Market Returns and a Tale of Two Types of Attention

Zhi Da, Jian Hua, Chih-Ching Hung, and Lin Peng[†]

ABSTRACT

We provide novel evidence that aggregate investor attention to stocks predicts marketwide returns, but with a striking difference across investor clienteles. Daily aggregate retail attention (ARA) negatively predicts one-week-ahead market returns, is associated with aggregate retail order imbalance and flows to equity mutual funds, and exhibits a stronger predictability during periods of high marketwide uncertainty, poor liquidity, or more costly short selling. In contrast, aggregate institutional attention (AIA), when observed before major news announcements, positively predict future marketwide returns. In cross-sectional analysis, we show that the predictability is stronger for ARA among illiquid stocks, and for AIA among high-beta stocks. The predictability results are robust out-of-sample and correspond to meaningful expected utility gains even for diversified investors. The findings are consistent with the idea that attention-driven retail buying can generate an aggregate price pressure on the stock market, whereas institutional attention precedes the resolution of marketwide uncertainty and the accrual of risk premiums.

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[†] This draft: May 16, 2024. Zhi Da: Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556, zda@nd.edu; Jian Hua: Department of Economics and Finance, Zicklin School of Business, Baruch College, CUNY, One Baruch Way, Box B10-225. New York, NY 10010, Jian.Hua@baruch.cuny.edu; Chih-Ching Hung: Department of Finance, National Taiwan University, No. 1, Sec. 4, Roosevelt Rd., Taipei City 106, Taiwan (ROC), timcchung@ntu.edu.tw; Lin Peng: Department of Economics and Finance, Zicklin School of Business, Baruch College, CUNY, One Baruch Way, Box B10-225, New York, NY 10010, Lin.Peng@baruch.cuny.edu. Jian Hua acknowledges the PSC-CUNY Research Foundation for financial support; Lin Peng acknowledges the Wasserman Summer Research Grant and the Krell Research Fund for financial support; Chih-Ching Hung acknowledges research support from the Ministry of Science and Technology (110-2410-H-002-245). We thank Turan Bali, Brad Barber, Yixin Chen (discussant), Lauren Cohen, Joey Engelberg, Huseyin Gulen (discussant), Gur Huberman, David McLean, Cameron Peng (discussant), Josh Pollet, Jeff Pontiff, Orly Sade, Paul Tetlock, Quan Wen (discussant), Jianfeng Yu, Xiaoyan Zhang, Guofu Zhou, and seminar participants at Academia Sinica, Baruch College, National Taiwan University, the 2020 Midwest Finance Association Meeting, the 2021 China International Conference in Finance, the 2021 Northern Finance Association Meeting, and the 2023 American Finance Association Meeting for helpful comments and suggestions. We thank Shuai Hao and Yukun Liu for excellent research assistance. All errors remain our responsibility.

There is a growing body of literature suggesting that investor attention is critical in shaping investors' learning and trading of individual stocks, as well as stock-level return dynamics.[1] In particular, studies have shown that the relationship between investor attention and stock returns differs substantially depending on investor clienteles. For example, Barber and Odean (2008), Da, Engelberg, and Gao (2011) and Barber et al. (2022) find that stocks that attract more attention from retail investors experience a positive, transitory, price pressure first, followed by a subsequent reversal. In contrast, Ben-Rephael, Da, and Israelsen (2017) find that stocks that are subject to more institutional attention tend to have more efficient prices.

Despite the strong evidence at the stock level, the impact of investor attention on market-wide outcomes remains unclear. As pointed out by Engelberg et al. (2023), cross-sectional predictors do not generally contain systematic information and hence may not be reliable time-series predictors. Hence, the documented stock-level attention effects may be inconsequential for the broad market and for well-diversified investors if the effects are idiosyncratic or are only associated with small stocks.[2] This is a significant issue because market return predictability is central to finance and has far-reaching implications for asset pricing, corporate finance, and other economic decisions (Cochrane 2008).

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[1] Several papers show that underreaction to information is mitigated when investors pay more attention (Hirshleifer and Teoh 2003; Hirshleifer et al. 2004; Peng 2005; DellaVigna and Pollet 2007, 2009; Cohen and Frazzini 2008; Hirshleifer, Lim, and Teoh 2009; Hirshleifer, Hsu, and Li 2013; Bali et al. 2014; among others). On the other hand, attention can trigger overreactions to news (Huberman and Regev 2001), short-term price pressure (Barber and Odean 2008), excessive comovements (Peng and Xiong 2006; Huang, Huang, and Lin 2019), and the overvaluation of stocks with lottery features (Atilgan et al. 2020; Bali et al. 2021).

[2] For example, Da, Engelberg, and Gao (2011) find that retail attention-induced price pressure and reversal are only significant among smaller stocks and are largely absent for large stocks. Similarly, even if institutional attention facilitates the incorporation of news to individual stock prices (Ben-Rephael, Da, and Israelsen 2017), there is no guarantee that the result will aggregate to the market level if the news is mostly idiosyncratic in nature. Furthermore, even if the effects of attention are correlated among multiple stocks, the asynchronous nature of the effects can diminish such effects when aggregated in time series analysis. For example, Guo et al. (2022) and Chen et al. (2023) document that retail attention spills over from one stock to another with a delay. That is, at a given point in time, the price reversal on the first stock may coincide with the upward price pressure on the second, such that their impact on prices averages out when aggregated into market returns.

Our paper provides new insights into the crucial question of whether investor attention, when aggregated, is still able to predict marketwide returns, and if so, in what ways. We construct bottom-up measures of aggregate investor attention and find that the measures remain significant predictors of future market returns, but the predictability of retail attention differs substantially from that of institutional attention. Specifically, an increase in aggregate retail attention (ARA) significantly predicts a future marketwide decline, while an increase in aggregate institutional attention (AIA), when observed before major news announcements, forecasts higher market returns. Our findings have important implications for investors, suggesting that it is crucial to understand how aggregate investor attention is associated with market returns and to differentiate the clientele effects. We further show that, by incorporating this information into investment decisions, investors can realize meaningful expected utility gains.

To construct aggregate attention variables, we start at the individual stock level and first measure the attention of retail and institutional investors using abnormal Google search volume and Bloomberg's daily maximum readership for a given stock, respectively, following Da, Engelberg, and Gao (2011) and Ben-Rephael, Da, and Israelsen (2017). We then construct ARA and AIA as the value-weighted averages of the corresponding stock-level attention measures.

Our first finding is that ARA strongly and negatively forecasts one-week-ahead market returns. The economic magnitudes are substantial—a one standard deviation increase in ARA lowers market returns by 22.67 basis points in the week that follows. To further explore the underlying economic mechanisms, we investigate the conditions under which ARA's negative predictability is more pronounced. We find that this is the case during periods of high marketwide uncertainty, poor marketwide liquidity, and when short sale constraints are more binding—times when retail investors are likely to generate greater influence on stock markets. These findings are consistent with the explanation that ARA triggers a transitory price pressure that is followed by a rapid reversal.

We then provide direct evidence for this explanation by examining retail trading activities. Our first measure of retail trading follows Barber et al. (BHJOS 2024), where we estimate retail order imbalances at the individual stock level and then construct value-weighted aggregate retail order imbalances. The second measure uses aggregate mutual fund flows to capture retail participation in the stock market (Yuan 2015). We find that ARA is positively and significantly associated with both the contemporaneous retail order imbalance and abnormal equity fund flows. This evidence provides further support for our hypothesis that aggregate retail attention drives aggregate buying pressure from retail investors, which then results in a transitory marketwide overvaluation that subsequently reverses.

We next turn to institutional investor attention and observe that an increase in AIA, when observed prior to scheduled macroeconomic news releases or clustered earnings announcements, is followed by positive market returns in the next week. Economically, a one standard deviation increase in AIA leads to an 18.77 basis point increase in the following week's market returns. The finding is consistent with two non-mutually exclusive explanations. First, given the finding in previous studies that a substantial amount of return premium for individual stocks is realized around significant news releases,[3] we expect that announcements that attract higher levels of AIA, a sign that the news is likely to impact many stocks simultaneously, are more likely to be associated with a marketwide return premium, compared to the low-AIA announcements. Second, to the extent that institutions tend to devote more attention during periods of high marketwide uncertainty

[3] See, for example, Patton and Verardo (2012), Savor and Wilson (2013, 2014, and 2016), Ben-Rephael et al. (2021), and Chan and Marsh (2022).

(Benamar, Faucault, and Vega 2021), high AIA is thus also likely to be associated with higher future market returns resulting from the resolution of such uncertainty.

We further show that the return predictive power of AIA and ARA remain strong and robust out of sample and that Investors can utilize this information and obtain sizable economic gains. Specifically, under reasonable assumptions, a mean-variance investor would be willing to pay an annual fee of 226 basis points to access the information of ARA and a fee of 193 basis points for AIA. The results suggest that understanding the role of AIA and ARA is important even for well-diversified investors.

We conduct a range of robustness checks. Our results remain similar when we exclude the crisis period of December 2007 to June 2009, the month of December, and extreme low-attention periods. We check alternative empirical specifications, which include using Hodrick (1992)'s standard errors to compute *t*-statistics, controlling for lagged attention measures and weekday fixed effects, and measuring attention with moving averages. Our findings are also robust after controlling for an alternative aggregate attention measure used in Chen et al. (2022). In addition, we consider alternative aggregation methods to construct AIA and ARA and show that the results reported are conservative and can be further strengthened with partial least squares-based measures.

Our main results use bottom-up attention measures, which we then compare with alternative top-down measures that rely on Google searches of market indices or Bloomberg user readership activities on the ticker "SPY." We show that the results based on top-down measures are weak and lack consistency. There are several reasons why bottom-up measures are superior in predicting market returns. Regarding retail attention, given that retail investors mostly hold a handful of individual stocks (see Campbell 2006; Barber and Odean 2008; Guiso and Sodini 2013), their aggregate effect on market returns stems from their direct effect on the individual stocks that they hold and trade, which is better captured by the bottom-up ARA. Regarding institutional attention, the bottom-up AIA can be viewed as measuring the percentage of the stock universe that the institutional investors are paying attention to at a given point in time. Thus, a high AIA, by design, reveals that the underlying event is of systematic importance to the stock market. Additionally, the reason for the poor performance of top-down measures could also be due to the lack of good proxies for retail and institutional attention to the overall market. For example, Google searches of market indices and Bloomberg readership activities on the ticker "SPY" that we employ may not adequately capture the true amount of attention investors pay to the market.

In further cross-sectional analysis. We find that ARA's negative return predictability is more pronounced for less-liquid stocks, where retail purchases have a greater transitory price impact. Regarding AIA, we use a stock's market beta to capture its price sensitivity to the resolution of marketwide uncertainty. We discover that AIA's predictive power is stronger for high-beta stocks. Thus, the findings substantiate the time-series evidence and provide further support for our proposed mechanism on the return predictability of retail and institutional attention, respectively.

The predictive nature of our findings is valuable for investors decision making, irrespective of whether the relation is causal. That being said, we are able to provide further causal evidence for how ARA affects market returns. To this end, we employ an instrumental variable approach using exogenous shocks to retail investor attention. Specifically, we construct a "distraction" measure based on exogenous episodes of sensational news (Eisensee and Strömberg 2007 and Peress and Schmidt 2020). We validate the instrument by showing that ARA is significantly lower on distraction days. Using this instrument, we find that ARA's negative return predictability remains robust, indicating a causal effect of ARA on future market returns.

Our research uncovers important relationships between aggregate investor attention and market returns. In our final analysis, we provide an application of this knowledge in explaining a financial market puzzle that was recently discovered. While previous studies have established that news releases are associated with positive return premiums, typically realized *after* the news releases, Chen, Cohen, and Wang (2021) find that much of the premium occurs on a handful of days *before* the after-hours earnings announcements of major firms. We investigate this and find that this pre-news return premium exists only when ARA is high and disappears with low ARA. This suggests a more-nuanced interplay between announcement return premium and retail trading. Before the announcement, an increase in retail attention across many stocks triggers excessive retail buying and a positive aggregate price pressure. Post-announcement, the reversal of the price pressure offsets the positive return premium associated with the announcement, resulting in an insignificant net return premium. This example illustrates how a better understanding of aggregate investor attention contributes new insights to our understanding of financial markets.

Our study adds to the growing body of literature on investor attention. Rational inattention models postulate that investors' attention allocation decisions are outcomes of investor optimization, depending on their attention capacity and the nature of news.[4] This framework tends to align with the way in which institutional investors deliberately allocate their attention. On the other hand, people's attention is naturally drawn to "salient" stimuli and can be automatic and involuntary. This can then distract from deliberate attention and result in suboptimal decisions.[5] The existing empirical literature investigates the way in which these two types of investor attention differ at the individual stock level.[6] A natural question is whether these differences matter in

[4] See, for example, Sims (2003, 2006), Peng (2005), Peng and Xiong (2006), Mondria (2010), Van Nieuwerburgh and Veldkamp (2010), Gondhi (2021), and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016).
[5] See, for example, Bordalo, Gennaioli, and Shleifer. (2012, 2013a,b, 2020).
[6] For papers on retail investor attention, see, for example, Barber and Odean (2008), Da, Engelberg, and Gao (2011),

aggregate, when the marginal investor holds a well-diversified portfolio and can, presumably, diversify stock-specific factors.

Our evidence indicates that the two types of attention, when aggregated, are associated with distinct patterns of marketwide returns. We find that institutional attention is associated with uncertainty resolution and permanent price changes, consistent with deliberate attention allocation. In contrast, our results on retail attention, trading, and price reversals around salient news releases are consistent with this salience-based attention. Compared to Chen et al. (2022), who explore aggregate attention and discovered that a common component of 12 investor attention proxies is *negatively* linked to future market returns, our findings provide a more nuanced understanding of the differences between retail and institutional attention and suggest that important conceptual insights obtained from the previous literature remain relevant when considering diversified investors and aggregate prices.

Our paper also contributes to the vast literature on market return predictability by showing that one mechanism behind this predictability is related to how retail and institutional investors process and react to information.[7] Our findings are particularly relevant for the growing literature on return premiums and uncertainty resolution around important news releases.[8] Fisher, Martineau,

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and Barber et al. (2022). For papers on institutional attention, see Ben-Rephael, Da, and Israelsen (2017) and Ben-Rephael et al. (2021). In addition, Liu, Peng, and Tang (2023) and Hirshleifer and Sheng (2022) examine institutional and retail attention when macroeconomic news releases and individual firm earnings announcements coincide.

[7] For the literature on market return predictability, see Fama and Schwert (1977), Campbell (1987), French, Schwert, and Stambaugh (1987), Campbell and Shiller (1988), Fama and French (1988), Breen, Glosten, and Jagannathan (1989), Kothari and Shanken (1997), Pontiff and Schall (1998), Campbell and Cochrane (1999), Baker and Wurgler (2000, 2007), Lettau and Ludvigson (2001), Campbell and Vuolteenaho (2004), Campbell and Yogo, (2006), Guo (2006), Ang and Bekaert (2007), Welch and Goyal (2008), Cooper and Priestley (2009), Kelly and Pruitt (2013), Huang et al. (2015), and Jiang et al. (2019).

[8] For papers on firms' earnings announcements, see, for example, Beaver (1968), Chari, Jagannathan, and Ofer (1988), Bernard and Thomas (1989), Ball and Kothari (1991), Cohen et al. (2007), Frazzini and Lamont (2007), Patton and Verardo (2012), Barth and So (2014), Savor and Wilson (2016), and Johnson and So (2018). For the effect of macroeconomics news releases, see, for example, Savor and Wilson (2013, 2014), Lucca and Moench (2015), Bernile, Hu, and Tang (2016), Ai and Bansal (2018), Kurov, Wolfe, and Gilbert (2021), Cieslak, Morse, and Vissing-Jorgensen (2019), Ben-Rephael et al. (2021), and Hu et al. (2022).

and Sheng (2022) recently demonstrate that attention to macroeconomic news, measured by news article counts, predicts announcement risk premiums. However, our results suggest that the effect of attention is more nuanced: while return premiums are positively associated with institutional investor attention to news, the premiums can also be substantially offset by a swift price correction following retail attention-driven buying. This discovery partially explains the preannouncement return premium puzzle (Chen, Cohen, and Wang 2021) and suggests that considering high-frequency investor attention dynamics can enhance our comprehension of the patterns of risk premiums around news.

1. Data, Variable Descriptions, and Summary Statistics

Our sample consists of all common shares (SHRCD = 10 and 11) traded on the NYSE, AMEX, NASDAQ, and NYSE Arca from July 2004 through December 2019.[9] Retail investor attention is constructed using data from Google Trends (available since 2004), and institutional investor attention data are from Bloomberg (available since 2010). We obtain firm-level stock data from CRSP and accounting and financial statement variables from the merged CRSP-Compustat database.

We define a stock's abnormal retail attention (ASVI) as the percentage change between Google's daily Search Volume Index (SVI) for a stock ticker and its past six-month median (Da, Engelberg, and Gao 2011).[10] We then define aggregate market-level retail attention (ARA) as the

[9] We eliminated stocks with closing prices less than $5.

[10] The SVI is a relative search popularity score, defined on a scale of 0 to 100, based on the number of searches for a term relative to the total number of searches for a specific geographic area and a given period. We focus on searches made on weekdays in the US market. We manually screen all tickers to select those that do not have a generic meaning (e.g., "GPS" for GAP Inc., "M" for Macy's) to ensure that the search results we obtain are truly for the stock and not for other generic items or firm products. Different from Da, Engelberg, and Gao (2011), we use daily, not weekly, SVIs. In Section A.1, we provide more details about our data collection process for Google SVI, for which we obtained three vintages between 2015 and 2020. We rigorous cross check for data consistency across the three vintages and

market cap weighted average of firm-specific ASVI. We obtain the daily maximum readership for a stock (DMR) from Bloomberg and define the high institutional attention indicator as equal to one when DMR has a score of 3 or 4, and zero when DMR is below 3 (Ben-Rephael, Da, and Israelsen 2017). [11] We then construct aggregate institutional attention (AIA) as the value-weighted average of the individual stocks' high institutional attention indicators. Intuitively, AIA measures the fraction of the market that institutional investors are paying attention to each day. ARA is available for 2004– 2019, and AIA is available for 2010–2019.

