It Depends on Where You Search: Institutional Investor Attention and Underreaction to News

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We propose a direct measure of abnormal institutional investor attention (AIA) using news searching and news reading activity for specific stocks on Bloomberg terminals. AIA is highly correlated with institutional trading measures and related to, but different from, other investor attention proxies. Contrasting AIA with retail attention measured by Google search activity, we find that institutional attention responds more quickly to major news events, leads retail attention, and facilitates permanent price adjustment. The well-documented price drifts following both earnings announcements and analyst recommendation changes are driven by announcements to which institutional investors fail to pay sufficient attention. (*JEL* D83, G02, G12, G14, G23)

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Information needs to attract investor attention before it can be processed and incorporated into asset prices via trading. Attention, however, is a limited cognitive resource (Kahneman 1973). A voluminous literature has

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demonstrated that limited investor attention is often associated with slow information diffusion and underreaction to news.[1]

When examining the impact of limited investor attention on prices, an empiricist must decide whether to focus on retail investors, institutional investors, or both. According to French (2008) and Stambaugh (2014), the fraction of U.S. common equity owned directly by individuals fell by more than half from 48% in 1980 to around 20% by 2012. Given the dominant role played by institutional investors, it is important to study the impact of their attention on asset prices. The empirical challenge is the lack of direct measures of institutional investor attention. For example, the direct attention measure that uses Google search activity in Da, Engelberg, and Gao (2011) captures mostly retail investor attention.

We propose a novel measure of institutional investor attention using the news searching and news reading activity for specific stocks on Bloomberg terminals. Terminals are used primarily by institutional investors.[2] A search of terminal users' profiles reveals that almost 80% work in financial industries (including banking, asset management, and institutional financial services). Their most common job titles include portfolio/fund/investment managers, analyst, trader, executive, director, president, and managing director.

Bloomberg records the number of times each article is read by its users, as well as the number of times users search for news for a specific stock. They then rank these numbers against user behavior over the same stock during the previous 30 days and provide the transformed data. We define *abnormal institutional attention* (hereafter, AIA) as a dummy variable that is equal to one when there is a spike in institutional investor attention during that day, and zero otherwise.[3] Compared to other measures that are indirect or based on equilibrium outcomes, such as returns and trading volume, AIA directly reveals institutional investor attention.[4]

Figure 1 contains an example of AIA for Overstock.com (NASDAQ: OSTK) during 2013. Vertical bars mark the days associated with abnormal institutional investor attention ($AIA = 1$). The four quarterly earnings announcement days are indicated with an "E" above the figure. Figure 1 also plots the daily number of relevant news articles about the firm on the Dow Jones newswire (the right

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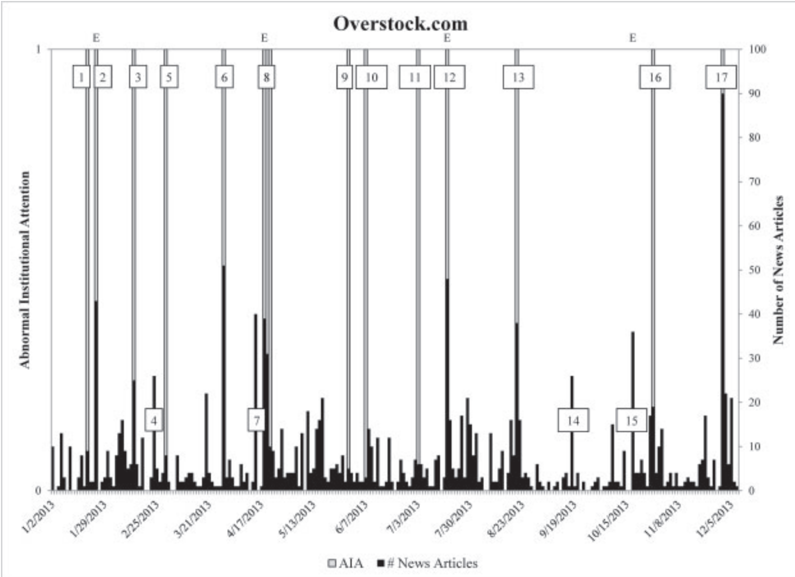
1 Examples include Hirshleifer and Teoh (2003), Peng and Xiong (2006), Cohen and Frazzini (2008), DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009, 2011), Da, Gurun, and Warachka (2014), and Hendershott, Li, Menkveld, and Seasholes (2013), among many others.

2 Bloomberg has approximately 325,000 subscribers (see https://www.bloomberg.com/professional/collaboration/) with terminal leases ranging between $20,000 and $25,000. Strasburg, J. "This is how much a Bloomberg terminal costs. *Quartz*, May 15, 2013. http://qz.com/84961/this-is-how-much-a-bloomberg-terminal-costs/.

3 The dummy variable allows easier interpretation of the differential impact of high versus low institutional attention shocks on economic outcomes. We also examine a more continuous version of the variable in our empirical analysis and obtain similar results.

4 Examples include extreme returns (Barber and Odean 2008), trading volume (Barber and Odean 2008; Gervais, Kaniel, and Mingelgrin 2001; Hou, Peng, and Xiong 2009), news and headlines (Barber and Odean 2008; Yuan 2015), advertising expense (Chemmanur and Yan 2009; Grullon, Kanatas, and Weston 2004; Lou 2014; Madsen and Niessner 2014), and price limits (Seasholes and Guojun 2007).



Event	Date	AIA	Sample Headline
1	1/18/2013	1	*Airport police: Overstock CEO arrested for having gun in luggage*
2	1/24/2013	1	*Overstock.com 4Q EPS 37c*
3	2/12/2013	1	*Overstock.com CEO to Take Medical Leave of Absence*
4	2/22/2013	0	*Overstock.com Inc Announces President Change-Form 8-K*
5	2/28/2013	1	*Groupon Shares Plunge on Profit, International Concerns*
6	3/28/2013	1	*Overstock.com Eyeing Supreme Court Appeal of Adverse NY Internet Tax Decision*
7	4/15/2013	0	*DJ Overstock CEO Byrne Resumes Duties After Medical Leave of Absence*
8	4/18/2013	1	*Overstock.com Reports Q1 2013 Results*
8	4/19/2013	1	*Overstock.com Raised to Buy From Underperform by BofA-Merrill Lynch*
9	5/30/2013	1	*Top 10 Nasdaq-traded stocks posting largest percentage decreases*
10	6/7/2013	1	*Officer JOHNSON III Sells 2,000 Of OVERSTOCK.COM INC*
11	7/3/2013	1	*Overstock.com downgraded at BofA/Merrill*
12	7/18/2013	1	*Overstock 2nd-quarter profit grows more than sevenfold, shares surge to multiyear high*
13	8/21/2013	1	*Overstock.com Victorious In Federal Lawsuit*
14	9/18/2013	0	*Overstock.com's 'The Good Good' sweepstakes awards entrants and their favorite charity*
15	10/17/2013	0	*Overstock.com's 3rd-quarter net income rises 31 percent as sales jump*
16	10/28/2013	1	*Overstock.com Presents Hot 99.5's Second Annual Jingle Ball in Washington, D.C.*
17	12/2/2013	1	*U.S. Supreme Court Won't Review New York Sales-Tax Law For Online Retailers*

Figure 1
Institutional abnormal attention, earnings announcements and news
The figure plots the daily *AIA* values for Overstock.com in 2013. As in Table 1, *AIA* is our measure of abnormal institutional attention from Bloomberg. In addition, the figure plots earnings announcements days (indicated with an "E" above the plot) and the total number of news articles published on the firm in the RavenPack database. Sample headlines (from Factiva) for 17 indicated events are listed below the figure.

axis) with major events described below the figure. The figure indicates that the company experienced institutional attention shocks on 15 days during the year. While three of these shocks are driven by earnings announcements, not all earnings announcements result in abnormal institutional attention. In addition, almost all abnormal institutional attention can be traced back to news about the firm (CEO turnover, outcome of a lawsuit, analyst recommendation change, large price movement, etc.). In other words, news coverage and institutional attention are clearly correlated. However, news coverage does not guarantee attention and AIA directly identifies the news that attracts institutional attention.

We find similar determinants of AIA when we examine a broad sample of Russell 3000 stocks from February 2010 to December 2015. Firm-specific news is the most important driver of AIA. Equilibrium outcomes during the day, such as absolute returns, trading volume, intra-day volatility, and closeness to a 52-week high/low, are also significantly related to AIA. In addition, AIA displays strong seasonality within the week. The likelihood of an institutional attention shock decreases monotonically from Monday to Friday. For example, a stock is 25% less likely to have an attention shock on a Friday compared to a Monday, consistent with the results in DellaVigna and Pollet (2009) and the pattern displayed by retail attention documented in Liu and Peng (2015). Finally, in the cross-section, larger and more volatile stocks with greater analyst coverage are more likely to experience institutional attention shocks.

Most interestingly, we find our institutional investor attention measured using AIA to be distinct from retail investor attention measured using abnormal daily Google search volume. While AIA and the Google search-based measure are positively and significantly correlated at the daily frequency, they explain less than 2% of each other's variation. When we correlate both measures with contemporaneous measures of abnormal trading volume, we find that only AIA has a significantly higher correlation with abnormal institutional trading volume than with abnormal total trading volume. This finding supports the notion that AIA, not the Google search-based measure, directly measures institutional investors' attention. Finally, a vector autoregression (VAR) analysis reveals that AIA leads retail attention, but not vice versa, confirming that institutional investors have greater resources and stronger incentives to quickly pay attention to news. Moreover, attention constraints are more likely to be binding for retail investors. For example, we find that retail attention allocated to a given stock is significantly lower when other stocks are in the news on the same day, consistent with the evidence in Liu and Peng (2015). No such relation is observed with AIA.

We then examine how institutional investor attention affects the incorporation of information into asset prices. We focus on two types of firm-level announcements, quarterly earnings announcements and analyst recommendation changes (that are not immediately driven by earnings announcements), for four reasons. First, both announcements contain important value-relevant information to which institutional investors are likely to pay attention and react.[5,6] Second, information released in both announcements is

[5] For example, Schmidt (2015) finds that professional asset managers with a large fraction of portfolio stocks exhibiting an earnings announcement are significantly less likely to trade in other stocks, suggesting that many earnings announcements indeed grab institutional investor attention. In fact, since earnings announcements are usually prescheduled, investors may be prepared to allocate more attention on the earnings announcement days. We confirm that AIA is, on average, higher on earnings announcement days than on the days of recommendation changes, which are usually not prescheduled.

[6] Along these lines, Boudoukh et al. (2013) use textual analysis to identify relevant news (from the set of all news). They find that when focusing on relevant news, there is considerably more evidence of a strong relation between stock price changes and information.

quantifiable which allows us to control for both the magnitude and implications of the information and tease out the incremental impact of the attention. Third, both announcements have been documented in the literature to generate post-announcement drift (e.g., Ball and Brown 1968 and Livnat and Mendenhall 2006 for earnings announcements; see Stickel 1995 and Womack 1996 for analyst recommendation changes). In other words, investors underreact to both announcements, on average. We test whether institutional attention on the announcement day facilitates information incorporation and alleviates price underreaction to news. Finally, by examining two distinct types of events we can determine whether institutional attention plays a broad or limited role.

Ex ante, it is not clear that abnormal institutional attention should alleviate post-announcement price drift. For example, Frazzini (2006) proposes an explanation of post-earnings announcement drift based on the disposition effect displayed by institutional investors, such as mutual fund managers. Positive earnings announcements prompt these investors to sell winning stocks. The resultant downward price pressure causes underpricing and the subsequent positive price drift is a correction of this underpricing. In this case, increased institutional investor attention at the earnings announcement could exacerbate such a disposition effect and lead to an even stronger post-announcement drift. The impact of institutional investor attention on asset prices is ultimately an empirical question we examine in the data.

We find strong and consistent evidence that institutional attention facilitates information incorporation for both types of announcements. After controlling for the information content of the announcement and a comprehensive set of relevant stock characteristics, announcements accompanied with abnormal institutional attention experience larger returns (in absolute terms) during the announcement day and very little subsequent price drift. Thus, the well-documented post-announcement drifts come almost exclusively from announcements with limited institutional investor attention. When institutional investors fail to pay sufficient attention, price initially underreacts to information, resulting in a drift.

We confirm the incremental value of AIA by including additional interaction terms with other attention proxies in our regressions. Thus, the relation between AIA and price reaction to news announcements is not driven by AIA's correlations with other variables that have been documented to be related to post-announcement drift. Not surprisingly, in sharp contrast to institutional attention, we find that retail attention does not facilitate the incorporation of information during earnings and recommendation change announcements.

We also examine the profitability of calendar time portfolio strategies using earnings announcement and recommendation change events. Our results confirm that a long-short portfolio of stocks with AIA equal to zero that is long on positive news events and short on negative news events earns around 63 to 95 basis points over a period of five to ten trading days. In contrast, a similar portfolio of stocks with AIA equal to one earns insignificant returns, which confirms our findings of zero drift following high attention. Finally, a portfolio that captures the differences in drifts (i.e., low AIA minus high AIA) reveals a positive and statistically significant difference in drifts that is economically large.

It is possible that some unobservable features of the announcements may be driving the high AIA on the announcement day. While such features may explain the higher announcement day return (in absolute terms), it is more challenging for them to also explain a lower post-announcement drift. For example, while important news may drive both higher AIA and a higher absolute announcement day return, it tends to be associated with stronger, not weaker, drift going forward. In fact, Chan, Jegadeesh, and Lakonishok (1996) find that higher (absolute) earnings announcement window returns predict stronger, not weaker, post-earnings announcement drift, on average.

To rule out the reverse causality story that a higher announcement day (absolute) return itself leads to high AIA, we focus on earnings announcements taking place after the market closes from 4 p.m. to 12 a.m. For these announcements, which make up about half of our sample, high AIA on the same day cannot be driven by the earnings announcement return. Yet, we find very similar results in this reduced sample: high AIA is associated with lower subsequent price drift.

The impact of investor attention on price reaction to news announcements has been examined before. A few papers use indirect proxies for attention. For example, Hirshleifer, Lim, and Teoh (2009) find that when there are more firms reporting earnings on the same day, stocks have smaller reactions on the announcement date and greater drift going forward. DellaVigna and Pollet (2009) find similar results when announcements are made on Fridays. Several papers use trading volume as a measure of attention. Hou, Peng, and Xiong (2009) determine that stocks with higher trading volume experience smaller post-earnings-announcement drift. Similarly, Loh (2010) finds that stocks with higher trading volume react more to stock recommendations during the announcement and experience smaller subsequent price drift. Boehmer and Wu (2013) use short-selling volume as a proxy for investor attention and show that there is little drift when there are negative earnings surprises and short selling volume is high. The advantage of our AIA measure is twofold. First, it allows us to focus on institutional investor attention, which is more important than retail attention for driving permanent price change. Second, relative to trading volume and short interest, which are equilibrium outcomes that may reflect many economic forces other than investor attention, AIA reveals institutional investor attention.

