Market Returns and a Tale of Two Types of Attention

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ABSTRACT

Daily aggregate retail attention to stocks (ARA) negatively predicts the one-week-ahead market returns, whereas aggregate institutional attention (AIA) positively predicts market returns around scheduled major news announcements. The results are robust out of sample and are economically significant. ARA's predictability is also stronger for illiquid stocks, while AIA's predictability is higher for high-beta stocks. The findings suggest that attention-driven retail buying generates a transitory marketwide price pressure, whereas institutional attention precedes the resolution of aggregate uncertainty and the accrual of risk premiums.

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There is a growing body of literature suggesting that investor attention is critical in shaping investors' learning and trading activities, as well as the dynamics of individual stock prices. On the one hand, increased attention can improve price efficiency by reducing uncertainty. On the other hand, excessive attention may cause overreactions and amplify behavioral biases, reducing efficiency.[1] Despite the evidence at the stock level, the impact of investor attention on market-wide outcomes remains unclear. 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).

Previous work focusing on individual stocks has shown that the type of investor plays an important role in the effects of attention. For example, Barber and Odean (2008), Da, Engelberg, and Gao (2011) and Barber et al. (2022) have shown that stocks that attract more attention from retail investors experience a transitory and positive price pressure first, followed by a reversal. In contrast, Ben-Rephael, Da, and Israelsen (2017) finds that stocks that are subject to more institutional attention tend to have more efficient prices. However, the impact of investor attention on the efficiency of the broad market may be limited if the attention effects previously observed at the individual stock level are idiosyncratic or driven by small stocks.[2] Moreover, as Engelberg et al. (2022) point out, cross-sectional predictors may not be reliable time-series predictors.

[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) finds that the retail attention induced price pressure and reversal is only significant among smaller stocks. In addition, recent papers including An et al. (2022) and Guo et al. (2022) document that retail attention can spillover from one stock to the other with a delay. As a result, the price reversal on the first stock may coincide with the upward price pressure on the second, resulting in no return predictability in market return. Similarly, even if institutional attention facilitates the incorporation of news to individual stock price, there is no guarantee that aggregate institutional attention will predict the market return if the news is idiosyncratic in nature.

Our paper provides new insights into the crucial question of how investor attention affects future market returns. We find that bottom-up measures of investor attention are significant predictors of future market returns, but there is a stark contrast between the roles of retail and institutional attention. Specifically, our analysis reveals that an increase in aggregate retail attention (ARA) is a strong indicator of a future decline in market returns, while an increase in aggregate institutional attention (AIA) is associated with higher future market returns around major news announcements. Our results have important implications for investors, as they suggest that it is crucial to differentiate between the attention of retail and institutional investors in forecasting future marketwide returns. By incorporating this information into investment decisions, investors can realize meaningful expected utility gains.

To construct the bottom-up measures of attention, we follow prior research and first measure the attention of retail and institutional investors to an individual stock using abnormal Google search volume and Bloomberg's daily maximum readership, respectively. 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 the 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 influences on stock markets. Our results suggest that ARA triggers a transitory price pressure that leads to rapid future reversals.

We next turn to institutional investor attention and observe that AIA *positively* predicts the following week's market returns during scheduled macroeconomic news releases or clustered earnings announcements. Economically, a one standard deviation increase in AIA leads to an 18.77 basis point increase in the following week's market returns. Our findings align two alternative explanations. First, a growing literature attributes the return premiums around significant news releases to the resolution of marketwide uncertainty (see, for example, Patton and Verardo 2012; Savor and Wilson 2013, 2014, and 2016; Ben-Rephael et al. 2021; Chan and Marsh 2022). A high AIA signifies high institutional investor attention to many stocks, indicating that the scheduled news announcements are likely to impact many stocks simultaneously, making it more systematic in nature. As a result, such announcements will have a greater risk premium. Second, institutions may choose to pay more attention when marketwide uncertainty is high (Benamar, Faucault, and Vega 2021). Thus, an increase in AIA anticipates a greater realization of the equity premium.

We further show that the return predictive power of AIA and ARA remain strong and robust out of sample. 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 the 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 the bottom-up attention measures, which we compare with alternative top-down attention measures that rely on Google searches of market indices or Bloomberg's market news counts. We show that the results based on top-down attention measures are weak and lack consistency. The superiority of our bottom-up attention measures arises from the fact that they better capture retail attention induced price pressure on individual stocks and institutional attention spillover across individual stocks which signals a systematic risk premium.

We further support our time-series results with additional 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 bolster the hypothesis on the distinctive manners in which retail and institutional attention are associated with future market returns.

Our study contributes new evidence that ARA and AIA have distinct roles in predicting future market returns, which is important for investors' decision-making in capital markets. One may be concerned with the underlying mechanism, that omitted variables may both influence attention and market returns. To address this, 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) and show that ARA is significantly lower on distraction days, validating our instrument.

Using this instrument, we find that ARA's negative return predictability remains robust, indicating a causal effect of ARA on future market returns. While we are unable to establish a causal relation for AIA,[3] the predictive nature of our findings is still valuable for investors making decisions based on market returns.

Our research highlights the importance of understanding the behavior of both retail and institutional investors to gain a better understanding of market returns. In our final analysis, we applied this knowledge to explain a puzzling phenomenon in the market. Previous studies have established that news releases typically lead to positive return premiums, realized after the news releases and reflecting the resolution of marketwide uncertainty. However, 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 (denoted as "earnings cluster days"). We discover that this pre-news return premium only exists when ARA is high; it disappears when ARA is low. This finding suggests that an increase in retail attention ahead of the upcoming announcements triggers excessive buying across many stocks, creating positive aggregate price pressure before the announcements. Subsequently, this pressure quickly reverses, offsetting the risk premium that would normally be realized the day after the announcement, resulting in a more subdued return premium. This example therefore underscores the importance of considering both retail and institutional investor attention in understanding market dynamics.

