

It Depends on Where You Search: A Comparison of Institutional and Retail Attention

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Abstract

We propose a direct measure of abnormal institutional investor attention (AIA) at the daily frequency using the news-searching and news-reading activity for specific stocks on Bloomberg terminals. We find AIA to be highly correlated with measures of contemporaneous institutional trading, and related to but different from other investor attention proxies, including user requests at EDGAR which are limited to specific regulatory filings. 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. In sharp contrast to retail attention which results in positive and temporary price pressure, AIA facilitates permanent price adjustment and alleviates price under-reaction to news. The well-documented price drifts following both earnings announcements and analyst recommendation changes come only from announcements where institutional investors fail to pay attention, according to our measure.

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1. Introduction

Information needs to attract investor attention before it can be processed and incorporated into asset prices via trading. Attention, however, is a scarce cognitive resource (Kahneman, 1973).¹ A voluminous literature has demonstrated that limited investor attention is often associated with slow information diffusion and under-reaction to news.²

When empirically examining the impact of limited investor attention on price reaction to information, it is important to differentiate retail investor attention from institutional investor attention. Retail investors are less likely to immediately act on information when it arrives. Additionally, since retail investors rarely short, retail attention on average results in positive and temporary price pressure (Barber and Odean, 2008). Such positive price pressure is confirmed by Da, Engelberg, and Gao (2011) using Google search as a direct measure of retail attention. In sharp contrast, institutional investors have greater resources and stronger incentives to quickly react to news and are more likely to be the marginal investors in moving prices. As such, institutional investor attention is likely far more important in facilitating the incorporation of new information into asset prices. In this paper, we focus on institutional investor attention and confirm that its impact on asset prices is very different from that of retail attention.

We propose a novel measure of institutional investor attention using the news-searching and news-reading activity for specific stocks on Bloomberg terminals. Because Bloomberg terminals are expensive – annual subscriptions cost \$20,000 to \$24,000, per machine – and are leased on a 2-year basis, they are much more likely to be used by institutional investors than retail investors.³ In fact, the number of subscriptions is limited to about 320,000 worldwide.⁴ 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 us with the transformed

¹ By attention, we mean the cognitive resources required in order to reduce the information entropy, following Sims (2003) and Peng (2005).

² 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, Guron, and Warachka (2014), Hendershott, Li, Menkveld, and Seasholes (2013), among many others.

³ Strasburg, J. (2013, May 15). This is How Much a Bloomberg Terminal Costs. *Quartz*. <http://qz.com/84961/this-is-how-much-a-bloomberg-terminal-costs/>

⁴ Bloomberg. Retrieved from <http://www.bloomberg.com/professional/tools-analytics/collaboration/> on August 27, 2014.

data. We define *abnormal institutional attention* (hereafter, “AIA”) as a dummy variable equal to one when attention during the day exceeds levels of attention during at least 94% of the hours over the previous month, and zero otherwise.⁵ In other words, an AIA equal to one indicates a spike in institutional investor attention on that stock during that day. Compared to other measures that are indirect or based on equilibrium outcomes such as return and institutional trading volume, AIA directly reveals institutional investor attention.⁶

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. The figure shows 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.

Figure 1 also plots the daily number of relevant news articles (the right axis) with major events described below the figure. Almost all abnormal institutional attention can be traced back to some salient news on the firm (CEO turnover, outcome of lawsuit, analyst recommendation change, etc.). In other words, news coverage and institutional attention are clearly correlated. Nevertheless, news coverage does not guarantee attention and AIA directly identifies the news that attracts the institutional attention. Finally, abnormal institutional attention on Overstock.com is also correlated with extreme price movement.

We find similar determinants of AIA when we examine a broad sample of Russell 3000 stocks during the period from February 2010 to June 2013. Firm-specific news is the most important driver of AIA. Equilibrium outcomes during the day such as absolute return, trading volume, intra-day volatility, and closeness to 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

⁵ While 94% may seem like an arbitrary cutoff, this number based on the way Bloomberg constructs its measure. See Section 2.2 for more details on the data provided by Bloomberg and on our measure.

⁶ Examples include extreme returns (Barber and Odean (2008)), trading volume (Barber and Odean (2008), Gervais, Kaniel, and Mingelgrin (2001), and Hou, Peng, and Xiong (2009)), news and headlines (Barber and Odean (2008) and Yuan (2015)), advertising expense (Chemmanur and Yan (2009), Grullon, Kanatas, and Weston (2004), Lou (2014), Madsen and Niessner (2014)), and price limits (Seasholes and Wu (2007)).

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 more analyst coverage are more likely to experience institutional attention shocks, while advertisement expenditure and institutional holdings are not significantly related.

User request at the Securities and Exchange Commission's (SEC) EDGAR (Electronic Data Gathering, Analysis, and Retrieval) online system have also been used to track investor attention.⁷ Compared to investors who search for information on Google, investors 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.⁸ One important distinction between the two measures is that AIA is based on all news searches while hits on EDGAR are limited to specific regulatory filings. Not surprisingly, controlling for the EDGAR measure in our subsequent analysis hardly changes our results.

Most interestingly, we find our institutional investor attention measured using AIA to be distinct from retail investor attention measured using abnormal daily Google search. 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 to 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 confirms that AIA, not the Google-search-based measure, directly measures institutional investors' attention. Importantly, conditional on major news events, AIA leads retail attentions, but not vice versa, confirming that institutional investors have greater resources and stronger incentives to quickly pay attention to news. Finally, attention constraints are more likely to be binding for retail investors. For example, we find retail attention to be significantly lower if there are more events during the same day, consistent with the evidence in Liu and Peng (2015). No such relation is observed with AIA.

⁷ 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.

⁸ 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.

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.^{9,10} Second, information released in both announcements is 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 (see for example, Ball and Brown, 1968 and Livnat and Mendenhall, 2006 for earnings announcements; and Stickel, 1995 and Womack, 1996 for analyst recommendation changes). In other words, investors underreact to both announcements on average. It is only a natural question to ask if institutional attention on the announcement day facilitates information incorporation and alleviates price under-reaction to news. Finally, by examining two distinct types events of we can determine whether institutional attention plays a broad role, or is more limited.

We find strong and consistent evidence that institutional attention facilitates information incorporation for both types of announcements. The evidence is summarized in Figure 2 (earnings announcements) and Figure 3 (analyst recommendation changes). 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 return (in absolute term) during the announcement day and very little subsequent price drift. In other words, 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.

⁹ 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 pre-scheduled, 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 pre-scheduled.

¹⁰ Along these lines, Boudoukh, Feldman, Kokan and Richardson (2013) use textual analysis to identify relevant news (from the set of all news). They show that focusing on relevant news, there is considerably more evidence of a strong relationship between stock price changes and information.

We confirm the incremental value of AIA in a two-step exercise. In the first step, we orthogonalize AIA by regressing it on a broad set of variables we show to be related to AIA. These variables include equilibrium outcomes such as abnormal volume and intraday volatility, firm characteristics, news, analyst coverage, institutional holdings, seasonality and other direct attention measures. The residual is the unexpected AIA which, by construction, captures abnormal institutional attention unrelated to the independent variables. In the second step, we replace AIA with the residual AIA in the return regressions and find very similar results. 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-drifts.