Our paper makes several contributions to the literature on investor attention. First, we introduce a new, direct measure of institutional investor attention. Importantly, because this measure is not limited to events associated with a firm's regulatory filings, it can capture a more broad set of events that may draw the attention of institutional investors, allowing us to examine its role across multiple types of news events. Because AIA is broadly analogous to the direct measure of retail attention from Google searches, an additional contribution lies in documenting the relation between the two types of attention. Our results complement the investor attention literature that focuses on retail attention.

Since Bloomberg terminals are important in disseminating news to institutional investors, our paper also contributes to the broader literature linking the news media to asset prices, including Tetlock (2007), Fang and Peress (2009), Loughran and McDonald (2011), Engelberg and Parsons (2011), Gurun and Butler (2012), Peress (2014), and Peress and Schmidt (2014), among others. Our results suggest that institutional attention is necessary for new information to be incorporated into prices on a timely basis.

1. Data and Summary Statistics

1.1 Sample construction

Bloomberg is a private company and does not provide detailed information about its clients. To get a sense of who uses Bloomberg terminals, we conduct an extensive search of the user profiles on August 26, 2016 using Bloomberg's user profile search function (PEOP). Figure 2 breaks down users by their job titles (panel A) and industries (panel B). The most common job titles are portfolio/fund/investment manager (21%), analyst (17%), trader (11%), executive (7%), director (7%), president (6%), and managing director (6%). About 80% of Bloomberg users work in the financial industries including banking (36%), asset management (26%), and institutional financial services (17%). While 7% of them work in the technology industry, about 78% of these users are Bloomberg employees. In addition, academic users are relatively few. For example, only 0.3% of all Bloomberg terminal users have "university," "school," or "college" listed as one of their current positions or have an .edu email address associated with their profile. Overall, it is clear that majority of Bloomberg terminal users are likely to be institutional investors who have both the incentives and financial resources to quickly react to important news about a firm.

Bloomberg provides data that include transformed measures of news reading and news searching activity on Bloomberg's terminals. Our sample period ranges from February 2010 to December 2015, based on data availability.[7] Following Da, Engelberg, and Gao (2011), we begin with the sample of Russell 3000 stocks. We then require the stocks in our sample to satisfy the following conditions: (1) have measures of news-searching and news-reading activity on Bloomberg terminals; (2) have a share code of 10 or 11 in the Center for Research in Securities Prices (CRSP) database; and (3) have book-to-market information for the DGTW risk adjustment (Daniel et al. 1997). These conditions reduce our sample to 2,669 stocks. This is the main sample of our analysis (Full Sample).

[7] Bloomberg's historical attention measures begin on 2/17/2010. Historical data are missing for the periods of 12/6/2010–1/7/2011 and 8/17/2011–11/2/2011.

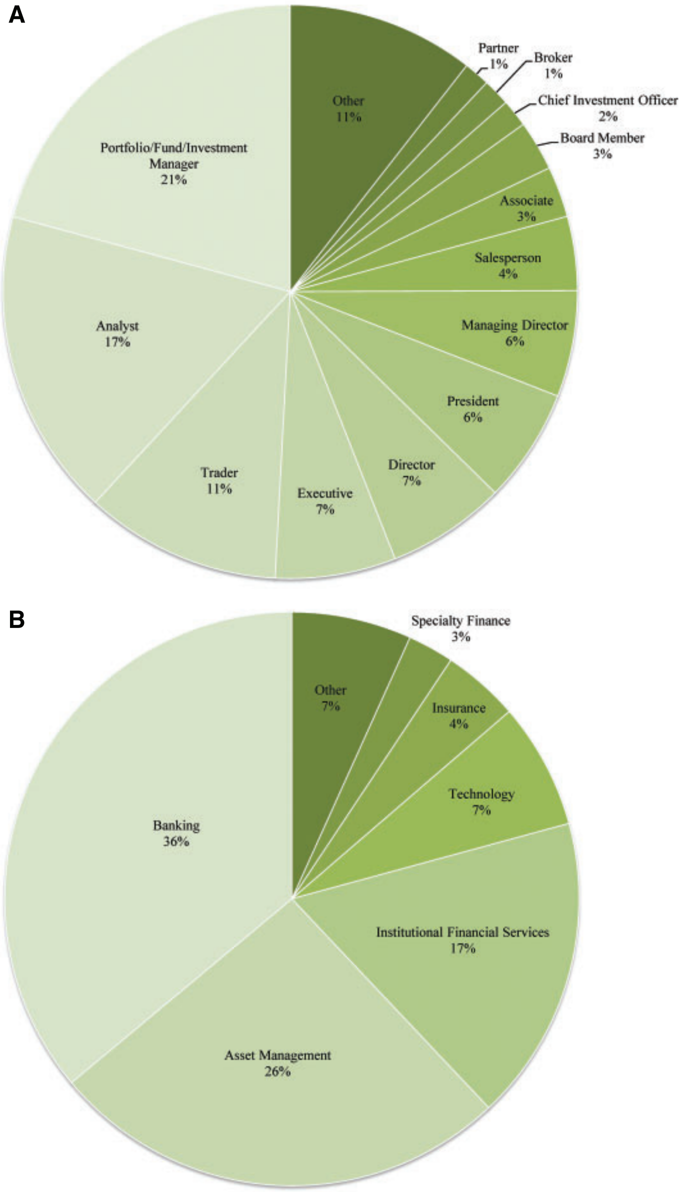


Figure 2
Breakdown of Bloomberg terminal users
The figure displays the relative frequency of job titles (*A*) and industries (*B*) from Bloomberg terminal users' profiles. Data are collected from a Bloomberg terminal by performing a people search (Bloomberg terminal function PEOP) within all Bloomberg users. User titles data are tabulated by searching for all Bloomberg users and choosing each possible title category using the "Role" search option. To avoid double counting, users with multiple titles are assigned to the more specific category. For example, a user with the titles "Portfolio Manager" and "Executive" is assigned to the category "Portfolio Manager" since "Executive" is a generic title. User industries are tabulated by searching for all Bloomberg users and choosing all possible industries and subindustries under the "Industry" search option. Data were collected from searches on August 26, 2016.

To arrive at the sample used to analyze earnings announcements, we start with the Full Sample and require that at least two analysts in I/B/E/S make earnings forecasts prior to the announcements. According to Livnat and Mendenhall (2006), measures of institutional trading following earnings announcements respond more to analyst consensus-based earnings surprises rather than time series-based earnings surprises. As a result, we compute quarterly standardized unexpected earnings (*SUE*) relative to the analyst forecast consensus. The requirement for analyst forecasts reduces the sample of stocks from 2,669 to 2,231 (*EarnAnn* Sample) and yields a final sample of 34,400 earnings announcements.

To arrive at the sample used to analyze analyst recommendation change, we start with the Full Sample and follow the filters in Jegadeesh and Kim (2010), Loh and Stulz (2011), and Kadan, Michaely, and Moulton (2013). In particular, we (1) remove recommendation changes that occur on the same day as, or the day following, earnings announcements; (2) remove recommendation changes on days when multiple analysts issue recommendations for the same firm; (3) require at least one analyst to have issued a recommendation for the stock and revised the recommendation within 180 calendar days; (4) require at least two analysts to have active recommendations for the stock as of the day before the revision; and (5) consider a recommendation to be active for up to 180 days after it is issued or until I/B/E/S indicates that the analyst has stopped issuing recommendations for that stock. After applying all of these filters, we end up with 16,312 recommendation changes covering 2,068 stocks. This forms the subsample of our recommendation change analysis (*RecChng* Sample).

Finally, institutional trading activity data were obtained from Ancerno, Ltd. Ancerno is a widely recognized transaction cost consulting firm to institutional investors, and our database contains all trades made by Ancerno's base of clients. Ancerno data primarily includes trades by mutual funds and pension plans. A detailed explanation concerning Ancerno variables can be found in the appendix of Puckett and Yan (2011). Our sample of transactions from Ancerno ends on June, 2015. As a result, the sample used in our trading analysis ends on that date.

1.2 AIA Measure

To construct their own measure of attention, Bloomberg records the number of times news articles on a particular stock are read by its terminal users and the number of times users actively search for news about a specific stock. Searching for news requires users to actively type the firm's stock ticker symbol followed by the function "CN" (Company News). In contrast, users may read an article without initially realizing it refers to a specific firm. To place more emphasis on deliberate news seeking for a specific firm, Bloomberg assigns a score of ten when users search for news and one when users read a news article. These numbers are then aggregated into hourly counts. Using the hourly counts, Bloomberg then creates a numerical attention score each hour by comparing the average hourly count during the previous 8 hours to all hourly counts over the previous month for the same stock. They assign a score of 0 if the rolling average is in the lowest 80% of the hourly counts over the previous 30 days. Similarly, Bloomberg assigns a score of 1, 2, 3 or 4 if the average is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the previous 30 days' hourly counts, respectively. Finally, Bloomberg aggregates up to the daily frequency by taking a maximum of all hourly scores throughout the calendar day. Bloomberg provides these latter transformed scores, but does not provide the raw hourly counts or scores. The data appendix contains detailed instructions explaining how to download the data from the Bloomberg terminal.[8] Since we are interested in abnormal attention, and not just the level of attention, our abnormal institutional attention measure (*AIA*) measure is a dummy variable that takes a value of one if Bloomberg's daily maximum is 3 or 4, and zero otherwise. This captures the right tail of the measure's distribution. In other words, an *AIA* equal to one indicates the existence of institutional investor attention shock on that stock during that day. The dummy variable allows easier interpretation of the differential impact of high versus low institutional attention shocks on economic outcomes.

We also transform Bloomberg's 0, 1, 2, 3, and 4 scores to continuous values, *AIAC*, using the conditional means of truncated normal distribution. Under the normal distributional assumption, the corresponding *AIAC* values are −0.350, 1.045, 1.409, 1.647, and 2.154.[9] We use *AIAC* instead of *AIA* in the vector autoregression (VAR) analysis that requires a more continuous variable. We also confirm in our Internet Appendix that *AIAC* delivers similar results in other tests. Hence, the findings in our paper are not driven by the definition of AIA that captures the tail of the distribution of attention shock.

1.3 Other variables

We compare institutional attention to retail attention. Following Da, Engelberg, and Gao (2011), retail attention is measured using the daily Google Search Volume Index (*DSVI*). Abnormal *DSVI* (*ADSVI*) is calculated as the natural log of the ratio of *DSVI* to the average of *DSVI* over the previous month. To reduce the noise of ticker search on Google, we follow Niessner (2015) and require that searching for the stock ticker in Google actually brings up the stock price or a box with information about the firms. We only relax these filters when we analyze the *EarnAnn* Sample and *RecChng* Sample since a spike in *DSVI* in those samples is more likely to be driven by these events.

To facilitate the comparison with *AIA* which is a dummy variable, we also create a dummy variable version of *ADSVI* following Bloomberg's

[8] Please see the online data appendix at the authors' Web sites for detailed instructions on downloading the Bloomberg search data: http://kelley.iu.edu/abenreph/ , http://www3.nd.edu/žda/, or http://ryan.israelsen.com.

[9] For example, a Bloomberg score of three translates to an AIAC of 1.647 since 1.647 is the conditional mean of a standard normal random variable x for x between NORMINV(0.94) and NORMINV(0.96), where NORMINV() denotes the standard normal inverse cumulative distribution function.

methodology (*DADSVI*). Specifically, we assign *DSVI* on day t one of the potential 0, 1, 2, 3, or 4 scores using the firm's past 30 trading day *DSVI* values. For example, if *DSVI* on day t is in the lowest 80% of past *DSVI* values, it receives a score of zero. Then, on day t, the dummy variable *DADSVI* is set to one if the score is 3 or 4, and 0 otherwise. In other words, a *DADSVI* of one indicates a spike in retail attention on that day.

We obtain news coverage of our sample stocks from RavenPack. *ANews* is the log of the ratio of one plus the number of news articles published on the Dow Jones newswire during the day about the firm to its average over the previous month.

User requests at the Securities and Exchange Commission's (SEC) EDGAR (Electronic Data Gathering, Analysis, and Retrieval) online system also have been used to track investor attention.[10] We obtain the EDGAR server logs data from the SEC. Each day, for each stock, we calculate the total number of hits. To filter the data in order to exclude mass automated hits and mistakes, we follow the procedure used in Loughran and McDonald (2015) and our results are robust to using the filters described in deHaan, Shevlin, and Thornock (2015). Specifically, we exclude hits flagged as webcrawlers and exclude IP addresses that access more than 50 unique firms' filings in a given day. We also exclude retrievals of index files and hits resulting in errors (defined as log file status codes 300 or above). After filtering out these observations, we define *EDGAR* as the total number of hits on a given day. *AEDGAR* is then calculated as the natural log of the ratio of *EDGAR* to the average of *EDGAR* over the previous month. We use the WRDS CIK-CUSIP table to link the EDGAR data with CRSP.

Compared to individuals who search for information on Google, those requesting information on EDGAR are more likely to be institutional investors. While the EDGAR measure is positively and significantly related to AIA, its explanatory power is small compared to the occurrence of news. One important distinction between the two measures is that AIA is based on all news reading and news searching activity, while hits on EDGAR are limited to specific regulatory filings. Not surprisingly, controlling for the EDGAR measure in our analysis does not change our results.

Other variables used in our analysis are constructed from the standard databases: Compustat, CRSP, and I/B/E/S. Table 1 defines all of the variables used in this paper.

In terms of timing, day t is an earnings announcement day for firm i if the firm announces its earnings during the period from 4 p.m. on day t-1 to 4 p.m. on day t. Similarly, day t is a recommendation change day for stock i if there is a recommendation change on the stock from 4 p.m. on day t-1 to 4 p.m. on day t. The time stamps associated with both events are obtained from I/B/E/S.

[10] For example, see Bauguess, Cooney, and Hanley (2013), Drake, Roulstone, and Thornock (2015), Lee, Ma, and Wang (2015), deHaan, Shevlin, and Thornock (2015), and Loughran and McDonald (2015) for recent applications of the EDGAR data.