Our study adds to the growing body of literature on investor attention, which has primarily focused on analyzing individual stocks.[4] Recently, Chen et al. (2022) explored aggregate attention

[3] We do not observe significant changes in AIA on distraction dates; therefore, we are not able to conduct the instrumental variables analysis for AIA.
[4] For papers on retail investor attention, see, for example, Barber and Odean (2008), Da, Engelberg, and Gao (2011), 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 (2022) and Hirshleifer and Sheng (2022) examine institutional

and discovered that a common component of 12 investor attention proxies is *negatively* linked to future market returns. In contrast, we are the first to examine the market return predictability of the attention of different types of investors. Our novel finding is that, unlike aggregate retail attention, aggregate institutional attention *positively* predicts market returns surrounding scheduled major news announcements. These results suggest that investor attention to information is a crucial factor in explaining aggregate outcomes, and the impact of attention can vary depending on the investor clientele. Consequently, our paper also contributes to the vast literature on market return predictability.[5] Our findings suggest that one mechanism behind this predictability is related to how retail and institutional investors process and react to information.

Our findings also offer fresh insights to the growing literature on return premiums and uncertainty resolution around important news releases.[6] Fisher, Martineau, 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 can be 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-

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and retail attention when macroeconomic news releases and individual firm earnings announcements coincide.

[5] 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).

[6] 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 (2018), Cieslak, Morse, and Vissing-Jorgensen (2019), Ben-Rephael et al. (2021), and Hu et al. (2022).

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.[7] 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).[8] We then define aggregate market-level retail attention (ARA) as the 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).[9] We then construct aggregate institutional attention (AIA) as the value-weighted

[7] We eliminated stocks with closing prices less than $5.
[8] 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.
[9] 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.

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:[10] the Baker-Wurgler sentiment (BW), the term spread (TMS), the default yield spread (DFY), 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 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).[11]

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[10] 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).

[11] 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

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.[12]

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 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.[13]

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.[14]

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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.

[12] 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.

[13] 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.

[14] 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.

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:

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

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.[15]

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 –0.749 to –0.885 in predicting market returns for up to six days. As mentioned earlier, we focus

[15] 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.

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 –4.183 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 4.80 basis points. Similarly, column (8) shows that the corresponding market return decrease in the following week is 22.67 basis points, or 11.79% 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.

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 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.[16]

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 deviation increase in ARA leads to a significant decrease of 29.10 basis points in the following week's market return during the high-VIX state but an insignificant decrease of 6.01 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 –6.388. 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 33.23 basis points in the one-week-ahead market return in periods of low market liquidity (high spread) and an insignificant decrease of 3.62 basis points for the one-week-ahead returns when market liquidity is high.

[16] 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.

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 75.93 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.

Regarding AIA's return predictability, Table 3 Panel B indicates no significant differences across sample periods sorted by VIX and market liquidity. Columns (1) and (2) show that the coefficient of AIA during the high-VIX period is somewhat higher than the coefficient during the low-VIX period, though the difference is not always statistically significant.[17] 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.[18]

[17] 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.
[18] 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.

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 2022) 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, 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 *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.[19]

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.[20] 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 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 1.979 and 1.884, 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 18.77 to 19.84 basis points for the following week. The corresponding annualized return is between 9.76% and 10.32%. 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.

[19] 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.
[20] 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.

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. In addition, AIA and ARA may interact in an interesting way around important scheduled news days, which we will examine in the next subsection.

2.4 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

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

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 $\widehat{\sigma_{[t+2:t+6]}^2}$ 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 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.

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.

2.5 Robustness Checks and Alternative Methodologies

2.5.1 Robustness Checks

In this subsection, we perform the following robustness checks shown 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.[21] Given that the weekday seasonality can be a nontrivial factor in influencing investor attention,[22] we include a weekday fixed effect in the model specification. 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. 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.

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[21] Due to data limitations, we are unable to conduct a similar analysis for AIA as its coverage only starts in 2010.
[22] See, for example, DellaVigna and Pollet (2009), Liu, Peng, and Tang (2022), and Noh, So, and Verdi (2021).

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.

2.5.2 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, 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.

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 29.10 basis points in the following week's market returns.[23] 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,

[23] Considering the size effect that we have discussed in the previous subsection, the weaker results from equal-weighted retail attention measures are not surprising.

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). ARA^{PC} exhibits in-sample but only marginal out-of-sample market return predictability. ARA^{EW} does not exhibit statistically significant market predictability both in- and out-of-sample.

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 2.14% and from 0.33 to 0.40 during *All News* subsamples. The other two approaches do not predict future market returns.

2.5.3 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 (2022). 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 use two approaches via the Bloomberg terminal: 1) we first collect the number of story-counts associated with “Dow Jones” and “S&P 500”; we then follow the definition how Ben-Rephael, Da, and Israelsen (2017) transform DMR into the abnormal institutional attention to construct an indicator variable that takes the value of one when the daily number of story-counts is above 94th percentile (where DMR takes the value of 3 or 4) comparing to the previous month and zero otherwise; 2) we collect the DMR for index-ETFs such as SPY and QQQ; 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 coefficients are negative for story-counts and QQQ but only positive for SPY. Similar to retail attention, the top-down institutional attention measures do not exhibit out-of-sample predictability or generate economic profits.

The superiority of our bottom-up attention measures supports the economic channels underlying their market return predictability. For example, 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.

2.6 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.

2.6.1 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 –5.689, which is statistically more negative than the coefficient for the most liquid portfolio (–3.496); the differences are highly significant with a *t*-statistic of –3.59. Economically, a one standard deviation increase in ARA is followed by a 30.72 basis point decrease in the illiquid portfolio returns and only an 18.88 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.

2.6.2 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 3.045 and 1.151, respectively, and the difference is statistically significant. Economically, a one standard deviation increase in AIA leads to a 30.45 basis point increase in the highest beta portfolio in the following week, whereas the corresponding return increase is only 11.51 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.[24]

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

[24] 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.

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.

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).[25] 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

[25] 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/).

with the highest news pressure, excluding days of major financial market movements.[26] 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 of 17.88, 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 –23.70.[27] On the other hand, columns (3) and (4)

[26] 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.

[27] 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 75.27 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.

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 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. [28]

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 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

[28] 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.

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 33.95 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 plays a crucial role for the information processing, belief formation, and trading decisions of investors. In this paper, we find that aggregate retail investor attention (ARA) and aggregate institutional attention (AIA) have distinctly different power in predicting market returns.