Our market return measure is the CRSP value-weighted return. Although the market returns are measured with closing prices at 4:00 p.m. eastern standard time (EST), Google's daily SVI measures are based on midnight-to-midnight Greenwich mean time (GMT). This results in a four-hour overlap of search activities measured on day t and the close-to-close returns measured between day t and t+1 (which we refer to as the *day t+1 return*). Similarly, AIAs are based on calendar days, so AIA on day t and the returns on day t+1 overlap by eight hours. Therefore, we skip the t+1 day return in our predictive regressions to avoid any look-ahead bias in the regressors.

We also include the following control variables that prior studies have shown to predict market returns:[12] the Baker-Wurgler sentiment (BW), the term spread (TMS), the default yield spread (DFY), the value-weighted abnormal volume of firm specific news (AbnNews), changes in the economic policy uncertainty index (ΔEPU) of Baker, Bloom, and Davis (2016), and changes in the business condition index (ΔADS) of Aruoba, Diebold, and Scotti (2009). In addition, we

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show that our results are robust across all vintages.

[11] Bloomberg records hourly user activities (including searches and readership) for a given stock relative to its distribution during the past 30 days. The daily maximum readership score, DMR, equals zero, one, two, three, or four if the maximum of the hourly Bloomberg terminal user activities for the day is less than 80%, between 80% and 90%, between 90% and 94%, between 94% and 96%, or greater than 96% of the past sample distribution of the stock, respectively. The Bloomberg News Readership is not available between August 19, 2011, and November 2, 2011.

[12] See, for example, Campbell (1987), Fama and French (1989), Campbell, Grossman, and Wang (1993), Baker and Wurgler (2006, 2007), Welch and Goyal (2008), and Da, Engelberg and Gao (2015).

control for the following variables and their corresponding lags for up to four lags: the Chicago Board Options Exchange Volatility Index (VIX), daily market returns (MktRet), and aggregate abnormal turnover (AbnTurn), which is defined as the value-weighted average of the log of stock-level turnover detrended by the stock's prior year average (Llorente et al. 2002).[13]

Table 1, Panel A presents summary statistics for our variables, at daily frequencies. ARA has an average of 0.065, a median of 0.060, and a standard deviation of 0.054; the corresponding values for AIA are 0.254, 0.252, and 0.1, respectively. Both attention measures are persistent: the daily autocorrelation coefficients are 0.77 for ARA and 0.57 for AIA. In comparison, the corresponding values for stock-level attention measures are less persistent, at averages of 0.41 and 0.24, respectively, suggesting that the common component of the stock-level attention shocks tends to be more persistent than the idiosyncratic components. On the other hand, ARA and AIA are substantially less persistent than some of the control variables (such as VIX, term spread, and default yield spread) and are far from being unit roots.[14]

Figure 1, Panels A and B present the time-series plot of ARA and AIA, respectively. The plots suggest that significant time-series variations exist in the two types of investor attention, and they spike at the onset of financial crises. Table 1, Panel B presents the time-series correlation

[13] The Baker-Wurgler sentiment reflects investors' optimism and negatively predicts future market returns (Baker and Wurgler 2006, 2007). The term spread and default yield spread capture business conditions and predict future stock returns (Campbell 1987; Fama and French 1989; Welch and Goyal 2008). Campbell, Grossman, and Wang (1993) find a decline in stock returns following high turnovers. The change in the economic policy uncertainty index, the change in the ADS business condition index, and VIX are the controls in Da, Engelberg, and Gao (2015). We also confirm that our results are robust to including the FEARs of Da, Engelberg, and Gao (2015) as a control. The result is not reported because the FEARS index is only available through 2016, hence results in a much shorter sample. The result with this shorter sample is available upon request.

[14] We follow the literature to include VIX, TMS, DFY, and BW. The persistent nature of these variables may produce artificially high *t*-statistics in predictive regressions. We therefore conduct robustness checks and find that excluding these variables from our predictive regressions yields similar results.

coefficients of the variables and shows that ARA and AIA are positively correlated and have a coefficient of 28.2%. ARA also differs from AIA in the correlation with VIX.[15]

To understand the relationship between retail and institutional attention, we conduct a vector autoregressive analysis of AIA and ARA along with market return, abnormal turnover, and VIX.[16] Figure 2, Panels A and B present the cumulative impulse response functions of ARA to AIA shocks and of AIA to ARA shocks, respectively. We pretreat the attention series to remove month and weekday seasonality and present the 95% confidence intervals with shaded areas. Panel A shows that a one-unit shock in AIA leads to a significant increase of 0.219 units in ARA, which remains significant over the following nine days. On the other hand, as shown in Panel B, a one-unit shock in ARA leads to an insignificant initial increase in AIA (by 0.079 units) the following day, followed by a gradual reduction over the next ten days.

2. Attention and Market Returns

2.1 Baseline Results

To investigate the ability of aggregate investor attention measures to predict market returns, we estimate the following time-series regressions using daily observations:

$$MktRet_{t+n} = \alpha + \beta_1 Attention_t + \emptyset X_t + \varepsilon_{t+n}, \quad (1)$$

[15]At first glance, the negative and significant correlation between AIA and VIX (at –7.8%) may appear counterintuitive, as a large body of literature on rational inattention predicts that agents should allocate more attention when volatility is high. We note that this correlation coefficient should not be interpreted at face value because VIX is highly persistent whereas AIA captures high-frequency attention spikes. The true dynamic association of the two series, measured with the correlation coefficient between changes in VIX (relative to its past ten-day mean) and AIA, is 5.32% and highly significant.

[16] We choose five lags according to the Bayesian information criterion. We also tried several numbers of lags ranging from 1 to 10, and the lead-lag relationship between ARA and AIA remains robust among these selections.

where $MktRet_{t+n}$ is the CRSP value-weighted returns for the next *n* days; *Attention* is either ARA or AIA, the aggregate retail or institutional attention, respectively. *X* consists of a list of control variables that are listed in Section 1 measured as of day t. Standard errors are adjusted using Newey-West corrections with 30 lags unless otherwise mentioned.[17]

We present the results in Table 2, with Panels A and B corresponding to ARA and AIA, respectively. Panel A shows that ARA has a significant and negative coefficient that ranges from –0.655 to –0.902 in predicting market returns for up to six days. As mentioned earlier, we focus on the market return predictability from day t+2 onward to avoid the potential look-ahead bias in the attention measures. The coefficient of ARA on the cumulative market returns for the following week (t+2 to t+6) is –4.137 and highly significant. In terms of economic magnitudes, column (2) shows that a one standard deviation increase in ARA (0.054) reduces t+2 market returns by 4.87 basis points. Similarly, column (8) shows that the corresponding market return decrease in the following week is 22.34 basis points, or 11.62% in annualized returns.

Turning to aggregate institutional attention, Panel B of Table 2 reports the market return predictability of AIA. Columns (1)–(6) show that AIA positively predicts daily market returns, and the coefficient is significant for the one-day-ahead market returns but becomes insignificant for the other columns.[18]

Overall, Table 2 uncovers distinctly different patterns in the power of aggregate retail and institutional attention measures in predicting future market returns. While higher aggregate retail

[17] To account for the autocorrelation in the cumulative returns that resulted from overlapping periods, we report the Hodrick (1992) standard errors when predicting cumulative market returns in the robustness check section. The results remain robust.

[18] One potential concern is that ARA and AIA are not directly comparable. Due to the inherent differences in the data sources, ARA is constructed from continuous ASVI measures, whereas AIA is constructed from dummy variables. In Section A.2, we develop an alternative ARA measure that is aligned with the construction of AIA and demonstrate in Appendix Table 1 that the relationship between the alternative ARA measure and future market returns remains robust.

attention is associated with significantly negative market returns for the week that follows, aggregate institutional attention is not significantly associated with market returns in unconditional tests. In the next subsections, we explore possible underlying economic mechanisms by investigating whether the association between aggregate attention measures and market returns is attributable to investors' trading activities and is related to the way in which investors allocate their attention to important information releases.

2.2 Aggregate Attention and Market States

We first investigate what mechanisms underlie the return predictability of ARA. As suggested by Barber and Odean (2008), since retail investors rarely short, their attention results in net retail buying and positive price pressure on average. To the extent that retail buying at the market level is uninformative, the buying generates a transitory positive price pressure that subsequently reverts. Therefore, we hypothesize that the negative ARA-market return relation is attributable to the aggregate price pressure caused by the excessive marketwide buying activities of retail investors when they become more attentive. If so, the price pressure would be stronger when the market suffers from poor liquidity or when short sales are costly, all else being equal. We examine these hypotheses in this subsection.

Specifically, we provide tests of the price pressure hypothesis by exploring market states that correspond to variations in marketwide liquidity and short sale constraints. We hypothesize that retail demand for stocks can generate stronger upward price pressure when market liquidity is lower and when short sale constraints are more binding. We therefore expect ARA's negative return predictability to be stronger on days of higher illiquidity and on days with greater short sale costs.

We use two proxies for market liquidity states: 1) the VIX index, which proxies for market makers' required compensation for liquidity provision (Nagel 2012); and 2) the level of market liquidity as measured by a value-weighted effective spread across stocks. More specifically, we classify a daily observation into the high-VIX state if its VIX is above the sample median and into the low-VIX state otherwise. Similarly, a daily observation belongs to a high-spread (illiquid) state when the aggregate effective spread is above its sample median and belongs to a low-spread (liquid) state otherwise.

We obtain daily equity lending fees between July 2006 and December 2011 from Data Explorers. We aggregate the stock-level equity lending fee to the market-level fee using the market capitalization as the weight and obtain the abnormal fee as the percentage difference between the market-level short sale fee and its past three-month average. An observation belongs to the high-fee period if the abnormal fee of that day is above the median of the full sample; otherwise the observation belongs to the low-fee period.

Table 3 presents the results of a daily time-series estimation of equation (1) for subsamples sorted by VIX, effective spreads, and short sale fees. Panel A presents the result for ARA and Panel B for AIA. We report the White standard error, the bootstrapped standard error, and the Hodrick (1992) standard error to account for potential heteroscedasticity.[19]

Panel A column (1) shows that, during the high-VIX period, ARA significantly and negatively predicts one-week-ahead market returns. In contrast, column (2) shows that when VIX is low, ARA's market return predictability disappears. In terms of economic magnitude, a one standard

[19] The Hodrick (1992) standard error is designed to account for serial correlation that arises from predicting overlapping returns by summing over the variance of the residual terms of the same horizon length. We adopt Hodrick standard errors for the subsample analysis to be conservative in the statistical inferences as the subsample returns do not necessarily overlap.

deviation increase in ARA leads to a significant decrease of 27.96 basis points in the following week's market return during the high-VIX state but an insignificant decrease of 6.29 basis points for the following week's market return when VIX is low.

When market liquidity is measured by aggregate bid-ask spreads, column (3) shows that when the market is illiquid, ARA significantly negatively predicts one-week-ahead market returns with a coefficient of –6.303. In contrast, column (4) shows that, in a more liquid market (low spread), ARA's market return predictability largely disappears. In terms of economic magnitude, a one standard deviation increase in ARA leads to a significant decrease of 32.79 basis points in the one-week-ahead market return in periods of low market liquidity (high spread) and an insignificant decrease of 3.46 basis points for the one-week-ahead returns when market liquidity is high.

Next, we examine the return predictability of aggregate attention measures conditional on short sale fees. Column (5) and (6) show that the ARA coefficient is substantially negative and significant in the high-fee period but much smaller and insignificant in the low-fee period. The coefficient difference between the high-fee period and the low-fee period is also significant. For the high-fee period, one standard deviation increase in ARA leads to a 75.70 basis point decrease in the following week's market returns. This indicates that ARA's negative market return predictability is more pronounced when the short sale cost is high, consistent with our story that retail buying pressure contributes to ARA's return predictability.

In short, we document that the ARA's market return predictability is asymmetric and is more prominent during periods of high uncertainty, low liquidity, or high short sale costs, providing further support to the hypothesis that aggregate retail attention causes transient pressure on market prices that reverses within a week.[20]

Regarding AIA's return predictability, Table 3, Panel B indicates a significant difference across sample periods sorted by VIX, but no significant difference across the periods by market liquidity. Columns (1) and (2) show that the coefficient of AIA during the high-VIX period is significantly higher than the coefficient during the low-VIX period.[21] Columns (3) and (4) reveal no significant variation in AIA's return predictability in either liquid or illiquid markets. Therefore, the results suggest that the return predictability of AIA is associated with mechanisms that are distinctly different from that of ARA, and we will explore this further in the next subsection.[22]

2.3 Aggregate Attention Around Major News Releases

In this subsection, we examine the factors that may contribute to the positive association between AIA and future market returns. Two possible explanations exist for this positive association. First, institutional attention may facilitate efficient information processing. Studies have shown that institutional attention increases significantly for individual stocks surrounding macro and earnings announcements (Ben-Rephael, Da, and Israelsen 2017; Liu, Peng, and Tang 2023) and can contribute to stock-level risk premium (Ben-Rephael et al. 2021). It remains unclear whether these stock-level patterns are idiosyncratic or extend to the market level. Additionally,

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[20] We also investigate whether there is any asymmetry in our results depending on positive and negative news. Since good marketwide news tends to be associated with positive market returns and bad marketwide news associated with negative market returns, we define good (bad) news days as days when market returns are positive (negative). We then conduct subsample analysis for good and bad news days, respectively. Appendix Table 2 shows that the negative relationship between ARA and the one-week-ahead market returns are robust across both subsamples.

[21] The result is consistent with the explanation that, with a high level of ex ante uncertainty, institutional attention and information processing may result in the resolution of uncertainty and the realization of an equity premium. We will further explore this hypothesis in the next subsection.

[22] We are unable to conduct a similar analysis for AIA due to the limited overlapping (February 2010 to December 2011) between the coverage periods of Data Explorers' and Bloomberg DMR's data.

high institutional attention may anticipate significant macroeconomic uncertainty associated with the upcoming macroeconomics announcements (Benamar, Faucault, and Vega 2021; Fisher, Martineau, and Sheng 2022). If an announcement resolves uncertainty, we would expect that institutional attention to be positively associated with subsequent risk premium realizations.

We therefore examine whether AIA's market return predictability is stronger around important scheduled news announcements. Specifically, we use two indicator variables, *Macro News* and *All News,* to identify days with major macroeconomic news and earnings announcements from the most important firms. The major macro announcements include Federal Open Market Committee (FOMC) meetings, nonfarm payroll, and the producer price index (PPI) as these types of macro news attract the most attention from institutional investors on Bloomberg terminals (Ben-Rephael, Da, and Israelsen 2017). We define *Macro News* as equal to one if the daily observation is associated with one of the major macro news announcements, and zero otherwise. Next, we calculate the market cap ratio of all firms who announce earnings on day t over the total CRSP market capitalization. We define $\textit{All News}_t$ as equal to one for days with macro announcements or for days when the market capitalization ratio of announcement firms belongs to the top 5% of the distribution, and zero otherwise.[23]

We then classify daily observations into subsamples based on whether the observation is associated with major news events in the next window of two to six days.[24] Days preceding news arrivals are associated with significantly higher levels of AIA than other days. Specifically, the average AIA preceding news days is 0.266, which is statistically higher (*t*-statistic = 5.84) than the

[23] The top 5% breakpoints of the market cap ratio are 5.86% for the sample period of ARA, that is, 2005–2019, and 5.95% for the sample period of AIA, that is, 2010–2019.
[24] Our findings remain robust for each of the news days ranging from t+2 to t+6. We also investigate the market return predictability based on the announcement ratio alone. The results are all consistent and are available upon request.

average AIA (0.241) of other days. Meanwhile, the level of AIA does not differ significantly across different types of news released subsequently (i.e., FOMC as opposed to nonfarm payroll announcements), suggesting that these important types of news generate consistent increases in AIA.

Next, we formally estimate the time-series regression of daily returns as shown in equation (1) for the subsample classified by the proceeding of *Macro News* and *All News*, respectively. Table 4, Panel A shows that the coefficients of AIA are 2.076 and 2.072, conditioned on future *Macro News* and *All News* in the next two to six days. Economically, a one standard deviation increase in AIA leads to a significantly higher market return of 20.64 to 20.82 basis points for the following week. The corresponding annualized return is between 10.73% and 10.83%. On the other hand, when there is no major news release, the AIA coefficient is insignificant. The differences in the coefficient of AIA on news and no-news days are also highly significant statistically. In contrast, in Panel B, ARA's return predictability is not significantly different across news and no-news days, although the coefficients for news days are somewhat larger than that for days without news.

In sum, these findings support the hypothesis that institutional investors anticipate the arrival of information, and their increased attention and information acquisition coincide with a greater reduction of uncertainty and a realization of a market risk premium. The divergent return predictability patterns between AIA and ARA across news and no-news days further highlight the differences in the way institutional and retail investors react to news and affect aggregate returns.

If the return predictability of AIA is at least partially driven by greater institutional demand for information ahead of news releases, which tends to be accompanied by higher uncertainty associated with the event (as in Benamar, Foucault, and Vega 2021), a related question is whether institutional investors anticipate this high uncertainty. If the higher uncertainty was previously ignored by investors, then investors' recognition of this uncertainty would be accompanied by lower contemporaneous returns. On the other hand, to the extent that the high uncertainty is expected, we may not observe any notable contemporaneous return patterns.

We address the question by examining the correlation between AIA and market returns for a window prior to the scheduled macro events, [t−4, t]. The correlation coefficients are small and insignificant, at 0.011, 0.017, 0.038, 0.031, and 0.013, respectively, consistent with such high uncertainty being anticipated by institutional investors.