Table 1
Variable definitions

Variable	Definition
Bloomberg attention variables	
AIA	Bloomberg records the number of times news articles on a particular stock are read by its terminal users and the number of times users actively search for news for a specific stock. Bloomberg then assigns a value of one for each article read and ten for each news search. These numbers are then aggregated into an hourly count. Using the hourly count, Bloomberg then creates a numerical attention score each hour by comparing the past eight-hour average count to all hourly counts over the previous month for the same stock. They assign a value of zero if the rolling average is in the lowest 80% of the hourly counts over the previous 30 days. Similarly, Bloomberg assigns a score of 1, 2, 3, or 4 if the average is between 80% and 90%, 90% and 94%, 94% and 96%, or greater than 96% of the previous 30 days' hourly counts, respectively. Finally, Bloomberg aggregates up to the daily frequency by taking a maximum of all hourly scores throughout the day. These are the data provided to us by Bloomberg. Since we are interested in abnormal attention, our *AIA* measure is a dummy variable that receives a value of one if Bloomberg's score is 3 or 4, and zero otherwise. This captures the right tail of the measure's distribution
AIAC	We transform Bloomberg's 0, 1, 2, 3, and 4 scores to continuous values using the conditional means of the truncated normal distribution. The values are −0.35, 1.045, 1.409, 1.647, and 2.154, respectively. For example, 1.647 is the conditional mean of a standard normal random variable x, for x between NORMINV(0.94) and NORMINV(0.96), where NORMINV is the standard normal inverse cumulative distribution function
Other direct attention variables	
ADSVI	Da, Engelberg, and Gao's (2011) abnormal retail attention measure calculated as the natural log of the ratio of *DSVI* on day t to the average of *DSVI* over the previous month. *DSVI* is Google's daily Search Volume Index (*SVI*)
DADSVI	We follow Bloomberg's methodology and assign *DSVI* on day t one of the potential 0, 1, 2, 3, or 4 scores using the firm's past 30 trading day *DSVI* values. For example, if *DSVI* on day t is in the lowest 80% of past *DSVI* values, it receives the score zero. *DADSVI* is one on day t if the score is 3 or 4, and zero otherwise
EDGAR	The daily number of unique requests for firm filings on the SEC EDGAR server (Loughran and McDonald 2015). *EDGAR* is available until March 2015
AEDGAR	The natural log of the ratio of *EDGAR* on day t to the average of *EDGAR* over the previous month
Other variables	
ANews	The natural log of the ratio of one plus the number of news articles published on the Dow Jones newswire during the day to its average over the previous month. News data are provided by RavenPack
Ancerno-AVol	The stock's Ancerno daily volume divided by the previous eight-week average Ancerno trading volume. Ancerno data are available until June 2015
CRSP-AVol	The stock's total daily volume in CRSP divided by the previous eight-week average total trading volume
EarnDum	A dummy variable that is equal to one on earnings announcements days and zero otherwise
RecChngDum	A dummy variable that is equal to one on days with a change in analyst recommendations and zero otherwise
SUE	The quarterly standardized unexpected earnings calculated from I/B/E/S as the quarter's actual earnings minus the average of the most recent analyst forecast, divided by the standard deviation of that forecast
RecChng	The change in analyst recommendations. The variable ranges from −4 to 4, where a positive (negative) number refers to an upgrade (a downgrade)
Ret	CRSP's daily stock return
AbsRet	Absolute value of *Ret*
DGTW	CRSP's daily stock return minus the stock's benchmark portfolio daily return following Daniel et al. (1997)
AbsDGTW	Absolute value of *DGTW*
AVol	The stock's abnormal trading volume calculated following Barber and Odean (2008) as the stock's daily volume divided by the previous 252 day average trading volume

(*continued*)

Table 1
Continued

Variable	Definition
HLtoH	The ratio between the stock's daily high and low price difference and the daily high price
52HighDum	A dummy variable that is equal to one if the stock's price exceeds its 52-week high price and zero otherwise
52LowDum	A dummy variable that is equal to one if the stock's price falls below its 52-week low price and zero otherwise
Turnover	The daily stock turnover
Dvol	The daily dollar trading volume in millions of dollars
Relative Spread	[(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes
SizeInM	Stock's market capitalization, rebalanced every June, in millions of dollars
LnSize	The log of the stock's average size in millions of dollars from day *t-27* to *t-6*
LnBM	The natural logarithm of the firm's book-to-market ratio rebalanced every June following Fama-French (1992)
SDRET	The standard deviation of daily stock returns from day t-27 to day t-6
InstHold	The percentage of shares held by institutional investors obtained from the Thomson Reuters CDA/Spectrum institutional holdings' (S34) database
NumEst	The number of analysts covering the stock using the most recent information
LnNumEst	Log(1+*NumEst*)
AdvExpToSales	The firm's advertising expenses to sales as in Da, Engelberg, and Gao (2011) and using the most recent information
Tuesday – Friday	Dummy variables equal to one if the stock's day of the week is Tuesday-Friday, respectively, and zero otherwise

According to Michaely, Rubin, and Vedrashko (2014), these time stamps are very accurate and should result in very few misclassification errors at a daily frequency. Stock returns on day t are measured from the market close (4 p.m.) on day t-1 to the market close (4 p.m.) on day t. *AIA*, *DSVI*, and *EDGAR* on day t are measured during the 24 hours on that calendar day.

1.4 Summary statistics

Table 2 provides summary statistics of our full sample and the two subsamples used for earnings announcements and recommendation change analysis. Panel A indicates that the AIA frequency is 0.089 in the full sample suggesting that the average stock in our sample experiences institutional attention shocks on 8.9% of all trading days. The average frequency of retail attention shocks is similar at 0.092.[11]

AIA frequency increases to 0.62 for the *EarnAnn* Sample suggesting that 62% of the announcement days coincide with an institutional attention shock. This is not surprising as earnings announcements are likely to attract institutional investor attention. At the same time, we note that not all earnings announcements coincide with institutional attention shocks. This heterogeneity is important and allows us to study the impact of institutional attention on asset prices after controlling for the magnitude of earnings surprise.

There are several potential reasons why not every earnings announcement is associated with AIA equal to one. First, firms may strategically time the

[11] For both *AIA* and *DADSVI*, their unconditional averages are higher than 0.06. For *AIA*, it is due to the use of maximum hourly attention throughout the day. For *DADSVI*, it is because of a slight upward time trend in *DSVI* during our sample period.

Table 2
Summary statistics of *AIA* and other selected variables

A. Cross-sectional statistics

	Full sample			*EarnAnn* sample			*RecChng* sample		
Variables	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Num firms	2,669			2,231			2,068		
AIA	0.089	0.070	0.082	0.620			0.478		
DADSVI	0.092	0.096	0.030	0.173			0.132		
SizeInM	6,171	1,120	21,529	6,511	1,211	22,460	7,258	1,609	23,007
BM	0.69	0.61	0.78	0.62	0.54	0.45	0.61	0.51	0.55
SDRET	2.25	2.05	0.96	2.10	1.87	1.04	2.24	1.97	1.22
Ret %	0.05	0.06	0.12	0.17	0.19	2.81	0.25	0.21	4.55
DGTW %	0.01	0.01	0.11	0.14	0.13	2.67	0.17	0.14	4.39
Turnover	0.01	0.01	0.01	0.03	0.02	0.03	0.02	0.02	0.03
Dvol	55.33	10.66	198.30	141.15	31.02	508.27	107.10	33.51	303.56
HLtoH	0.03	0.03	0.01	0.07	0.06	0.03	0.05	0.04	0.03
InstHold	0.60	0.62	0.20	0.59	0.64	0.19	0.63	0.67	0.19
NumEst	9.12	7.04	7.06	9.45	7.38	6.74	10.98	9.10	6.94
Abs SUE/REC	N/A	N/A	N/A	2.75	2.31	2.03	1.37	1.33	0.31
EDGAR	51.82	31.59	86.71	97.33	61.63	139.55	72.02	41.58	119.51
AEDGAR	−0.04	−0.02	0.07	0.56	0.56	0.33	0.15	0.12	0.41

B. Sample averages conditioning on AIA

	Full sample		*EarnAnn* sample		*RecChng* sample	
Variables	AIA=0	AIA=1	AIA=0	AIA=1	AIA=0	AIA=1
AbsRet %	1.55	3.29	4.47	5.85	2.75	4.67
AbsDGTW %	1.26	2.94	4.19	5.47	2.43	4.33
Turnover	0.009	0.020	0.019	0.031	0.019	0.032
Dvol	49.88	80.02	69.74	159.65	87.85	151.06
HLtoH	0.030	0.047	0.065	0.072	0.040	0.051
Relative spread	0.0010	0.0008	0.0010	0.0006	0.005	0.0004
NumEst	9.11	9.47	7.57	10.26	11.23	12.58
InstHold	0.60	0.59	0.58	0.62	0.64	0.65
Abs SUE/REC	n/a	n/a	2.74	2.87	1.37	1.38
DADSVI	0.086	0.145	0.130	0.191	0.112	0.154
EDGAR	49.73	67.84	69.62	105.19	67.34	85.83
AEDGAR	−0.073	0.206	0.470	0.627	0.081	0.220

The table reports the summary statistics of our Abnormal Institutional Attention measure (*AIA*) from Bloomberg and other selected variables from February 2010 to December 2015. Our initial sample includes all Russell 3000 stocks with CRSP share codes 10 and 11, *AIA* information, and book-to-market information for the DGTW risk adjustment (Daniel et al. 1997). We report results for the full sample (*Full sample*), earnings announcements sample (*EarnAnn sample*), and the analyst recommendation changes sample (*RecChng sample*). *Full sample* includes 3,144,109 day stock observations, the *EarnAnn Sample* includes 34,400 *EarnAnn* stock observations, and the *RecChng sample* includes 16,312 *RecChng* stock observations. Panel A presents the mean, median, and standard deviation of the firms' time-series averages for each sample. Panel B provides the conditional means conditioning on AIA=0 and AIA=1. AIA and other variables are defined in Table 1.
Num firms reports the number of unique firms. *AIA* and *DADVI* report *AIA* and *DADSVI* frequency for all three samples, respectively. To calculate the frequency of *AIA* (*DADSVI*) in the case of the *Full sample*, we divide each firm's total number of days where *AIA* (*DADSVI*) is equal to one by the firm's total trading days during its sample period. Then we calculate the cross-sectional Mean, Median and SD. For *EarnAnn* and *RecChng* samples, we divide the number of firm-event cases in which AIA is equal to one by the total number of firm-event observations. For all of the other variables, mean, median, and SD refer to the cross-sectional average, median, and standard deviation of the firms' time-series averages.

announcements during the day in order to avoid institutional attention. In addition, some news articles on Bloomberg terminals may not include the exact earnings surprise numbers. Thus, institutional investors may overlook announcements even with large surprises. Finally, there could be important news about the firm released close to the earnings announcement day. High institutional attention on the announcement day may not appear to be abnormally high related to its recent average.

AIA frequency is slightly lower at 0.48 for the *RecChng* sample suggesting that 48% of the recommendation change days are associated with institutional attention shocks. One difference between earnings announcements and recommendation changes is that the former are usually prescheduled so institutional investors can optimally allocate more attention to the announcement day, while timing of the latter cannot typically be anticipated in advance. When compared to *AIA*, *DADSVI* frequency is much lower for both the *EarnAnn* sample (17%) and the *RecChng* sample (13%) implying that important firm events are more likely to immediately grab institutional attention than retail attention.

Exploring other stock characteristics across the three samples indicates that these are not small firms. The average (median) size is around 6.2 (1.1) billion. Naturally, the firms in the *RecChng* Sample are larger due to our recommendation filters that require at least two active analysts covering the firm. Not surprisingly, trading volume and intraday volatility are higher during the *EarnAnn* and *RecChng* announcement days. On average, institutional holdings make up around 59%-67% of shares outstanding, consistent with the well-documented increase in institutional holdings over time. Nine analysts, on average, cover a stock, and this number is naturally higher in the *RecChng* sample given the additional filters used in creating that sample. The average absolute value of the earnings surprise (change in analyst recommendation) is 2.75 (1.37).

Finally, panel A also reports the sample statistics of the EDGAR measures. On average, there are about 52 hits (excluding robots) on EDGAR on a given day for stocks in the Full Sample. This number increases to about 97 in the *EarnAnn* Sample and 72 in the *RecChng* Sample. These patterns are also evident in the abnormal measure. On average, *AEDGAR* increases by around 56% in *EarnAnn* sample and around 15% in *RecChng* sample. The difference in abnormal attention across these two events may not be surprising since earnings announcements are prescheduled events, while changes in analyst recommendations are typically less predictable.

In panel B, we present sample averages conditioning on *AIA* for the three samples. The panel indicates that across all three samples, absolute returns, turnover, dollar trading volume, and intraday price movements are higher during attention shocks. The average number of analysts is also higher consistent with greater information processing. Interestingly, both the magnitude of the earnings surprise and the magnitude of the changes in analyst recommendation are quite similar across the *AIA* subsamples. This suggests that the magnitude of the surprise is not the primary driver behind abnormal institutional investor attention. Finally, activity is higher on both EDGAR and Google suggesting that *AIA* is contemporaneously positively correlated with these attention measures. In Table 3, we examine these relations in a multivariate regression framework.

2. What Drives Institutional Attention?

2.1 Determinants of abnormal institutional and retail attention

We explore a wide set of variables that are associated with our abnormal institutional attention shocks. For comparison, we also investigate how these variables are associated with abnormal retail attention shocks. To examine these determinants, we conduct probit panel regressions in Table 3 using daily *AIA* as

Table 3
Contemporaneous relation between abnormal institutional attention, abnormal retail attention, attention proxies, and other explanatory variables

A.* AIA *as a dependent variable

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ANews t	0.400					0.374
	(86.16)					(77.66)
EarnAnnDum t	1.029					0.616
	(50.22)					(27.32)
RecChngDum t	1.116					0.767
	(62.31)					(43.68)
AbsDGTW t		0.063				0.041
		(20.23)				(7.36)
AVol t		0.055				0.034
		(6.09)				(6.19)
HLtoH t		3.196				11.275
		(10.01)				(14.48)
52 high dum t		0.364				−0.065
		(33.57)				(−5.57)
52 low dum t		0.100				−0.353
		(5.17)				(−13.77)
LnSize			0.153			0.226
			(26.20)			(35.48)
LnBM			0.019			0.032
			(1.97)			(3.19)
SDRET			0.037			−0.033
			(11.27)			(−5.64)
AdvExpToSale			0.192			0.090
			(1.20)			(0.54)
LnNumEst			0.286			0.268
			(20.87)			(18.28)
InstHold			−0.061			0.071
			(−2.19)			(2.21)
ADSVI t				0.176		0.081
				(13.37)		(8.48)
AEDGAR t				0.233		0.121
				(32.33)		(18.18)
Tuesday					−0.025	−0.077
					−1.58	(−3.71)
Wednesday					−0.056	−0.115
					−3.35	(−5.52)
Thursday					−0.057	−0.148
					−3.39	(−6.97)
Friday					−0.247	−0.312
					−14.97	(−14.07)
P-RSQ	5.14%	2.51%	5.10%	1.46%	0.22%	13.00%

(*continued*)

Table 3
Continued

B.* DADSVI *as a dependent variable

Variable	(1)	(2)	(3)	(4)	(5)	(6)
ANews t	0.055					0.019
	(12.89)					(5.16)
EarnAnnDum t	0.303					0.164
	(11.95)					(7.00)
RecChngDum t	0.127					0.040
	(7.09)					(2.32)
AbsDGTW t		0.025				0.019
		(12.93)				(10.27)
AVol t		0.026				0.021
		(6.23)				(3.86)
HLtoH t		−0.283				0.756
		(−1.62)				(4.68)
52 high dum t		0.087				0.042
		(9.07)				(4.41)
52 low dum t		0.100				0.066
		(5.94)				(4.04)
LnSize			0.007			0.009
			(2.22)			(2.57)
LnBM			0.001			0.002
			(0.23)			(0.58)
SDRET			−0.014			−0.027
			(−5.87)			(−9.94)
AdvExpToSale			0.114			0.100
			(1.14)			(0.96)
LnNumEst			0.012			0.000
			(1.83)			(0.03)
InstHold			0.010			0.036
			(0.62)			(2.24)
AIA t				0.208		0.118
				(20.25)		(12.70)
AEDGAR t				0.028		0.011
				(8.06)		(3.56)
Tuesday					−0.011	−0.013
					−0.86	(−1.01)
Wednesday					−0.065	−0.066
					−4.74	(−4.87)
Thursday					−0.083	−0.089
					−5.76	(−6.24)
Friday					−0.137	−0.136
					−7.46	(−7.40)
P-RSQ	0.15%	0.21%	0.04%	0.20%	0.08%	0.50%

The table reports the results of the contemporaneous relation between our Abnormal Institutional Attention measure (*AIA*) from Bloomberg (panel A) and the abnormal retail attention dummy (*DADSVI*) based on Google's daily Search Volume Index (panel B) on selected explanatory variables. *AIA*, *DADSVI*, and other variables are defined in Table 1.