Daily ARA negatively predicts the one-week-ahead market returns, especially during periods of poor market liquidity. 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. 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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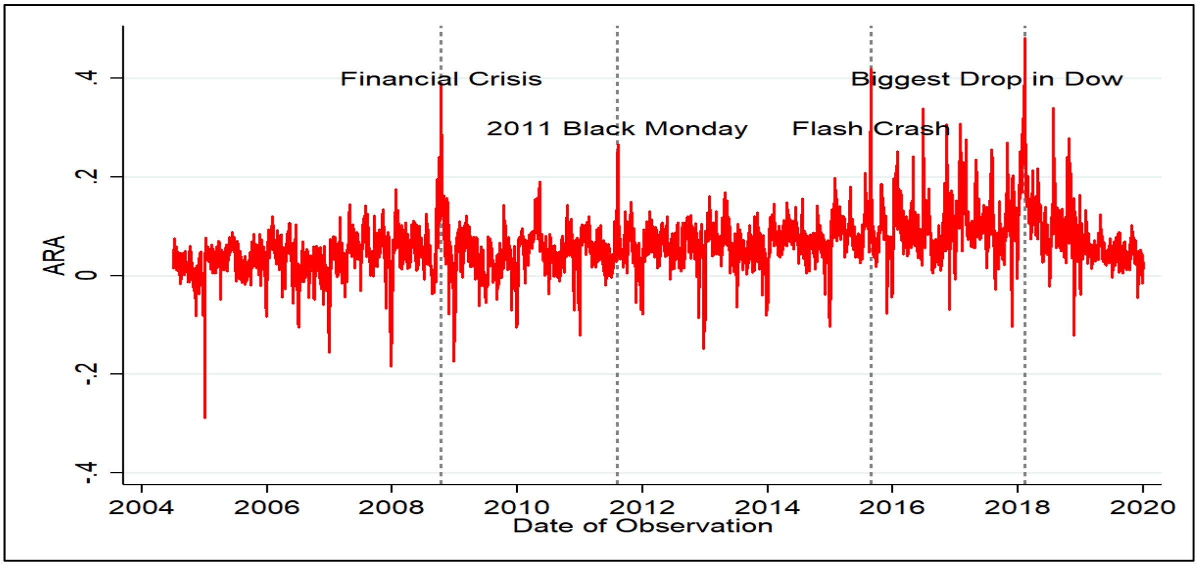
Panel A. Aggregate retail attention (ARA)



Panel B. Aggregate institutional attention (AIA)

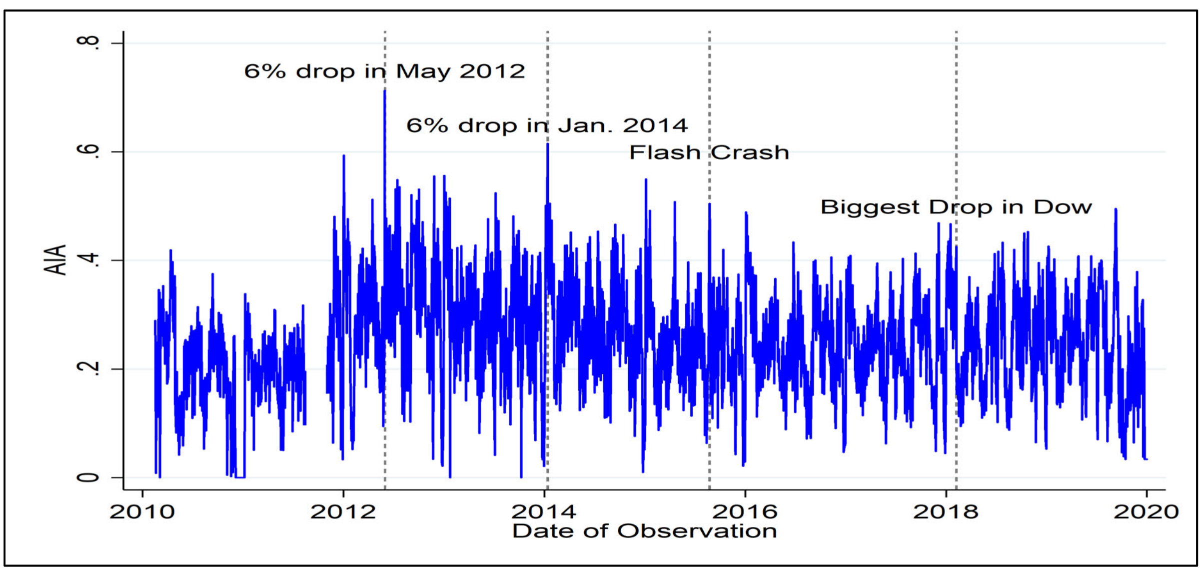
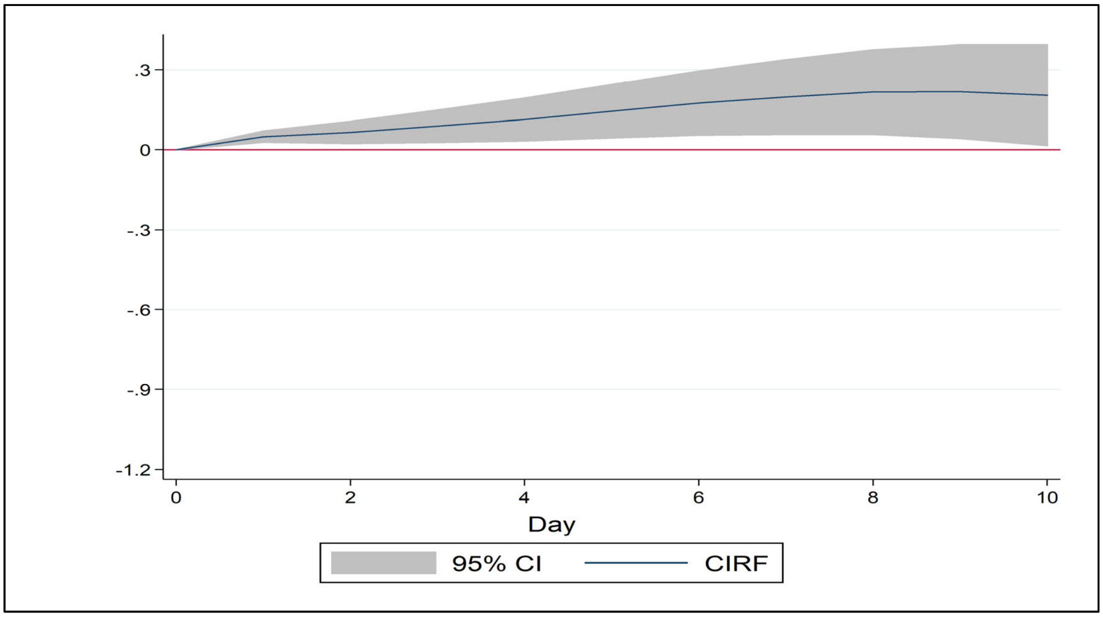