2.4 Retail Trading

We have previously argued that the negative relationship between ARA and market returns is attributable to aggregate price pressure caused by attention-driven buying by retail investors. While retail investors could pay attention to both positive and negative news, retail attention is more likely to be followed by retail net buying activities due to the fact that retail investors rarely short (see Barber and Odean 2008; Barber et al. 2022).[25] In this subsection, we provide further evidence for these arguments by directly investigating the trading activities of retail investors.

To capture retail trading, we adopt the methods used by Barber et al. (BHJOS 2024) and estimate retail order imbalances at the individual stock level for the period from 2010 to 2019. We then aggregate these stock-level measures to the market level, using each stock's market capitalization as weights. We obtain two types of retail order imbalances, ROIB1 and ROIB2, where the order imbalance is scaled by total retail orders and by total orders, respectively.[26]

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[25] According to Barber and Odean (2008), *"because individual investors hold small portfolios and do not sell short, attention is more important when choosing stocks to buy—from a huge set of choices—than when choosing stocks to sell—from a small set"* (p.808).
[26] We note a caveat related to the results obtained with the retail order imbalance (ROIB) measures, as these measures may be subject to both Type I and Type II errors. For further details, see the studies by Barber et al. (2024), Battalio et al. (2024), and Barardehi et al. (2024). Aggregating the measures at the market level also helps to alleviate the

Another dimension reflecting retail investor participation in the stock markets is mutual fund flows (Yuan 2015). To explore this, we obtain daily US equity mutual fund flow and Total Net Assets (TNA) data from TrimTab for the period from July 2004 to July 2016. We aggregate these data to the market level by summing up the daily flows and TNAs across all funds, respectively. We then calculate the abnormal equity fund flow as the ratio of market-level daily flow to market-level TNA, after adjusting for seasonality effects (year, month, and day-of-week fixed effects) by regressing on the seasonal indicator variables mentioned above and extracting the residuals.

Appendix Table 3, Panel A, shows that ARA is positively and significantly associated with the contemporaneous retail order imbalance and abnormal equity fund flows. A one-standard-deviation increase in ARA is associated with an 18.84 bps increase in ROIB1 (1.26 bps in ROIB2), which represents 5.89% (5.86%) of the variable's standard deviation. Similarly, a one-standard-deviation increase in ARA is associated with a 1.05 bps increase in the aggregate mutual fund flow, representing 6.50% of the variable's standard deviation. This evidence supports our hypothesis that retail attention is associated with net retail buying, more inflows to mutual funds, and overvaluation, followed by subsequent price reversals.

To better understand why an increase in retail attention forecasts negative future market returns, even at the presence of negative news, we dive deeper and examine retail order imbalances and mutual fund flows for the positive and negative news subsamples, respectively. Appendix Table 4, Panel A shows that high retail attention is associated with a higher-level of net retail buying even on negative market return days.

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measurement errors.

We further investigate the possibility that retail attention may exacerbate negative shocks and even trigger liquidity spiral on market crash days. If this is the case, we would expect retail selling pressure on those days, especially when they pay attention. To investigate this, we zoom into a set of days on which the market has dropped by 1.548% from 2010 to 2019 (125 days) and by 1.856% from July 2004 to July 2016 (150 days), namely, the bottom 5% within each period. We then regress retail trade imbalances and mutual fund flows on ARA along with the standard set of controls. Appendix Table 4, Panel B shows that we still observe positive and significant coefficients for aggregate retail order imbalance indices and positive but insignificant coefficient for abnormal mutual fund flow, suggesting on these large negative market return days, retail investors buy more after paying more attention.

The positive and significant relationship between ARA and retail net buying on negative market return days is consistent with the retail contrarian trading behavior documented in previous literature (Kaniel et al. 2012, Luo et al. 2022, Grinblatt and Keloharju 2000, 2001).[27] The association on positive market return days is also positive but insignificant.

To measure aggregate institutional investor trading, we first define non-retail initiated buy and sell orders at the stock level as the differences between the Lee and Ready (1991) orders and the BHJOS retail orders. We then compute the order imbalances at the stock level and construct the aggregate non-retail order imbalance index, non-ROIB, using a procedure similar to the construction of ROIB.[28] Appendix Table 3, Panel B reports that, unconditionally, AIA is not

[27] Kaniel et al. (2012) study retail trading of a large cross-section of NYSE stocks during 2000-2003 and find that retail investors, as a group, tend to trade in the opposite direction of earnings surprises. Moreover, based on account-level data from a large U.S. brokerage firm for the period of 2010-2014, Luo et al. (2022) found that retail investors exhibit contrarian trading behavior in response to earnings surprises, particularly among attentive investors and in the case of negative announcements. Additional evidence of retail contrarian trades has also been documented by Grinblatt and Keloharju (2000, 2001), who found increased buying activity by Finnish households following negative returns.

[28] We do not use mutual fund holding changes, which are only available at a quarterly frequency, while the impact of AIA on asset prices operates at a much higher daily frequency.

associated with the contemporaneous aggregate non-ROIB. The result needs to be interpreted with caution, as non-ROIB could be a very noisy measure of daily institutional trading. Unfortunately, our analyses at daily frequency prevent us from using quarterly holding changes to measure institutional trading.

2.5 Out-of-Sample Tests and Asset Allocation Analysis

Our analysis so far has been in sample, which provides more-efficient parameter estimates and more-precise return forecasts because of its utilization of all available data. As pointed out by Welch and Goyal (2008) among others, out-of-sample tests allow for the assessment of return predictability that can be implemented in real time. In this subsection, we evaluate the out-of-sample market return predictive performance as well as the economic gain from asset allocation analysis of the aggregate investor attention measures, ARA and AIA, respectively.

Following the prior literature (see e.g., Welch and Goyal 2008; Huang et al. 2015), we estimate univariate predictive regressions and focus on the cumulative market return for the t+2 to t+6 window. For retail attention, we use July 2004 through July 2006 as the training period and begin our forecasts in August 2006. For institutional attention, the training period is January 2010 to February 2012, and we start the forecast in March 2012. We estimate the coefficient on the attention measures using a rolling window of 500 days. For the benchmark case, we estimate a random walk model in which the expected return is the past average of returns in the estimation window. We define out-of-sample R^2 as the improved prediction power of using attention variables compared to the random walk benchmark:

$$R_{OOS}^2 = 1 - (MktRet_{[t+2:t+6]} - \widehat{MktRet_{[t+2:t+6]}})^2 / (MktRet_{[t+2:t+6]} - \overline{MktRet_{[t+2:t+6]}})^2, \quad (3)$$

where $\widehat{MktRet_{[t+2:t+6]}}$ is the predicted return using attention measures, and $\overline{MktRet_{[t+2:t+6]}}$ is the predicted return based on the random walk model (the average returns in the 500-day rolling window).

Following Campbell and Thompson (2008) and Chen et al. (2022), we access the economic value of attention measures under an asset allocation analysis. We consider a risk-averse mean-variance investor who rebalances her portfolio between market returns and Treasury bills according to the return forecast she observes from our attention measures. The weights of equities in the portfolio are determined by

$$w_t = \frac{1}{\gamma}\frac{\widehat{MktRet_{[t+2:t+6]}}}{\widehat{\sigma^2_{[t+2:t+6]}}},$$

where γ is the degree of risk aversion, $\widehat{MktRet_{[t+2:t+6]}}$ is the predicted *t+2*- to *t+6*-ahead return using attention measures, and $\widehat{\sigma^2_{[t+2:t+6]}}$ is the forecast of its variance. At each period, she invests w_t of her asset in the market return and $(1 - w_t)$ in Treasury bills.

The certainty equivalent return (CER) of the portfolio is

$$CER_p = \widehat{\mu_p} - 0.5\gamma\widehat{\sigma_p^2},$$

where $\widehat{\mu_p}$ is the sample mean of her portfolio, and $\widehat{\sigma_p^2}$ is the variance. Last, we obtain the CER gain by taking the difference between the CER from attention measures and the CER from the return forecasts based on the historical mean. We also compute the annualized Sharpe ratio for the portfolios.

Table 5, Panel A presents the out-of-sample market return prediction analysis and asset allocation analysis for ARA and AIA. ARA attains an out-of-sample R^2 of 1.49% for the testing period (August 2006 to December 2019). The corresponding Diebold and Mariano (2002) test statistic is 2.20, and the Clark and West (2007) test statistics is 2.16. This analysis indicates that ARA, beyond its in-sample significance, has strong out-of-sample forecasting power and outperforms the random walk benchmark. Following Campbell and Thompson (2008), we set the degree of risk aversion to 3 and consider a transaction cost of 50 basis points. The corresponding CER gain is 2.26%, suggesting that the investor would be willing to pay an annual fee of 226 basis points to access the information of aggregated retail attention. In contrast, AIA fails to outperform the benchmark when predicting the out-of-sample market returns.

Given our prior finding that the effects of ARA tend to be stronger during illiquid markets and periods of high VIX and that AIA's predictive power mainly exists prior to major news events, we also conduct out-of-sample analysis for the corresponding subsamples. Specifically, we focus on retail attention's predictability during illiquid markets (high aggregate spreads) and states of great aggregate uncertainty (high VIX), and institutional attention's predictability ahead of pre-scheduled news releases. Consistent with the in-sample findings, Table 5 shows that ARA has stronger forecasting ability when VIX is high (R^2 = 2.70%, CER gain = 2.76%) or aggregate spread is large (R^2 = 2.23%, CER gain = 2.75%), whereas AIA forecasts better prior to all news or macro news releases (R^2 = 1.08% and 1.19%, CER gain = 1.93% and 1.83%). This suggests that investors are willing to pay an annual fee of 275 to 276 basis points for ARA information during periods of high uncertainty and low liquidity, and 183 to 193 for AIA information in anticipation of important macroeconomic news.

To alleviate the concern that the out-of-sample performance may be affected by outliers, we follow Campbell and Thompson (2008) and impose restrictions on the market return forecasts. Specifically, using the 10% and 90% percentile numbers from thirty-year data of weekly market returns prior to our sample period (1974 to 2003), we winsorize forecasted returns based on these two cutoff points. The corresponding out-of-sample results are in Table 5, Panel B. The R^2, CER gain, and Sharpe Ratio barely change for AIA, and the out-of-sample performance of ARA is largely similar to the baseline results (no winsorization in the forecasts). In Table 5, Panel C, we also use the S&P 500 returns as the dependent variable. The results are largely similar to that of the CRSP value-weighted market return with some slight reduction in significance.[29]

Overall, the strong and consistent out-of-sample performance strengthens the economic significance of ARA and suggests that there are potentially large investment profits based on ARA. Furthermore, AIA possesses robust forecasting power when there are upcoming news releases, lending additional support to the role of institutional investors in information processing and uncertainty resolution.

2.6 Robustness Checks and Alternative Methodologies

2.6.1 Robustness Checks

In this subsection, we perform the following robustness checks and present the results in Table 6, Panel A. To mitigate the concern that our findings may be driven by the special period of the 2008 financial crisis, we repeat the main analysis excluding the crisis period of December 2007 to June 2009, as defined by the NBER.[30] Given that the weekday seasonality can be a nontrivial factor in influencing investor attention,[31] we include a weekday fixed effect in the model specification.

[29] In Appendix Table 5, we also report the gross Sharpe ratio (i.e., without fees), the turnover implied by our model and the benchmark random walk model. The gross Sharpe ratios for ARA in the full sample, high VIX subsample, and high spread subsample are 0.48, 0.54, and 0.57, respectively. As expected, they are larger than the net-of-fees Sharpe ratios (0.47, 0.54, and 0.56). The gross Sharpe ratios for AIA in the All News subsample and the Macro News subsample are 0.34 for both subsamples. The random walk benchmark model implies as much as four times turnover than our model.

[30] Due to data limitations, we are unable to conduct a similar analysis for AIA as its coverage only starts in 2010.

[31] See, for example, DellaVigna and Pollet (2009), Liu, Peng, and Tang (2023), and Noh, So, and Verdi (2021).

We also exclude samples within December and samples with our attention measures in the bottom 5% to rule out the possibility that the results may be driven simply by the episode of low year-end attention and overall high stock returns in January. We also report *t*-statistics estimated according to Hodrick (1992) standard errors to account for potential serial correlations in cumulative returns. In addition, we control for the lagged attention measure, and we replace the daily attention measure with its three-day moving averages. Furthermore, we replace the CRSP value-weighted market return with the S&P 500 return. As shown in Panel A, our results are robust to these variations: ARA negatively predicts future market returns, and AIA positively predicts future market returns preceding major news announcements.

In the last row of Table 6, Panel A, we conduct our analysis by including the monthly attention index (CTYZ, hereafter) by Chen et al. (2022) which is available till 2017. The CTYZ index is constructed from 12 attention proxies using the partial least square method and negatively predicts future market returns. We find that our results remain robust after this control.

2.6.2 Alternative Aggregation Methods

We further assess the return predictability of investor attention measures with alternative aggregation methods. Instead of value-weighting, we use partial least squares, principal component, 95^{th}-percentile-capped weighting, and equal-weighting methods.

For the principal component and partial least squares methods, we first aggregate firm-specific retail and institutional attention to the industry level based on the 49-industry definition in Fama and French (1997). For principal components, we deseasonalize the industry-based attention measures to avoid picking out common seasonalities. After obtaining the weights for each industry-level attention measure using partial least squares and principal component methods, we adjust the weights proportionally so the corresponding aggregated attention measure has a standard deviation of one.

To reduce the impact of firms with the enormous market cap (i.e., mega cap), we construct capped value-weighted ARA and AIA indices by winsorizing the market capitalization weights at the market capitalization of the top 25th, or at the 95th or 90th percentile of the market capitalization distribution. We denote the corresponding variables ARAcap25t, ARAcap95p, ARAcap90p, AIAcap25t, AIAcap95p, and AIAcap90p.[32]

Panel B of Table 6 reports the market return predictability of these alternative aggregation methods, including in-sample coefficient estimates, out-of-sample R^2, and the CER gain along with the Sharpe ratio from the asset allocation analysis. Of the retail attention measures, the partial least squares predictor (ARA^{PLS}) has the strongest predictive power both in terms of statistical significance and economic magnitude. A one standard deviation increase in ARA^{PLS} predicts a cumulative decrease of 29.00 basis points in the following week's market returns. ARA^{PLS} also attains significant out-of-sample R^2 of 2.14%, a CER gain of 4.00%, and a Sharpe ratio of 0.59, which are all stronger than the performance of the original ARA (1.49% out-of-sample R^2, 2.28% CER gain, and Sharpe ratio of 0.47). Both ARA^{PC} and ARA^{cap95p} exhibits in-sample and marginal out-of-sample market return predictability.[33]

[32] Appendix Table 6, Panel A illustrates the extent to which this procedure shrinks the total market capitalization of firms in our sample. For the ARA measures, winsorizing at the top 25th firm level and at the 95th and the 90th percentiles cap corresponds to a 17.24%, 35.85%, and 49.41% reduction in total market capitalization, respectively. For institutional attention indices, the corresponding reductions are 12.26%, 31.79%, and 44.94%, respectively. The result based on the 95th percentile winsorization is reported in Table 6, Panel B and the result based on all three winsorization methods is reported in Appendix Table 6, Panel B.

[33] ARA^{EW} does not exhibit statistically significant market predictability both in- and out-of-sample. Considering the size effect that we have discussed previously, the weaker results from equal-weighted retail attention measures are not surprising. In Appendix Table 6, Panel C, we show that ARA^{EW} exhibit negative in-sample predictability when forecasting the equal-weighted market return.

For institutional attention, the partial least squares predictor, AIA^{PLS}, also has significant and positive market return predictability before major news announcements. A one standard deviation increase in AIA^{PLS} leads to an increase of 23.10 basis points in the following week's market returns during *All News* subsamples. The out-of-sample R^2 is slightly improved for AIA^{PLS} compared to the original AIA, from 1.08% to 1.36% during *All News* subsamples. The CER gain and the Sharpe ratio are also slightly improved from 1.93% to 2.13% and from 0.33 to 0.40 during *All News* subsamples. In addition, the capped value-weighted AIA measures positively predict future market returns, both unconditionally and around major news announcements. The coefficients are statistically significant and similar to those obtained with the original measures.

These results provide strong support that the AIA and ARA's ability to predict market returns are not driven by a few mega-cap stocks and that our results remain robust when we drastically reduce the contribution of large cap stocks to the market portfolio, by as much as 44.94 percentage points.

2.6.3 Top-Down Measures

Our ARA and AIA measured are constructed via the bottom-up method, where we obtain abnormal retail/ institutional attention on individual stocks and aggregate them to market level. A question is whether direct attention to the overall market (i.e., a top-down approach) can generate similar findings.

To construct the top-down measures for retail attention, we collect the abnormal Google search volume (ASVI) for the seven market-related keywords, including "Dow", "DJIA", "Dow Today", "Dow Jones", "SP500", "S&P 500", "S&P 500 index" as in Liu, Peng, and Tang (2023). We then aggregate the ASVIs using partial least squares (PLS), principal components (PC), and equal weighting (EW) methods. For top-down institutional attention measures, we rely on one approach via the Bloomberg terminal: we collect the DMR for an index-ETF, SPY; Likewise, we transform them into indicator variables that takes the value of one when the DMR equals to 3 or 4 and zero otherwise. Lastly, we standardize all the top-down attention measures so that they all have unit standard deviations.

Table 6, Panel C reports the market return predictability of top-down retail and institutional attention measures, including in-sample coefficient estimates, out-of-sample R^2, CER gain, and the Sharpe ratio from the asset allocation analysis as in Panel B. For top-down retail attention measures, the signs of the coefficients are all negative, consistent with the bottom-up ARA. However, only the PLS-aggregated measure exhibits marginal in-sample predictability. None of the top-down retail attention measures predicts the market in out-of-sample tests. The corresponding CER gains and Sharpe Ratios are also low and do not generate economically meaningful profits. As for the top-down institutional measures, the in-sample coefficient is positive. Similar to retail attention, the top-down institutional attention measure does not exhibit out-of-sample predictability or generate economic profits.