Panel A includes 3,144,109 day stock observations, and panel B includes 1,338,203 day stock observations. We handle *DADSVI*'s missing observations when analyzing *AIA* in panel A using Pontiff and Woodgate's (2008) approach. First, we define a dummy variable that takes a value of one whenever the *DADSVI* exists and zero otherwise. Then we replace *DADSVI* missing values with zeros. We repeat the same procedure for *AEDGAR*.

Each panel includes six identical specifications. For example in panel A, Specification 1 examines the relation between *AIA* and "News" variables; Specification 2 examines the relation between *AIA* and price related variables; Specification 3 examines the relation between *AIA* and other firm characteristics; Specification 4 examines the relation between *AIA* and other attention measures; Specification 5 examines the effect of the day of the week effect on *AIA*; and Specification 6 examines all five categories together. *P-RSQ* is the probit model's pseudo *R*-squared. Standard errors are clustered by firm and day and *t*-statistics are reported below the coefficient estimates.

the dependent variable in panel A and daily *DADSVI* as the dependent variable in panel B.

Motivated by the example of Overstock.com in Figure 1, we focus on five categories of variables when we analyze *AIA* and *DADSVI*. Starting with *AIA*, in Column (1) of panel A, we examine variables that are related to news. They include abnormal news coverage (*ANews)* and dummy variables to indicate earning announcements and recommendation changes. These news-related variables have the highest explanatory power of institutional attention shocks with a pseudo R-squared of 5.14%. All three news variables are significant.

In Column (2), we examine variables that are related to equilibrium outcomes of trading on that day. They include absolute DGTW-adjusted return (*AbsDgtw*), abnormal trading volume (*AVol*), measure of intraday volatility (*HLtoH*), and dummy variables indicating whether the current price beats the 52-week high or low (*52 high dum* and *52 low dum*). Many of these equilibrium outcomes have been used as proxies for investor attention (Gervais, Kaniel, and Mingelgrin 2001; Barber and Odean 2008; Hou, Peng, and Xiong 2009, among others). The regression coefficients reported in Column (2) confirm that these equilibrium outcomes are related to institutional attention shocks as well. Nevertheless, equilibrium outcomes have lower explanatory power when compared to news (pseudo R-squared is 2.51%) since they can be driven by many factors, such as risk and liquidity.

In Column (3), we examine various firm characteristics. We find that larger firms with greater analyst coverage are associated with significantly more institutional attention shocks, on average. The results are similar to those found in the prior literature using other measures of investor attention (Grullon, Kanatas, and Weston 2004; Da, Engelberg, and Gao 2011; Liu and Peng 2015). Alternatively, controlling for the other variables, we do not find a significant relation between advertising expenditures and institutional attention. Altogether, firm characteristics have a combined pseudo R-squared of 5.10%.

In Column (4), we include the other direct measures of attention, *AEDGAR*, and abnormal retail attention, *ADSVI*. Both measures are positively related to *AIA*. Strikingly, the pseudo R-squared is only 1.46%. One possible reason is that the EDGAR measure is limited to a subset of mandatory filings, while *AIA* captures abnormal institutional attention to a broader set of news events. Indeed, Drake, Roulstone, and Thornock (2015) find that 86% of the users accessing EDGAR do so infrequently and only around 2% of the users access EDGAR actively during a given quarter. Similarly, retail attention is more likely to be reactive (to occurrence of news) rather than proactive as a result of an optimal attention allocation decision.

In Column (5), we find strong within-week seasonality associated with institutional attention. The likelihood of an institutional attention shock decreases monotonically from Monday to Friday. For example, a stock is 25% less likely to have an attention shock on a Friday compared to a Monday, consistent with the results in DellaVigna and Pollet (2009). The total explanatory power of the seasonality effect is low with a pseudo R-squared of only 0.22%.

Finally, in Column (6), we include all five categories of explanatory variables and obtain a pseudo R-squared of 13%. The result suggests that existing proxies of investor attention explain a small fraction of institutional attention shocks. Of course, the low pseudo R-squared could be partially driven by measurement errors in *AIA*. Despite any such errors, our subsequent analysis confirms that the component of AIA orthogonal to other investor attention proxies continue to exert significant impact on asset prices.

Next, to better understand differences in what drives institutional attention and retail attention, we examine *DADSVI* in panel B. Column (1) indicates that the relation between *DADSVI* and news-related measures is qualitatively similar to what we find with institutional attention. However, with an adjusted $R-$squared of only 0.15%, these variables explain very little of the variation in retail attention. In fact, this is true of all six specifications in panel B.

Results using the equilibrium outcome measures in Column (2) look relatively similar to those for *AIA*, with one exception. Instead of a positive relation between the intraday price range and attention, there is a negative relation, although it is not significant. Column (3) of panel B indicates that abnormal institutional and retail attention behaves differently with respect to firm characteristics. While larger firms are more likely to draw both types of attention, the only additional variable with a statistically significant relation to abnormal retail attention is *SDRET*. The negative coefficient on *SDRET* is potentially driven by the fact that *SDRET* is measured from day t-27 to day t-6. A high *SDRET* likely correlates with high *DSVI*s in that backward window and therefore lower *ADSVI* on day t. Column (4) shows that both *AIA* and *AEDGAR* are positively related to retail attention, though the adjusted $R-$squared is only 0.20%. As was the case with *AIA*, there is within-week seasonality in *DADSVI*. Column (5) reports that retail attention is significantly lower on Friday than on Monday.

Finally, in Column (6), we regress abnormal retail attention on all five categories of variables. The results are generally similar to those in the first five columns. Jointly, these variables explain less than 0.50% of the variation in the direct measure of abnormal retail attention. In similar analysis in Da, Engelberg, and Gao (2011), a set of attention related variables explains about 3% of the variation in abnormal SVI at a weekly frequency. Variations in daily abnormal SVI seem even harder to explain.

2.2 Institutional attention, retail attention, and abnormal trading volume

Investor attention often triggers trading. If *AIA* truly measures abnormal institutional attention, we would expect there to be a strong contemporaneous correlation between *AIA* and investor trading. Moreover, we would expect the impact of AIA on trading to be the most pronounced for institutional investors. In contrast, we wouldn't expect to find similar patterns using abnormal retail attention. We test this conjecture in Table 4. In particular, we calculate two measures of abnormal trading using Ancerno and CRSP. Abnormal institutional trading volume (*Ancerno-AVol*) is calculated as the stock's Ancerno daily volume divided by the previous eight-week average Ancerno trading volume. As a benchmark, abnormal total trading volume (*CRSP-AVol*) is calculated as the stock's CRSP daily volume divided by the previous eight-week average

Table 4
Abnormal institutional attention, abnormal retail attention, and abnormal trading volume

A.* AIA and *abnormal trading volume

Variable	(1)	(2)	(3)	(4)	(5)	(6)
CRSP-AVol-diff	0.686	0.490	0.263	0.234	0.229	0.237
	(35.76)	(26.91)	(16.69)	(15.50)	(15.45)	(15.41)
Ancerno-AVol- diff	0.797	0.580	0.339	0.309	0.299	0.312
	(32.82)	(26.60)	(15.72)	(16.11)	(15.67)	(15.85)
Diff-In-diff	0.111	0.090	0.077	0.075	0.070	0.076
	(8.91)	(7.39)	(5.68)	(5.44)	(5.21)	(5.48)
Table 3 controls						
Control set 1		Yes	Yes	Yes	Yes	Yes
Control set 2			Yes	Yes	Yes	Yes
Control set 3				Yes	Yes	Yes
Control set 4					Yes	Yes
Control set 5						Yes
Adj-RSQ	0.61%	0.86%	2.27%	3.72%	3.74%	3.79%

B.* DADSVI *and Abnormal Trading Volume

Variable	(1)	(2)	(3)	(4)	(5)	(6)
CRSP-AVol-diff	0.137	0.109	0.068	0.060	0.052	0.055
	(14.85)	(13.67)	(12.49)	(11.93)	(11.09)	(11.80)
Ancerno-AVol- diff	0.142	0.113	0.065	0.061	0.051	0.056
	(10.18)	(8.60)	(5.43)	(5.14)	(4.29)	(4.64)
Diff-In-diff	0.005	0.004	−0.003	0.000	−0.001	0.001
	(0.80)	(0.58)	(−0.30)	(0.04)	(−0.13)	(0.09)
Table 3 controls						
Control set 1		Yes	Yes	Yes	Yes	Yes
Control set 2			Yes	Yes	Yes	Yes
Control set 3				Yes	Yes	Yes
Control set 4					Yes	Yes
Control set 5						Yes
Adj-RSQ	0.06%	0.80%	3.09%	3.47%	3.49%	3.55%

The table reports the results of panel regressions of abnormal trading volume on abnormal institutional attention, *AIA* (panel A), and the abnormal retail attention dummy, *DADSVI* (panel B), controlling for Table 3's attention determinants. *AIA*, *DADSVI*, and other control variables are defined in Table 1. We explore two samples of trading volume. The first is based on CRSP, where we use *CRSP-AVol* as our abnormal volume measure. The second sample is obtained from Ancerno, Ltd. and captures institutional investors' trading volume, where we use *Ancerno-Avol* as our abnormal volume measure. After matching the CRSP and Ancerno samples and accounting for *DADSVI*'s data availability, panel A (B) includes 2,429,356 (1,023,071) day stock observations.
Panel A includes six specifications, where we sequentially add the five sets of control variables associated with institutional attention explored in Table 3. For example, *Control set 1* includes the *ANews*, *EarnAnnDum*, and *RecChngDum* control variables. Note that we exclude abnormal volume from *ControlSet* 2 as abnormal volume is our dependent variable. Recall that *AIA* is a dummy variable. Thus, its coefficient captures the additional effect abnormal institutional attention (i.e., AIA=1). For brevity, we only report AIA's coefficient. *CRSP-AVol-diff* (*Ancerno-AVol-diff*) is the difference in the average abnormal volume of AIA=1 and AIA=0, where *CRSP-AVol* (*Ancerno-AVol*) is the dependent variable. *Diff-in-diff* is the difference between the samples' average differences using the difference-in-differences regression approach. Panel B includes the same specifications. Panel B repeats the same analysis conducted in panel A with *DADSVI* instead of *AIA*. Similar to panel A, *CRSP-AVol-diff* (*Ancerno-AVol-diff*) is the difference between *DASAVI*=1 and *DADSVI*=0, where *CRSP-AVol* (*Ancerno-AVol*) is the dependent variable and *Diff-in-diff* is the difference using the difference-in-differences regression approach. Standard errors are clustered by firm and day. *t*-statistics are reported below the regression coefficients.

CRSP trading volume. The tests end in June 2015 due to the availability of the Ancerno data.

We regress these abnormal trading volume measures on *AIA* (panel A) and *DADSVI* (panel B). The panels include six regression specifications, where we sequentially add the five sets of control variables associated with institutional attention from Table 3. For each measure, we report the first difference (i.e., the difference in coefficients between *AIA*=0 and *AIA*=1 in panel A and *DADSVI*=0 and *DADSVI*=1 in panel B), together with the difference in difference (*Diff-in-diff*) and its statistical significance. For example, the *CRSP-AVol-diff* coefficient estimate in panel A captures the additional response of CRSP's abnormal volume to a shock in *AIA*.

Focusing on the final column of panel A, where we include all five sets of control variables, we find a statistically significant coefficient of 0.237 on *CRSP-AVol-diff*. The result suggests that an institutional attention spike is accompanied with a 23.7% increase in abnormal total trading volume, relative to the case of *AIA*=0. The coefficient on *Ancerno-AVol-diff* is larger with a value of 0.312 confirming that the same institutional attention spike correlates much more with abnormal institutional trading volume. The difference between the two coefficients (i.e., *Diff-in-diff*) of 0.076 is significant with a t-statistic of 5.48.

While there is no direct daily measure of abnormal retail trading, we can infer the impact of *AIA* on retail trading by making two additional assumptions. First, suppose 40% of all trading is retail trading (given that the average institutional ownership is 60% for stocks in our sample). Second, assume Ancerno trading is proportional to total institutional trading. Given these assumptions, the impact of *AIA* on total trading (0.237), on institutional trading (0.312) and on retail trading (RT) should then be linked via $0.237 = 0.6 \times 0.312 + 0.4 \times \text{RT}$, implying a RT of 0.125. Recall that Ancerno data consists primarily of trades by mutual funds and pension plans who are not the most active institutional investors, so the impact of *AIA* on institutional trading could be even higher than 0.312. In addition, institutional trading accounts for more than 60% of the total trading.[12] In both cases, the impact of *AIA* on retail trading will be even lower.

The retail attention shock examined in panel B clearly presents a different pattern. First, although the coefficients on *CRSP-AVol-diff* are positive in all six specifications, their magnitudes are only around one-fifth of the magnitudes presented in panel A. Moreover, the coefficients on *Ancerno-AVol-diff* are not significantly different from those on *CRSP-AVol-diff* suggesting that retail attention does not impact CRSP volume and Ancerno volume differently. Finally, a Wald test confirms that the *Diff-in-diff* coefficients in panels A and B are significantly different from each other.

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12 Average institutional ownership for a given stock in our sample is around 60%. However, this doesn't imply that 40% of all equity trading comes from retail investors. For example, high-frequency-trading accounts for roughly half of U.S. equity trading (Deutsche Bank research briefing on May 24, 2016); however, high-frequency equity ownership stake is probably close to 0% of all shares.