Figure 1. Time-series of retail and institutional attention

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

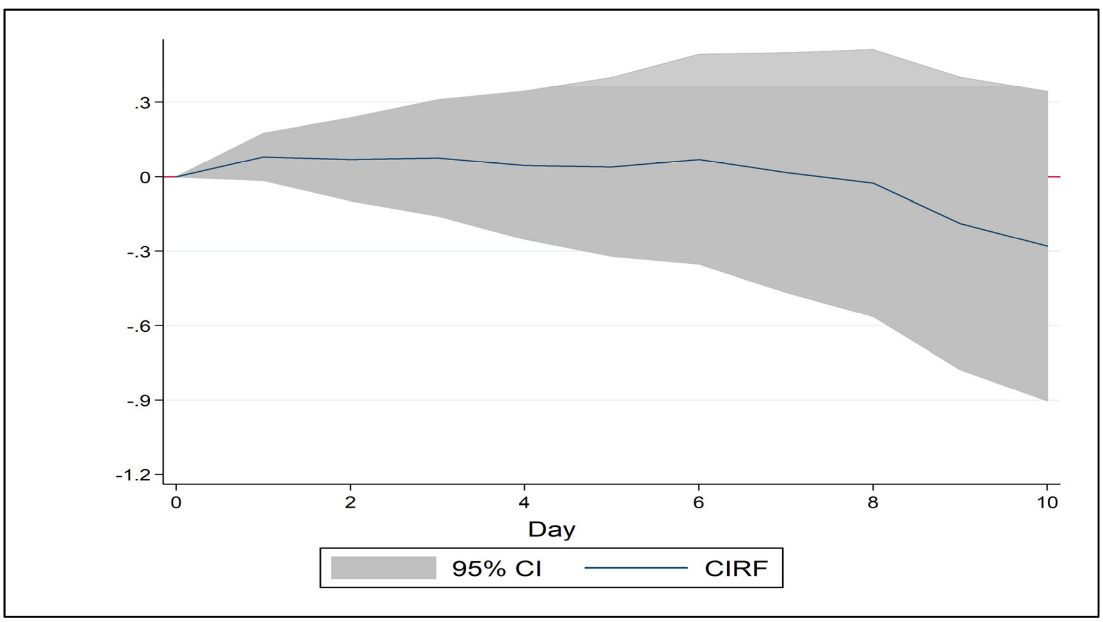
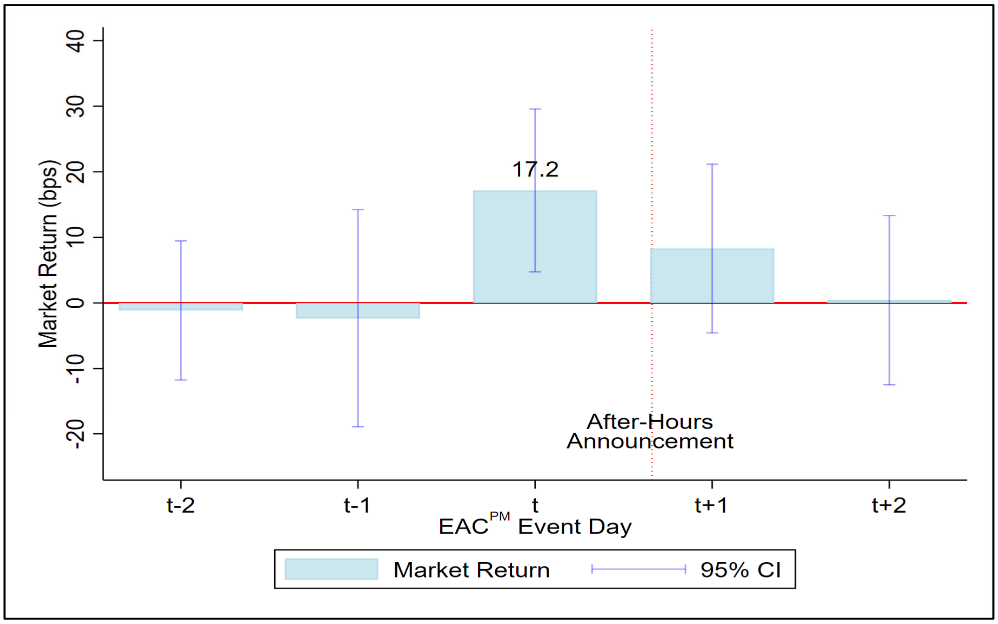