One would expect the bottom-up attention measures to carry more relevant information in terms of market return predictability for both retail and institutional attention. The effect of retail attention on market returns is better manifested through individuals' actions on specific stocks, since retail investors tend to hold a small number of individual stocks (see Campbell, 2006; Barber and Odean, 2008; Guiso and Sodini, 2013). According to Campbell (2006) and the Survey of Consumer Finance (SCF), the median number of stocks directly held by US households ranges from 2 to 3 in early 2000s.[34] Appendix Table 7 further shows that, even as recent as 2022, the median holding is only eight stocks. Furthermore, using the stock popularity data from Robintrack for the period from May 2018 to February 2020, we analyze the number of Robinhood users holding a stock and find that the top 30 most popular stocks are all individual stocks. In contrast, the popularity of market-wide ETFs is substantially lower. For example, the popularity rankings of the ETFs, VOO, SPY, VTI, QQQ, and IVV, are 38, 48, 69, 99, and 340, respectively. This evidence supports the notion that retail investors are more likely to pay attention to the individual stocks that they own and this results in attention-driven buying (Barber and Odean 2008). As a result, the bottom-up ARA better captures attention-induced correlated retail buying pressure from individual stocks.

In contrast, top-down ARAs perform worse because retail investors may not devote timely attention to marketwide news and may not actively trade the market portfolio due to their concentrated holdings in individual stocks. Even if they do pay attention to the market, such attention may affect their trading of individual stocks only asynchronously. For example, after focusing on the market on day t, retail investors may turn their attention to some stocks on day t and others on days t+1, t+2, etc. As a result, subsequent price reversals on one stock could be offset by delayed retail attention and buying pressure on another stock, limiting the impact of such trading on aggregate returns.

For institutional investor attention, the bottom-up AIA can be viewed as measuring the percentage of the stock universe that institutional investors are paying attention to. A high AIA

[34] The Survey of Consumer Finance is a triennial cross-sectional survey of conducted by the Board of Governors of the Federal Reserve System (https://www.federalreserve.gov/econres/scfindex.htm). In each wave of the survey, the Federal Reserve Board asks around 30,000 non-repeating households that are representative to the US population about their financial status and decisions, such as direct and indirect stock holdings, participation in the pension fund, mortgage, personal debt, etc.

value reveals the systematic importance of the underlying event to which institutional investors direct their attention, and hence, it is associated with future market returns. The top-down AIA measure is unavailable. Instead, we use the AIA on SPY to capture top-down institutional investor attention and find it to have weaker market return predictive power. One possible reason is that the institutional investors' Bloomberg viewing activities of the SPY ETF may not adequately capture their attention to the overall market.

To summarize, the superiority of our bottom-up attention measures supports the economic channels underlying their market return predictability. Retail attention induced price pressure requires retail trading and retail investors typically hold and trade individual stocks, so the bottom-up ARA is a better way to capture such a price pressure at the market level. Similarly, the bottom-up ARA uniquely measures the fraction of the market that institutional investors are paying attention to simultaneously. A high value thus indicates how systematically important the upcoming announcement is.

2.7 Cross-Sectional Evidence

So far, our evidence for ARA suggests that high ARA leads to excessive demand from retail investors, which causes transitory price pressure that subsequently reverts, resulting in negative return predictability. In contrast, our evidence for AIA is consistent with the hypothesize that AIA is associated with uncertainty resolution and the realization of a risk premium.

In this subsection, we aim to further validate our time-series findings in the cross-section. Specifically, we test two hypotheses: first, that the market return predictability of ARA is more pronounced for less-liquid stocks, and second, that the market return predictability of AIA is stronger for stocks with higher exposure to systematic risk. We provide empirical evidence for these hypotheses in the following analysis.

2.7.1 The Return Predictability of ARA, by Liquidity

We first sort stocks into quintile portfolios based on the stock's average daily Amihud (2002) illiquidity measure (the absolute return divided by trading volume) over the past month. Quintiles 1 and 5 refer to the most illiquid and liquid portfolios, respectively. Table 7, Panel A presents the results, with column (1) for the full sample period, columns (2)–(3) for high/low-VIX subsample periods, and columns (4)–(5) for high/low spread subsample periods. The dependent variable is the cumulative return from day t+2 to t+6 for each portfolio.

Column (1) shows that ARA negatively predicts the return in the following week for all five portfolios. More importantly, the coefficient for the most illiquid portfolio is –5.675, which is statistically more negative than the coefficient for the most liquid portfolio (–3.443); the differences are highly significant with a *t*-statistic of –3.63. Economically, a one standard deviation increase in ARA is followed by a 30.65 basis point decrease in the illiquid portfolio returns and only an 18.59 basis point decrease in the subsequent returns of the liquid portfolio, suggesting that the illiquid portfolio is more likely to suffer from price pressure that leads to greater reversal afterward.

Columns (2) and (3) show that ARA has stronger return predictability for all five portfolios during high-VIX periods than during low-VIX periods. Across both VIX subsamples, ARA predicts more negative returns for the illiquid portfolio compared to that of the liquid portfolio. From columns (4) and (5), we also see that ARA predicts more-negative returns for all five portfolios in the high-spread days although the cross-sectional difference is marginally significant.

Perhaps during high-spread periods, all portfolios suffer from illiquidity and thus do not exhibit further significant differences in return reversals.

2.7.2 The Return Predictability of AIA, by Systematic Risk Exposure

As suggested earlier, AIA is associated with the resolution of systematic uncertainty; therefore, we expect AIA's predictability to be stronger for stocks with higher systematic risk exposures.

To test the hypothesis, we estimate a stock's CAPM beta using a five-year rolling window of monthly returns and sort stocks into quintile portfolios according to their beta. The median beta values for each of the quintile portfolios are 0.13, 0.61, 0.99, 1.37, and 2.23, respectively. We obtain daily value-weighted portfolio returns for each quintile portfolio and investigate the ability of AIA to predict beta-sorted quintile portfolio returns, as measured by the regression coefficients on AIA.

Table 7, Panel B presents the coefficient of AIA; column (1) shows the full sample and columns (2)–(3) and (4)–(5) correspond to two alternative news-day definitions, *All News* and *Macro News,* respectively. Columns (2) and (3) show that, similar to Table 2, Panel B, AIA positively predicts market returns, and the effects are present mostly when there is upcoming major news and insignificant when there is no news.

More importantly, column (2) shows that AIA's return predictability tends to be higher for the high-beta portfolio returns than for the low-beta portfolio returns. The AIA coefficients for the highest and the lowest beta quintile portfolios are 3.325 and 1.369, respectively, and the difference is statistically significant. Economically, a one standard deviation increase in AIA leads to a 33.25 basis point increase in the highest beta portfolio in the following week, whereas the corresponding return increase is only 13.69 basis points for the lowest beta portfolio. Columns (4) and (5) show a pattern similar to columns (2) and (3) prior to major macro news releases.[35]

In sum, the results show that the positive market return predictability of AIA is stronger for portfolios with higher exposures to systematic risk, providing further support to the hypothesis that institutional attention is associated with the resolution of systematic uncertainties.

3. Additional Analyses

This section provides additional analyses on our attention indices. We first provide identification with plausible exogenous variations in ARA to shed light on its causal relationship with future market returns. We then explore ARA and the abnormal market returns on clustered after-hour earnings announcements days to shed light onto a puzzle documented by Chen, Cohen, and Wang (2021).

3.1 Instrumental Variable Analysis: News Distractions

Because investor attention is likely endogenous, the relationship between attention and future returns may be driven by omitted variables. Our prior analysis mitigates such a concern in several ways. First, we control for a rich set of variables that the prior literature has employed in predicting market returns. Second, the predictive nature of our analysis alleviates the reverse causality issue that is often associated with the endogeneity problem. We provide further analysis by taking advantage of exogenous shocks to investor attention and use an instrumental variable approach to provide identification.

[35] ARA's return predictability is also stronger for portfolios with high beta, although there is no discernable pattern between news days and no-news days.

Specifically, we obtain daily news pressure based on the median number of minutes that US news broadcasts devoted to the first three news segments (Eisensee and Strömberg 2007).[36] Using the news pressure variable to construct an exogenous measure of "attention distraction," Peress and Schmidt (2020) find that episodes of sensational news distract noise traders and reduce trading activities, liquidity, and volatility for stocks with high retail ownership. Similarly, for each calendar year, we construct a distraction indicator, Dist, by selecting the 10% of business days with the highest news pressure, excluding days of major financial market movements.[37] We obtain 229 distraction days for the sample period of July 2004 through December 2018.

Table 8, Panel A presents the average level of ARA and AIA during the distraction days (Dist = 1) and nondistraction days (Dist = 0), respectively. It shows that the average ARA of 0.050 for the distraction days is significantly lower than the value of 0.067 for the nondistraction days, confirming the attention distraction effect of sensational news and the validity of the instrument. In contrast, AIA remains at a similar level, suggesting that institutional investors are less affected by sensational news and that therefore, the distraction measure is not a valid instrument for AIA.

We then use Dist as an instrumental variable and conduct two-stage least squares analysis to identify the causal relationship between retail attention and future market returns. Table 8, Panel B presents the results for the two stages, with columns (1)–(2) and (3)–(4) corresponding to the predictability analysis of ARA and AIA, respectively. Column (1) describes the first-stage results when ARA is regressed on Dist. It shows that the coefficient on Dist is significantly negative, consistent with the univariate analysis in Panel A. The inclusion of Dist contributes to an *F*-statistic

[36] We are grateful to David Strömberg for providing us with an updated time series of daily news pressure (available at http://perseus.iies.su.se/~dstro/).
[37] These include days with major macro news releases (Federal Open Market Committee meetings, nonfarm payroll, ISM Manufacturing Index, the Consumer Prices Index, or Producer Price Index News Releases), days with high absolute market returns (the highest 15% in the year), and the crisis year of 2008.

of 19.67, suggesting that Dist is not a weak instrument. In the second stage, we use the instrumented ARA to predict the following week's market returns. Column (2) shows that the coefficient of ARA is negative and significant, at –23.74.[38] On the other hand, columns (3) and (4) show that Dist does not predict AIA, and the *F*-statistic is also low in the first stage, suggesting that sensational news distracts retail attention but not institutional attention.

In sum, by employing the nonfundamental and exogenous news pressure shock to retail attention, we establish a causal relationship between ARA and future market returns.

3.2 Attention on Days of Clustered Earnings Announcements

We have shown that the negative market return predictability of ARA is in striking contrast to the positive return predictability of AIA. The results are consistent with ARA's triggering excessive buying activities from retail investors across a wide range of stocks, whereas AIA corresponds to the resolution of aggregate uncertainty. These findings suggest that understanding investor attention patterns can help us better understand how market returns react to information.

In this subsection, we apply these insights to an intriguing finding identified by Chen, Cohen, and Wang (2021)—while there is a substantial preannouncement return premium *preceding* clustered after-hours earnings announcements from major firms, such premiums are absent for morning announcements before 9:30 a.m. The preannouncement return premium is hard to explain

[38] The predicted ARA has a standard deviation of 0.031, which is much smaller than the 0.054 of the raw ARA. A one standard deviation increase in the predicted ARA leads to a decrease of 73.59 basis points in the following week's market return. The economic magnitude is much larger compared to that of the raw ARA. Nevertheless, the economic magnitude of the raw ARA represents the average association between all ARA variations and all the corresponding future market return variations. On the other hand, the two-stage least squares estimation only represents a local effect rooted in low retail attention due to the distraction by sensational news.

with rational models in which the bulk of uncertainty resolution occurs *after* major macro announcements.

We ask whether the patterns of ARA around clustered earnings announcement days could help shed light on this puzzle. Specifically, we obtain the announcement timestamps from I/B/E/S and construct clustered earnings announcement day indicators, EAC^{AM} and EAC^{PM}, as the top four days according to the total market capitalization of firms making announcements before (AM) or after (PM) trading hours in the months of January, April, July, and October. [39]

We begin by replicate Chen, Cohen, and Wang (2021) and present the average market return around the EAC^{PM} event window in Figure 3, Panel A. we observe that the market return on the event day is 17.16 basis points, before the clustered after-hours announcements, and is substantially higher than the return on the next day. In comparison, the unconditional market return premium on the macro announcement days is 11 basis points, with a substantial amount of returns being realized *after* the announcement (Savor and Wilson 2013; Ai and Bansal 2018).

To investigate the role of ARA, we conduct univariate analysis by evenly splitting the EAC^{PM} days according to the level of ARA on that day and plot the corresponding return premium. Figure 3, Panel B shows that the market return on the event day with high ARA is 29.39 basis points and highly significant, whereas the market return on the event day with low ARA is at an insignificant 4.93 basis points. In addition, the market return in the following day is –9.76 basis points if retail

[39] Chen, Cohen, and Wang (2021) use the announcement time stamps from Wall Street Horizon to construct clustered AM and PM earnings announcement indicators for pre markets and after markets, respectively. They focus on the top three days within January, April, July, and October when the most announcements are made. We were able to obtain similar results using the time stamps from I/B/E/S. Given our sample period, we expand the selection to be the top four days instead of three.

investors are attentive on the event day, while the market return in the following day is 26.37 basis points if retail investors are inattentive.

In Table 9, we further perform a regression analysis of market returns on the clustered earnings announcement indicator variable and its interactions with high-ARA indicators while controlling for the Baker-Wurgler sentiment index (BW), the term spread (TMS), the default yield spread (DFY), the change in the economic policy uncertainty index (ΔEPU), the change in the Aruoba-Diebold-Scotti business condition index (ΔADS), and the following variables and their lagged values for up to four lags: the Chicago Board Options Exchange Volatility Index (VIX), daily market returns (MktRet), and aggregate abnormal turnover (AbnTurn).

Column (1) shows that the market return is, on average, 21.07 basis points higher during EAC^{PM} days, consistent with Chen, Cohen, and Wang (2021). More importantly, on the EAC^{PM} days when aggregate retail attention is high, the market return is 33.48 basis points higher than the returns on days without clustered earnings announcements. The next-day return, as shown in column (3), is insignificant. In contrast, column (2) shows that when retail investors are inattentive to the stock market, the market return is insignificant on the announcement day. In this case, market returns become positive and significant (26.46 basis points) for the subsequent day, as shown in column (4).

This evidence suggests that the early realization of market returns in clustered after-hours earnings announcement days may be a result of excessive buying triggered by retail investor attention. Such price pressure preannouncement effectively shifts the return premium from day t+1 to day t. Our evidence provides direct support to the explanation proposed by Chen, Cohen, and Wang (2021) that investor attention triggers disagreements, leading to temporary overvaluation due to short-sale constraints.

4. Conclusion

Attention has been shown to play a crucial role in the information processing and trading decisions of investors and in the returns of individual stocks. In this paper, we provide new evidence that attention effects can aggregate and predict market returns, with distinctly different predictability depending on whether the attention is from retail or institutional investors.

We find that daily ARA negatively predicts the one-week-ahead market returns, especially during periods of poor market liquidity, high uncertainty, or more costly short selling. In contrast, daily AIA positively predicts future market returns prior to the release of important macroeconomic news or major firms' earnings announcements. The results are robust in out-of-sample tests, and the effect of ARA on subsequent returns is causal. Furthermore, ARA is positively associated with aggregate retail order imbalance and abnormal inflows to equity mutual funds. In the cross-section, ARA's return predictability is stronger among illiquid stocks, while AIA's return predictability is higher for stocks with higher market beta.

The findings are consistent with an explanation in which aggregate retail attention triggers a transitory marketwide price pressure that rapidly reverts, whereas aggregate institutional attention is positively associated with the systematic accrual of risk premiums. The rise of aggregate retail attention preceding clustered earnings days also provides insights into the preannouncement market return premium puzzle.

Together, our evidence suggests that attention effects are significant even for investors with well-diversified portfolios, and its crucial to consider the attention of various types of investors to understand aggregate economics outcomes.   Future work that explores high-frequency attention dynamics of different types of investors can provide new insights into important outcomes such as market efficiency and price formation.