2.3 Institutional attention, retail attention, and news: Lead-lag relation

To examine the lead-lag relation between institutional attention shocks and retail attention shocks and how they respond differently to news, we use the Vector auto regression (VAR) analysis. Because the dummy variable *AIA* is not appropriate for the VAR analysis, we instead use *AIAC*. We standardize the abnormal retail attention measure *ADSVI* and the abnormal news coverage measure *ANews* so the coefficients in the VAR can be interpreted as the impact of a one standard deviation shock. We run the VAR analysis with firm fixed effects in our full sample.[13] We also include *AEDGAR* in the VAR in our Internet Appendix. The inclusion of *AEDGAR* does not change our results as EDGAR downloads are primarily triggered by specific regulatory filings.

The coefficients from the VAR analysis are presented in Table 5. The main findings can be visually illustrated by various impulse response functions plotted in Figure 3. For example, Subplot (1) of Graph 3.A plots the cumulative response of *AIAC* to a one standard deviation shock in the *ADSVI*. The predictability of *ADSVI* on *AIAC* on day 1 is positive, but insignificant both statistically and economically. Importantly, this relation becomes negative afterward. Overall, there is very weak evidence that retail attention shocks lead institutional attention shocks.

Subplot (2) of Graph 3.A plots the cumulative response of *ADSVI* to a one standard deviation shock in *AIAC*. In sharp contrast to Subplot (1), Subplot (2) shows that *AIAC* positively and significantly predicts *ADSVI* and such predictability is persistent. Hence, there is strong evidence that institutional attention shocks lead to retail attention shocks. This finding is not surprising as institutional investors have greater resources and stronger financial incentives to monitor the market and are more likely to pay attention to news and react immediately. In contrast, retail attention may only be triggered by subsequent newspaper and other media coverage with a delay.

Graph 3.B provides direct supporting evidence using impulse response functions to shocks in news coverage. Subplot (1) plots the cumulative response of *AIAC* to a one standard deviation shock in *ANews*. It is clear that shocks in news coverage do not have a persistent positive impact on institutional attention in the future. Subplot (2) plots the cumulative response of *ADSVI* to the same shock in *ANews* and shows a different pattern. Shocks in news coverage do have a persistent positive impact on retail attention in the future suggesting that retail investors react to news coverage with a delay.

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13 Since firms observations are pooled together, we include firm fixed effects to remove any firm-specific determinants that might affect the coefficient estimation. One potential caveat is that Nickell (1981) shows that coefficient estimates of dynamic panel data models that include autoregressive terms and fixed effects are biased in finite samples. However, Nickell further shows that the bias diminishes with the length of the time series. Since we have around 1.3 million observations this shouldn't have a significant effect on our estimations. To alleviate any concerns, we rerun analysis, excluding firm fixed effects, and find that the coefficient estimates are qualitatively similar.

Table 5
Lead-lag analysis of AIA, ADSVI and ANews

	AIAC t			*ADSVI t*		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
AIAC t-1	0.276	0.245	0.245	0.028	0.019	0.019
	(80.34)	(72.10)	(72.30)	(11.94)	(8.90)	(8.90)
AIAC t-2	0.070	0.073	0.072	−0.003	−0.003	−0.003
	(27.57)	(29.63)	(29.64)	(−1.89)	(−1.70)	(−1.70)
AIAC t-3	0.057	0.058	0.058	−0.005	−0.005	−0.005
	(24.95)	(26.11)	(26.19)	(−2.89)	(−2.75)	(−2.75)
AIAC t-4	0.046	0.049	0.049	−0.009	−0.009	−0.009
	(19.88)	(21.37)	(21.29)	(−5.28)	(−4.99)	(−5.00)
AIAC t-5	0.075	0.076	0.076	0.000	0.000	0.000
	(28.19)	(28.87)	(28.91)	(0.14)	(0.26)	(0.26)
ADSVI t-1	0.003	0.000	0.000	0.260	0.259	0.259
	(2.13)	(−0.36)	(−0.37)	(53.94)	(53.77)	(53.77)
ADSVI t-2	−0.003	−0.003	−0.003	0.092	0.092	0.092
	(−4.22)	(−4.75)	(−4.66)	(36.31)	(36.26)	(36.26)
ADSVI t-3	−0.003	−0.003	−0.003	0.058	0.058	0.058
	(−3.84)	(−4.34)	(−4.27)	(27.37)	(27.26)	(27.25)
ADSVI t-4	−0.002	−0.001	−0.002	0.068	0.068	0.068
	(−2.08)	(−1.92)	(−1.98)	(24.37)	(24.41)	(24.42)
ADSVI t-5	−0.003	−0.002	−0.002	0.108	0.108	0.108
	(−3.35)	(−2.89)	(−2.78)	(28.23)	(28.25)	(28.25)
ANews t-1	0.015	0.006	0.006	0.010	0.007	0.007
	(5.64)	(4.37)	(4.31)	(5.75)	(4.32)	(4.32)
ANews t-2	−0.002	−0.010	−0.010	0.002	0.000	0.000
	(−1.82)	(−7.80)	(−7.86)	(1.14)	(−0.19)	(−0.20)
ANews t-3	−0.001	−0.008	−0.008	0.003	0.001	0.001
	(−0.57)	(−6.58)	(−6.67)	(2.32)	(0.95)	(0.95)
ANews t-4	−0.004	−0.012	−0.012	−0.001	−0.003	−0.003
	(−3.23)	(−10.22)	(−10.36)	(−0.46)	(−1.81)	(−1.81)
ANews t-5	−0.025	−0.029	−0.029	0.000	−0.001	−0.001
	(−18.12)	(−22.23)	(−22.55)	(0.10)	(−0.53)	(−0.55)
AVol t		0.046	0.046		0.016	0.016
		(8.64)	(8.63)		(6.80)	(6.81)
AbsRet t		0.049	0.049		0.017	0.017
		(16.70)	(16.69)		(13.45)	(13.45)
EarnAnnDum t		0.877	0.875		0.177	0.177
		(42.84)	(42.76)		(9.92)	(9.91)
RecChngDum t		0.593	0.593		0.044	0.044
		(37.51)	(37.48)		(3.66)	(3.67)
AveMktNews t			0.125			−0.039
			(3.14)			(1.89)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
AIAC-ADSVI diff						0.164
Wald test p-value						(0.01)
AdjRSQ	13.45%	19.03%	19.05%	15.96%	16.16%	16.16%

The table reports the results from panel vector autoregressions of *AIAC* and *ADSVI* on lagged *AIAC*, *ADSVI*, *ANews*, and other explanatory variables. The sample includes 1,338,203 day stock observations. See Tables 1 and 2 for variable and sample definitions. Because *ADSVI* and *ANews* are standardized, coefficients can be interpreted as the impact of one standard deviation shocks. In the table, *AveMktNews t* is the cross sectional average of firm news, where news is measured as a dummy variable that is equal to one in case of news and zero otherwise. This basically captures market-wide news intensity. For each of the lagged explanatory variables, the suffix t-j refers to the jth lag of the corresponding variable, where j is from 1-5. For example, *AIAC t*-1 is the first lag of *AIAC*. *AIAC-ADSVI diff* is the difference between AIAC and *ADSVI*'s *AveMktNews* coefficients (Specifications 3 and 6). Wald test p-value is the p-value for the difference between these coefficients, where the coefficient covariance matrix accounts for firm and day clustering. All regressions include firm fixed effects. Standard errors are clustered by firm and day. t-statistics are reported below the regression coefficients.

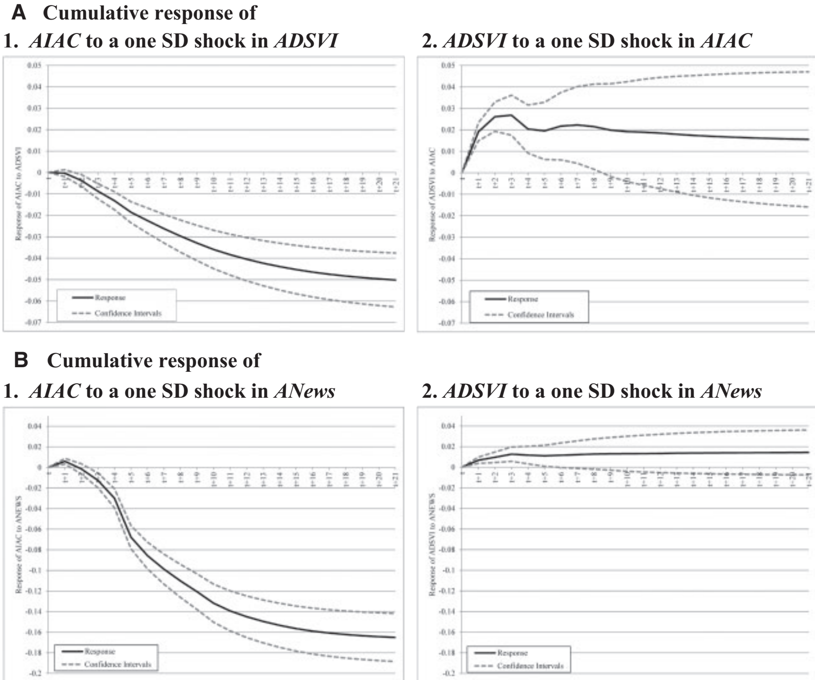

Figure 3
Cumulative impulse response functions of AIAC and ADSVI
These figures depict the cumulative impulse response functions of *AIAC*, *ADSVI* using a three-equation panel *VAR* system with five lags of each of the dependent variables. In particular, the VAR estimation is based on Specifications (3) and (6) of Table 5 with firm fixed effects and additional exogenous variables:

$$AIAC_{i,t} = \alpha_1 + \sum_{t=1}^{5} \beta_{1j} AIAC_{i,t-j} + \sum_{t=1}^{5} \gamma_{1j} ADSVI_{i,t-j} + \sum_{t=1}^{5} \delta_{1j} ANews_{i,t-j} + ExoVar_{i,t} + FirmFE + \varepsilon_{1i,t}$$

$$ADSVI_{i.t} = \alpha_2 + \sum_{t=1}^{5} \beta_{2j} AIAC_{i,t-j} + \sum_{t=1}^{5} \gamma_{2i} ADSVI_{i,t-j} + \sum_{t=1}^{5} \delta_{2j} ANews_{i,t-j} + ExoVar_{i,t} + FirmFE + \varepsilon_{2i,t}$$

$$ANews_{i,t} = \alpha_3 + \sum_{t=1}^{5} \beta_{3j} AIAC_{i,t-j} + \sum_{t=1}^{5} \gamma_{3j} ADSVI_{i,t-j} + \sum_{t=1}^{5} \delta_{3j} ANews_{i,t-j} + ExoVar_{i,t} + FirmFE + \varepsilon_{3i,t}$$

Graph 3A1 depicts the cumulative response of *AIAC* (*ADSVI*) to a one standard deviation shock in *ADSVI (AIAC)*. Graph 3B1 depicts the cumulative response of *AIAC* (*ADSVI*) to a one standard deviation shock in *ANews*. In each graph, the solid black line represents the cumulative impulse response and the dashed gray lines represent the 95% confidence intervals. Standard errors and confidence intervals of the impulse response functions are estimated via 100,000 simulations. In each simulation round, we calculate the impulse response functions based on a new draw of the model's parameters. Each draw is based on the original parameter estimates and the parameters' covariance matrix accounting for firm and day clustered standard errors (see Hamilton 1994, 336–7 for more detail).

In Columns (3) and (6) of Table 5, we also include a time series variable, *AveMktNews*, computed as the cross-sectional average of firm news. Thus, on days with high *AveMktNews*, there is more news in the market to be processed. Column (3) reports that *AIAC* loads positively and significantly on *AveMktNews* implying that institutional investors also allocate more attention on those days. In sharp contrast, Column (6) reports that *SVIC* loads negatively on *AveMktNews* (t-value = 1.89). Thus, retail investor attention is more constrained than institutional investor attention suggesting that the *investor distraction* hypothesis of Hirshleifer, Lim, and Teoh (2009) is more relevant for retail investors than for institutional investors.

To summarize, we find that institutional attention measured using *AIA* is unique. While it is related to existing proxies of investor attention in an intuitive way, a large fraction of *AIA* remains unexplained even with the existing proxies combined. Equipped with our *AIA* measures, we can then directly examine how institutional investor attention affects asset prices in response to information. This is the focus of our analysis in the next section.

3. Institutional Attention and Price Response to Information

The announcements of corporate earnings and analyst recommendation changes are both important value-relevant information events for a firm. A voluminous literature has documented post-announcement price drift following both events. Investors seemingly underreact to both announcements, on average. In this section, we examine whether institutional attention on the announcement day facilitates faster information incorporation and alleviates price underreaction to news.

3.1 Earnings announcements

We examine the impact of institutional attention on earnings announcement day returns and post-earnings announcement drifts using panel regressions. The results are reported in Table 6. If institutional investors facilitate information incorporation through attention and information processing, we would expect this information to be incorporated on the earnings announcement day t. More importantly, it would result in less (if any) drift over subsequent days (day t+1 onward). Alternatively, if institutional attention amplifies behavioral bias, such as the disposition effect studied in Frazzini (2006), it might result in price pressure on day t in the opposite direction of the earnings surprise. The price pressure, when reverted, will exacerbate the price drift over subsequent days.

Since many factors (observable and unobservable) can affect day t returns, it is virtually impossible to provide direct evidence of a causal relation on day t. However, less drift going forward would be clear evidence of information incorporation on day t. Accordingly, in this subsection, we provide clear evidence of less (if any) drift in stocks with high abnormal attention. Regarding the impact of *AIA* on day t returns, we discuss three potential explanations and argue that a causal effect of *AIA* on day t is the most likely explanation given the full set of our results. Finally, we show that the impact of retail attention, while consistent with previous findings, is completely different from the impact of institutional attention.