Figure 2. Cumulative impulse response functions of ARA and AIA

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

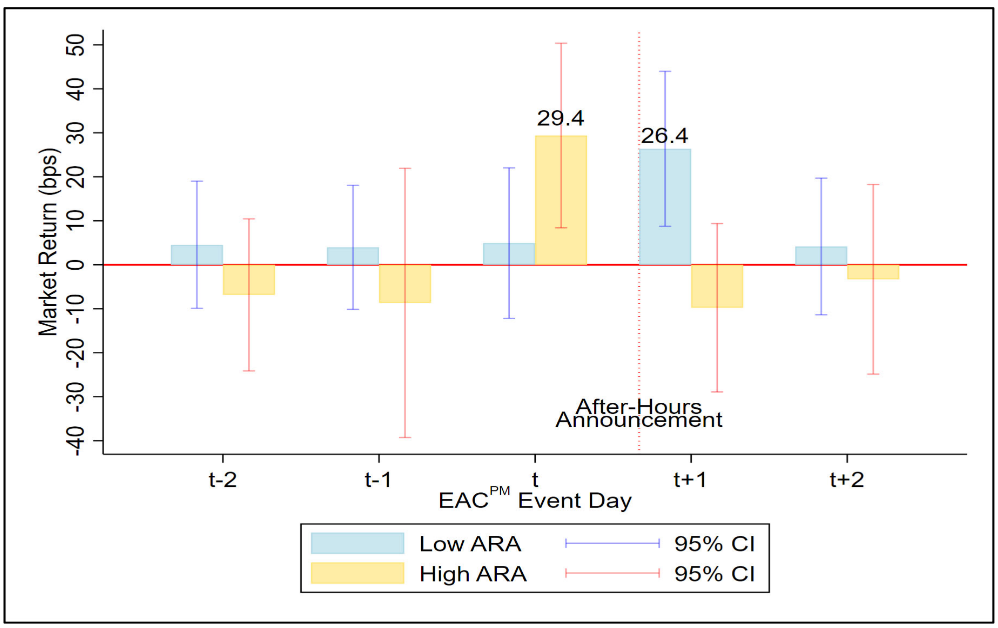


Figure 3. Market returns on clustered after-hours earnings announcement days

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). 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
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	TMS	DFY	ΔADS	ΔEPU
ARA	–0.5							
AIA	–0.3	28.2***						
AbnTurn	–9.9***	45.6***	24.7***					
TMS	0.1	–6.7***	–4.1**	–8.4***				
DFY	–0.6	–7.5***	4.4**	8.8***	36.7***			
ΔADS	–3.7**	8.3***	0.4	3.8**	5.1***	2.2		
ΔEPU	0.9	–3.1*	–2.0	–0.7	–0.2	–0.2	–1.2	
VIX	–13.5***	1.3	–7.8***	28.9***	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 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)

MktRet	(1) *t+1*	(2) *t+2*	(3) *t+3*	(4) *t+4*	(5) *t+5*	(6) *t+6*	(7) *t+2:t+6*	(8) *t+2:t+6*
ARA_t	–0.749**	–0.885**	–0.804**	–0.789**	–0.803**	–0.791**	–2.879**	–4.183***
	[–2.10]	[–2.25]	[–2.06]	[–2.41]	[–2.06]	[–2.58]	[–2.22]	[–2.92]
BW_t	–0.215**	–0.207**	–0.198**	–0.217**	–0.208**	–0.194**		–1.040**
	[–2.05]	[–2.02]	[–2.06]	[–2.15]	[–2.14]	[–2.18]		[–2.24]
TMS_t	–0.041***	–0.038**	–0.033**	–0.032**	–0.028**	–0.024**		–0.156**
	[–2.72]	[–2.59]	[–2.48]	[–2.33]	[–2.15]	[–2.05]		[–2.49]
DFY_t	–0.166	–0.152	–0.087	–0.084	–0.064	–0.056		–0.453
	[–1.63]	[–1.63]	[–0.98]	[–0.88]	[–0.71]	[–0.62]		[–1.06]
ΔADS_t	–1.734	–1.034	–1.229	–1.413	–0.398	–0.969		–4.953
	[–1.55]	[–0.91]	[–0.96]	[–1.40]	[–0.43]	[–1.07]		[–1.14]
ΔEPU_t	–0.001	0.001*	0.001	–0.001	0.000	0.000		0.000
	[–1.15]	[1.81]	[1.55]	[–1.29]	[0.01]	[–0.79]		[0.67]
VIX_t	0.047	0.053	0.002	0.048	0.012	0.004		0.119*
	[1.12]	[1.19]	[0.07]	[1.55]	[0.55]	[0.12]		[1.95]
VIX_{t-1}	0.020	–0.041	0.046	–0.024	0.000	–0.018		–0.035
	[0.36]	[–0.70]	[0.99]	[–0.58]	[–0.01]	[–0.44]		[–0.71]
VIX_{t-2}	–0.045	0.042	–0.025	–0.007	–0.018	0.013		0.008
	[–0.81]	[0.91]	[–0.60]	[–0.16]	[–0.45]	[0.29]		[0.16]
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}	–0.045	–0.014	–0.013	0.006	–0.003	0.018		–0.006
	[–1.32]	[–0.62]	[–0.39]	[0.19]	[–0.10]	[0.68]		[–0.09]
$AbnTurn_t$	–0.022	0.016	0.019	0.026	–0.039	0.017		0.039
	[–0.46]	[0.37]	[0.48]	[0.48]	[–0.99]	[0.26]		[0.44]
$AbnTurn_{t-1}$	0.018	0.025	0.025	–0.035	0.018	–0.030		0.006
	[0.41]	[0.61]	[0.45]	[–0.90]	[0.28]	[–0.54]		[0.07]
$AbnTurn_{t-2}$	0.022	0.027	–0.035	0.014	–0.027	0.002		–0.015
	[0.52]	[0.50]	[–0.88]	[0.23]	[–0.46]	[0.04]		[–0.18]
$AbnTurn_{t-3}$	0.023	–0.043	0.013	–0.025	0.005	–0.028		–0.076
	[0.42]	[–1.02]	[0.21]	[–0.43]	[0.09]	[–0.63]		[–0.84]
$AbnTurn_{t-4}$	–0.063	0.003	–0.018	–0.003	–0.013	0.037		0.015
	[–1.62]	[0.11]	[–0.45]	[–0.07]	[–0.52]	[1.04]		[0.21]
$MktRet_t$	–0.062	0.020	–0.068	–0.072	–0.025	–0.041		–0.187
	[–0.39]	[0.18]	[–0.58]	[–0.61]	[–0.19]	[–0.36]		[–0.63]
$MktRet_{t-1}$	–0.001	–0.094	–0.065	–0.020	–0.082	0.176		–0.094
	[–0.01]	[–0.77]	[–0.55]	[–0.15]	[–0.65]	[1.23]		[–0.55]
$MktRet_{t-2}$	–0.089	–0.043	–0.011	–0.080	0.168	0.029		0.057
	[–0.76]	[–0.37]	[–0.08]	[–0.64]	[1.17]	[0.27]		[0.40]
$MktRet_{t-3}$	–0.030	0.001	–0.076	0.193	0.023	0.021		0.166
	[–0.27]	[0.01]	[–0.60]	[1.32]	[0.20]	[0.13]		[0.83]
$MktRet_{t-4}$	0.033	0.051	0.218	0.027	–0.003	–0.035		0.255
	[0.28]	[0.46]	[1.52]	[0.28]	[–0.03]	[–0.27]		[0.89]
Intercept	0.132	0.161	0.167*	0.178*	0.191**	0.191**	0.344***	0.921**
	[1.35]	[1.60]	[1.69]	[1.80]	[1.97]	[2.14]	[3.33]	[2.06]
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	0.001	0.000	0.004	0.023