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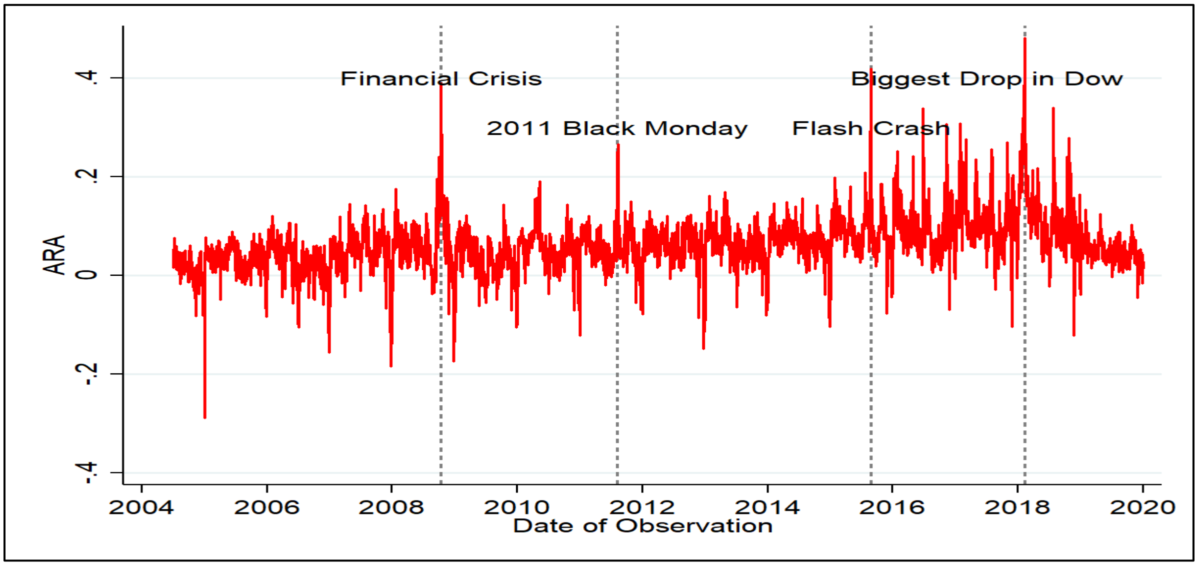
Panel A. Aggregate retail attention (ARA)



Panel B. Aggregate institutional attention (AIA)

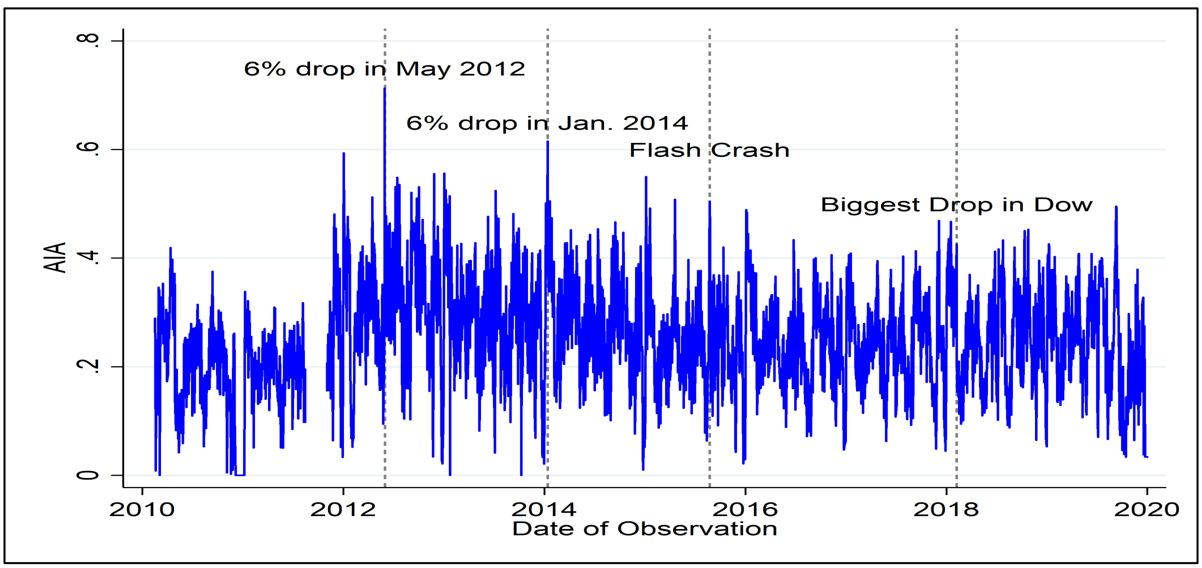
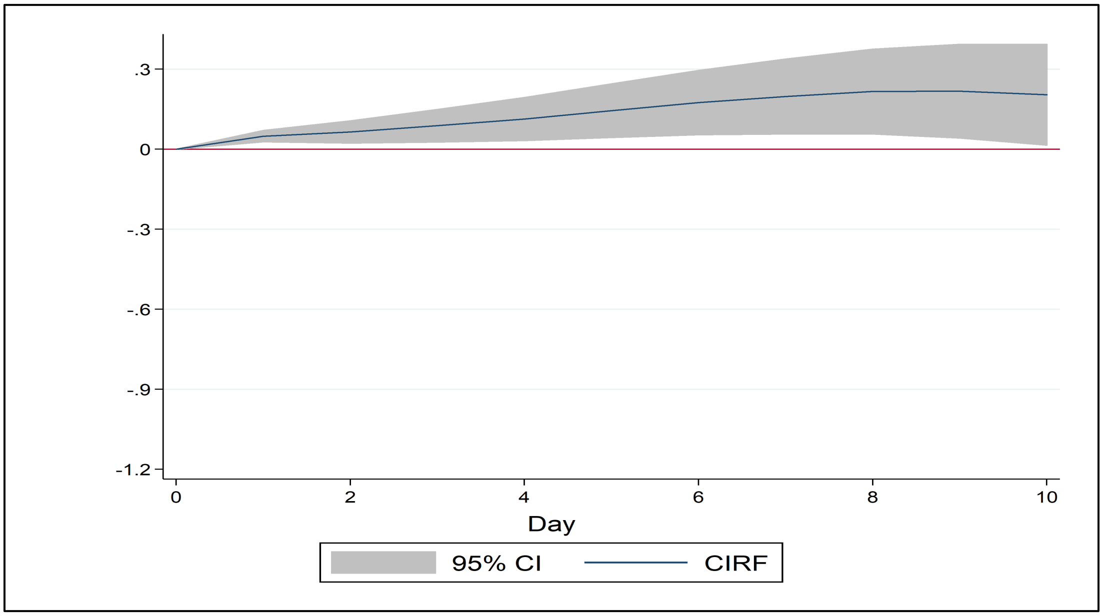


Figure 1. Time-series of retail and institutional attention

Panel A presents the daily aggregate retail attention (ARA) from July 2004 through December 2019. Panel B presents the daily aggregate institutional attention (AIA) from February 2010 through December 2019. The gray dashed lines correspond to major market events that coincide with attention spikes.

Panel A. CIRF of AIA on ARA



Panel B. CIRF of ARA on AIA

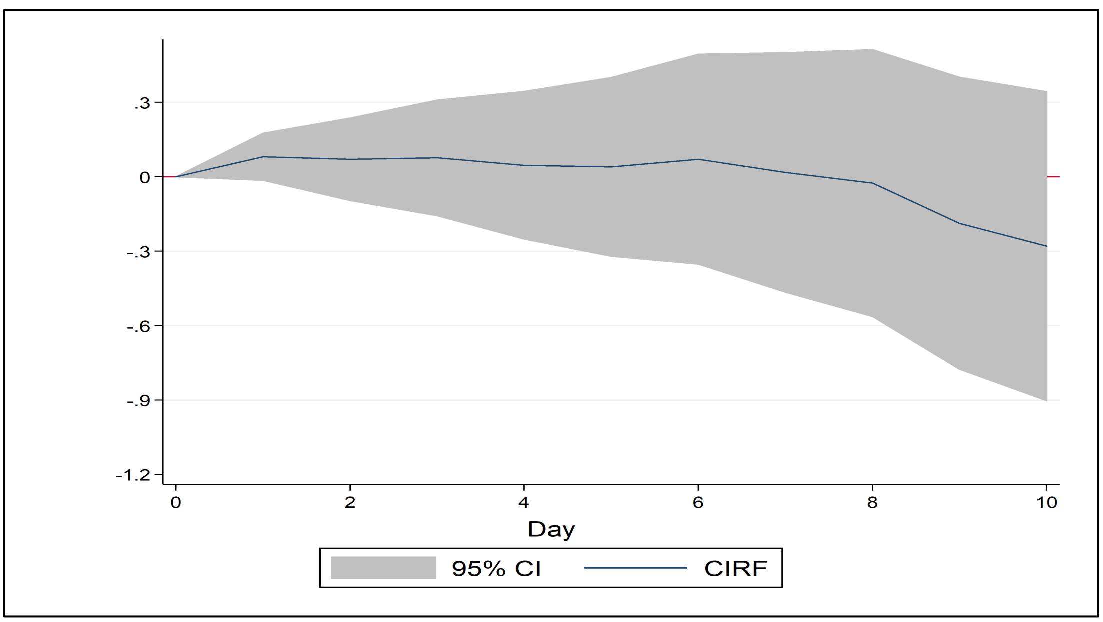
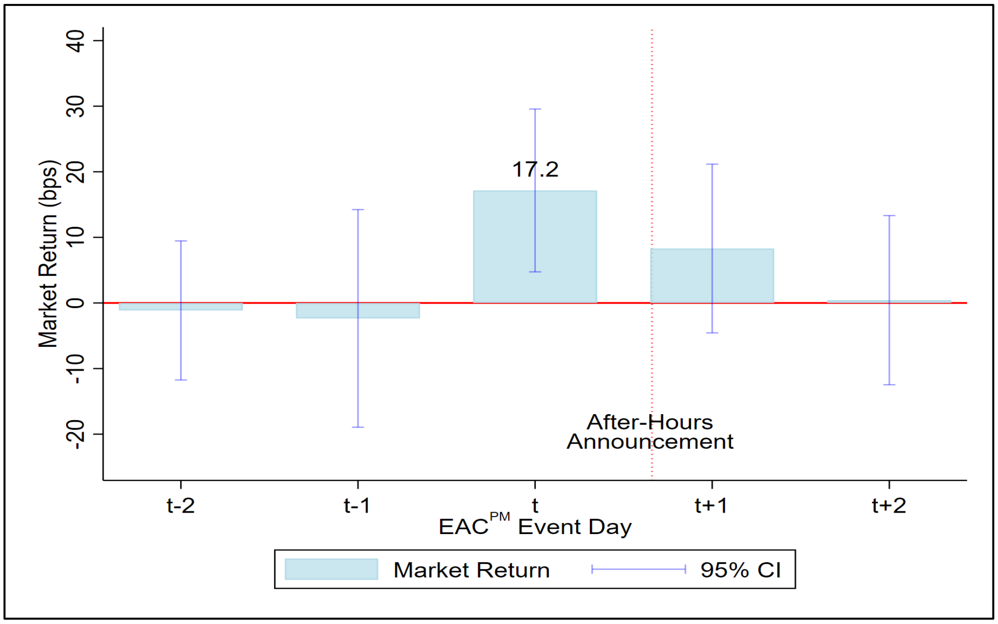


Figure 2. Cumulative impulse response functions of ARA and AIA

The figure presents the cumulative impulse response functions (CIRF) of ARA on AIA shocks (Panel A) and AIA on ARA shocks (Panel B). The VAR is estimated with daily observations and with up to six lags included. Both ARA and AIA are the deseasonalized residuals from regressing the corresponding raw measures on weekday and month fixed effects. The shaded areas correspond to the 95% confidence intervals (CI).

Panel A. Market returns on EAC^{PM} days



Panel B. Market returns on EAC^{PM} days with high/low ARA

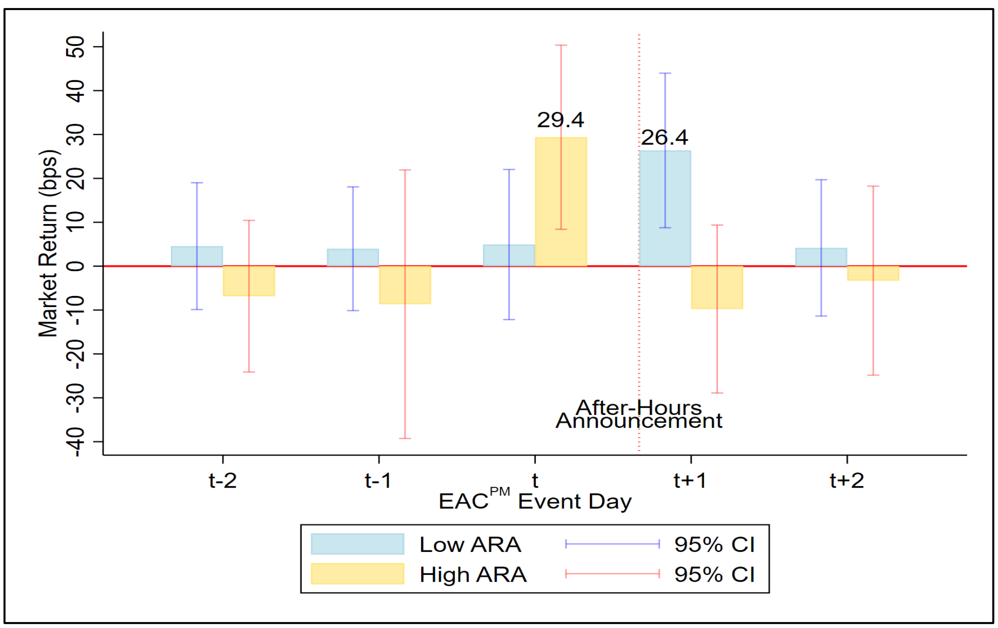


Figure 3. Market returns on clustered after-hours earnings announcement days

The figure presents the CRSP value-weighted market returns during the clustered after-hours earnings announcement (EAC^{PM}) event window. Panel A presents the market returns in the *t-2* to *t+2* EAC^{PM} event window; Panel B splits the events evenly into high/low ARA level according to its median.

Table 1. Descriptive statistics

Panel A reports the summary statistics of the attention measures and other variables. Panel B shows the correlation between attention measures and other daily variables. Aggregate retail attention (ARA) is the value-weighted firm-level abnormal Google search volume, which is the percentage change between the current Google Search Volume Index and its median in the previous six months. Aggregate institutional attention (AIA) is the value-weighted average across a firm-specific institutional attention indicator, where the indicator is one when the Bloomberg daily maximum readership is 3 or higher, and zero otherwise. Both ARA and AIA cover the entire CRSP universe. AbnTurn is the value-weighted, firm-level abnormal turnover ratio following Llorente et al. (2002). AbnNews is the aggregated abnormal volume (log difference relative to the past 30-day median) of news report from Ravenpack adjusted for seasonalities. ΔADS is the change in the Aruoba, Diebold, and Scotti (2009) business condition index. ΔEPU is the change in the economic policy uncertainty index from Baker, Bloom, and Davis (2016). VIX is the Chicago Board Options Exchange Volatility Index. BW is the Baker and Wurgler (2006) sentiment measure. TMS is the term spread, calculated as the difference between the long-term yield on government bonds and Treasury bills. DFY is the default yield spread, calculated as the difference between the BAA- and AAA-rated corporate bond yields. MktRet is the CRSP value-weighted return. All variables are at daily frequency except for BW, which is updated monthly. The sample covers the period from July 2004 through December 2019, except for AIA (which begins in February 2010). In Panel B, *$p < 0.1$; **$p < .05$; ***$p < .01$.

Panel A. Summary statistics

	N	Mean	Std	Min	Max	P25	Median	P75	Kurt	ρ
Attention Measures										
ARA	3,903	0.065	0.054	–0.289	0.473	0.035	0.060	0.089	8.21	0.77
AIA	2,431	0.254	0.100	0.000	0.711	0.190	0.252	0.319	3.22	0.57
Other Variables										
AbnTurn	3,903	–0.115	0.220	–1.570	0.916	–0.235	–0.123	–0.002	6.73	0.65
AbnNews	3,903	0.000	0.106	–0.313	0.327	–0.064	–0.004	0.062	4.03	–0.02
TMS (%)	3,903	2.991	1.745	–0.148	6.565	1.438	3.080	4.411	1.83	0.99
DFY (%)	3,903	1.063	0.466	0.530	3.500	0.830	0.930	1.170	13.00	0.99
ΔADS	3,903	0.000	0.028	–0.332	0.282	–0.010	–0.001	0.010	20.95	0.65
ΔEPU	3,903	–0.001	53.81	–304.29	351.78	–27.40	–0.63	26.03	7.57	–0.37
VIX	3,903	18.28	8.71	9.14	80.86	12.90	15.57	20.71	12.99	0.98
BW	3,903	–0.032	0.333	–0.894	0.866	–0.174	–0.022	0.154	3.56	0.94
MktRet (%)	3,903	0.032	1.146	–8.990	11.49	–0.402	0.070	0.539	14.24	–0.07

Panel B. Correlation (%)

	MktRet	ARA	AIA	AbnTurn	AbnNews	TMS	DFY	ΔADS	ΔEPU
ARA	–0.5								
AIA	–0.3	28.2***							
AbnTurn	–9.9***	45.6***	24.7***						
AbnNews	–1.1	20.0***	40.0***	28.9***					
TMS	0.1	–6.7***	–4.1**	–8.4***	–1.7				
DFY	–0.6	–7.5***	4.4**	8.8***	1.1	36.7***			
ΔADS	–3.7**	8.3***	0.4	3.8**	–2.5	5.1***	2.2		
ΔEPU	0.9	–3.1*	–2.0	–0.7	1.1	–0.2	–0.2	–1.2	
VIX	–13.5***	1.3	–7.8***	28.9***	0.4	46.9***	81.2***	2.8*	0.7

Table 2. Attention and market returns

This table reports the daily time-series regressions of future market returns on aggregate investor attention measures. The dependent variable is MktRet, which is the future CRSP value-weighted returns, for up to one week. ARA and AIA are aggregate retail and institutional attention, respectively. We include the following set of control variables: the abnormal volume of news reports from Ravenpack (AbnNews), the Baker-Wurgler sentiment index (BW), the term spread (TMS), the default yield spread (DFY), the change in the economic policy uncertainty index (ΔEPU), and the change in the Aruoba-Diebold-Scotti business condition index (ΔADS). In addition, we control for the following variables and their corresponding lagged values (for up to four lags): the Chicago Board Options Exchange Volatility Index (VIX), daily market returns (MktRet), and aggregate abnormal turnover (AbnTurn). Standard errors are adjusted using Newey-West corrections with 30 lags. Panel A reports results for ARA, and Panel B reports results for AIA. Newey-West *t*-statistics are reported in brackets. *$p < 0.1$; **$p < .05$; ***$p < .01$.