The dependent variables are day t *DGTW* risk-adjusted returns and $t+1$ to $t+40$ risk-adjusted cumulative returns where day t represents the earnings

Table 6
Institutional attention and earnings announcements returns

A. Base case

	Day	Drift							
Variables	*t*	*t+1_t+1*	*t+1_t+2*	*t+1_t+3*	*t+1_t+5*	*t+1_t+10*	*t+1_t+20*	*t+1_t+30*	*t+1_t+40*
AIA t	0.0014	−0.0001	−0.0003	−0.0003	−0.0002	0.0000	0.0000	0.0017	0.0014
	(1.35)	(−0.21)	(−0.54)	(−0.40)	(−0.29)	(0.04)	(−0.00)	(0.96)	(0.75)
SUE t	0.0037	0.0006	0.0007	0.0009	0.0009	0.0013	0.0016	0.0014	0.0014
	(15.36)	(7.44)	(7.57)	(8.02)	(8.43)	(8.40)	(7.50)	(6.24)	(5.53)
SUE_AIA t	0.0008	−0.0003	−0.0003	−0.0005	−0.0005	−0.0008	−0.0009	−0.0009	−0.0010
	(2.69)	(2.64)	(−2.48)	(−4.00)	(−3.59)	(−4.30)	(−3.54)	(−3.03)	(−2.78)
ANews t	0.0018	0.0002	0.0003	0.0004	0.0005	0.0006	0.0008	0.0011	0.0016
	(4.37)	(1.11)	(1.19)	(1.51)	(1.37)	(1.44)	(1.53)	(1.54)	(2.04)
DADSVI t	0.0003	−0.0011	−0.0014	−0.0012	−0.0008	−0.0017	−0.0001	0.0006	0.0005
	(0.24)	(−1.96)	(−2.21)	(−1.66)	(−0.86)	(−1.35)	(−0.07)	(0.31)	(0.21)
AEDGAR t	−0.0011	0.0000	0.0001	−0.0002	−0.0001	0.0004	−0.0002	0.0002	−0.0012
	(−2.04)	(−0.04)	(0.38)	(−0.56)	(−0.11)	(0.76)	(−0.35)	(0.23)	(−1.18)
AVol t	−0.0012	0.0004	0.0004	0.0004	0.0005	0.0009	0.0011	0.0012	0.0011
	(−1.61)	(3.37)	(2.72)	(2.49)	(2.49)	(3.59)	(3.06)	(3.20)	(2.93)
HLtoH t	−0.1155	−0.0301	−0.0403	−0.0383	−0.0344	−0.0514	−0.0523	−0.0458	−0.0987
	(−3.29)	(−4.17)	(−3.72)	(−2.97)	(−2.03)	(−2.65)	(−1.97)	(−1.56)	(−2.97)
Ret t-5_t-1	−0.0007	0.0000	0.0000	0.0000	0.0000	−0.0001	−0.0004	−0.0004	0.0002
	(−5.32)	(0.32)	(0.77)	(0.41)	(−0.13)	(−0.75)	(−1.71)	(−1.38)	(0.67)
Turnover t-5_t-1	−0.1491	0.0061	0.0059	0.0617	0.0975	0.1175	−0.0394	−0.2679	−0.4344
	(−2.41)	(0.21)	(0.17)	(1.36)	(1.44)	(1.35)	(−0.34)	(−2.02)	(−2.75)
Spread t-5_t-1	−0.0704	−0.1926	−0.2600	−0.0487	−0.0373	−0.0641	0.2721	0.8670	1.2520
	(−0.15)	(−0.50)	(−0.57)	(−0.10)	(−0.06)	(−0.09)	(0.29)	(0.81)	(1.09)
SDRET	0.0011	0.0004	0.0004	0.0003	0.0000	0.0002	0.0008	0.0010	0.0037
	(1.96)	(1.65)	(1.27)	(0.59)	(0.09)	(0.25)	(0.60)	(0.67)	(1.35)
LnSize	−0.0027	−0.0001	−0.0002	−0.0004	−0.0007	−0.0014	−0.0010	−0.0011	−0.0007
	(−5.69)	(−0.50)	(−0.87)	(−1.20)	(−1.98)	(−2.86)	(−1.52)	(−1.34)	(−0.82)
LnBM	−0.0015	0.0001	0.0003	0.0004	0.0006	0.0003	0.0004	−0.0009	−0.0018
	(−2.75)	(0.22)	(0.74)	(1.14)	(1.10)	(0.39)	(0.43)	(−0.81)	(−1.37)
InstHold	0.0043	−0.0001	0.0000	0.0000	−0.0001	0.0000	0.0003	0.0004	0.0001
	(2.52)	(−0.17)	(−0.00)	(0.03)	(−0.09)	(0.01)	(0.12)	(0.12)	(0.02)
LnNumEst	0.0000	−0.0002	0.0002	0.0002	0.0002	0.0003	−0.0003	−0.0007	−0.0019
	(−0.03)	(−0.51)	(0.29)	(0.28)	(0.26)	(0.31)	(−0.18)	(−0.40)	(−0.94)

B. Adding interactions

AIA t	0.0016	−0.0001	−0.0003	−0.0002	−0.0002	0.0001	0.0001	0.0016	0.0014
	(1.55)	(−0.14)	(−0.47)	(−0.33)	(−0.26)	(0.06)	(0.04)	(0.92)	(0.74)
DADSVI t	−0.0005	−0.0014	−0.0017	−0.0015	−0.0010	−0.0016	0.0002	0.0002	0.0003
	(−0.32)	(−2.40)	(−2.40)	(−1.95)	(−0.98)	(−1.25)	(0.13)	(0.10)	(0.12)
AEDGAR t	−0.0007	0.0000	0.0001	−0.0003	0.0000	0.0004	−0.0001	0.0001	−0.0011
	(−1.20)	(−0.10)	(0.38)	(−0.71)	(−0.09)	(0.68)	(−0.07)	(0.12)	(−0.95)
AVol t	−0.0014	0.0004	0.0004	0.0004	0.0005	0.0009	0.0011	0.0012	0.0011
	(−2.37)	(3.36)	(2.72)	(2.46)	(2.54)	(3.49)	(3.13)	(3.17)	(2.77)
ANEWS t	0.0011	0.0003	0.0003	0.0004	0.0005	0.0007	0.0008	0.0011	0.0016
	(2.94)	(1.40)	(1.26)	(1.62)	(1.47)	(1.62)	(1.32)	(1.45)	(1.90)
SUE t	0.0000	0.0006	0.0006	0.0008	0.0009	0.0012	0.0011	0.0011	0.0013
	(0.06)	(6.24)	(3.64)	(5.09)	(4.66)	(5.00)	(3.88)	(3.12)	(2.97)
SUE_AIA t	0.0002	−0.0003	−0.0003	−0.0005	−0.0005	−0.0008	−0.0008	−0.0008	−0.0010
	(0.76)	(−3.64)	(−2.73)	(−4.19)	(−3.58)	(−4.08)	(−3.09)	(−2.79)	(−2.85)
SUE_DADSVI t	0.0007	0.0003	0.0003	0.0003	0.0001	−0.0001	0.0000	0.0000	0.0002
	(1.42)	(1.83)	(1.31)	(1.62)	(0.54)	(−0.18)	(−0.02)	(−0.02)	(0.37)
SUE_AEDGAR t	−0.0001	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	−0.0001	−0.0002
	(−0.53)	(0.30)	(0.09)	(0.61)	(0.00)	(0.49)	(−0.22)	(−0.29)	(−0.70)
SUE_AVol t	0.0008	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001
	(5.78)	(0.81)	(0.82)	(0.99)	(1.26)	(1.47)	(1.80)	(1.38)	(1.32)
SUE_ANewst	0.0007	−0.0001	0.0000	0.0000	−0.0001	−0.0001	−0.0001	−0.0001	0.0000
	(5.13)	(−1.41)	(−0.21)	(−0.63)	(−0.68)	(−1.16)	(−0.41)	(−0.41)	(−0.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DADSVI-AIA Interaction diff	0.00048	0.00058	0.00060	0.00085	0.00067	0.00076	0.00079	0.00081	0.00117
Wald test *p*-value	0.37	0.00	0.01	0.00	0.02	0.03	0.06	0.07	0.05

(*continued*)

Table 6
Continued

C. Earnings announcements after market close

	Day	Drift							
Variables	*t*	*t+1_t+1*	*t+1_t+2*	*t+1_t+3*	*t+1_t+5*	*t+1_t+10*	*t+1_t+20*	*t+1_t+30*	*t+1_t+40*
AIA t-1	0.0008	−0.0002	0.0000	0.0000	0.0008	0.0005	0.0026	0.0031	0.0010
	(0.53)	(−0.44)	(−0.04)	(−0.06)	(0.78)	(0.34)	(1.34)	(1.27)	(0.36)
SUE t-1	0.0044	0.0006	0.0007	0.0008	0.0009	0.0012	0.0015	0.0010	0.0008
	(10.27)	(5.71)	(5.36)	(5.53)	(4.69)	(4.51)	(4.95)	(2.39)	(1.57)
SUE t -1_AIA t-1	0.0001	−0.0004	−0.0005	−0.0006	−0.0006	−0.0010	−0.0009	−0.0006	−0.0004
	(0.14)	(−3.29)	(−2.80)	(−2.91)	(−2.35)	(−3.04)	(−2.33)	(−1.89)	(−1.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the results of panel regressions of earnings announcements' day-t and cumulative day t+1 to t+40 *DGTW* risk-adjusted returns on abnormal institutional attention and other explanatory variables. The sample includes 34,440 firm-quarter observations (see Tables 1 and 2 for variable and sample definitions). In panel A, we present our base case. In panel B, we explore the robustness of our results by adding additional interaction variables. In panel C, we focus on a reduced sample of earnings announcements that occur from 4:00 p.m.-11:59 p.m. of day t-1 (after market close). We use I/B/E/S timestamps, which are reasonable for this analysis (see Table 1 in Michaely, Rubin, and Vedrashko 2014). The after-market-close sample includes 17,229 stock-quarter observations.

In all panels, *SUE* is the quarterly standardized unexpected earnings calculated from I/B/E/S as the quarter's actual earnings minus the average of the most recent analyst forecast, divided by the standard deviation of that forecast. *SUE_AIA* is the interaction between *SUE* and *AIA*. Since *AIA* is a dummy variable, the interaction between *SUE* and *AIA* measures the additional sensitivity of the *AIA*=1 group. In a similar manner, *SUE_DADSVI* measures the additional sensitivity of the *DADSVI*=1 group. *Ret* t-5_t-1 is the cumulative return from day t-5 to t-1. *Turnover* t-5_t-1 is the stock's average turnover from day t-5 to t-1. *Spread t-5_t-1* is the average relative half bid-ask spread from day t-5 to t-1, calculated as [(Ask-Bid)/Midpoint]/2 using *CRSP* end of day quotes. In panel 6.B, *DADSVI-AIA interaction diff* is the difference between the *SUE_AIA* and *SUE_DADSVI* coefficients. Wald test p-value is the p-value for the difference between these coefficients. Standard errors are clustered by firm and day and each model includes quarter and day-of-the-week fixed effects. In panel C, *AIA* is estimated on day t-1 to match *SUE* timing (i.e., 4:00 p.m.-11:59 p.m.), and *SUE* t-1_*AIA* t-1 is the interaction between *SUE* and *AIA* on day t-1. t-statistics are reported below the coefficient estimates.

announcement day. In panel A, the main dependent variables are: *AIA* (on day t), the quarterly standardized unexpected earnings (*SUE*), and their interaction term (*SUE_AIA*). To the extent that *SUE* controls for the fundamental information content at the announcement, the coefficient on *SUE_AIA* identifies the incremental impact of having institutional attention. We also include a comprehensive set of control variables that might affect returns.

The positive and significant coefficients on *SUE* confirm both the day t impact of the announcement and the existence of post-earnings announcement drift (PEAD). Stock prices react strongly to earnings surprises on the announcement day and continue to drift in the direction of *SUE* over the next 40 trading days. The coefficients on the interaction term *SUE_AIA* suggest that institutional attention facilitates information incorporation at the announcement and alleviates future drift. The positive coefficient on the announcement day suggests that when institutional investors pay attention, the stock's price reaction is stronger. Note that this additional price response is consistent with our conjecture that institutional attention facilitates information incorporation. Of course, unobservable factors associated with the content of the announcement may drive both the abnormal institutional attention and the additional price response. For example, earnings surprises with implications for long-term cash flows may result in a large price response and also generate uncertainty which, in turn, prompts institutional investors to search the firm on the Bloomberg terminal. However, if *AIA* on the earnings announcement day reflects uncertainty, it is likely to be associated with more initial underreaction and subsequently stronger price drift. In contrast, if *AIA* facilitates information incorporation on the announcement day, it should predict less price drift in the future.

When we examine price drifts after the announcement day, we find that the coefficients on the interaction term *SUE_AIA* are negative and significant starting from day t+1 up to day t+40. Strikingly, the magnitude of the coefficient is about −0.0010 by the end of t+40, which is close to the coefficient on *SUE* in absolute terms by t+40 (0.0014). Hence, when institutional investors pay more attention at the earnings announcement, there is almost no PEAD at all.

Our main results thus far in this subsection are nicely summarized in Figure 4. To construct this figure, we use the estimated regression coefficients from panel A of Table 6 and the conditional means of each group of interest (the four groups are based on the intersection between Positive *SUE*, negative *SUE*, *AIA*=0, and *AIA*=1). Figure 4 illustrates that the well-documented PEAD comes almost exclusively from announcements with limited institutional investor attention. The confidence bands suggest that the price drifts are significantly different between the *AIA*=1 and *AIA*=0 groups up to the first 40 days. Thus, our results

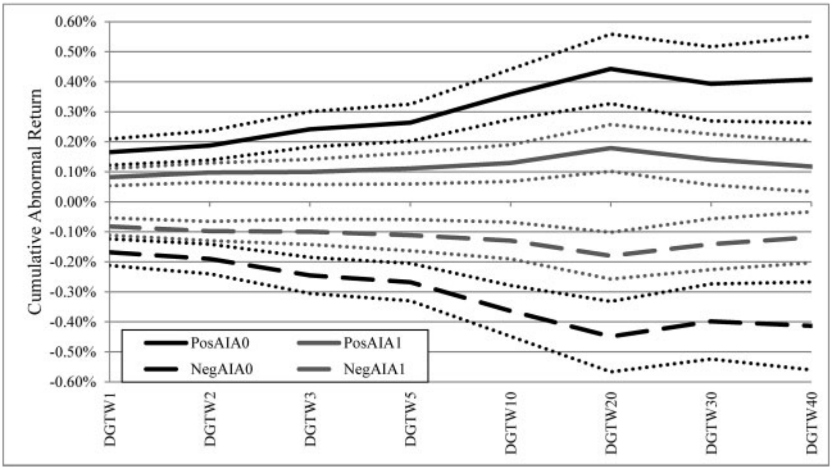

Figure 4
Abnormal institutional attention and earnings announcements returns
The figure plots the effect of earnings announcements on day t+1 to t+40 cumulative risk-adjusted returns for the following four cases: (1) positive *SUE* with *AIA* equal to zero (*PosAIA0*); (2) positive *SUE* with *AIA* equal to one (*PosAIA1*); (3) negative *SUE* with *AIA* equal to zero (*NegAIA0*); and (4) negative *SUE* with *AIA* equal to one (*NegAIA1*). To estimate the conditional returns, for each group, we multiply the group's relevant *SUE* regression coefficient, estimated in Table 6A, with the group's *SUE* average (i.e., the group's conditional mean). Since *AIA* is a dummy variable, we use the *SUE* regressions coefficient for *AIA* equal to zero, and use the sum of *SUE* and *SUE_AIA* regression coefficients for *AIA* equal to one. The dotted lines represent the 95% confidence intervals.

offer direct support that limited investor attention, especially that of institutional investors, is the driving force behind PEAD. The confidence bands are widening over time and it is possible that the volatility in post-announcement returns may prevent us from detecting a significant difference in the price drifts beyond day 40.