Table 2

Panel B. Institutional attention (AIA)

MktRet	(1) *t+1*	(2) *t+2*	(3) *t+3*	(4) *t+4*	(5) *t+5*	(6) *t+6*	(7) *t+2:t+6*	(8) *t+2:t+6*	(9) *t+2:t+6*
AIA_t	0.431**	0.323	0.175	0.155	–0.012	0.085	0.296	0.722	0.934
	[2.01]	[1.51]	[1.07]	[0.88]	[–0.07]	[0.51]	[0.55]	[1.30]	[1.59]
ARA_t									–2.739*
									[–1.78]
BW_t	–0.133	–0.108	–0.107	–0.110	–0.085	–0.057		–0.467	–0.577
	[–1.02]	[–0.88]	[–0.83]	[–0.85]	[–0.65]	[–0.49]		[–0.77]	[–0.93]
TMS_t	–0.026*	–0.020	–0.024	–0.019	–0.014	–0.015		–0.093	–0.107
	[–1.79]	[–1.42]	[–1.60]	[–1.36]	[–1.03]	[–1.14]		[–1.38]	[–1.55]
DFY_t	–0.179	–0.146	–0.159	–0.104	–0.079	–0.093		–0.577	–0.610
	[–1.62]	[–1.39]	[–1.54]	[–1.01]	[–0.72]	[–0.91]		[–1.18]	[–1.24]
ΔADS_t	–0.912	–0.824	–0.581	–0.952	–1.027	–0.230		–3.617	–3.498
	[–1.24]	[–1.11]	[–0.77]	[–1.18]	[–1.45]	[–0.36]		[–1.22]	[–1.20]
ΔEPU_t	0.000	0.001**	0.000	0.000	0.000	–0.001***		0.000	0.000
	[–0.38]	[2.06]	[0.02]	[–0.16]	[0.49]	[–2.69]		[–0.05]	[–0.23]
VIX_t	0.049	–0.021	0.030	0.029	0.006	–0.029		0.013	0.016
	[1.03]	[–0.77]	[0.60]	[1.35]	[0.25]	[–0.89]		[0.27]	[0.33]
VIX_{t-1}	–0.046	0.045	0.007	–0.017	–0.037	0.064*		0.064	0.072*
	[–0.85]	[0.79]	[0.15]	[–0.57]	[–1.08]	[1.87]		[1.53]	[1.78]
VIX_{t-2}	0.023	0.010	–0.017	–0.042	0.051	–0.026		–0.023	–0.031
	[0.45]	[0.22]	[–0.60]	[–1.22]	[1.60]	[–0.75]		[–0.33]	[–0.44]
VIX_{t-3}	0.015	–0.008	–0.048	0.052	–0.008	–0.004		–0.016	–0.021
	[0.37]	[–0.30]	[–1.37]	[1.52]	[–0.26]	[–0.09]		[–0.40]	[–0.52]
VIX_{t-4}	–0.025	–0.014	0.042	–0.012	–0.005	0.005		0.015	0.009
	[–1.13]	[–0.68]	[1.43]	[–0.68]	[–0.18]	[0.18]		[0.20]	[0.12]
$AbnTurn_t$	0.012	0.003	0.005	0.006	–0.071	–0.058		–0.116	–0.099
	[0.22]	[0.06]	[0.09]	[0.12]	[–1.27]	[–1.14]		[–1.34]	[–1.15]
$AbnTurn_{t-1}$	0.017	0.006	0.007	–0.070	–0.055	0.056*		–0.058	–0.031
	[0.32]	[0.11]	[0.14]	[–1.37]	[–1.08]	[1.68]		[–0.62]	[–0.34]
$AbnTurn_{t-2}$	–0.001	0.008	–0.067	–0.057	0.051	–0.014		–0.077	–0.067
	[–0.03]	[0.18]	[–1.46]	[–1.10]	[1.57]	[–0.30]		[–0.65]	[–0.57]
$AbnTurn_{t-3}$	0.008	–0.058	–0.059	0.046	–0.008	–0.016		–0.093	–0.089
	[0.17]	[–1.25]	[–1.16]	[1.47]	[–0.18]	[–0.33]		[–0.77]	[–0.74]
$AbnTurn_{t-4}$	–0.077**	–0.002	0.030	–0.012	–0.023	0.024		0.018	0.017
	[–2.04]	[–0.06]	[1.15]	[–0.37]	[–1.02]	[0.79]		[0.26]	[0.25]
$MktRet_t$	–0.398**	0.018	–0.145	–0.020	–0.061	0.044		–0.168	0.123
	[–2.00]	[0.13]	[–1.19]	[–0.15]	[–0.51]	[0.36]		[–0.64]	[0.41]
$MktRet_{t-1}$	0.192	–0.166	0.034	–0.068	0.057	–0.140		–0.292*	–0.204
	[1.18]	[–1.24]	[0.25]	[–0.53]	[0.39]	[–1.10]		[–1.66]	[–1.10]
$MktRet_{t-2}$	–0.119	0.035	–0.024	0.050	–0.104	0.061		0.019	0.052
	[–0.91]	[0.25]	[–0.18]	[0.34]	[–0.82]	[0.53]		[0.11]	[0.30]
$MktRet_{t-3}$	0.072	–0.041	0.062	–0.107	0.065	0.038		0.017	0.040
	[0.55]	[–0.30]	[0.41]	[–0.84]	[0.54]	[0.27]		[0.10]	[0.23]
$MktRet_{t-4}$	–0.019	0.038	–0.078	0.071	–0.036	–0.106		–0.110	–0.039
	[–0.16]	[0.27]	[–0.67]	[0.65]	[–0.33]	[–0.78]		[–0.42]	[–0.15]
Intercept	–0.137	–0.065	–0.051	–0.022	0.027	–0.040	0.127	–0.151	0.270
	[–1.37]	[–0.60]	[–0.53]	[–0.23]	[0.30]	[–0.46]	[0.72]	[–0.36]	[0.53]
N	2,431	2,431	2,431	2,431	2,431	2,431	2,431	2,431	2,431
adj. R^2	0.013	0.008	0.007	0.004	0.003	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, $\text{MktRet}_{[t+2:t+6]}$. 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	–5.376	–1.117	–4.260	–6.388	–0.698	–5.690	–18.022	–4.361	–13.660
White *t*-stat	[–3.05]***	[–1.18]	[–2.13]**	[–3.64]***	[–0.62]	[–2.73]***	[–3.50]***	[–0.98]	[–2.00]**
Boot *t*-stat	[–2.99]***	[–1.14]	[–2.15]**	[–3.54]***	[–0.63]	[–2.73]***	[–3.54]***	[–0.95]	[–1.98]**
Hodrick *t*-stat	[–2.11]**	[–1.21]	[–2.26]**	[–2.16]**	[–0.46]	[–2.17]**	[–2.75]***	[–0.52]	[–1.80]*
1 std. mag. (bps)	–29.10	–6.01		–33.23	–3.62		–75.93	–22.44	
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	1.152	–0.149	1.300	0.471	–0.024	0.495
White *t*-stat	[1.63]	[–0.33]	[1.55]	[0.77]	[–0.04]	[0.60]
Boot *t*-stat	[1.67]*	[–0.34]	[1.55]	[0.79]	[–0.04]	[0.61]
Hodrick *t*-stat	[1.49]	[–0.34]	[2.02]**	[0.51]	[–0.04]	[0.60]
1 std. mag. (bps)	12.01	–1.42		5.21	–0.21	
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	1.979	–0.686	2.665	1.884	–0.977	2.861
White *t*-stat	[3.17]***	[–1.18]	[3.12]***	[3.28]***	[–1.48]	[3.27]***
Boot *t*-stat	[3.17]***	[–1.14]	[2.93]***	[3.43]***	[–1.44]	[3.03]***
Hodrick *t*-stat	[2.31]**	[–0.85]	[3.19]***	[2.38]**	[–1.09]	[3.36]***
1 std. mag. (bps)	19.84	–6.84		18.77	–9.63	
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	–2.391	–5.444	3.054	–3.335	–4.177	0.842
White *t*-stat	[–1.62]	[–4.70]***	[1.63]	[–2.55]**	[–3.20]***	[0.46]
Boot *t*-stat	[–1.76]*	[–4.57]***	[1.64]	[–2.61]**	[–3.30]***	[0.46]
Hodrick *t*-stat	[–0.92]	[–2.52]***	[1.36]	[–1.69]*	[–1.81]***	[0.35]
1 std. mag. (bps)	–13.36	–28.45		–18.27	–22.23	
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. **p* < 0.1; ***p* <. 05; ****p* < .01.