We fully acknowledge the possibility that other features of the announcements that we have not controlled for may be driving the high AIA on the announcement day itself. After all, the allocation of attention is an endogenous decision. While it is easy for such “unidentified” features to 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) document that higher (absolute) earnings-announcement-window-returns predict stronger, not weaker, post-earnings-announcement drift on average. One may also argue that higher AIA reflects higher uncertainty or disagreement that prompts institutional investors to acquire more information on Bloomberg, but it is harder to explain why prices fully adjust to news associated with more uncertainty and disagreement but only partially adjust when there is little uncertainty. In the end, we believe that institutional investor attention seems the most natural economic force that simultaneously explains both a higher price response immediately upon the announcement and a lower subsequent price drift.

To rule out a reverse causality story where a higher announcement-day (absolute) return actually leads to high AIA, we focus on earnings announcements taking place after the market closes – from 4pm to 12am. For these announcements, which make up half of our sample, high

AIA on the same day cannot be driven by the earnings-announcement return.^{11,12} Yet we find very similar results in this reduced sample: high AIA is associated with stronger price adjustment on the first trading day following the announcement and lower price drift afterwards even after controlling for the size of the earnings surprise and other stock characteristics.

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. In fact, regardless of the content of the news, retail attention tends to result in positive price pressure, consistent with evidence in the prior literature (see Barber and Odean, 2008, and others).¹³

The impact of investor attention on the 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) document 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 for driving permanent price change. Second, while trading volume and short interest are equilibrium outcomes that reflect many economic forces other than investor attention, AIA directly reveals institutional investor attention.

¹¹ In contrast to earnings announcements, only 15% of the recommendation changes in our sample take place after the market has closed.

¹² 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 which tends to come right after market close.

¹³ Consistent with the positive price effect, Lee (1992) shows that small traders are net buyers following both positive and negative earnings surprises.

Our paper makes several contributions to the literature on investor attention. First, we introduce a new, direct measure of institutional investor attention based on institutional investors' news searching and news reading activity. 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, which allows us to examine its role across multiple types of news events. Second, 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. For example, we show that institutional attention leads retail attention. Moreover, we find that institutional investor attention is less constrained than that of retail investors. Finally, using two distinct types of information events, and controlling for a comprehensive set of other proxies for attention, we confirm that institutional attention plays an important role in the quick incorporation of information into asset prices.

Our paper also contributes to the broader literature that links news media to asset prices, including Tetlock (2007), Fang and Peress (2009), Loughran and McDonald (2011), Engelberg and Parsons (2011) and Gurun and Butler (2012), Peress (2014), 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. Our findings confirm the important role played by institutional investors in various other financial contexts.¹⁴

The remainder of the paper is organized as follows. Section 2 describes our samples and the construction of our AIA measure in detail. Section 3 examines factors that are related to AIA and compares AIA to retail attention measure. Section 4 studies the impact of AIA on asset prices following the announcements of firm earnings and analyst recommendation changes. Section 5 concludes.

¹⁴ Among many examples, see Alti and Sulaeman (2012) for the case of seasoned equity offerings (SEOs), Bauguess, Cooney, and Hanley (2013) for the case of initial public offerings (IPOs), and Sulaeman and Wei (2014) for the case of cost of equity capital.

2. Data and Summary Statistics

2.1 Sample Construction

Bloomberg provide us with data which include transformed measures of news reading and news searching activity on Bloomberg's terminals. Based on data availability, our sample period ranges from February 2010 to June 2013. Following Da, Engelberg and Gao (2011), we start with the sample of Russell 3000 stocks. We then require the stocks in our sample to satisfy the following conditions: (1) have search and news reading information on Bloomberg terminals; (2) have a share code of 10 or 11 in the Center for Research in Securities Prices (CRSP) database; (3) have book-to-market information for the DGTW risk adjustment (Daniel, Grinblatt, Titman and Wermers, 1997). These conditions reduce our sample from 3,000 to 2,298 stocks. This is the main sample of our analysis ("Full Sample").

To arrive at the sample for analyzing earnings announcements, we start with the Full sample and require at least two analysts in IBES making earnings forecasts prior to the announcements. According to Battalio and Mendenhall (2005), 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 will compute quarterly standardized unexpected earnings (*SUE*) relative to the analyst forecast consensus. The requirement for analyst forecasts reduces the sample of stocks from 2,298 to 1,952 ("*EarnAnn* sample") and yields a final sample of 18,543 earnings announcements.

To arrive at the sample for analyzing 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, other than the revising analyst, to have active recommendations for the stock as of the day before the revision; (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

these filters, we end up with 7,041 recommendation changes covering 1,376 stocks. This forms the subsample of our recommendation change analysis (“*RecChng* Sample”).

Finally, institutional trading activity data is 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 mainly includes trades by mutual funds and pension plans. A detailed explanation about Ancerno variables can be found in the Appendix of Puckett and Yan (2011). Our sample of transactions from Ancerno ends on March 31, 2013. As a result, the sample used in our trading analysis ends on that date.

2.2 Abnormal Institutional Attention (AIA) Measure

In order 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 for a specific stock. Bloomberg then assigns the value of 1 for each article read and 10 for each news search. 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 less than 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 us with these latter transformed scores, but does not provide us with the raw hourly counts or scores. 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 which receives the value of 1 if Bloomberg’s daily max is 3 or 4, and 0 otherwise. This captures the right tail of the measure’s distribution.¹⁵ In other words, an AIA equal to one indicates the existence of institutional investor attention shock on that stock during that day.

¹⁵ Our empirical results are similar if we exclude 3 from the definition of abnormal or include 2.

2.3 Other Variables

We compare institutional attention to retail attention. Following Da, Engelberg and Gao (2011), retail attention is measured using Google’s Search Volume Index (*SVI*). Abnormal daily *SVI* (hereafter, “*LnAbnDSVI*”) is calculated as the natural log of the ratio of *SVI* to the average of *SVI* over the previous month.

We obtain news coverage of our sample stock from RavenPack. “*LnNews*” is the log of 1 plus the number of news articles published on the Dow Jones newswire during the day.

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).¹⁶ 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. “*LnAbnEDGAR*” 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.

Other variables used in our analysis are constructed from the standard databases: COMPUSTAT / CRSP / IBES. “*SizeInM*” is the firm market capitalization, rebalanced every June, in millions of dollars. “*LnBM*” is the firm natural logarithm of the firm book-to-market ratio, rebalanced every June following Fama-French (1992). “*SDRET*” is the firm daily standard deviation of return, calculated based on the previous 21 trading days. “*Ret*” is the CRSP daily return, in %. “*Dgtw*” is *Ret* minus the stock’s daily benchmark portfolio daily return following Daniel, Grinblatt, Titman and Wermers (1997). “*Turnover*”, is the daily turnover. “*Dvol in M*” is the daily dollar trading volume, in millions of dollars. “*AbnVol*” is 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. “*HLtoH*” is the ratio between the stock’s daily high-and-low price difference and the daily high price. “*LnNumEst*” is the log of 1 plus the number of

¹⁶ All of our results are robust to using the filters described in deHaan, Shevlin, and Thornock (2015).

analysts covering the stock. “*52HighDum*” (“*52LowDum*”) is a dummy variable which receives the value of 1 if the stock’s price beat its 52-week high (low) price and 0 otherwise. “*AdvExpToSales*” is the firm advertising expenses to sales.