Table 2

Panel A. Retail attention (ARA)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MktRet	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*	*t+6*	*t+2:t+6*	*t+2:t+6*
ARA_t	–0.814**	–0.902**	–0.801**	–0.859***	–0.655	–0.805***	–2.879**	–4.137***
	[–2.24]	[–2.30]	[–2.03]	[–2.58]	[–1.62]	[–2.64]	[–2.22]	[–2.86]
$AbnNews_t$	0.294	0.079	–0.012	0.317*	–0.673***	0.062		–0.211
	[1.46]	[0.41]	[–0.06]	[1.66]	[–3.86]	[0.36]		[–0.57]
BW_t	–0.216**	–0.207**	–0.198**	–0.218**	–0.206**	–0.194**		–1.040**
	[–2.06]	[–2.02]	[–2.06]	[–2.16]	[–2.10]	[–2.18]		[–2.24]
TMS_t	–0.041***	–0.038***	–0.033**	–0.032**	–0.027**	–0.024**		–0.156**
	[–2.74]	[–2.60]	[–2.49]	[–2.36]	[–2.07]	[–2.06]		[–2.49]
DFY_t	–0.170*	–0.153	–0.087	–0.089	–0.054	–0.057		–0.450
	[–1.67]	[–1.64]	[–0.98]	[–0.92]	[–0.60]	[–0.63]		[–1.05]
ΔADS_t	–1.696	–1.023	–1.230	–1.372	–0.486	–0.961		–4.981
	[–1.52]	[–0.90]	[–0.95]	[–1.36]	[–0.52]	[–1.06]		[–1.15]
ΔEPU_t	–0.001	0.001*	0.001	–0.001	0.000	0.000		0.000
	[–1.17]	[1.80]	[1.55]	[–1.30]	[0.05]	[–0.79]		[0.68]
VIX_t	0.047	0.053	0.002	0.048	0.012	0.004		0.119*
	[1.12]	[1.20]	[0.07]	[1.55]	[0.54]	[0.12]		[1.94]
VIX_{t-1}	0.021	–0.040	0.046	–0.022	–0.005	–0.017		–0.036
	[0.39]	[–0.69]	[0.98]	[–0.52]	[–0.11]	[–0.43]		[–0.74]
VIX_{t-2}	–0.047	0.042	–0.025	–0.008	–0.016	0.013		0.009
	[–0.83]	[0.90]	[–0.60]	[–0.19]	[–0.38]	[0.28]		[0.18]
VIX_{t-3}	0.035	–0.031	–0.005	–0.020	0.011	–0.017		–0.066
	[0.81]	[–0.77]	[–0.13]	[–0.47]	[0.22]	[–0.36]		[–1.42]
VIX_{t-4}	–0.046	–0.014	–0.013	0.005	–0.002	0.018		–0.005
	[–1.33]	[–0.62]	[–0.39]	[0.18]	[–0.07]	[0.67]		[–0.09]
$AbnTurn_t$	–0.134	0.000	–0.065	–0.149	0.139	–0.056		–0.135
	[–0.77]	[0.00]	[–0.52]	[–1.16]	[1.00]	[–0.47]		[–0.47]
$AbnTurn_{t-1}$	0.034	–0.084	–0.067	0.018	–0.163	0.184		–0.119
	[0.26]	[–0.68]	[–0.57]	[0.14]	[–1.23]	[1.30]		[–0.65]
$AbnTurn_{t-2}$	–0.077	–0.039	–0.012	–0.067	0.140	0.031		0.049
	[–0.66]	[–0.34]	[–0.09]	[–0.53]	[0.97]	[0.29]		[0.34]
$AbnTurn_{t-3}$	–0.029	0.001	–0.076	28.900	0.021	0.021		0.166
	[–0.26]	[0.01]	[–0.60]	[1.32]	[0.19]	[0.13]		[0.83]
$AbnTurn_{t-4}$	0.043	0.053	0.218	0.038	–0.026	–0.033		0.247
	[0.36]	[0.49]	[1.51]	[0.39]	[–0.21]	[–0.25]		[0.87]
$MktRet_t$	–0.023	0.016	0.019	0.025	–0.036	0.017		0.040
	[–0.49]	[0.36]	[0.48]	[0.46]	[–0.92]	[0.26]		[0.45]
$MktRet_{t-1}$	0.020	0.025	0.025	–0.034	0.015	–0.030		0.005
	[0.43]	[0.62]	[0.45]	[–0.87]	[0.24]	[–0.53]		[0.06]
$MktRet_{t-2}$	0.022	0.027	–0.035	0.014	–0.026	0.002		–0.015
	[0.52]	[0.50]	[–0.88]	[0.23]	[–0.45]	[0.04]		[–0.18]
$MktRet_{t-3}$	0.023	–0.043	0.013	–0.025	0.005	–0.028		–0.076
	[0.42]	[–1.02]	[0.21]	[–0.42]	[0.08]	[–0.63]		[–0.84]
$MktRet_{t-4}$	–0.064	0.003	–0.018	–0.003	–0.011	0.036		0.016
	[–1.64]	[0.10]	[–0.45]	[–0.09]	[–0.45]	[1.03]		[0.22]
Intercept	0.136	0.161	0.167*	0.182*	0.183*	0.191**	0.344***	0.918**
	[1.38]	[1.61]	[1.68]	[1.84]	[1.87]	[2.15]	[3.33]	[2.05]
N	3,903	3,903	3,903	3,903	3,903	3,903	3,903	3,903
adj. R^2	0.017	0.010	0.006	0.006	0.004	0.000	0.004	0.022

Table 2

Panel B. Institutional attention (AIA)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MktRet	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*	*t+6*	*t+2:t+6*	*t+2:t+6*	*t+2:t+6*
AIA$_t$	0.396*	0.240	0.225	0.114	0.299	0.053	0.296	0.927	1.089*
	[1.75]	[1.18]	[1.15]	[0.61]	[1.63]	[0.32]	[0.55]	[1.52]	[1.72]
ARA$_t$									–2.643*
									[–1.71]
AbnNews$_t$	0.101	0.234	–0.141	0.115	–0.873	0.090		–0.576	–0.455
	[0.49]	[1.23]	[–0.61]	[0.62]	[–3.80]	[0.53]		[–1.32]	[–1.04]
BW$_t$	–0.131	–0.102	–0.111	–0.107	–0.107	–0.055		–0.482	–0.585
	[–0.99]	[–0.83]	[–0.85]	[–0.83]	[–0.81]	[–0.47]		[–0.79]	[–0.94]
TMS$_t$	–0.026*	–0.019	–0.025	–0.019	–0.017	–0.015		–0.094	–0.108
	[–1.77]	[–1.39]	[–1.61]	[–1.34]	[–1.18]	[–1.12]		[–1.40]	[–1.55]
DFY$_t$	–0.177	–0.143	–0.161	–0.102	–0.093	–0.092		–0.586	–0.616
	[–1.60]	[–1.35]	[–1.57]	[–0.99]	[–0.85]	[–0.90]		[–1.20]	[–1.25]
ΔADS$_t$	–0.901	–0.799	–0.596	–0.940	–1.120	–0.221		–3.678	–3.551
	[–1.22]	[–1.06]	[–0.79]	[–1.17]	[–1.58]	[–0.34]		[–1.24]	[–1.22]
ΔEPU$_t$	0.000	0.001	0.000	0.000	0.000	–0.001		0.000	0.000
	[–0.38]	[2.05]	[0.03]	[–0.17]	[0.56]	[–2.70]		[–0.02]	[–0.20]
VIX$_t$	0.049	–0.021	0.030	0.029	0.008	–0.029		0.014	0.017
	[1.03]	[–0.78]	[0.60]	[1.34]	[0.30]	[–0.90]		[0.29]	[0.34]
VIX$_{t-1}$	–0.046	0.046	0.006	–0.016	–0.042	0.064		0.061	0.069*
	[–0.84]	[0.81]	[0.13]	[–0.55]	[–1.20]	[1.88]		[1.45]	[1.71]
VIX$_{t-2}$	0.023	0.009	–0.016	–0.043	0.054*	–0.026		–0.021	–0.029
	[0.44]	[0.20]	[–0.58]	[–1.23]	[1.70]	[–0.76]		[–0.30]	[–0.41]
VIX$_{t-3}$	0.015	–0.009	–0.048	0.051	–0.005	–0.004		–0.014	–0.020
	[0.37]	[–0.33]	[–1.36]	[1.50]	[–0.17]	[–0.10]		[–0.36]	[–0.48]
VIX$_{t-4}$	–0.025	–0.014	0.042	–0.012	–0.007	0.005		0.014	0.008
	[–1.12]	[–0.66]	[1.43]	[–0.67]	[–0.22]	[0.18]		[0.19]	[0.11]
AbnTurn$_t$	–0.415**	–0.024	–0.120	–0.040	0.093	0.028		–0.066	0.193
	[–2.04]	[–0.16]	[–0.97]	[–0.29]	[0.70]	[0.21]		[–0.25]	[0.64]
AbnTurn$_{t-1}$	0.200	–0.146	0.022	–0.058	–0.018	–0.132		–0.341*	–0.246
	[1.22]	[–1.06]	[0.17]	[–0.45]	[–0.12]	[–1.03]		[–1.85]	[–1.26]
AbnTurn$_{t-2}$	–0.113	0.050	–0.033	0.057	–0.162	0.067		–0.019	0.021
	[–0.86]	[0.37]	[–0.25]	[0.38]	[–1.26]	[0.57]		[–0.11]	[0.12]
AbnTurn$_{t-3}$	0.071	–0.045	0.064	–0.108	0.079	0.037		0.026	0.046
	[0.54]	[–0.33]	[0.43]	[–0.85]	[0.66]	[0.27]		[0.15]	[0.26]
AbnTurn$_{t-4}$	–0.019	0.039	–0.078	0.071	–0.040	–0.105		–0.112	–0.044
	[–0.16]	[0.28]	[–0.67]	[0.66]	[–0.37]	[–0.78]		[–0.42]	[–0.16]
MktRet$_t$	0.011	0.002	0.006	0.005	–0.064	–0.059		–0.112	–0.096
	[0.21]	[0.03]	[0.11]	[0.11]	[–1.18]	[–1.15]		[–1.29]	[–1.12]
MktRet$_{t-1}$	0.017	0.006	0.007	–0.070	–0.057	0.056*		–0.059	–0.032
	[0.32]	[0.12]	[0.13]	[–1.37]	[–1.10]	[1.69]		[–0.63]	[–0.35]
MktRet$_{t-2}$	–0.002	0.008	–0.067	–0.057	0.053	–0.014		–0.075	–0.066
	[–0.03]	[0.17]	[–1.46]	[–1.11]	[1.64]	[–0.31]		[–0.64]	[–0.56]
MktRet$_{t-3}$	0.008	–0.059	–0.058	0.046	–0.006	–0.016		–0.091	–0.088
	[0.16]	[–1.27]	[–1.16]	[1.46]	[–0.13]	[–0.33]		[–0.76]	[–0.73]
MktRet$_{t-4}$	–0.077**	–0.003	0.031	–0.013	–0.019	0.023		0.021	0.019
	[–2.05]	[–0.11]	[1.18]	[–0.39]	[–0.83]	[0.77]		[0.30]	[0.29]
Intercept	–0.128	–0.044	–0.064	–0.011	–0.051	–0.032	0.127	–0.203	0.214
	[–1.23]	[–0.41]	[–0.66]	[–0.12]	[–0.57]	[–0.37]	[0.72]	[–0.49]	[0.42]
N	2,431	2,431	2,431	2,431	2,431	2,431	2,431	2,431	2,431
adj. R^2	0.012	0.009	0.007	0.004	0.010	0.000	0.000	0.016	0.018

Table 3. Market return predictability: Market states

This table reports the daily time-series regression coefficients of investor attention measures across market states. The dependent variable is the future two-to-six-day market returns, $MktRet_{[t+2:t+6]}$. ARA and AIA are aggregate retail and institutional attention, respectively. The subsamples are defined by the level of VIX, aggregate effective spread, and the abnormal value of the aggregate short sale fee. High (low) VIX period is defined as when VIX is above (below) its sample median. High (low) spread periods are defined as when the value-weighted stock level effective spread is above (below) its sample median. High (low) fee period is defined as when the abnormal short sale fee, which is the ratio of the aggregate short sale fee to its past three-month moving average, is above (below) its sample median. The control variables are the same as in Table 2. The *t*-statistics, calculated from White standard errors, bootstrapped standard errors, and Hodrick standard errors, are reported in brackets. Panel A presents the results for ARA, and Panel B presents the results for AIA. The sample period is from July 2004 to December 2019 for ARA and from February 2010 to December 2019 for AIA, except that short sale fee is only available from October 2006 through December 2011. $*p < 0.1$; $**p < .05$; $***p < .01$.

Panel A. ARA

	VIX			Aggregated Effective Spread			Short Sale Fee		
	High	Low		High	Low		High	Low	
	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)	(5)	(6)	(5) – (6)
Coefficient	–5.167	–1.170	–3.997	–6.303	–0.667	–5.636	–17.968	–4.000	–13.968
White *t*-stat	[–2.92]***	[–1.23]	[–1.99]**	[–3.59]***	[–0.59]	[–2.70]***	[–3.47]***	[–0.90]	[–2.04]**
Boot *t*-stat	[–2.87]***	[–1.19]	[–2.01]**	[–3.48]***	[–0.60]	[–2.69]***	[–3.52]***	[–0.87]	[–2.01]**
Hodrick *t*-stat	[–2.02]**	[–1.28]	[–2.11]**	[–2.12]**	[–0.44]	[–2.14]**	[–2.75]***	[–0.48]	[–1.83]*
1 std. mag. (bps)	–27.96	–6.29		–32.79	–3.46		–75.70	–20.59	
N	1,951	1,952		1,951	1,952		627	628	

Panel B. AIA

	VIX			Aggregated Effective Spread		
	High	Low		High	Low	
	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)
Coefficient	1.480	–0.200	1.680	0.920	–0.409	1.329
White *t*-stat	[2.13]**	[–0.40]	[1.96]**	[1.49]	[–0.69]	[1.55]
Boot *t*-stat	[2.11]**	[–0.41]	[1.93]*	[1.57]	[–0.68]	[1.54]
Hodrick *t*-stat	[1.88]*	[–0.42]	[2.50]**	[0.98]	[–0.58]	[1.54]
1 std. mag. (bps)	15.42	–1.90		10.18	–3.57	
N	1,213	1,218		1,216	1,215	

Table 4. Market return predictability: News days

This table reports the daily time-series regression coefficients of investor attention measures across market states. The dependent variable is the future two-to-six-day market returns, $MktRet_{[t+2:t+6]}$. ARA and AIA are aggregate retail and institutional attention, respectively. The subsamples are defined by macro and firms earnings announcements. The *Macro News* indicator variable is defined as one when the macro news announcements of FOMC meetings, nonfarm payroll, or PPI are made in day t+2 to t+6. The *All News* indicator variable is defined as one when there are announcements on day t+2 to t+6 of either macro news or earnings of major firms. The control variables are the same as in Table 2. The *t*-statistics, calculated from White standard errors, bootstrapped standard errors, and Hodrick standard errors, are reported in brackets. Panel A presents the results for AIA, and Panel B presents the results for ARA. The sample period is from July 2004 to December 2019 for ARA and from February 2010 to December 2019 for AIA. *$p < 0.1$; **$p < .05$; ***$p < .01$.

Panel A. AIA

	Macro News			All News		
	Yes	No		Yes	No	
	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)
Coefficient	2.076	–0.375	2.451	2.072	–0.714	2.786
White *t*-stat	[3.20]***	[–0.63]	[2.78]***	[3.48]***	[–1.06]	[3.10]***
Boot *t*-stat	[3.25]***	[–0.60]	[2.58]***	[3.65]***	[–1.03]	[2.84]***
Hodrick *t*-stat	[2.33]**	[–0.44]	[2.79]***	[2.49]**	[–0.76]	[3.11]***
1 std. mag. (bps)	20.82	–3.74		20.64	–7.04	
N	1,219	1,212		1,395	1,036	

Panel B. ARA

	Macro News			All News		
	Yes	No		Yes	No	
	(1)	(2)	(1) – (2)	(3)	(4)	(3) – (4)
Coefficient	–2.505	–5.225	2.720	–3.421	–3.985	0.564
White *t*-stat	[–1.69]*	[–4.50]***	[1.44]	[–2.60]***	[–3.05]***	[0.30]
Boot *t*-stat	[–1.83]*	[–4.40]***	[1.45]	[–2.66]***	[–3.13]***	[0.30]
Hodrick *t*-stat	[–0.96]	[–2.43]**	[1.20]	[–1.51]	[–1.74]*	[0.24]
1 std. mag. (bps)	–14.00	–27.30		–18.74	–21.21	
N	2,048	1,855		2,363	1,540	

Table 5. Out-of-sample tests

This table reports the out-of-sample analysis of ARA's and AIA's ability to predict future two-to-six-day market returns. We report R^2, the improved prediction power compared to the random walk hypothesis, the Diebold Mariano (DM) *t*-statistics, and the Clark and West (CW) *t*-statistics. Following Campbell and Thompson (2008) and Chen et al. (2022), we report the certainty equivalent return (CER) gain for the risk-aversion level of 3 and the corresponding Sharpe ratio, and they are all computed with a 50 basis points transaction cost. This table presents the out-of-sample tests for ARA and AIA, for the full sample, and by market states and news releases. Out-of-sample test begins in August 2006 for ARA and March 2012 for AIA. Panel A reports the baseline (as described above) out-of-sample results. Panel B is for the forecasted market return that is winsorized at both 10% and 90%. Panel C is for forecasting the S&P500 return instead of the CRSP value-weighted return. $^{*}p < 0.1$; $^{**}p <. 05$; $^{***}p < .01$.