	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		

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 market returns, $\text{MktRet}_{[t+2:t+6]}$. In Panel A, we conduct robustness checks of Table 2 Panel A for the regression of market returns on ARA 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, and control for CTYZ attention measure from Chen et al. (2022). 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), 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	–2.868**	3,507	0.026			
	[–2.48]					
Control for weekday FE	–4.319***	3,903	0.022	2.362***	1,395	0.020
	[–2.90]			[3.84]		
Exclude December	–4.585***	3,567	0.024	1.915***	1,308	0.020
	[–3.00]			[3.21]		
Exclude bottom 5% ARA/AIA	–4.184***	3,691	0.023	2.235***	1,340	0.020
	[–2.67]			[3.46]		
Hodrick standard errors	–4.183**	3,903	0.023	1.884**	1,395	0.020
	[–2.39]			[2.38]		
Control for lagged attention	–3.227***	3,902	0.023	1.578**	1,394	0.022
	[–2.95]			[2.33]		
3-day moving average attention	–4.901***	3,903	0.022	2.260***	1,395	0.020
	[–2.71]			[3.23]		
Control for CTYZ attention	–4.815***	3,400	0.040	2.139***	1,117	0.046
	[–2.99]			[3.22]		

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

		In-Sample Coeff.	*OOS-R*^{2}	CER Gain	Sharpe Ratio
ARA					
	Partial Least Squares	–0.291***	2.14%**	4.00%	0.59
		[–3.66]	[2.41]		
	Principal Component	–0.165***	1.08%*	0.83%	0.37
		[–2.60]	[1.77]		
	Equal weight	–0.093	0.21%	0.12%	0.26
		[–1.53]	[0.57]		
AIA-News					
	Partial Least Squares	0.231***	1.36%*	2.13%	0.40
		[3.72]	[1.83]		
	Principal Component	0.050	0.32%	0.23%	0.18
		[0.90]	[0.81]		
	Equal weight	0.060	0.66%	0.83%	0.22
		[1.00]	[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
		[–1.68]	[0.64]		
	Principal Component	–0.310	0.59%	0.36%	0.13
		[–1.59]	[0.53]		
	Equal weight	0.017	0.20%	0.32%	0.11
		[0.37]	[0.32]		
Top-down institutional attention					
	Story Counts	–0.101*	0.73%	0.23%	0.17
		[–1.66]	[0.62]		
	DMR(SPY)	0.111*	0.42%	0.16%	0.17
		[1.94]	[0.56]		
	DMR(QQQ)	–0.236**	0.64%	0.17%	0.27
		[–2.20]	[1.45]		