2.4 Summary Statistics

Table 1 provides summary statistics of our full sample and the two subsamples used for the earnings announcement and recommendation change analysis. Panel A shows that AIA frequency is 0.098 in the full sample, suggesting that the average stock in our sample experiences institutional attention shocks on 9.8% of all trading days.¹⁷

AIA frequency increases to 0.567 for the *EarnAnn* sample, suggesting that 56.7% 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 trigger 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.

AIA frequency is slightly lower at 0.447 for the *RecChng* Sample, suggesting that 44.7% 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 pre-scheduled so institutional investors can optimally allocate more attention to the announcement day.

Exploring other stock characteristics across the three samples indicates that these are not small firms. The average (median) size is around 5.5 (1) Billion. Naturally, the firms in the *RecChng* sample are larger due to our recommendation filters which require at least 3 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 60 to 70 percent of shares outstanding, consistent with the well-documented increase

¹⁷ Because AIA is calculated using the maximum hourly attention throughout the day, this number need not be the 6% that the 94% cutoff may suggest.

in institutional holdings over time. The number of analysts covering a stock is 9, on average, and 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 2.68 (1.34).

Finally, Panel A also reports the sample statistics of the EDGAR and DSVI attention measures. On average, there are about 42 hits (excluding robots) on EDGAR on a given day for stocks in the full sample. This number increases to about 80 in the *EarnAnn* sample and 68 in the *RecChng* sample. These patterns are also evident in the abnormal measure. On average, *LnAbnEDGAR* increases by around 66% in *EarnAnn* sample and around 10% in *RecChng* sample.¹⁸ The differential in abnormal attention across these two events may not be surprising since earnings announcements are scheduled events, while changes in analyst recommendations are typically less predictable. Strikingly, our measure of abnormal retail attention, *LnAbnDSVI*, only presents an increase of around 2% on earnings announcement days and is essentially 0 on days with recommendation changes. Our subsequent analysis confirms that AIA responds to these news events much faster than *LnAbnDSVI*.

In Panel B, we present sample averages conditioning on AIA for the three samples. The panel shows 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 which is consistent with greater information processing. Interestingly, both the magnitude of the earnings surprise and 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 2, we examine these relations in a multivariate regression framework.

¹⁸ Since *LnAbnEDGAR* and *LnAbnDSVI* are calculated as a log of a ratio they have an interpretation of a percentage change.

3. What Drives Institutional Attention?

What factors are related to institutional attention shocks? How is institutional attention related to institutional trading? How are institutional attention shocks related to retail attention shocks? We examine these questions in this section.

3.1 Determinants of Institutional and Retail Abnormal Attention

We explore a wide set of variables which are associated with our abnormal institutional attention shocks. For comparison, we also explore how these variables are associated with abnormal retail attention shocks.¹⁹ To examine these determinants, we conduct Probit panel regressions in Panel A of Table 2, using daily AIA as the dependent variable, and OLS panel regressions in Panel B of Table 2 using daily *LnAbnDSVI* as the dependent variable.

Motivated by the example of Overstock.com in Figure 1, we focus on five categories of variables. In column (1), we examine variables that are related to news. They include log number of news articles on that stock that day (*LnNews*), 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 7.19%. All three news variables are highly significant.²⁰

In column (2), we examine variables that are related to equilibrium outcomes of trading on that day. They include absolute DGTW-adjust return (*AbsDgtw*), abnormal trading volume (*AbnVol*), measure of intraday volatility (*HLtoH*), and dummy variables indicating if the current price beats 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 (see Gervais, Kaniel, and Mingelgrin (2001), Barber and Odean (2008), and Hou, Peng, and Xiong (2009) among others). The

¹⁹ See also Drake, Roulstone and Thornock (2012) who explore retail attention in the sample of S&P 500 stocks during 2005-2008.

²⁰ The pseudo *R*-squared from a univariate regression of AIA on *EarnAnnDum* (*RecChngDum*) is 1.74% (0.30%), consistent with the fact that earnings announcements are pre-scheduled.

regression coefficients reported to column (2) confirm that these equilibrium outcomes are related to institutional attention shocks as well. Nevertheless, equilibrium outcomes have lower explanatory power compared to news (pseudo R -squared is 2.49%).

In column (3), we examine various firm characteristics. We find that larger firms with more volatile returns, more analyst coverage are associated with significantly more institutional attention shocks on average. The results are similar to those documented in the prior literature using other measures of investor attention (see Grullon, Kanatas, and Weston (2004), Da, Engelberg and Gao (2011) and Liu and Peng (2015)). On the other hand, controlling for the other variables, we do not find a significant relation between advertisement expenses and institutional attention. Strikingly, the percentage of institutional holdings does not seem to have a significant relation with AIA. Altogether, firm characteristics have a combined pseudo R -squared of 4.89%.

In column (4), we include the other direct measures of attention, $LnAbnEDGAR$ and abnormal retail attention, $LnAbnDSVI$. Both measures are positively related to AIA. Strikingly, the pseudo R -squared is only 1.63%. 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 optimal attention allocation decision.

In column (5), we document strong within-week seasonality associated with institutional attention. The likelihood of an institutional attention shocks 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 0.26%.

Finally, in column (6), we include all five categories of explanatory variables and obtain a pseudo R -squared of 12.05%. 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 these errors, our subsequent

analysis confirms that component of AIA orthogonal to other investor attention proxies continue to exert significant impact on asset prices.

Next, in order to better understand differences in what drives institutional attention and retail attention, we estimate OLS panel regressions of abnormal daily SVI on the same sets of variables as in the previous analysis and present results in Panel B.

Column (1) shows that the relation between *LnAbnDSVI* and news-related measures is qualitatively similar to what we find with institutional attention. However, with an adjusted *R*-squared of only 0.08%, these variables explain very little of the variation in retail attention. In fact, this is true of all 6 specifications in Panel B.

Results using the equilibrium outcome measures in Column (2) look relatively similar to those for AIA, with two exceptions. Instead of a positive relation between the intraday price range and attention, there is a negative relation. Additionally, while retail attention is likely to be higher when a stock hits its 52-week high, the same is not true of the 52-week low.

Column (3) of Panel B shows that abnormal institutional and retail attentions behave 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*. In contrast to the case of institutional attention, less volatile stocks draw retail attention.

Column (4) shows that both AIA and *LnAbnEDGAR* are positively related to retail attention, though the adjusted *R*-squared is only 0.10%.

As was the case with AIA, there is within-week seasonality in *LnAbnDSVI*. Column (5) shows that retail attention is significantly lower on Friday than on Monday. Abnormal retail attention on Tuesday is actually greater than on Monday, though this result is only statistically significant at the 10% level.