Panel A. Baseline results

	R^2	DM *t*-stats	CW *t*-stats	N	CER Gain	Sharpe Ratio
ARA						
Full sample	1.49%**	[2.20]	[2.16]	3,378	2.26%	0.47
High VIX	2.70%***	[2.79]	[2.77]	1,637	2.76%	0.54
Low VIX	–0.39%	[–0.43]	[–0.45]	1,741		
High spread	2.23%**	[2.47]	[2.44]	1,423	2.75%	0.56
Low spread	–0.50%	[–0.86]	[–0.80]	1,952		
AIA						
Full sample	–0.36%	[–1.16]	[–0.96]	1,972	–0.74%	0.16
All News	1.08%*	[1.76]	[1.77]	1,120	1.93%	0.33
No News	–0.60%	[–0.55]	[–0.61]	852		
Macro News	1.19%*	[1.95]	[1.89]	978	1.83%	0.33
No News	–0.39%	[–0.57]	[–0.61]	994		

Panel B. Winsorizing forecasted market returns

Winsorized	R^2	DM *t*-stats	CW *t*-stats	N	CER Gain	Sharpe Ratio
ARA						
Full sample	1.50%**	[2.21]	[2.17]	3,378	2.27%	0.47
High VIX	2.27%***	[2.80]	[2.78]	1,637	2.68%	0.51
Low VIX	–0.29%	[–0.37]	[–0.40]	1,741		
High spread	2.24%**	[2.47]	[2.43]	1,423	2.77%	0.55
Low spread	–0.49%	[–0.85]	[–0.80]	1,952		
AIA						
Full sample	–0.36%	[–1.16]	[–0.96]	1,972	–0.74%	0.16
All News	1.08%*	[1.76]	[1.77]	1,120	1.93%	0.33
No News	–0.60%	[–0.53]	[–0.60]	852		
Macro News	1.19%*	[1.95]	[1.89]	978	1.83%	0.33
No News	–0.39%	[–0.57]	[–0.61]	994		

Panel C. S&P500 returns

S&P 500 Ret	R^2	DM *t*-stats	CW *t*-stats	N	CER Gain	Sharpe Ratio
ARA						
Full sample	1.28%**	[2.02]	[1.96]	3,378	1.89%	0.46
High VIX	2.04%**	[2.68]	[2.44]	1,637	2.60%	0.51
Low VIX	–0.20%	[–0.39]	[–0.41]	1,741		
High spread	1.96%**	[2.28]	[2.22]	1,423	2.59%	0.49
Low spread	–0.45%	[–0.86]	[–0.82]	1,952		
AIA						
Full sample	–0.35%	[–1.21]	[–1.00]	1,972	–0.42%	0.18
All News	0.96%*	[1.66]	[1.61]	1,120	1.76%	0.35
No News	–0.49%	[–0.55]	[–0.53]	852		
Macro News	1.04%*	[1.89]	[1.79]	978	1.67%	0.34
No News	–0.47%	[–0.42]	[–0.40]	994		

Table 6. Robustness checks and alternative attention measures

Panel A reports additional robustness checks for the return predictability of investor attention. ARA and AIA are aggregate retail and institutional attention, respectively. The dependent variable is the future two-to-six-day CRSP value-weighted market returns, $MktRet_{[t+2:t+6]}$. In Panel A, we conduct robustness checks of Table 2, Panel A for the regression of market returns on ARA/AIA with the following: exclude the NBER-defined crisis period (December 2007 through June 2009), control for weekday fixed effects, exclude December, exclude the bottom 5% of ARA/AIA, estimate *t*-statistics using Hodrick (1992) standard errors, include the lagged attention measure, use three-day moving averages as the attention measure, control for CTYZ attention measure from Chen et al. (2022), and use the future two-to-six-day S&P 500 returns as the dependent variable. Panel B conduct robustness checks of Table 4 and Table 5 and reports the regression of market returns on alternative ARA and AIA measures, constructed from the stock-level attention measures using partial least squares (PLS), principal components (PC), value weighting with the market cap winsorized at the 95th percentile weighting (Cap95), and equal weighting (EW). We present the results of ARA for the full sample and AIA using the *All News* sample as defined in Table 4, respectively. We report the in-sample coefficients, out-of-sample R^2, and CER gain with the risk-aversion and transaction cost parameters described in Table 5. Panel C follows the same set up as in Panel B, but with alternative retail and institutional attention measured constructed using top-down methods. The control variables are described in Tables 2 Panel A and Table 4, respectively. Similarly, Panel A reports Newey-West (White heteroskedasticity-robust) *t*-statistics in brackets for ARA (AIA) and separately reports the result with Hodrick standard errors. Panel B and Panel C report, in brackets, Newey-West (White heteroskedasticity-robust) *t*-statistics for the in-sample coefficients and Clark and West *t*-statistics for the out-of-sample R^2. *$p < 0.1$; **$p < .05$; ***$p < .01$.

Panel A. Robustness checks

	ARA	*N*	*adj.* R^2	AIA-News	*N*	*adj.* R^2
Exclude the crisis period	–2.871**	3,507	0.026			
	[–2.46]					
Control for weekday FE	–4.279***	3,903	0.022	2.501***	1,395	0.019
	[–2.83]			[4.00]		
Exclude December	–4.524***	3,567	0.024	2.188***	1,308	0.020
	[–2.94]			[3.53]		
Exclude bottom 5% ARA/AIA	–4.111***	3,691	0.023	2.600***	1,340	0.021
	[–2.61]			[3.75]		
Hodrick standard errors	–4.137**	3,903	0.022	2.072**	1,395	0.020
	[–2.34]			[2.49]		
Control for lagged attention	–3.101***	3,902	0.023	1.791**	1,394	0.022
	[–2.83]			[2.47]		
3-day moving average attention	–4.859***	3,903	0.023	2.271***	1,395	0.019
	[–2.68]			[3.24]		
S&P500 $return_{[t+2:t+6]}$	–3.595***	3,897	0.020	2.031***	1,395	0.018
	[–2.64]			[3.50]		
Control for CTYZ attention	–4.809***	3,400	0.040	2.430***	1,117	0.028
	[–2.96]			[3.52]		

Panel B. Bottom-up attention measures with alternative aggregation methods

		In-Sample Coeff.	*OOS-R^2*	CER Gain	Sharpe Ratio
ARA					
	Partial Least Squares	–0.290***	2.14%**	4.00%	0.59
		[–3.66]	[2.41]		
	Principal Component	–0.163**	1.08%*	0.83%	0.37
		[–2.56]	[1.77]		
	ARAcap95p	–0.153**	1.07%*	1.83%	0.38
		[–2.25]	[1.83]		
	Equal weight	–0.089	0.21%	0.12%	0.26
		[–1.51]	[0.57]		
AIA-News					
	Partial Least Squares	0.231***	1.36%*	2.13%	0.40
		[3.71]	[1.83]		
	Principal Component	0.048	0.32%	0.23%	0.18
		[0.83]	[0.81]		
	AIAcap95p	0.124**	0.95%	1.38%	0.29
		[2.08]	[1.64]		
	Equal weight	0.060	0.66%	0.83%	0.22
		[0.97]	[1.35]		

Panel C. Alternative Top-Down attention measures

		In-Sample Coeff.	*OOS-R^2*	CER Gain	Sharpe Ratio
Top-down retail attention					
	Partial Least Squares	–0.086*	0.54%	0.34%	0.14
		[–1.67]	[0.64]		
	Principal Component	–0.314	0.59%	0.36%	0.13
		[–1.61]	[0.53]		
	Equal weight	0.017	0.20%	0.32%	0.11
		[0.37]	[0.32]		
Top-down institutional attention					
	DMR(SPY)	0.110*	0.42%	0.16%	0.17
		[1.94]	[0.56]		

Table 7. Attention and the cross-section of portfolios

This table reports the time-series regression coefficients of ARA (aggregate retail attention) and AIA (aggregate institutional attention) on future two-to-six-day cumulative portfolio returns. Panel A reports the coefficients of ARA to predict liquid and illiquid portfolio future returns for high/low VIX markets and high/low spread markets. The high/low VIX and spread subsamples are defined by their full sample median. Stocks are sorted into quintile portfolios based on their average Amihud illiquidity measure in the past month. Panel B reports the coefficients of AIA to predict beta-sorted portfolio future returns for news and no-news days The *Macro News* indicator variable is defined as one when the following macro news announcements of FOMC meetings, nonfarm payroll, or PPI take place on day t+2 to t+6. The *All News* indicator variable is defined as one when there are announcements on day t+2 to t+6 of either macro news or earnings of major firms. Stocks are sorted into quintile portfolios based on their CAPM betas. For both panels, the dependent variable is the future two-to-six-day returns of quintile portfolios, and the control variables are the same as in Table 2. The *t*-statistics are calculated from White standard errors. *$p < 0.1$; **$p < .05$; ***$p < .01$.

Panel A. Retail attention and returns of liquidity-sorted portfolios

	Full Sample (1)	High VIX (2)	Low VIX (3)	(2) – (3)	High spread (4)	Low spread (5)	(4) – (5)
1	–3.443**	–4.276**	–0.956	–3.320*	–5.699***	–0.579	–5.120**
(Liquid)	[–2.54]	[–2.51]	[–0.98]	[–1.69]	[–3.42]	[–0.51]	[–2.54]
2	–4.497***	–5.490***	–1.230	–4.260*	–6.975***	–0.631	–6.343***
	[–2.61]	[–2.77]	[–1.25]	[–1.92]	[–3.50]	[–0.54]	[–2.75]
3	–5.445***	–6.964***	–1.271	–5.693**	–7.287***	–1.323	–5.964**
	[–2.75]	[–3.21]	[–1.18]	[–2.35]	[–3.33]	[–1.09]	[–2.38]
4	–5.411***	–6.455***	–1.549	–4.906**	–7.515***	–1.194	–6.321**
	[–2.86]	[–2.95]	[–1.45]	[–2.02]	[–3.42]	[–0.95]	[–2.50]
5	–5.675***	–6.581***	–1.949*	–4.632**	–7.036***	–1.509	–5.527**
(Illiquid)	[–3.41]	[–3.19]	[–1.93]	[–2.02]	[–3.44]	[–1.25]	[–2.33]
5–1	–2.232***	–2.305***	–0.994**	–1.312	–1.337*	–0.930*	–0.407
	[–3.63]	[–3.42]	[–2.15]	[–1.60]	[–1.94]	[–1.85]	[–0.48]

Panel B. Institutional attention and returns of CAPM beta-sorted portfolios

	Full Sample (1)	All News (2)	No News (3)	(2) – (3)	Macro News (4)	No News (5)	(4) – (5)
1	0.859**	1.369***	0.119	1.250**	1.284***	0.398	0.886
(Low)	[2.04]	[3.40]	[0.24]	[1.97]	[2.98]	[0.89]	[1.43]
2	0.965*	1.826***	–0.257	2.083***	1.846***	–0.025	1.872**
	[1.84]	[3.57]	[–0.43]	[2.66]	[3.36]	[–0.05]	[2.44]
3	0.778	1.842***	–0.719	2.561***	1.655**	–0.290	1.945*
	[1.17]	[2.62]	[–1.03]	[2.58]	[2.13]	[–0.46]	[1.95]
4	0.889	2.259***	–1.093	3.352***	2.358***	–0.764	3.121***
	[1.21]	[3.13]	[–1.38]	[3.13]	[2.99]	[–1.09]	[2.96]
5	1.315	3.325***	–1.574	4.899***	3.512***	–1.230	4.742***
(High)	[1.36]	[3.57]	[–1.52]	[3.53]	[3.45]	[–1.35]	[3.47]
5–1	0.456	1.956***	–1.693**	3.649**	2.228***	–1.628**	3.857***
	[0.59]	[2.68]	[–2.15]	[2.49]	[2.77]	[–2.35]	[2.58]

Table 8. Instrumental variable analysis

This table reports the instrumental variable analysis of attention's return predictability. We define a "distraction" indicator, Dist, as when the Eisensee and Strömberg (2007) news pressure variable belongs to the top 10% of its annual distribution. We exclude the days with macro announcements (FOMC meetings, nonfarm payroll, ISM Manufacturing index, CPI, or PPI), days with high absolute market returns, and the crisis period. Panel A reports the average of ARA and AIA during distraction and nondistraction days, respectively. Panel B reports the two-stage least squares results using Dist as an instrumental variable. The dependent variable is $MktRet_{[t+2:t+6]}$, which is the CRSP value-weighted return. The independent variables are instrumented ARA and AIA. The control variables are the same as in Table 2. Newey-West *t*-statistics are reported in brackets. * $p< 0.1$; ** $p < .05$; *** $p < .01$.

Panel A. Univariate contrast

	Dist = 0	Dist = 1	Diff
ARA	0.067	0.050	0.017***
N	3,422	229	[4.40]
AIA	0.256	0.252	0.004
N	2,038	141	[0.51]

Panel B. Two-stage least squares

Dependent variable		First stage ARA (1)	Second stage $MktRet_{[t+2:t+6]}$ (2)	First stage AIA (3)	Second stage $MktRet_{[t+2:t+6]}$ (4)
Predicted ARA			–23.737		
	N-W *t*-stats		[–1.87]*		
	Hodrick t-stats		[–2.23]**		
Predicted AIA					49.899
	N-W *t*-stats				[1.78]
	Hodrick t-stats				[1.89]
Dist		–0.014***		0.006	
	N-W *t*-stats	[–3.50]		[0.82]	
N		3,651	3,651	2,179	2,179
First-stage *F*-statistics		19.673		0.687	
adj. R^2		0.332	0.016	0.257	0.014

Table 9. Market return predictability: Clustered earnings announcement days

This table reports the daily time-series regressions with clustered earnings announcement days. The dependent variable is daily MktRet (presented in basis points), which is the CRSP value-weighted returns. EAC^{PM} (EAC^{AM}) is an indicator variable that takes the value of one for the top four days that have the highest total market capitalization of after-market (premarket) earnings-announcing firms in January, April, July, and October, similar to Chen, Cohen, and Wang (2021). HighARA is an indicator variable that takes the value of one when ARA is above the median of the sample of these PM announcement days. We then interact the high-ARA dummy, HighARA, with the clustered PM announcement days, EAC^{PM}. The control variables are the same as in Table 2. Standard errors are adjusted using Newey-West corrections with 30 lags. Newey-West *t*-statistics are reported in brackets. $^{*}p < 0.1$; $^{**}p < .05$; $^{***}p < .01$.

Table 9.

MktRet (bps)	(1) *t*	(2) *t*	(3) *t+1*	(4) *t+1*
EAC^{AM}	–9.105	–9.987	–6.159	–4.832
	[–0.75]	[–0.84]	[–0.83]	[–0.65]
EAC^{PM}	20.825**		9.252	
	[2.44]		[1.29]	
EAC^{PM} *HighARA		33.478***		–9.794
		[2.80]		[–0.92]
EAC^{PM} *(1– HighARA)		9.396		26.455***
		[0.84]		[2.67]
$AbnNews_{t-1}$	22.670	21.821	2.824	4.101
	[1.12]	[1.07]	[0.14]	[0.21]
BW_t	–14.661	–14.338	–16.638*	–17.124*
	[–1.64]	[–1.59]	[–1.87]	[–1.93]
TMS_{t-1}	–3.752***	–3.735***	–3.573***	–3.599***
	[–2.61]	[–2.60]	[–2.58]	[–2.59]
DFY_{t-1}	–20.016**	–19.860**	–14.819	–15.054
	[–2.02]	[–2.00]	[–1.55]	[–1.58]
ΔADS_{t-1}	–166.724	–167.179	–110.932	–110.246
	[–1.50]	[–1.51]	[–0.95]	[–0.94]
ΔEPU_{t-1}	–0.045	–0.046	0.097*	0.098*
	[–1.04]	[–1.05]	[1.83]	[1.83]
VIX_{t-1}	3.974	3.906	5.098	5.200
	[0.96]	[0.95]	[1.16]	[1.18]
VIX_{t-2}	2.069	2.216	–4.099	–4.319
	[0.37]	[0.39]	[–0.70]	[–0.73]
VIX_{t-3}	–4.792	–4.838	4.054	4.124
	[–0.85]	[–0.85]	[0.87]	[0.88]
VIX_{t-4}	0.239	0.200	–3.999	–3.939
	[0.07]	[0.06]	[–1.19]	[–1.17]
$AbnTurn_{t-1}$	–18.126	–18.427	–8.372	–7.919
	[–1.04]	[–1.05]	[–0.70]	[–0.66]
$AbnTurn_{t-2}$	1.953	1.436	–10.303	–9.524
	[0.15]	[0.11]	[–0.84]	[–0.77]
$AbnTurn_{t-3}$	–7.726	–7.746	–4.380	–4.351
	[–0.65]	[–0.66]	[–0.38]	[–0.38]
$AbnTurn_{t-4}$	–1.855	–2.073	0.557	0.885
	[–0.17]	[–0.19]	[0.05]	[0.08]
$MktRet_{t-1}$	–3.100	–3.156	1.173	1.258
	[–0.68]	[–0.70]	[0.26]	[0.28]
$MktRet_{t-2}$	1.049	1.167	2.085	1.906
	[0.23]	[0.26]	[0.50]	[0.46]
$MktRet_{t-3}$	1.471	1.453	2.163	2.190
	[0.34]	[0.34]	[0.40]	[0.40]
$MktRet_{t-4}$	–2.512	–2.517	–5.903	–5.895
	[–0.84]	[–0.84]	[–1.52]	[–1.51]
Intercept	3.405	3.240	5.996	6.245
	[0.41]	[0.39]	[0.75]	[0.80]
N	3,902	3,902	3,902	3,902
adj. R^2	0.013	0.013	0.010	0.011

Appendix

A.1 Vintage data for Google searches

Our data collection effort occurred in three phases, between 2015 and 2020, during which we obtain three vintages of data. We rigorously cross check for data consistency across the three vintages and for the robustness of our findings.

Specifically, the first vintage is collected at the end of 2015, for which we collected SVI for the period from 2004 through 2014. Then, in the mid of 2019, we collected the second vintage for the period 2013 through 2018. At the end of 2020, we obtained the third vintage for the period 2017 through 2019. We cross-validate the data from different vintages by comparing the value of SVI for observations in the overlapping window and cross-check for data consistency. We then conduct robustness checks and replicate the main regression with different vintages. In Appendix Table 8, columns (2) and (3), we report the results of the predictive regression analysis (corresponding to Table 2) using only information collected from the first vintage, and from the first and second vintages, respectively. We show that our results remain robust. These analyses therefore give credence to our findings, indicating that the results are unlikely to be due to backward filling by Google Trends when it periodically updates its methodology.

A.2 Alternative ARA measure

We have shown that ARA and AIA are related to future market returns oppositely. One potential concern is that the opposite signs might be driven by the differences in the way these two variables are constructed. ARA is the value-weighted abnormal Google search index (ASVI) of stock tickers, which is calculated as the percentage change relative to the past 6-month median. On the other hand, AIA is the value-weighted indicator variable of Bloomberg maximum daily news readership (DMR) relative to the past 30-day distribution. Since we do not have access to the raw data behind DMR, we transform the retail attention index following the approach for the construction of DMR so that we obtain comparable measures of retail and institutional attention.