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	–3.496***	–4.495***	–0.905	–3.590*	–5.791***	–0.600	–5.192***
(Liquid)	[–2.61]	[–2.64]	[–0.94]	[–1.84]	[–3.48]	[–0.53]	[–2.58]
2	–4.523***	–5.666***	–1.163	–4.502**	–7.034***	–0.658	–6.376***
	[–2.65]	[–2.86]	[–1.19]	[–2.04]	[–3.53]	[–0.57]	[–2.77]
3	–5.505***	–7.219***	–1.208	–6.010**	–7.410***	–1.350	–6.060**
	[–2.81]	[–3.33]	[–1.14]	[–2.49]	[–3.39]	[–1.12]	[–2.43]
4	–5.434***	–6.660***	–1.457	–5.203**	–7.597***	–1.185	–6.412**
	[–2.90]	[–3.06]	[–1.37]	[–2.15]	[–3.46]	[–0.95]	[–2.54]
5	–5.689***	–6.770***	–1.855*	–4.915**	–7.109***	–1.491	–5.618**
(Illiquid)	[–3.45]	[–3.29]	[–1.85]	[–2.15]	[–3.47]	[–1.24]	[–2.37]
5–1	–2.193***	–2.275***	–0.949**	–1.326	–1.318*	–0.891*	–0.426
	[–3.59]	[–3.38]	[–2.09]	[–1.63]	[–1.91]	[–1.78]	[–0.50]

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	0.646	1.151***	–0.143	1.294**	1.158***	0.068	1.090*
(Low)	[1.53]	[2.94]	[–0.30]	[2.09]	[2.75]	[0.16]	[1.81]
2	0.717	1.549***	–0.489	2.038***	1.670***	–0.348	2.018***
	[1.48]	[3.13]	[–0.84]	[2.67]	[3.14]	[–0.67]	[2.72]
3	0.700	1.859***	–0.960	2.818***	1.798***	–0.581	2.379**
	[1.18]	[2.78]	[–1.40]	[2.94]	[2.43]	[–0.96]	[2.49]
4	0.691	2.095***	–1.369*	3.464***	2.275***	–1.073	3.349***
	[1.04]	[3.01]	[–1.76]	[3.32]	[2.99]	[–1.57]	[3.28]
5	0.992	3.045***	–1.958*	5.003***	3.312***	–1.637*	4.949***
(High)	[1.12]	[3.36]	[–1.93]	[3.68]	[3.36]	[–1.85]	[3.73]
5–1	0.346	1.894***	–1.815**	3.709***	2.154***	–1.705**	3.859***
	[0.49]	[2.64]	[–2.36]	[2.70]	[2.75]	[–2.54]	[2.75]

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			–23.698		
	N-W *t*-stats		[–1.88]*		
	Hodrick t-stats		[–2.23]**		
Predicted AIA					115.226
	N-W *t*-stats				[1.81]
	Hodrick t-stats				[1.92]
Dist		–0.014***		0.003	
	N-W *t*-stats	[–3.51]		[0.32]	
N		3,651	3,651	2,179	2,179
First-stage *F*-statistics		19.583		0.115	
adj. R^2		0.325	0.016	0.145	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}	–7.996	–8.937	–6.021	–4.634
	[–0.68]	[–0.77]	[–0.82]	[–0.63]
EAC^{PM}	21.071**		9.282	
	[2.45]		[1.30]	
EAC^{PM} *HighARA		33.952***		–9.704
		[2.84]		[–0.91]
EAC^{PM} *(1− HighARA)		9.417		26.459***
		[0.84]		[2.67]
BW_t	–14.929*	–14.589	–16.671*	–17.171*
	[–1.65]	[–1.61]	[–1.88]	[–1.94]
TMS_{t-1}	–3.758***	–3.740***	–3.573***	–3.600***
	[–2.61]	[–2.60]	[–2.58]	[–2.59]
DFY_{t-1}	–19.730**	–19.581**	–14.783	–15.002
	[–2.01]	[–1.99]	[–1.55]	[–1.58]
ΔADS_{t-1}	–169.473	–169.833	–111.274	–110.745
	[–1.52]	[–1.53]	[–0.95]	[–0.94]
ΔEPU_{t-1}	–0.045	–0.045	0.097	0.098
	[–1.03]	[–1.04]	[1.83]	[1.83]
VIX_{t-1}	3.979	3.910	5.099	5.200
	[0.96]	[0.95]	[1.16]	[1.18]
VIX_{t-2}	1.952	2.106	–4.113	–4.340
	[0.35]	[0.38]	[–0.70]	[–0.74]
VIX_{t-3}	–4.708	–4.759	4.064	4.139
	[–0.83]	[–0.84]	[0.87]	[0.88]
VIX_{t-4}	0.245	0.204	–3.998	–3.939
	[0.07]	[0.06]	[–1.19]	[–1.17]
$AbnTurn_{t-1}$	–12.209	–12.741	–7.635	–6.850
	[–0.76]	[–0.79]	[–0.74]	[–0.67]
$AbnTurn_{t-2}$	–0.733	–1.158	–10.637	–10.011
	[–0.06]	[–0.09]	[–0.88]	[–0.83]
$AbnTurn_{t-3}$	–8.632	–8.618	–4.493	–4.515
	[–0.74]	[–0.74]	[–0.40]	[–0.40]
$AbnTurn_{t-4}$	–2.327	–2.532	0.498	0.799
	[–0.21]	[–0.23]	[0.04]	[0.07]
$MktRet_{t-1}$	–2.995	–3.056	1.187	1.277
	[–0.66]	[–0.67]	[0.27]	[0.29]
$MktRet_{t-2}$	0.995	1.118	2.078	1.897
	[0.22]	[0.25]	[0.50]	[0.46]
$MktRet_{t-3}$	1.521	1.500	2.169	2.199
	[0.35]	[0.35]	[0.40]	[0.40]
$MktRet_{t-4}$	–2.502	–2.508	–5.901	–5.894
	[–0.84]	[–0.84]	[–1.52]	[–1.51]
Intercept	3.658	3.480	6.028	6.290
	[0.44]	[0.41]	[0.76]	[0.80]
N	3,902	3,902	3,902	3,902
adj. R^2	0.013	0.013	0.010	0.011