Finally, in Column (6), we regress abnormal retail attention on all 5 categories of variables. Results are generally similar to those in the first five columns. However, *EarnAnnDum*, *RecChngDum*, and *HLtoH* are no longer statistically significant at 5%. Jointly, these variables explain less than 0.4% 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 weekly frequency. Variations in daily abnormal SVI seem harder to explain.

3.2 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. By contrast, we wouldn't expect to find similar patterns using abnormal retail attention. We examine this point in Table 3. In particular, we calculate two measures of abnormal attention using Ancerno and CRSP. Abnormal institutional trading volume (*Ancerno-AbnVol*) is calculated as the stock's Ancerno daily volume divided by the previous 8-week average Ancerno trading volume. As a benchmark, abnormal total trading volume (*CRSP-AbnVol*) is calculated as the stock's CRSP daily volume divided by the previous 8-week average CRSP trading volume.

We regress these abnormal trading volume measures on AIA (Panel A) and *LnAbnDSVI* (Panel B). The specifications are similar across the both panels. To make the analysis comparable across the two measures, we transform *LnAbnDSVI* into a dummy variable ("DSVIDUM") which receives the value of 1 if *LnAbnDSVI* is in the top decile on a given day and 0 otherwise. To top DSVIDUM decile captures the 10% of the cases with highest attention which are comparable in frequency to our AIA measure (see Table 1).

The panels include six regression specifications, where we sequentially add the five sets of control variables associated with institutional attention from Table 2. For each measure, we report the first difference (i.e., the difference in coefficients between AIA=0 and AIA=1 in Panel A and DSVIDUM=0 and DSVIDUM=1 in Panel B), together with the difference in difference ("Diff-in-Diff") and its statistical significance. For example, "*CRSP-AbnVol-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 strongly significant coefficient of 0.240 on *CRSP-AbnVol*. The result suggests that an institutional attention spike is accompanied with a 24.0% increase in abnormal total trading volume, relative to the case of $AIA=0$. The coefficient on *Ancerno-AbnVol* is larger with a value of 0.318, 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 0.079 is highly significant with a t-statistic of 3.14.

Recall that Ancerno data primarily consist of trades by mutual funds and pension plans who are not the most active institutional investors. We would expect an even stronger link between AIA and institutional trading were we to focus on trading by hedge funds, for example. Moreover, the aggregate CRSP volume measure includes both individual and institutional investors, which biases the test against finding a significant difference. Thus, choosing a benchmark made up of only retail investors' trades should magnify our findings.

Overall the evidence in Panel A supports the notion that AIA measures attention shocks among institutional investors. In Panel B, we examine whether there is a similar relation between retail attention and institutional trading using the same analysis in Panel A.

Focusing on abnormal retail attention, Panel B of Table 3 clearly presents a different pattern. First, although the coefficients on the CRSP abnormal volume measure are positive in all six specifications, the magnitudes are only around 1/10 of the magnitude presented in Panel A. Moreover, the coefficients on the ANCERNO sample are not significant after controlling for firm characteristics. Finally, there is no statistically significant difference in differences in the impact on the two types of abnormal trading volume based on retail attention for any of the six specifications.

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 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.

4. Institutional Attention and Price Response to Information

The announcements of firm earnings and analyst recommendation changes are both important value-relevant information events. A voluminous literature has documented post-announcement price drift following both events. In other words, investors underreact to both announcements on average. In this section, we examine whether institutional attention on the announcement day facilitates information incorporation and alleviates price under-reaction to news.

4.1 Earnings Announcements

We examine the impact of institutional attention on earnings-announcement-window returns and post-earnings-announcement drifts using panel regressions. The results are reported in Table 4. If institutional investors facilitate information incorporation through attention and information processing, we would expect such information to be incorporated on day-0. More importantly, that would result in a less (if any) drift over subsequent days. Since many factors (observable and unobservable) can affect day-0 return, it is virtually impossible to provide direct evidence of a causal relation on day-0. However, less drift going forward would be clear evidence of information incorporation on day-0. Accordingly, in this section we provide clear evidence of less (if any) drift in stocks with high abnormal attention. Regarding the impact of AIA on day-0 returns, we discuss three potential explanations and argue that a causal effect of AIA on day-0 is the most likely explanation given the full set of our results. Finally, we show that the impact of retail attention is completely different and consistent with previous findings.

We match the timing of returns, AIA, and announcements by shifting earnings announcements that occur after trading hours to the following day. The dependent variables are day-0 *DGTW* risk adjusted return and $t+1$ to $t+40$ risk adjusted cumulative returns where day 0 represents the earnings announcement day. In panel A, the main dependent variables are: *AIA*, 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-0 impact of the announcement and the existence of post-earnings-announcement drifts (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 coefficient of 0.0019 on the announcement day suggests that when institutional investors pay attention, stock price reaction is 19bps larger for a one unit change in *SUE*. Note that this additional price response is consistent with our prior.

Next, focusing on the drift, 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 -0.0015 by the end of $t+40$, which is close to the coefficient on *SUE* in absolute term by $t+40$ (0.0020). In other words, when institutional investors pay more attention at the earnings announcement, there is almost no PEAD at all.

Having established that abnormal institutional attention is associated with weaker drift, we return to the announcement return findings. In particular, there are three possible explanations for the day-0 result. First, institutional investor attention facilitates information incorporation, and as a result, price underreaction to information is smaller. Alternatively, the relation between attention and the large price response on the announcement day could be driven by endogeneity (both attention and the market respond without being directly related. In other words, holding *SUE* constant, institutional investors endogenously allocate more attention to the types of announcements that have greater price impact) or reverse causality (larger price reaction on the announcement day actually triggers institutional attention).²¹ We address the potential reverse causality explanation in Panel C of Table 4. Importantly, although we cannot address the potential endogeneity explanation in our setting, the distinction between the three explanations is that only the first would predict a smaller price drift going forward, which we clearly find.²²

²¹ We use the term endogenous to refer to the relation between attention and return, not to investors' choices of attention allocation.

²² One can rightly argue that while the magnitude of the earnings surprise is the same, unobservable factors which are associated with the content of the announcement may differ and could attract abnormal institutional search. One potential explanation could be that abnormal AIA captures disagreement. That is, there is ambiguity about the news which non-randomly triggers attention. However, although disagreement may explain abnormal searches, it cannot

Our main results thus far in this subsection are nicely summarized in Figure 2. To construct this figure, we use the estimated regression coefficients from Panel A of Table 4 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 2 shows that the well-documented PEAD comes almost exclusively from announcements with limited institutional investor attention. When institutional investors fail to pay sufficient attention, price initially underreacts to information (as evident in panel A), resulting in a drift (as evident in Panel B). Thus, our results offer direct support that limited investor attention, especially those from institutional investors, is the driving force behind PEAD.

Recall that Table 2 documents a significant link between AIA and measures of equilibrium outcomes such as abnormal trading volume, return volatility, average spread, and size. The prior literature has used some of these equilibrium outcomes as investor attention proxy to study PEAD. For example, Hou, Peng, and Xiong (2009) documents 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 for 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 2 also shows that AIA is also 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. Although $LnAbnEDGAR$ explains only a small part of the variation in AIA, we directly control for $LnAbnEDGAR$ in Panel A. Additionally, in an untabulated set of results, we include both $LnAbnEDGAR$ and its interaction with SUE directly in the regression with AIA. We find that the coefficients on AIA and its interaction with SUE are qualitatively unchanged. More importantly, the coefficients on the interaction of the EDGAR measure with SUE are no longer statistically significant. Including $LnAbnDSVI$ produces similar results.