Recall that Table 3 provides a significant link between *AIA* and measures of equilibrium outcomes. The prior literature has used some of these equilibrium outcomes as an investor attention proxy to study PEAD. For example, Hou, Peng, and Xiong (2009) find that stocks with higher trading volume experience smaller post-earnings announcement drift. The advantage of our *AIA* measure is twofold. First, it allows us to focus on institutional investor attention, which is more important in driving permanent price change. Second, while trading volume is an equilibrium outcome that reflects many economic forces other than investor attention, *AIA* directly reveals institutional investor attention. Table 3 also indicates that *AIA* is related to more direct measures of attention. In particular, Drake, Roulstone, and Thornock (2015) find that more hits on EDGAR on the day of and the day after an earnings announcement are related to a smaller PEAD.

Panel B of Table 6 controls for the impact of other attention proxies on PEAD by including additional interaction terms. Specifically, we also interact *SUE* with abnormal retail attention, abnormal EDGAR downloads, abnormal trading volume, and abnormal news coverage.[14] While we continue to find that *AIA* significantly alleviates PEAD, none of the other interaction terms is significant. In fact, retail attention seems to exacerbate the drift for a few days as is evidenced by positive coefficients on *SUE_DADSVI* up to day t+5. More importantly, Wald tests confirm that the coefficients on *SUE_AIA* are significantly different from those on *SUE_DADSVI* when price drifts are examined. In other words, it is the institutional attention, not retail attention that alleviates the PEAD.

In our final set of tests in this subsection, we address a potential reverse causality explanation. In particular, because *AIA* on day t is measured on that calendar day, while returns are measured from 4 p.m. on day t-1 to 4 p.m. on day t (close-to-close), it is possible that announcement day returns lead attention and not vice versa. For example, consider a large earnings surprise announced the morning before the market opens on day t. The earnings surprise is fully incorporated into the price when the market closes on day t, resulting in a large announcement day return and zero price drift going forward. The large earnings announcement-day return then is likely to cause institutional investors to pay abnormal attention after market close on day t, resulting in a large *AIA* on calendar day t.

[14] The correlation between SUE_AIA and the other interaction terms ranges from 0.07 to 0.61. To alleviate any concerns regarding collinearity across the interaction terms, we run the analysis for each interaction variable separately (i.e., excluding the other interaction terms). We find that the interaction terms' coefficient estimates are qualitatively similar. We repeat the same analysis in Table 7B and reach similar conclusions.

To rule out such a reverse causality explanation, we focus on the subset of earnings announcements occurring between 4 p.m. and 11:59 p.m. after the market has closed on day t-1 and *AIA* on day t-1. Roughly 50% of our earnings announcements sample events (9,308 firm quarter observations, 50.4%) take place between 4 p.m. and 11:59 p.m. (consistent with Michaely, Rubin, and Vedrashko 2014). If we observe *AIA* equal to one on day t-1 for these earnings announcements, to the extent that after market-close price discovery is limited, the institutional attention cannot be caused by the announcement day return (from the close on day t-1 to the close on day t).[15] Panel C reports the results where we repeat our regression analysis used in panel A for this reduced sample using *AIA* on day t-1. Our results are robust in this sample. Again, we find significant negative coefficients on the interaction terms between *SUE* and *AIA* and that the coefficients are similar in magnitude to those on *SUE*.

Finally, it may be argued that a higher return on day t, which is associated with *AIA*=1, mechanically causes less drift going forward. This is unlikely for a few reasons. First, Chan, Jegadeesh, and Lakonishok (1996) find that higher (absolute) earnings announcement window return predicts stronger, not weaker, post-earnings announcement drift, on average. Second, in untabulated results, we directly control for announcement day returns in the regressions when examining post-announcement drifts. We confirm that controlling for the returns on announcement day t barely changes the impact of *AIA* on post-earnings announcement returns from day t+1 up to day t+40.

3.2 Analyst recommendation changes

In this subsection, we study price reaction during and after analyst recommendation changes using similar panel regressions. We focus on recommendation change day t and the subsequent ten trading days. The results are reported in Table 7. As detailed in Section 2.1, in constructing the *RecChng* Sample, we only keep recommendation changes with unambiguous information content that is different from that in the earnings announcements. Thus, our *RecChng* Sample contains additional information events that are relatively independent from those in the *EarnAnn* Sample. This additional set of tests provides strong evidence that our results are not specific to earnings announcements.

The regressions in Table 7A (7B) are similar to those in Table 6A (6B) except that we replace *SUE* with *RecChng*, which measures the change in analyst recommendations. Specifically, *RecChng* ranges from −4 to 4, where

[15] We acknowledge that trading does occur in OTC markets after market close. However, trading volume is by far smaller and less concentrated relative to the trading volume at the opening on day t. Thus, it is fair to assume that institutional investors are more likely to notice news than prices in the OTC market, especially news of an earnings announcement that tends to come right after market close. Jiang, Likitapiwat, and McInish (2012) study a sample of the S&P 500 that announced earnings after market close from 2004-2008. They find that while the price discovery during after market close is significant, the majority of the price discovery (63%) still occurs on the next day.

Table 7
Institutional attention and change-in-analyst-recommendations returns

A. Base case

	Day 0	Drift									
Variables	*t*	*t+1_t+1*	*t+1_t+2*	*t+1_t+3*	*t+1_t+4*	*t+1_t+5*	*t+1_t+6*	*t+1_t+7*	*t+1_t+8*	*t+1_t+9*	*t+1_t+10*
AIA t	0.0002	0.0001	0.0001	0.0001	0.0000	−0.0002	0.0006	0.0001	0.0000	0.0002	−0.0003
	(0.30)	(0.31)	(0.20)	(0.08)	(0.04)	(−0.20)	(0.69)	(0.15)	(0.02)	(0.19)	(−0.23)
RecChng t	0.0088	0.0015	0.0018	0.0019	0.0017	0.0018	0.0021	0.0022	0.0021	0.0025	0.0024
	(33.33)	(8.15)	(7.86)	(6.42)	(4.90)	(4.89)	(5.16)	(5.20)	(4.61)	(5.22)	(4.86)
RecChng_AIA t	0.0083	−0.0007	−0.0009	−0.0008	−0.0005	−0.0006	−0.0010	−0.0012	−0.0012	−0.0018	−0.0020
	(16.61)	(−2.71)	(−2.43)	(−1.94)	(−1.49)	(−1.53)	(−1.83)	(−2.00)	(−1.78)	(−2.64)	(−2.75)
ANews t	0.0000	−0.0001	0.0001	0.0003	0.0001	0.0000	−0.0001	0.0003	0.0002	0.0004	0.0004
	(0.04)	(−0.53)	(0.23)	(0.82)	(0.28)	(0.00)	(−0.20)	(0.55)	(0.41)	(0.65)	(0.67)
DADSVI t	0.0022	0.0001	0.0004	0.0004	0.0010	0.0011	0.0010	0.0015	0.0008	0.0013	0.0014
	(1.36)	(0.08)	(0.34)	(0.36)	(0.68)	(0.74)	(0.64)	(0.87)	(0.41)	(0.66)	(0.71)
AEDGAR t	0.0005	−0.0002	−0.0004	−0.0001	−0.0004	−0.0005	−0.0006	0.0002	0.0005	0.0004	0.0006
	(0.89)	(−0.70)	(−0.97)	(−0.19)	(−0.78)	(−0.82)	(−0.91)	(0.25)	(0.66)	(0.62)	(0.80)
AVol t	0.0013	0.0006	0.0002	0.0003	0.0003	0.0004	0.0003	0.0003	0.0003	0.0003	0.0004
	(1.55)	(2.00)	(1.18)	(1.52)	(1.75)	(2.09)	(1.18)	(1.08)	(1.01)	(1.11)	(1.59)
HLtoH t	−0.1921	−0.0368	−0.0252	−0.0371	0.0049	−0.0128	−0.0280	−0.0296	−0.0289	−0.0358	−0.0488
	(−3.27)	(−1.66)	(−0.76)	(−1.00)	(0.11)	(−0.32)	(−0.66)	(−0.68)	(−0.59)	(−0.75)	(−1.09)
Ret t-5_t-1	0.0001	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0000
	(1.23)	(0.16)	(0.57)	(0.24)	(0.55)	(0.61)	(0.93)	(0.98)	(0.83)	(0.71)	(0.23)
Turnover t-5_t-1	−0.0697	0.0118	−0.0050	−0.0228	−0.0472	−0.0409	−0.0422	−0.0304	−0.0635	−0.0658	−0.0691
	(−1.97)	(0.70)	(−0.18)	(−0.93)	(−1.69)	(−1.35)	(−1.30)	(−0.84)	(−1.69)	(−1.72)	(−1.78)
Spread t-5_t-1	−1.4321	0.1499	−0.1295	−0.0527	0.1855	−0.5804	−1.8651	−2.3099	−2.7174	−2.4451	−3.1247
	(−0.76)	(0.32)	(−0.20)	(−0.06)	(0.14)	(−0.37)	(−0.76)	(−1.04)	(−1.20)	(−0.96)	(−1.36)
SDRET	0.0005	0.0002	0.0004	0.0004	0.0004	0.0003	0.0000	0.0000	0.0001	−0.0001	−0.0001
	(1.07)	(0.87)	(1.36)	(0.98)	(0.70)	(0.48)	(−0.03)	(0.04)	(0.09)	(−0.09)	(−0.14)
LnSize	−0.0021	−0.0003	−0.0002	−0.0001	0.0000	−0.0001	−0.0005	−0.0001	−0.0004	−0.0003	−0.0004
	(−4.07)	(−1.48)	(−0.80)	(−0.46)	(0.03)	(−0.18)	(−0.94)	(−0.27)	(−0.65)	(−0.45)	(−0.66)
LnBM	0.0003	0.0004	0.0007	0.0003	−0.0001	−0.0002	−0.0004	−0.0007	−0.0004	−0.0006	−0.0004
	(0.53)	(1.59)	(2.02)	(0.79)	(−0.22)	(−0.31)	(−0.65)	(−1.14)	(−0.57)	(−0.78)	(−0.54)
InstHold	−0.0001	0.0013	−0.0003	0.0005	0.0034	0.0039	0.0050	0.0051	0.0051	0.0053	0.0053
	(−0.03)	(1.34)	(−0.22)	(0.31)	(1.83)	(1.91)	(2.11)	(2.03)	(1.93)	(1.91)	(1.88)
LnNumEst	0.0006	0.0005	0.0003	0.0004	0.0005	−0.0001	0.0000	−0.0007	−0.0002	−0.0004	−0.0009
	(0.59)	(1.22)	(0.47)	(0.49)	(0.56)	(−0.13)	(0.00)	(−0.61)	(−0.13)	(−0.28)	(−0.65)

(*continued*)

Table 7
Continued

B. Adding interactions

	Day 0	Drift									
Variables	*t*	*t+1_t+1*	*t+1_t+2*	*t+1_t+3*	*t+1_t+4*	*t+1_t+5*	*t+1_t+6*	*t+1_t+7*	*t+1_t+8*	*t+1_t+9*	*t+1_t+10*
AIA t	0.0001	0.0001	0.0001	0.0001	0.0000	−0.0002	0.0006	0.0001	0.0000	0.0002	−0.0002
	(0.19)	(0.29)	(0.19)	(0.09)	(0.03)	(−0.19)	(0.68)	(0.13)	(0.02)	(0.17)	(−0.20)
DADSVI t	0.0017	0.0002	0.0005	0.0007	0.0012	0.0013	0.0012	0.0017	0.0009	0.0014	0.0015
	(1.16)	(0.18)	(0.45)	(0.55)	(0.85)	(0.82)	(0.77)	(0.97)	(0.52)	(0.74)	(0.76)
AEDGAR t	0.0002	−0.0003	−0.0004	−0.0001	−0.0004	−0.0005	−0.0006	0.0001	0.0004	0.0004	0.0006
	(0.39)	(−0.66)	(−1.01)	(−0.25)	(−0.81)	(−0.83)	(−0.94)	(0.20)	(0.62)	(0.59)	(0.75)
AVol t	0.0025	0.0007	0.0003	0.0004	0.0004	0.0005	0.0004	0.0004	0.0004	0.0004	0.0006
	(2.45)	(2.18)	(1.62)	(2.05)	(1.90)	(2.41)	(1.47)	(1.37)	(1.28)	(1.36)	(2.06)
ANews t	−0.0004	−0.0001	0.0001	0.0003	0.0001	0.0000	−0.0001	0.0003	0.0002	0.0004	0.0004
	(−0.73)	(−0.61)	(0.23)	(0.83)	(0.32)	(0.05)	(−0.19)	(0.53)	(0.41)	(0.66)	(0.69)
RecChng t	0.0039	0.0010	0.0015	0.0015	0.0015	0.0014	0.0017	0.0018	0.0015	0.0020	0.0017
	(3.99)	(2.70)	(4.98)	(4.11)	(3.75)	(3.41)	(3.68)	(3.76)	(2.95)	(3.60)	(3.14)
RecChng_AIA t	0.0035	−0.0008	−0.0009	−0.0009	−0.0005	−0.0006	−0.0011	−0.0015	−0.0013	−0.0019	−0.0021
	(7.11)	(−2.97)	(−2.52)	(−2.01)	(−1.45)	(−1.49)	(−1.83)	(−2.20)	(−1.79)	(−2.48)	(−2.64)
RecChng_DADSVI t	0.0019	−0.0003	−0.0003	−0.0004	−0.0004	−0.0004	−0.0003	0.0000	−0.0001	0.0002	0.0000
	(1.61)	(−0.40)	(−0.37)	(−0.87)	(−0.58)	(−0.34)	(−0.64)	(−0.03)	(0.29)	(0.15)	(0.05)
RecChng_AEDGAR t	0.0012	0.0000	0.0001	0.0002	0.0002	0.0001	0.0001	−0.0001	−0.0002	−0.0002	−0.0002
	(2.93)	(−0.07)	(0.24)	(0.68)	(0.51)	(0.17)	(0.17)	(−0.19)	(−0.36)	(−0.44)	(−0.37)
RecChng_AVol t	0.0026	0.0003	0.0002	0.0003	0.0002	0.0002	0.0003	0.0003	0.0003	0.0003	0.0004
	(4.05)	(1.62)	(2.17)	(2.46)	(1.40)	(1.61)	(1.64)	(1.67)	(1.79)	(1.63)	(2.40)
RecChng_Anews t	0.0051	−0.0002	−0.0001	−0.0001	−0.0003	−0.0001	0.0000	0.0001	0.0000	−0.0001	−0.0001
	(10.88)	(−0.77)	(−0.34)	(−0.57)	(−1.17)	(−0.37)	(0.15)	(0.41)	(−0.10)	(−0.31)	(−0.24)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
DADSVI-AIA Interaction diff	−0.00166	0.00050	0.00063	0.00054	0.00004	0.00016	0.00080	0.00142	0.00125	0.00212	0.00214
Wald test p-value	0.19	0.39	0.41	0.35	0.88	0.80	0.32	0.21	0.30	0.11	0.07

The table reports the results of panel regressions of change in analyst recommendations' day-t and cumulative day t+1 to t+10 *DGTW* risk-adjusted returns on institutional attention and other explanatory variables. In constructing the sample, we follow Jegadeesh and Kim (2010), Loh and Stulz (2011), and Kadan, Michaely, and Moulton (2013) to identify relevant changes in analyst recommendations. In particular, we (1) remove recommendation changes that occur on the same day as, or the day following, earnings announcements; (2) remove recommendation changes on days when multiple analysts issue recommendations for the same firm; (3) require at least one analyst to have issued a recommendation for the stock and revised the recommendation within 180 calendar days; (4) require at least two analysts to have active recommendations for the stock as of the day before the revision; and (5) consider a recommendation to be active for up to 180 days after it is issued or until I/B/E/S indicates that the analyst has stopped issuing recommendations for that stock. After applying all of these filters, we obtain 16,312 changes in recommendations.