Specifically, we define an indicator variable, I_{SVI}, as equal to one when a stock's daily *SVI* is higher than the 75th percentile value of the stock's SVI distribution over the past 30 days, and 0 otherwise. We then define the aggregate retail attention index, ARA^c, as the value-weighted average of the individual I_{SVI}. ARA^c has a mean of 0.276 and a standard deviation of 0.079. In comparison, AIA has a similar mean and standard deviation, with the corresponding numbers at 0.254 and 0.100, respectively.

We replicate the main analysis in Tables 2 and 3 and present the results in Appendix Table 1. Column (1), ARA^c negatively predicts future market returns with the coefficient at −1.389 and is marginally significant with a *t*-statistics of −1.77. In terms of the economic magnitude, one standard-deviation increase in ARA^c leads to 10.97 basis points decrease in the market return in the following week ($-1.389\times0.079=-0.1097$). Furthermore, columns (2) to (7) explore heterogeneities in predictability and show that ARA^c's predictability is stronger when VIX is high; the market is illiquid; and when the short-sell fee is large. These results are consistent with those obtained with the original ARA measure.[40]

[40] It is perhaps not surprising that the results based on the alternative ARA are not as strong as those based on the original ARA, because the tests with the alternative measure lack power. The transformation from a continuous ARA to a binomial measure discards potentially valuable information, and the baseline level of attention using the shorter, 30-day window, is noisier than the level measured over the previous six-month window. The same logic applies to AIA, suggesting that our results for AIA, an imperfect measure of aggregate institutional attention, are likely a conservative representation of the true underlying association between AIA and market returns.

Appendix Table 1. Alternative ARA and future market returns

This table reports the daily time-series regressions of future market returns on an alternative ARA measure. The dependent variable is one week ahead CRSP value-weighted return (MktRet). ARA^c is the modified aggregate retail attention measure that is comparable to the construction of the aggregate institutional attention measure (AIA). Specifically, we first construct stock-level abnormal retail attention indicator variable by comparing the Google SVI on day t to the distribution in the past 30 days. To match the summary statistics of AIA, we set the threshold to be the 75^{th} percentile in the past 30 days. We then value-weight the stock-level retail attention indicator variable to obtain ARA^c. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we also control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and the dependent variable. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and MktRet. For column (1), standard errors are adjusted using Newey-West corrections with 30 lags. For column (2) to (7), the market states correspond to those of Table 3 (high/low VIX periods, high/low aggregate spread periods, and high/low short fee periods), and white robust *t*-statistics are reported in brackets. *$p < 0.1$; **$p < .05$; ***$p < .01$.

	(1) Full Sample	(2) High VIX	(3) Low VIX	(4) Illiquid	(5) Liquid	(6) High Fee	(7) Low Fee
ARA^c	−1.389*	−1.668*	−0.485	−2.488**	0.212	−6.069***	−2.796
	[−1.77]	[−1.69]	[−1.05]	[−2.56]	[0.36]	[−2.78]	[−1.31]
Controls	yes	yes	yes	yes	yes	yes	yes
Lagged variable	yes	yes	yes	yes	yes	yes	yes
N	3,903	1,951	1,952	1,951	1,952	627	628
adj. R^2	0.024	0.030	0.006	0.031	0.020	0.060	0.051

Appendix Table 2. ARA and market returns in up versus down markets

This table reports results from regressions of one week ahead CRSP value-weighted return (MktRet) on ARA (aggregate retail attention) for up versus down market days, respectively. The control variables are the same as in Table 2. Standard errors are adjusted using Newey-West corrections with 30 lags. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

	(1)	(2)
MktRet	*$MktRet_t$>0*	*$MktRet_t$<0*
ARA_t	−3.846**	−4.328***
	[−2.42]	[−2.70]
$AbnNews_t$	−0.285	−0.156
	[−0.49]	[−0.26]
BW_t	−1.160***	−0.894
	[−2.73]	[−1.60]
TMS_t	−0.161***	−0.148*
	[−2.97]	[−1.73]
DFY_t	−0.431	−0.424
	[−1.02]	[−0.83]
ΔADS_t	−4.455	−5.245
	[−1.37]	[−0.93]
ΔEPU_t	−0.001	0.002
	[−0.94]	[1.32]
VIX_t	0.155	0.115
	[1.47]	[1.28]
VIX_{t-1}	−0.038	−0.086
	[−0.39]	[−0.67]
VIX_{t-2}	−0.047	0.106
	[−0.71]	[0.99]
VIX_{t-3}	−0.124	0.003
	[−1.28]	[0.03]
VIX_{t-4}	0.084	−0.125
	[1.10]	[−1.07]
$AbnTurn_t$	0.027	−0.191
	[0.06]	[−0.43]
$AbnTurn_{t-1}$	−0.240	−0.004
	[−0.78]	[−0.01]
$AbnTurn_{t-2}$	0.238	−0.201
	[0.85]	[−0.64]
$AbnTurn_{t-3}$	0.299	−0.015
	[0.90]	[−0.04]
$AbnTurn_{t-4}$	0.000	0.591*
	[0.00]	[1.72]
$MktRet_t$	−0.077	−0.004
	[−0.50]	[−0.02]
$MktRet_{t-1}$	0.086	−0.134
	[0.93]	[−0.96]
$MktRet_{t-2}$	−0.122	0.094
	[−1.22]	[0.89]
$MktRet_{t-3}$	−0.152	0.000
	[−1.11]	[0.00]
$MktRet_{t-4}$	−0.026	0.081
	[−0.37]	[0.70]
Intercept	0.886**	0.953*
	[2.08]	[1.88]
N	2,126	1,777
adj. R^2	0.027	0.023

Appendix Table 3. Attention, order imbalance, and mutual fund flows

This table reports daily contemporaneous time-series regressions of aggregate order imbalance indices and aggregate mutual fund flow on aggregate investor attention measures. The dependent variables are: the value-weighted aggregate retail order imbalance indices (ROIB), the aggregate US equity mutual fund flow (MFflow) from TrimTab, and the value-weighted aggregate institutional order imbalance (IOIB). Retail trades are identified as in Barber, Huang, Jorion, Odean, and Schwarz (2024), which is a modified version of Boehmer, Jones, Zhang, and Zhang (2021). ROIB1 is scaled by retail orders and ROIB2 is scaled by all orders. We consider the remaining orders (excluding retail trades) are by non-retail trades and construct the corresponding institutional order imbalance that is scaled by the non-retail trades (NON-ROIB). ARA and AIA are aggregate retail and institutional attention, respectively. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and the dependent variable. Panel A reports the results for ARA and retail order imbalance indices as well as mutual fund flows. The sample periods are 2010-2019 for column (1) and (2) and July 2004 to July 2016 for column (3). Panel B reports the full sample and news subsample results for AIA and institutional order imbalance index from February 2010 to 2019. Standard errors are adjusted using Newey-West corrections with 30 lags. **p* < 0.1; ***p* <0.05; ****p* < 0.01.

Panel A. Retail attention and order imbalance

	(1) $ROIB1_t$	(2) $ROIB2_t$	(3) $MFflow_t$
ARA_t	3.555**	0.237**	0.187**
	[2.25]	[2.22]	[2.42]
Controls	yes	Yes	yes
Lagged variables	yes	Yes	yes
N	2,512	2,512	2,965
adj. R^2	0.305	0.224	0.065

Panel B. Institutional attention and non-retail order imbalance

$NON\text{-}ROIB_t$	(1) Full Sample	(2) Macro News	(3) All News
AIA_t	0.376	1.255**	0.914*
	[0.72]	[2.48]	[1.95]
Controls	yes	yes	yes
Lagged variables	yes	yes	yes
N	2,431	1,219	1,395
adj. R^2	0.188	0.254	0.268

Appendix Table 4. ARA and retail trading in up versus down markets

This table reports the relationship between ARA and retail trading for up versus down market days, respectively. Panel A regresses retail trading measures on ARA for subsamples when the market returns are positive (Columns (1)-(3)) and negative (Columns (4)-(6)). The dependent variables are: the value-weighted aggregate retail order imbalance indices (ROIB) and the aggregate US equity mutual fund flow (MFflow). ROIB1 is scaled by retail orders and ROIB2 is scaled by all orders. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and the dependent variable. The sample period for retail order imbalance is from January 2010 to December 2019 and for mutual fund flows from July 2004 to July 2016. Panel B regresses retail trading measures on ARA for the subsamples where the market return is among the bottom 5% within the sample period. Standard errors are adjusted using Newey-West corrections with 30 lags. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel A. ARA and retail trading on positive versus negative market return days

	Positive market return days			Negative market return days		
	(1)	(2)	(3)	(4)	(5)	(6)
	$ROIB1_t$	$ROIB2_t$	$MFflow_t$	$ROIB1_t$	$ROIB2_t$	$MFflow_t$
ARA_t	1.620	0.152	0.177	6.983***	0.411***	0.187*
	[0.80]	[1.12]	[1.17]	[2.63]	[2.60]	[1.69]
Controls	yes	yes	yes	yes	yes	yes
Lagged variables	yes	yes	yes	yes	yes	yes
N	1,367	1,367	1,600	1,145	1,145	1,365
adj. R^2	0.331	0.229	0.081	0.398	0.315	0.05

Panel B. Bottom 5% market return days

	(1)	(2)	(3)
	$ROIB1_t$	$ROIB2_t$	$MFflow_t$
ARA_t	13.491*	0.602*	0.225
	[1.87]	[1.77]	[0.72]
Controls	yes	yes	yes
Lagged variables	yes	yes	yes
N	125	125	150
adj. R^2	0.431	0.409	0.208

Appendix Table 5. Out-of-sample tests: Additional reporting

Following the out-of-sample analysis of ARA's and AIA as in Table 5, Panel A, this table reports the net of fees and gross (without fee) Sharpe ratios and the turnover ratios for both our approach and the random walk (RW) benchmark.

	Net of Fee Sharpe	Gross Sharpe	Turnover	Turnover RW
ARA				
Full sample	0.47	0.48	3.10%	12.70%
High VIX	0.54	0.54	3.09%	9.60%
High spread	0.56	0.57	2.34%	10.52%
AIA				
Full sample	0.16	0.17	3.15%	12.74%
All News	0.33	0.34	3.14%	12.67%
Macro News	0.33	0.34	3.14%	12.11%

Appendix Table 6. Cap-weighted attention indices and market returns

Panel A reports the fraction of firms affected by the cap-weighted method and the average reduction of total market capitalization after the winsorization. We first restricted the affected firms' market cap to the corresponding capped value (top 25 firms, top 5% and top 10%), then sum the capped and the original market capitalization of all firms separately on each trading day, and finally calculate the ratio of the aggregate capped market capitalization to the aggregate original market capitalization. We take the average ratio across all trading days and report the reduction value (i.e. one minus the average ratio). ARAcap25t is the value-weighted retail attention index capping the market cap weights for top 25 firms; ARAcap95p (ARAcap90p) is the value-weighted retail attention index capping the market cap weights for the top 5 (10) percent of the firms according to the NYSE breakpoints. AIAcap25t, AIAcap95p and AIAcap90p are the respective aggregate institutional attention indices constructed using the same approach as those ARA measures. Panel B reports the daily time-series regressions of the future week CRSP and S&P market return on aggregate investor attention measures constructed with different market cap weighting scheme. Panel C reports the daily time-series regressions of the future week equal-weighted market return with equal-weighted investor attention measures. Panel B and Panel C report the coefficients for the aggregate retail attention indices on future market returns with the above control variables under full sample periods, and the coefficients for the aggregate institutional attention indices on future market returns with the above control variables in the All_News and Macro News subsamples. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and the dependent variable. Standard errors are adjusted using Newey-West corrections with 30 lags. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Panel A. Impact of market cap winsorization

	Affected firms (%)	Affected firms (#)	Overall market cap reduction (%)
ARAcap25t	1.73%	25	17.24%
ARAcap95p	4.94%	71.29	35.85%
ARAcap90p	9.33%	134.59	49.41%
AIAcap25t	1.06%	25	12.26%
AIAcap95p	3.89%	91.07	31.79%
AIAcap90p	7.51%	176.11	44.94%

Appendix Table 6. Panel B. Attention and market returns

	CRSP Ret	S&P500 Ret
ARA	−4.137***	−3.595***
	[−2.86]	[−2.64]
ARAcap25t	−0.186**	−0.159**
	[−2.45]	[−2.23]
ARAcap95p	−0.153**	−0.130**
	[−2.25]	[−2.00]
ARAcap90p	−0.136**	−0.114*
	[−2.08]	[−1.84]
All News Subsample		
AIA	2.072***	2.031***
	[3.48]	[3.50]
AIAcap25t	0.163***	0.160***
	[2.77]	[2.79]
AIAcap95p	0.124**	0.121**
	[2.08]	[2.11]
AIAcap90p	0.099*	0.098*
	[1.67]	[1.69]
Macro News Subsample		
AIA	2.076***	2.020***
	[3.20]	[3.21]
AIAcap25t	0.165**	0.159**
	[2.57]	[2.57]
AIAcap95p	0.133**	0.128**
	[2.08]	[2.08]
AIAcap90p	0.115*	0.110*
	[1.80]	[1.79]

Appendix Table 6. Panel C. Equal-weighted attention and equal-weighted market return

	EW Mkt Ret
ARAew	−0.116**
	[−2.59]
All News Subsample	
AIAew	−0.019
	[−0.52]
Macro News Subsample	
AIAew	−0.023
	[−0.58]

Appendix Table 7. Number of stocks held directly by US households

This table reports summary statistics of the number of stocks held directly by US households according to the Survey of Consumer Finance (SCF) provided by the Board of Governors of the Federal Reserve System (https://www.federalreserve.gov/econres/scfindex.htm). The survey is conducted every three year. Specifically, we look at the X3914 variable (number of different publicly traded stocks) conditioning on the response to the X3913 variable (owning any publicly traded stock) is "YES". The numbers of participants show the fraction of households with direct stock market participation among the entire survey.

	Num of survey	Num of responses	Num of different stocks directly held				
Year	responses	with stock holdings	p10	p25	p50	p75	p90
2004	22,595	7,398	1	2	6	20	45
2007	22,085	6,947	1	2	5	20	50
2010	32,410	7,189	1	2	5	15	40
2013	30,075	6,620	1	2	6	20	50
2016	31,240	6,717	1	2	5	20	48
2019	28,885	6,852	1	2	5	20	45
2022	22,975	6,689	1	3	8	20	50

Appendix Table 8. Robustness check with vintage data for ARA

This table reports the daily time-series regressions of future market returns on aggregate investor attention measures constructed using different vintage samples. Our data collection effort occurred in three phases. The first vintage is collected at the end of 2015, for which we collected SVI for the period from 2004 through 2014. Then, in the mid of 2019, we collected the second vintage for the period 2013 through 2018. At the end of 2020, we obtained the third vintage for the period 2017 through 2019. Column (1) corresponds to the full sample combining all three vintages. Columns (2) and (3) correspond to data from the first vintage, and from the first and second vintages, respectively.
The dependent variable is one week ahead CRSP value-weighted return (MktRet). ARA is the aggregate retail attention. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we also control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and the dependent variable. We include the following control variables: BW, TMS, DFY, AbnNews, ΔEPU, and ΔADS. In addition, we control for the following variables and their corresponding lagged values (for up to four lags): VIX, AbnTurn, and MktRet. Standard errors are adjusted using Newey-West corrections with 30 lags. Newey-West *t*-statistics are reported in brackets. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Appendix Table 8.

MktRet	(1) 2004-2019	(2) 2004-2014	(3) 2004-2018
ARA_t	−4.137***	−5.952***	−3.966***
	[−2.86]	[−2.59]	[−2.65]
$AbnNews_t$	−0.211	−0.452	−0.309
	[−0.57]	[−0.98]	[−0.80]
BW_t	−1.040**	−1.247*	−0.970**
	[−2.24]	[−1.90]	[−2.00]
TMS_t	−0.156**	−0.204*	−0.141*
	[−2.49]	[−1.85]	[−1.91]
DFY_t	−0.450	−0.344	−0.417
	[−1.05]	[−0.65]	[−0.96]
ΔADS_t	−4.981	−3.561	−4.751
	[−1.15]	[−0.70]	[−1.04]
ΔEPU_t	0.000	0.001	0.001
	[0.68]	[0.64]	[0.83]
VIX_t	0.119*	0.143*	0.126**
	[1.94]	[1.77]	[1.98]
VIX_{t-1}	−0.036	−0.069	−0.039
	[−0.74]	[−1.05]	[−0.77]
VIX_{t-2}	0.009	−0.001	0.010
	[0.18]	[−0.02]	[0.21]
VIX_{t-3}	−0.066	−0.081	−0.075
	[−1.42]	[−1.39]	[−1.59]
VIX_{t-4}	−0.005	0.021	−0.004
	[−0.09]	[0.26]	[−0.07]
$AbnTurn_t$	−0.135	−0.120	−0.166
	[−0.47]	[−0.33]	[−0.54]
$AbnTurn_{t-1}$	−0.119	−0.187	−0.137
	[−0.65]	[−0.80]	[−0.70]
$AbnTurn_{t-2}$	0.049	−0.022	0.072
	[0.34]	[−0.12]	[0.47]
$AbnTurn_{t-3}$	0.166	0.268	0.182
	[0.83]	[1.02]	[0.85]
$AbnTurn_{t-4}$	0.247	0.049	0.205
	[0.87]	[0.13]	[0.68]
$MktRet_t$	0.040	0.061	0.048
	[0.45]	[0.58]	[0.53]
$MktRet_{t-1}$	0.005	−0.024	0.006
	[0.06]	[−0.23]	[0.07]
$MktRet_{t-2}$	−0.015	−0.042	−0.012
	[−0.18]	[−0.45]	[−0.14]
$MktRet_{t-3}$	−0.076	−0.123	−0.086
	[−0.84]	[−1.12]	[−0.93]
$MktRet_{t-4}$	0.016	0.018	0.003
	[0.22]	[0.21]	[0.04]
Intercept	0.918**	1.173**	0.872*
	[2.05]	[2.11]	[1.88]
N	3,903	2,645	3,651
adj. R^2	0.022	0.026	0.021