To alleviate any remaining concerns, we confirm the incremental value of AIA in a two-step exercise. In the first step, we orthogonalize AIA using all AIA determinants explored in

explain the fact the prices fully adjust and there is virtually zero drift going forward. On the other hand, agreement might explain a full price adjustment but is not consistent with abnormal searching activity.

Table 2. In particular, these variables include equilibrium outcomes, firm characteristics, news and analyst coverage, institutional holdings, seasonality and other direct attention measures. The residual is the unexpected AIA which, by construction, captures abnormal institutional attention unrelated to equilibrium outcomes or other proxies for attention. The pseudo R-squared of the first stage regression captures 27.75% of the variation in AIA. In the second step, we replace AIA with the residual AIA and find very similar results as reported in panel B.²³ Importantly, residual AIA continues to predict a significant reduction in PEAD and stocks with high unexpected AIA have almost zero PEAD.

In our final set of tests in this subsection, we address the potential reverse causality explanation. In particular, because AIA is measured daily from 12am to 12am while return is measured from 4pm to 4pm (close-to-close), it's possible that announcement-day returns lead to attention, and not vice-versa. For example, consider a large earnings surprise announced in the morning before the market opens on day t . The earnings surprise is almost fully incorporated into price on day t , resulting in a large announcement-day return and little price drift going forward. The large earnings-announcement day return then causes institutional investor to pay abnormal attention after market-close on day t .

To rule out a reverse causality explanation, we focus on the subset of earnings announcements occurring between 4pm and 12am after the market has closed on day $t-1$.²⁴ Roughly 50% of our earnings announcements sample events (9,308 firm-quarter observations, 50.4%) take place between 4pm and 12am (consistent with Michaely, Rubin, and Vedrashko, 2014). If we observe $AIA = 1$ on day $t-1$ for these earnings announcements, the institutional attention cannot be caused by the earnings-announcement day return. Panel C reports the results where we repeat our regression analysis in Panel A for this reduced sample using AIA on day $t-1$. Our results are robust in this sample.

Finally, one may argue that higher return on day t – which is associated with $AIA=1$ – mechanically causes less drift going forward, which would make the attention-drift relation

²³ Note that this is equivalent to including variable interactions terms in a full regression.

²⁴ 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 which tends to come right after market close.

mechanical. This is unlikely for a few reasons. First, Chan, Jegadeesh, and Lakonishok (1996) document 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 return in the regressions when examining post-announcement drifts. We confirm that controlling for the return on announcement day t barely changes the impact of AIA on post-earnings announcement returns from day $t+1$ up to day $t+40$.

4.2 Analyst Recommendation Changes

In this subsection, we study price reaction during and after analyst recommendation changes using similar panel regressions. Similar to earnings announcements, we shift recommendations that occur after trading hours by one trading day. We focus on day-0 and subsequent ten trading days. The results are reported in Table 5. 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 earnings announcements. In other words, 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 5A (5B) are similar to those in Table 4A (4B) except that we replace *SUE* with *RecChng* which measures the change in analyst recommendations. Specifically, *RecChng* ranges from -4 to 4, where 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 10 trading days.

The negative coefficients on the interaction term *RecChng_AIA* again suggest that institutional attention facilitates information incorporation at the announcement and alleviates future drift. In particular, the positive coefficient of 0.0081 on the announcement day suggests

that when institutional investors pay attention, stock price reacts by 81 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 $t+1$ to $t+10$. By the end of $t+10$, the coefficient is about -0.0027 by the end of $t+10$, equal to the corresponding coefficient on *RecChng* in absolute term (0.0027). In other words, when institutional investors pay more attention to analyst recommendation change, there is no post-announcement drift.

Similar to Figure 2, our results are nicely summarized in Figure 3. 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 REC, negative REC, $AIA=0$ and $AIA=1$). Figure 3 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 (as evident in panel A), resulting in a drift (as evident in Panel B). The patterns in Figure 3 are very similar to those in Figure 2. The patterns remain the same when residual AIA is used in Panel B.

Similar to Panel 4B, residual AIA produces consistent results.²⁵ As for an analysis using data after the market close, in contrast to earnings announcements, the vast majority of recommendation changes in our sample take place before the market has closed.²⁶ While this prevents us from focusing directly on after-hour 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.

Finally, exploring the predictive power of EDGAR around analyst recommendation changes shows that EDGAR cannot explain the drift (even without controlling for AIA). 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

²⁵ The Pseudo R-Squared from the first stage regression is 12.2% compared to the pseudo R-Squared of 27.75% found in the earnings announcements sample.

²⁶ Less than 15% of our 7,041 changes occur between 4pm and 12am.

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.

4.3 The Impact of Retail Attention

So far, our evidence suggests that institutional attention facilitates price discovery and alleviates under-reaction to news. Table 2 shows that institutional attention and retail attention are often correlated contemporaneously. It is natural to ask whether retail attention plays a similar role. We examine this important question in Table 6. We repeat the panel regressions analysis from Tables 4A and 5A after replacing AIA with *StdLnAbnDSVI* (the standardized abnormal search volume index).²⁷

In contrast to AIA, the coefficients on *StdLnAbnDSVI* are almost always positive and increasing (though not significant) following earnings announcements and recommendation changes. In other words, regardless of the content of the news, retail attention almost always results in positive price pressure, consistent with the evidence in the prior literature (see Barber and Odean, 2008, and others).

More importantly, the coefficients on the interaction terms between *StdLnAbnDSVI* and *SUE* or *RecChng* are always positive and in some cases statistically significant. Thus, it is clear that having more retail attention does not alleviate post-announcement price drifts.

To summarize, while institutional attention facilitates permanent price discovery, retail attention only results in a positive price effect. In this regard, the impact of institutional attention and retail attention on asset prices is fundamentally different.

²⁷ For ease of interpretation, *StdLnAbnDSVI* is standardized to reflect the impact of 1 standard deviation of *LnAbnDSVI* on returns. This was not necessary for AIA which is an indicator variable.

4.4 The Relation between Institutional and Retail Abnormal Attention

Having documented how the impact of attention on the incorporation of information differs across institutional and retail investors, we next investigate more directly how institutional and retail attention shocks are related to each other using our pooled sample of earnings announcements and analyst recommendation changes events. We examine this question with two sets of lead-lag regressions reported in Table 7. Note that the two measures are analogous since both measures focus on active investor searches.

In our first set of tests (Specifications 1-3), we regress AIA on its lags and on lags of *LnAbnDSVI*. Since AIA takes only the value of 0 or 1, we estimate the relation between AIA (as dependent) and *LnAbnDSVI* using Probit models.²⁸ To distinguish differences in attention across the two types of events, we include the variable *EarnDum*, which captures the incremental level of attention during earnings announcements. Additionally, following the *investor distraction* hypothesis of Hirshleifer, Lim and Teoh (2009), we include the variable “*LnNumEvents*”, which captures the (log of) the total number of earnings announcements and analyst recommendation changes occurring on day *t*.

