhi Da, and Ryan D. Israelsen, 2017, It depends on where you search: Institutional investor attention and underreaction to news, *Review of Financial Studies* 30, 3009–3047.

Berk, Jonathan B., and Jules H. Van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2012, Salience theory of choice under risk, *Quarterly Journal of Economics* 127, 1243–1285.

Brown, Stephen J., and William N. Goetzmann, 1997, Mutual fund styles, *Journal of Financial Economics* 43, 373–399.

Chan, Louis KC, Hsiu-Lang Chen, and Josef Lakonishok, 2002, On mutual fund investment styles, *Review of Financial Studies* 15, 1407–1437.

Chen, Huaizhi, Lauren Cohen, Umit Gurun, Dong Lou, and Christopher Malloy, 2020, IQ from IP: Simplifying search in portfolio choice, *Journal of Financial Economics* 138, 118–137.

Chevalier, Judith, and Glenn Ellison, 1999, Are some mutual fund managers better than others? cross-sectional patterns in behavior and performance, *Journal of Finance* 54, 875–899.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

Crane, Alan, Kevin Crotty, and Tarik Umar, 2023, Hedge funds and public information acquisition, *Management Science* 69, 3241–3262.

Cremers, Martijn, Miguel A. Ferreira, Pedro Matos, and Laura Starks, 2016, Indexing and active fund management: International evidence, *Journal of Financial Economics* 120, 539–560.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *Journal of Finance* 66, 1461–1499.

Da, Zhi, Jian Hua, Tim Chih-Ching Hung, and Lin Peng, 2025, Market returns and a tale of two types of attention, *Management Science* 71, 10505–10537

Dyer, Travis A., 2021, The demand for public information by local and nonlocal investors: Evidence from investor-level data, *Journal of Accounting and Economics* 72, 101417.

Fang, Lily, and Joel Peress, 2009, Media coverage and the cross-section of stock returns, *Journal of Finance* 64, 2023–2052.

Fisher, Adlai, Charles Martineau, and Jinfei Sheng, 2022, Macroeconomic attention and announcement risk premia, *Review of Financial Studies* 35, 5057–5093.

French, Kenneth R., and James M. Poterba, 1991, Investor diversification and international equity markets, *American Economic Review* 81, 222–226.

Friend, Irwin, and Marshall E. Blume, 1975, The demand for risky assets, *American Economic Review* 65, 900–922.

Gargano, Antonio, and Alberto G. Rossi, 2018, Does it pay to pay attention? *Review of Financial Studies* 31, 4595–4649.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephen Utkus, 2021, Five facts about beliefs and portfolios, *American Economic Review* 111, 1481–1522.

Glode, Vincent, 2011, Why mutual funds "underperform", *Journal of Financial Economics* 99, 546–559.

Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455–1484.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2016, A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571–626.

Kwan, Alan, Tse-Chun Lin, and Po-Yu Liu, 2022, Managerial learning from decoding noisy stock prices: New(s) evidence, Hong Kong University Working Paper Series.

Liu, Hongqi, Lin Peng, and Yi Tang, 2023, Retail attention, institutional attention, *Journal of Financial and Quantitative Analysis* 58, 1005–1038.

Liu, Yukun, and Ben Matthies, 2022, Long-run risk: Is it there?, *The Journal of Finance* 77, 1587–1633.

Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt, 2023, Rational inattention: A review, *Journal of Economic Literature* 61, 226–273.

Mackowiak, Bartosz, and Mirko Wiederholt, 2009, Optimal sticky prices under rational inattention, *American Economic Review* 99, 769–803.

Mackowiak, Bartosz, and Mirko Wiederholt, 2015, Business cycle dynamics under rational inattention, *Review of Economic Studies* 82, 1502–1532.

Manela, Asaf, and Alan Moreira, 2017, News implied volatility and disaster concerns, *Journal of Financial Economics* 123, 137–162.

Markowitz, Harry, 1952, Portfolio selection, *Journal of Finance* 7, 77–91.

Mascio, Rick Di, Anton Lines, and Narayan Naik, 2022, Alpha decay and institutional trading, Copenhagen Business School Working Paper Series.

Moscarini, Giuseppe, 2004, Limited information capacity as a source of inertia, *Journal of Economic Dynamics and Control* 28, 2003–2035.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Peng, Lin, Wei Xiong, and Tim Bollerslev, 2007, Investor attention and time-varying comovements, *European Financial Management* 13, 394–422.

Peress, Joel, 2014, The media and the diffusion of information in financial markets: Evidence from newspaper strikes, *Journal of Finance* 69, 2007–2043.

Sharpe, William, 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Sicherman, Nachum, George Loewenstein, Duane J. Seppi, and Stephen P. Utkus, 2016, Financial attention, *Review of Financial Studies* 29, 863–897.

Sims, Christopher A., 2003, Implications of rational inattention, *Journal of Monetary Economics* 50, 665–690.

Tetlock, Paul C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2009, Information immobility and the home bias puzzle, *Journal of Finance* 64, 1187–1215.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2010, Information acquisition and under-diversification, *Review of Economic Studies* 77, 779–805.

Von Beschwitz, Bastian, Sandro Lunghi, and Daniel Schmidt, 2022, Fundamental arbitrage under the microscope: Evidence from detailed hedge fund transaction data, *Review of Asset Pricing Studies* 12, 199–242.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

15406261, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jofi.70009, Wiley Online Library on [17/05/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License