In panel A, we present our base case. In panel B, we explore the robustness of our results by adding additional interaction variables. *RecChng* is the change in analyst recommendations. The variable ranges from −4 to 4, where a positive (negative) number refers to an upgrade (a downgrade). *RecChng_AIA* is the interaction between *RecChng* and *AIA*. Similar to Table 6, since *AIA* (*DADSVI*) is a dummy variable, the interaction with *RecChng* measures the additional sensitivity of the *AIA*=1 *(DADSVI*=1) group. In panel 7.B, *DASVI-AIA interaction diff* is the difference between the *RecChng_AIA* and *RecChng _DADSVI* coefficients. Wald test p-value is the p-value for the difference between these coefficients. Standard errors are clustered by firm and day and each model includes quarter and day-of-the-week fixed effects. t-statistics are reported below the coefficient estimates.

a positive (negative) number refers to an upgrade (a downgrade). The positive and significant coefficients on *RecChng* confirm that stock prices react to recommendation changes strongly on the announcement day and continue to drift in the direction of *RecChng* for the next ten trading days.

Similar to our earnings announcements findings, the negative coefficients on the interaction term *RecChng_AIA* suggest that institutional attention facilitates information incorporation at the announcement and alleviates future drift. In particular, the positive coefficient of 0.0083 on the announcement day suggests that when institutional investors pay attention, stock price reacts by 83 bps more for a one notch change in the recommendation.

Focusing on the drift, the coefficients on the interaction term are negative and significant from day $t+1$ through day $t+10$. By the end of day $t+10$, the coefficient is about -0.0020, which is similar to the corresponding coefficient on *RecChng* in absolute terms (0.0024). Therefore, when institutional investors pay more attention to analyst recommendation change, there is no post-announcement drift. Alternatively, when institutional investors fail to pay sufficient attention on the announcement date, the price initially underreacts by about 20 bps for a one notch change in the recommendation.

Similar to Figure 4, our results are nicely summarized in Figure 5. To construct this figure, we use the estimated regression coefficients from panel A of Table 7 and the conditional means of each group of interest (the four groups are based on the intersection between positive *RecChng*, negative *RecChng*, *AIA*=0 and *AIA*=1). Figure 5 confirms that price drift following a recommendation change comes almost exclusively from announcements with limited institutional investor attention. When institutional investors fail to pay sufficient attention, price initially underreacts to information, resulting in a drift. The patterns in Figure 5 are very similar to those in Figure 4.

Panel B of Table 7 indicates that controlling for other attention proxies using additional interaction terms does not affect the impact of *AIA*. In particular, we find that the interaction with *EDGAR* is insignificant. Thus, user activity on the SEC's EDGAR server around analyst recommendation changes cannot explain the drift.[16] This reveals the importance of *AIA* as a direct measure of institutional investor attention. In contrast to *EDGAR*, which is limited to a set of firms' regulatory filings, *AIA* (which is based on direct news reading and searching) allows exploration of a broader set of information events for which there may be no associated SEC filing. Consequently, using *AIA* in the setting of analyst recommendation changes delivers strikingly similar conclusions to those found using earnings surprises.

As for an analysis using data after the market close, in contrast to earnings announcements, the vast majority of recommendation changes in our sample

[16] In untabulated results, we find that this is true even without controlling for *AIA*.

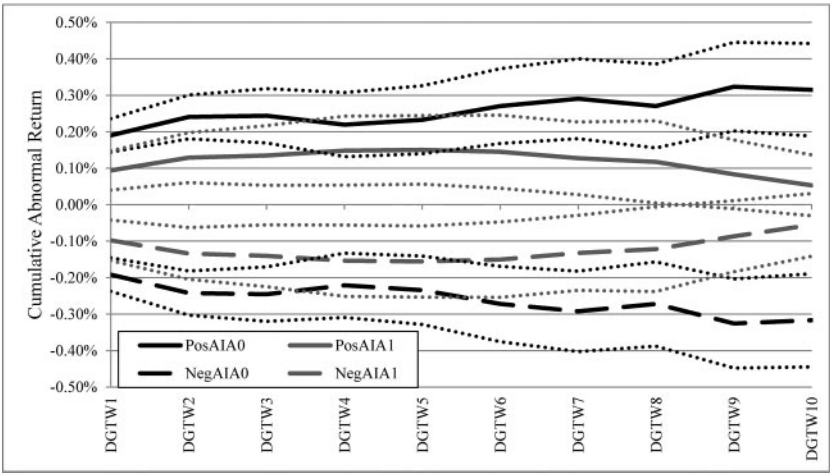

Figure 5
Abnormal institutional attention and change-in-analyst-recommendations returns
The figure plots the effect of change in analyst recommendations *(RecChng)* on day $t+1$ to $t+10$ cumulative risk-adjusted returns for the following four cases: (1) positive *RecChng* with *AIA* equal to zero (*PosAIA0*); (2) positive *RecChng* with *AIA* equal to one (*PosAIA1*); (3) negative *RecChng* with *AIA* equal to zero (*NegAIA0*); and (4) negative *RecChng* with *AIA* equal to one (*NegAIA1*). To estimate the conditional returns, for each group, we multiply the group's relevant *RecChng* regression coefficient, estimated in Table 7.A, with the group's *RecChng* average (i.e., the group's conditional mean). Since *AIA* is a dummy variable, we use the *RecChng* regressions coefficient for *AIA* equal to zero, and use the sum of the *RecChng* and *RecChng_AIA* regression coefficients for *AIA* equal to one. The dotted lines represent the 95% confidence intervals.

take place before the market has closed.[17] While this prevents us from focusing directly on after-market-close recommendation changes, in untabulated results, we find that including the announcement day return as an independent variable has no impact on the relation between *AIA* and future drift.

3.3 Calendar-time trading strategies of earnings announcements and analyst recommendation changes

We explore the profitability of trading strategies that are based on the drift patterns documented in Sections 4.1 and 4.2. We focus on calendar time, instead of event time, in order to explore the profitability of real time trading strategies. Accordingly, we use the calendar time portfolio approach.

Specifically, each day, a new portfolio is constructed based on a prespecified trading rule. The portfolios are then held based on the strategy's trading horizon. Thus, if the horizon is set to five trading days, on each given day, there should be five different portfolios. The daily calendar time portfolio return is the equally-weighted average return of all five portfolios that are held on that day. The alpha is then calculated by regressing the strategy's daily excess return on the Fama-French daily factors.

[17] Around 13% of our 16,312 changes occur between 4:00 p.m.-11:59 p.m.

Based on the earnings announcements, we create the following four subportfolios: *AIA*=0_*SUE*>0, *AIA*=0_*SUE*<0, *AIA*=1_*SUE*>0, and *AIA*=1_*SUE*<0. We use these portfolios to construct the following trading strategies: (1) [*AIA*=0_*SUE*>0 minus *AIA*=0_*SUE*<0], labeled *LS_AIA0*, is a long-short portfolio designed to capture the drift in *AIA*=0 stocks; (2) [*AIA*=1_*SUE*>0 minus *AIA*=1_*SUE*<0], labeled *LS_AIA1,* is a long-short portfolio designed to capture the zero drift in *AIA*=1 stocks; and (3) The "*DIFF*" portfolio, which is the difference between *LS_AIA0* and *LS_AIA1*. Note that the *DIFF* strategy sets a high hurdle since it requires both conditions to be met (i.e., a drift in the *AIA*=0 stocks and zero drift in the *AIA*=1 stocks).

Recall that we have only 34,400 earnings announcement observations and earnings announcements are not evenly distributed throughout the quarter. As a result, we apply the following filters to reduce the noise in our calendar time portfolio estimation: (1) since the majority of earnings announcements are clustered during a one-month period beginning about three weeks after the end of the quarter, we focus on days t+20 to t+50 (i.e., the active earnings announcement season period), and (2) when a subportfolio of the four portfolios has missing information (i.e., a relevant event did not occur on that day), we replace the subportfolio's missing return with the daily risk-free rate.[18]

The calendar time portfolio construction is similar for the announcements of analyst recommendation changes, except that we replace *SUE* with *RecChng*. Since changes in analyst recommendations are not concentrated in specific periods within the quarter, there are always enough events to calculate average returns each day.

Table 8 presents the results of our three strategies. Panel A (B) examines the earnings announcement (recommendation changes) events. We present results for daily raw returns (*RET*), daily three-factor and five-factor alphas, which are based on the intercept from a time-series regression of *RET* on the Fama-French three-factor model (FF3) and five-factor model (FF5), respectively. The daily averages of the five-day (ten-day) trading strategy are then multiplied by five (ten) to reflect a five-day (ten-day) strategy return.

Our trading strategies confirm the findings in Tables 6 and 7. Staring with earnings announcements, the *LS_AIA0* portfolio's five-day return is between 91 and 95 basis points and is statistically significant. This is consistent with the post-announcement drift documented earlier in stocks with low attention. The *LS_AIA1* portfolio's five-day return is between 23 and 29 basis points and not statistically significant. Thus, stocks with institutional attention shocks do not experience a drift. Even more impressive, the *DIFF* portfolio results confirm that the difference in drifts between the two portfolios is economically and

[18] Note that the aggregate within quarter distribution of earnings announcements is stable across the quarters in our sample. Moreover, given the time that is required to prepare the financial statements, starting our strategy three weeks after the end of the quarter seems reasonable. Additionally, these announcements are typically scheduled weeks in advance.

Table 8
Earnings announcements and analyst recommendation changes calendar time portfolios

A. Earnings announcements

	5 trading days			10 trading days		
	RET	FF3	FF5	RET	FF3	FF5
LS AIA=0	0.95%	0.92%	0.91%	1.07%	1.03%	1.03%
	(5.45)	(5.26)	(5.18)	(4.44)	(4.26)	(4.28)
LS AIA=1	0.29%	0.23%	0.23%	0.16%	0.07%	0.07%
	(1.70)	(1.62)	(1.59)	(0.81)	(0.32)	(0.37)
DIFF	0.65%	0.68%	0.67%	0.91%	0.96%	0.96%
	(3.20)	(3.31)	(3.26)	(2.44)	(2.55)	(2.52)
B. Analyst recommendation changes						
LS AIA=0	0.64%	0.63%	0.63%	0.66%	0.62%	0.61%
	(4.08)	(4.00)	(3.96)	(3.35)	(3.17)	(3.14)
LS AIA=1	0.19%	0.17%	0.17%	0.05%	0.04%	0.04%
	(1.76)	(1.67)	(1.66)	(0.41)	(0.23)	(0.21)
DIFF	0.45%	0.46%	0.46%	0.60%	0.58%	0.57%
	(1.65)	(1.88)	(1.85)	(2.17)	(2.36)	(2.31)

The table reports the results from calendar time portfolios of earnings announcements (panel A) and changes in analyst recommendation (panel B) strategies for portfolios that are held for five and ten trading days. See Tables 6 and 7 for event and sample definitions. To construct the earnings announcements strategies, we use these portfolios to construct the following trading strategies: (1) [AIA=0_SUE>0 minus AIA=0_SUE<0], labeled *LS_AIA0,* is a long-short portfolio designed to capture the drift in AIA=0 stocks; (2) [AIA=1_SUE>0 minus AIA=1_SUE<0], labeled *LS_AIA1*, is a long-short portfolio designed to capture the zero drift in AIA=1 stocks; (3) the *DIFF* portfolio, which is the difference between *LS_AIA0* and *LS_AIA*. We apply the following filters to reduce the noise in our calendar time portfolio estimation: (1) since the majority of earnings announcements are clustered during a one month period beginning about three weeks after the end of the quarter, we focus on days t+20 to t+50 (i.e., the active earnings announcement season period); (2) when a subportfolio of the four portfolios has missing information (i.e., a relevant event did not occur on that day), we replace the subportfolio's missing return with the daily risk-free rate. Using the same portfolios, we construct our analyst recommendation change strategies replacing *SUE* with *RecChng*. However, since changes in analyst recommendations are not concentrated in specific periods within the quarter, there are always enough events to calculate average returns each day. In the table, RET is the CRSP daily return in percent, and FF3 (FF5) refers to the alpha, which is the intercept from the time-series regression of the strategy return on the Fama-French three- (five-) factor model. The daily averages of the five-day (ten-day) trading strategy are multiplied by five (ten) to reflect a five-day (ten-day) strategy return.

statistically significant, with five-day (ten-day) returns of 65 to 68 (91 to 96) basis points. The recommendation change strategies results are qualitatively similar. The *LS_AIA0* portfolio's five-day (ten-day) return is between 63 and 64 (61 and 66) basis points and is statistically significant. The *LS_AIA1* returns are closer to zero, and the *DIFF* portfolio results confirm that the differences are statistically and economically significant.

4. Conclusion

To the best of our knowledge, we propose the first broad and direct measure of abnormal institutional investor attention. Our abnormal institutional investor attention measure (AIA) is based on the news searching and the news reading frequency for specific stocks on Bloomberg terminals, which are used almost exclusively by institutional investors. We find AIA to be related to, but different from, other investor attention proxies. In addition, AIA is highly correlated with contemporaneous measures of abnormal institutional trading.

More importantly, AIA enables us to directly contrast institutional attention with retail attention measured using Google search frequency. We find that institutional attention responds more quickly to major news events, triggers more trading, and is less constrained compared to retail attention.

Since institutional investors are more likely to react to news immediately and become marginal investors who trade, institutional investor attention is crucial in facilitating the incorporation of new information into asset prices. Indeed, we find that the well-documented price drifts following both earnings announcements and analyst recommendation changes come only from announcements in which institutional investors fail to pay attention according to our measure.

Earnings announcements and analyst recommendation changes are just two examples of important information events. AIA can be used to examine the differential impact of institutional and retail attention on market reaction to other corporate events, such as initial public offerings, mergers and acquistions, product launches, and dividend cuts. We leave these and other exciting applications of AIA for future research.

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