We immediately observe that AIA is persistent. We find positive and significant autocorrelations on all five lags of AIA. Moreover, in specification (1), the coefficient on the first lag of *LnAbnDSVI* is positive and statistically significant. However, once more lags of both measures are included, the latter coefficient is smaller and no longer significant. The coefficients on *EarnDum* are positive and statistically significant. This shouldn't come as a surprise since these events are pre-scheduled. Interestingly, the positive but statistically insignificant coefficient on *LnNumEvents* suggests that the frequency of simultaneous news events does not represent a constraint to institutional investor attention.

In the second set of tests (Specifications 4-6), we regress *LnAbnDSVI* on its own lags and on lags of AIA. We use OLS panel regressions, as *LnAbnDSVI* is a continuous variable. Similar to AIA, *StndASVI* is also positively autocorrelated – but only for the first lag. Interestingly, the coefficients on lagged AIAs are positive and many are statistically significant. Together with the results from specification (3), this provides strong evidence that institutional attention shocks

²⁸ Using linear probability regressions instead of Probit models yields qualitatively similar results.

lead retail attention shocks. These collective findings are not surprising as institutional investors have greater resources and stronger financial incentive to monitor the market and are more likely to pay attention to news and react immediately.

Along these lines, the regressions also provide some evidence which suggests that retail attention is reduced when there are many simultaneous news events. Thus, retail investor attention is more constrained than institutional investor attention, suggesting that the *investor distraction* hypothesis is more relevant for retail investors than for institutional investors.

5. Conclusion

To our best knowledge, we propose the first broad, direct measure of abnormal institutional investor attention. Our abnormal institutional investor attention measure (AIA) is based on the news-searching and 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 measures of abnormal institutional trading contemporaneously.

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

Since institutional investors are more likely to react to news immediately and become the marginal investors who act, 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 where institutional investors fail to pay attention according to our measure. In sharp contrast, retail attention almost always results in a positive price pressure that is eventually reverted.

Earnings announcements and analyst recommendation changes are just two examples of important information events. It will be interesting to use AIA to examine the differential impact of institutional and retail attention on market reaction to other corporate events such as IPOs,

M&As, product launches, and dividend cuts, we leave these and other exciting applications of AIA for future research.

References:

- Alti A. and J. Sulaeman, 2012, When do high stock returns trigger equity issues? *Journal of Financial Economics* 103, 61-87.
- Ball, R., & Brown, P., 1968, An empirical evaluation of accounting income numbers, *Journal of accounting research*, 159-178.
- Barber, B. M., and T. Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.
- Battalio, H. R., and R. R. Mendenhall, 2005, Earnings Expectations, investor trade size, and anomalous returns around earnings announcements, *Journal of Financial Economics* 77, 289-319.
- Bauguess, S., J. Cooney, K. W. Hanley, 2013, Investor demand for information in newly issued securities, working paper.
- Boehmer, E., and J. J. Wu, 2013, Short selling and the price discovery process, *Review of Financial Studies* 26, 287–322.
- Boudoukh, J., R. Feldman, S. Kokan and M. Richardson, 2013, which news moves stock prices? A textual analysis, working Paper.
- Chan, L., N. Jegadeesh, and Lakonishok, 1996, “Momentum Strategies,” *Journal of Finance* 51, 1681-1713.
- Cohen, L., and Frazzini, A., 2008, Economic links and predictable returns, *Journal of Finance*, 63(4), 1977-2011.
- Chemmanur, T., and A. Yan, 2009, Advertising, attention, and stock returns, Working paper, Boston College and Fordham University.
- Da, Z., J. Engelberg, and P. Gao, 2011, In search of attention, *Journal of Finance* 66, 1461-1499.
- Da, Z., U. G. Gurun, and M. Warachka, 2014, Frog in the pan: continuous information and momentum, *Journal of Finance*, forthcoming.
- DeHaan, E., T. Shevlin, and J. Thornock, 2015, Market (in)attention and the strategic scheduling and timing of earnings announcements, *Journal of Accounting and Economics* forthcoming.
- DellaVigna, S., and Pollet, J. M., 2009, Investor inattention and Friday earnings announcements, *Journal of Finance*, 64(2), 709-749.
- Daniel, K. D., M. Grinblatt, S. Titman, and R. Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.
- Drake M., D. Roulstone, and J. Thornock, 2012, Investor Information Demand: Evidence from Google Searches Around Earnings Announcements, *Journal of Accounting Research* 50(4), 1001-1040.

- Drake M., D. Roulstone, and J. Thornock, 2015, The determinants and consequences of information acquisition via EDGAR, *Contemporary Accounting Research* forthcoming.
- Engelberg, J. E., and Parsons, C. A. 2011, The causal impact of media in financial markets, *Journal of Finance*, 66(1), 67-97.
- Fang, L., and J. Peress, 2009, Media coverage and the cross-section of stock returns, *Journal of Finance* 64(5), 2023-2052.
- Fama, E. F., and K. R. French, 1992. The cross-section of expected stock returns, *Journal of Finance*, 47(2), 427-465.
- Gervais, S., R. Kaniel, and D. H. Mingelgrin, 2001, The high-volume return premium, *Journal of Finance* 56, 877-919.
- Grullon, G., G. Kanatas, and J. P. Weston, 2004, Advertising, breath of ownership, and liquidity, *Review of Financial Studies* 17, 439-461.
- Gurun, U. G., and A. W. Butler, 2012, Don't believe the hype: Local media slant, local advertising, and firm value, *Journal of Finance* 67(2), 561-598.
- Hendershott, T., S. X. Li, A. J. Menkveld, and M. S. Seasholes, 2013, Asset price dynamics with limited attention, working paper.
- Hirshleifer, D., and S. H. Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337-386.
- Hirshleifer, D., Lim, S. S., and Teoh, S. H, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, *Journal of Finance*, 64(5), 2289-2325.
- Hirshleifer, D., Lim, S. S., and Teoh, S. H., 2011, Limited investor attention and stock market misreactions to accounting information, *Review of Asset Pricing Studies* 1 (1): 35-73.
- Hou, K., L. Peng, and W. Xiong, 2009, A tale of two anomalies: The implications of investor attention for price and earnings momentum, Working paper, Ohio State University and Princeton University.
- Jegadeesh, N., and W. Kim, 2010, Do analysts herd? An analysis of recommendations and market reactions. *Review of Financial Studies* 23 (2): 901-937.
- Kadan, O., R. Michaely, and P. Moulton, 2013, Who Trades on and Who Profits from Analyst Recommendations? working paper.
- Kahneman, D., 1973. Attention and Effort. Prentice-Hall, Englewood Cliffs, NJ.
- Lee, C. MC., 1992, Earnings news and small traders: An intraday analysis. *Journal of Accounting and Economics*, 15(2), 265-302.
- Lee, C. MC., P. Ma, and C. Y. Wang, 2015, Search-based peer firms: Aggregating investor perceptions through internet co-searches, *Journal of Financial Economics* 116, 410-431.

Liu, H., and L. Peng, 2015, Investor Attention: Seasonal Patterns and Endogenous Allocations, Working Paper.

Livnat, J., and Mendenhall, R. R., 2006, Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research*, 44(1), 177-205.

Loh, R. K. 2010. Investor Inattention and the Underreaction to Stock Recommendations. *Financial Management* 39:1223–51.

Loh, R. K., and R. M. Stulz, 2011, When are analyst recommendation changes influential? *Review of Financial Studies* 24, 593-627.

Lou, D., 2014, Attracting investor attention through advertising, *Review of Financial Studies*, 27 (6): 1797-1829.

Loughran, T., and B. McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *Journal of Finance* 66(1), 35-65.

Loughran, T., and B. McDonald, 2015, Information decay and financial disclosures, working paper.

Madsen, J., and M. Niessner, 2014, Is investor attention for sale? the role of advertising in financial markets, Working paper.

Michaely, R., A. Rubin, and A. Vedrashko, 2014, Corporate governance and the timing of earnings announcements, *Review of Finance* 18(6), 2003-2044.

Peng, L., 2005, Learning with information capacity constraints, *Journal of Financial and Quantitative Analysis* 40, 307-329.

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

Peress, J., 2014, The media and the diffusion of information in financial markets: Evidence from newspaper strikes, *Journal of Finance* 69(5), 2007-2043.

Peress, J., and D. Schmidt, 2014, Glued to the TV: the trading activity of distracted investors, working paper.

Puckett, A., and X. S. Yan, 2011, The interim trading skills of institutional investors, *Journal of Finance* 66(2), 601-633.

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

Seasholes, Mark S., and Guojun Wu, 2007, Predictable behavior, profits, and attention, *Journal of Empirical Finance* 14.5: 590-610.

Stickel, Scott E., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* 51, 25-39.

Sulaeman, J. and C. Wei, 2014, Institutional Presence, working Paper.

Tetlock, P. C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62(3), 1139-1168.

Womack, K. L., 1996, Do brokerage analysts' recommendations have investment value?. *Journal of finance*, 137-167.

Yuan, Y, 2015, Market-wide attention, trading, and stock returns, *Journal of Financial Economics* 116 (3), 548-564.

Table 1 – Summary Statistics of Abnormal Institutional Attention (AIA) and Other Selected Variables

The table reports summary statistics of Abnormal Institutional Attention measure (“AIA”) from Bloomberg (hereafter, “AIA”) and other selected variables from February 2010 to June 2013. 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, Grinblatt, Titman and Wermers, 1997). We report results for the full sample (“Full Sample”), earnings announcements sample (“EarnAnn Sample”) and analyst recommendation changes sample (“RecChng Sample”). The Full Sample includes 1,714,610 day-stock observations; the EarnAnn Sample includes 18,453 EarnAnn-stock observations; and the RecChng Sample includes 7,041 RecChng-stock observations. Panel A reports for each sample the mean, median and standard deviation of the firms’ time series averages. Panel B reports the conditional means conditioning on AIA=0 and AIA=1.

In order to construct the measure, 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 1 for each article read and 10 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 past 8-hour average count to all hourly counts over the previous month for the same stock. They assign the value of 0 if the rolling average is less than 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 which receives the value of 1 if Bloomberg’s score is 3 or 4, and 0 otherwise. This captures the right tail of the measure’s distribution.

In the table, “Num Firms” reports the number of unique firms. “AIA Frequency” reports AIA frequency for all three samples. In the case of the Full Sample, we divide each firm’s total number of days where AIA is equal to 1 by the firm’s total trading days during its sample period. Then, we calculate the cross-sectional average. For the EarnAnn and RecChng samples, we divide the number of firm-event cases where AIA is equal to 1 by the total number of firm-event observations. For all other variables, Mean, Median and SD refer to the cross sectional average, median and standard deviation of the firms’ time series averages. “SizeInM” is the stock’s market capitalization, rebalanced every June, in millions of dollars. “LnBM” is the natural logarithm of the stock’s book-to-market ratio, rebalanced every June following Fama-French (1992). “SDRET” is the daily standard deviation of stock returns, calculated based on the previous 21 trading days. “Ret” is the daily stock return, in %. “AbsRet” is the absolute value of Ret. “DGTW” is Ret minus the stock’s daily benchmark portfolio daily return following Daniel, Grinblatt, Titman and Wermers (1997). “AbsDGTW” is the absolute value of DGTW. “Turnover”, is the daily stock turnover. “Dvol in M” is the daily dollar trading volume, in millions of dollars. “HLtoH” is the ratio between the stock’s daily high-and-low price difference and the daily high price. “InstHold” is the percentage of shares held by institutional investors obtained from the Thomson Reuters CDA/Spectrum institutional holdings’ (S34) database. “NumEst” is the the number of analysts covering the stock. “Abs SUE/REC” is the absolute value of the surprise in analyst forecast and analyst recommendation change. SUE and REC are defined in Tables 4 and 5, respectively. “Relative Spread” is calculated as the [(Ask-Bid)/Midpoint]/2 using CRSP end of day quotes. Panel A also reposts two additional variables which are associated with attention. “EDGAR” is the daily number of unique requests for firm filings on the SEC EDGAR server (Loughran and McDonald, 2015). “LnAbnEDGAR” is the natural log of the ratio of EDGAR on day t to the average of EDGAR over the previous month. “LnAbnDSVI” is Da, Engelberg and Gao (2011)’s abnormal retail attention measure based on Google’s Search Volume Index (SVI), calculated at the daily frequency (DSVI). Similar to EDGAR, “LnAbnDSVI” is calculated as the natural log of the ratio of DSVI on day t to the average of DSVI over the previous month. Due to daily SVI data availability, the Full, EarnAnn and RecChng samples include 1,012,855, 11,315, and 4,954 LnAbnDSVI observations, respectively.

Panel 1.A – Cross-Sectional Statistics

Variables	Full Sample			EarnAnn Sample			RecChng Sample		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
<i>Num Firms</i>	2,298			1,952			1,376		
<i>AIA frequency</i>	0.098			0.567			0.447		
<i>SizeInM</i>	5,575	945	19,810	5,718	1,000	20,275	8,585	2,075	24,582
<i>LnBM</i>	-0.63	-0.51	0.83	-0.67	-0.54	0.82	-0.76	-0.68	0.80
<i>SDRET</i>	2.23	2.10	0.84	2.08	1.94	0.91	2.22	2.00	1.21
<i>Ret %</i>	0.09	0.08	0.30	0.33	0.15	2.84	0.15	0.13	4.10
<i>DGTW %</i>	0.01	0.01	0.30	0.31	0.11	2.66	0.09	0.09	3.91
<i>Turnover</i>	0.01	0.01	0.01	0.02	0.02	0.03	0.02	0.01	0.04
<i>Dvol in M</i>	52.82	8.31	207.27	130.70	25.15	489.25	121.91	41.16	307.79
<i>HLtoH</i>	0.03	0.03	0.01	0.07	0.06	0.03	0.04	0.03	0.03
<i>InstHold</i>	0.62	0.67	0.22	0.65	0.68	0.20	0.70	0.74	0.18
<i>NumEst</i>	9.06	7.16	7.05	9.46	7.52	6.74	13.02	11.75	6.96
<i>Abs SUE/REC</i>	N/A	N/A	N/A	2.68	2.22	1.92	1.34	1.25	0.35
<i>EDGAR</i>	42.17	25.38	67.97	79.64	46.33	115.36	68.08	38.66	105.94
<i>LnAbnEDGAR</i>	-0.03	-0.02	0.06	0.66	0.66	0.42	0.10	0.11	0.56
<i>LnAbnDSVI</i>	-0.01	0.00	0.09	0.02	0.02	0.37	0.00	0.02	0.40

Panel 1.B – Sample Averages Conditioning on AIA

Variables	Full Sample		EarnAnn Sample		RecChng Sample	
	AIA=0	AIA=1	AIA=0	AIA=1	AIA=0	AIA=1
<i>AbsRet %</i>	1.55	3.09	4.11	5.70	2.08	3.69
<i>AbsDGTW %</i>	1.22	2.75	3.79	5.29	1.75	3.37
<i>Turnover</i>	0.0080	0.0180	0.0172	0.0296	0.0172	0.0299
<i>Dvol in M</i>	48.01	73.36	65.18	148.52	106.91	174.63
<i>HLtoH</i>	0.0290	0.0450	0.0620	0.0709	0.0352	0.0427
<i>Relative Spread</i>	0.0010	0.0008	0.0011	0.0006	0.0004	0.0004
<i>NumEst</i>	9.05	9.45	7.63	10.26	13.36	14.71
<i>InstHold</i>	0.62	0.64	0.61	0.68	0.71	0.71
<i>Abs SUE/REC</i>	N/A	N/A	2.68	2.85	1.33	1.36
<i>EDGAR</i>	40.40	55.27	57.11	88.31	63.94	85.68
<i>LnAbnEDGAR</i>	-0.108	0.212	0.574	0.709	0.030	0.182
<i>LnAbnDSVI</i>	-0.0014	0.0166	-0.012	0.040	-0.030	0.038

Table 2 – The Contemporaneous Relation between Abnormal Institutional Attention, Abnormal Retail Attention, Attention Proxies and Other Explanatory Variables

The table reports results of the contemporaneous relation between Abnormal Institutional Attention measure (“*AIA*”) from Bloomberg (Panel A) and abnormal retail attention (“*LnAbnDSVI*”) based on Google’s daily Search Volume Index (Panel B) on selected explanatory variables. “*AIA*” and “*LnAbnDSVI*” are defined in Table 1. In particular, Panel A (B) analyzes Probit panel models (OLS panel regressions) where *AIA* (*LnAbnDSVI*) is the dependent variable. Each panel includes 6 identical specifications. Focusing on Panel A, Specification 1 explores the relation between *AIA* and “News” variables; Specification 2 explores the relation between *AIA* and price related variables; Specification 3 explores the relation between *AIA* and other firm characteristics; Specification 4 explores the relation between *AIA* and other attention measures; Specification 5 explores the effect of the day of the week effect on *AIA*; and Specification 6 explores all 5 categories together. Due to daily SVI data availability, Panel A includes 1,714,610 day-stock observations and Panel B includes 1,012,855 day-stock observations. We handle *LnAbnDSVI*’s missing observations when analyzing *AIA* in Panel A using Pontiff and Woodgate’s (2008) approach. First, we define a dummy variable which takes the value of 1 whenever the *LnAbnDSVI* exists and 0 otherwise. Second, we replace *LnAbnDSVI* missing values with zeros.

In both panels, “*LnNews*” is the log of 1 plus the number of news articles published on the Dow Jones newswire during the day, provided by RavenPack. “*EarnDum*” is a dummy variable which receives the value of 1 on earnings announcements days and 0 otherwise. “*RecChngDum*” is a dummy variable which receives the value of 1 on days with change in analyst recommendations and 0 otherwise. “*Ret*” is the CRSP daily stock return. “*Dgtw*” is *Ret* minus the stock’s benchmark portfolio daily return following Daniel, Grinblatt, Titman and Wermers (1997). “*AbsDgtw*” is the absolute value of *Dgtw*. “*AbnVol*” is 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. “*HLtoH*” is the ratio between the stock’s daily high-and-low price difference and the daily high price. *52HighDum* (*52LowDum*) is a dummy variable which receives the value of 1 if the stock’s price beat its 52-week high (low) price and 0 otherwise. “*LnSize*” is the log of the stock’s average size in millions of dollars from day *t*-27 to *t*-6. “*LnBM*” is the natural logarithm of the firm’s book-to-market ratio, rebalanced every June following Fama-French (1992). *SDRET* is the standard deviation of daily stock returns from day *t*-27 to day *t*-6. “*InstHold*” is the percentage of shares held by institutional investors obtained from the Thomson Reuters CDA/Spectrum institutional holdings’ (S34) database. “*LnNumEst*” is the log of 1 plus the number of analysts covering the stock, using the most recent information. “*AdvExpToSales*” is the firm advertising expenses to sales as in Da, Engelberg and Gao (2011), using the most recent information. “*LnAbnEDGAR*” is defined in Table 1. “Tuesday” – “Friday” are dummy variables which receive the value of 1 if the stock’s day of the week is Tuesday-Friday, respectively, and 0 otherwise. “*P-RSQ*” (“*Adj-RSQ*”) is the Probit model’s (OLS panel regression’s) pseudo (adjusted) *R*-squared. Standard errors are clustered by stock and day and *t*-statistics are reported below the coefficient estimates.

Panel 2.A – AIA as a Dependent Variable

Variable	(1)	(2)	(3)	(4)	(5)	(6)
<i>LnNews t</i>	0.382					0.205
	38.16					20.33
<i>EarnAnnDum t</i>	0.943					0.793
	32.24					27.47
<i>RecChngDum t</i>	0.866					0.655
	36.45					29.30
<i>AbsDgtw t</i>		0.074				0.072
		17.99				9.74
<i>AbnVol t</i>		0.059				0.049
		3.42				4.59
<i>HLtoH t</i>		2.243				9.371
		5.51				8.14
<i>52 High Dum t</i>		0.356				0.048
		23.48				2.80
<i>52 Low Dum t</i>		0.105				-0.235
		3.74				-5.02
<i>LnSize</i>			0.154			0.134
			23.56			12.47
<i>LnBM</i>			-0.014			-0.027
			-1.63			-2.97
<i>SDRET</i>			0.024			-0.078
			5.01			-9.03
<i>InstHold</i>			-0.010			0.042
			0.27			1.40
<i>LnNumEst</i>			0.235			0.231
			16.52			13.14
<i>AdvExpToSale</i>			-0.005			-0.403
			-0.02			-1.56
<i>LnAbnDSVI</i>				0.114		0.059
				7.72		5.86
<i>LnAbnEDGAR</i>				0.207		0.114
				29.82		18.61
<i>Tuesday</i>					-0.008	-0.081
					-0.41	-3.19
<i>Wednesday</i>					-0.043	-0.127
					-2.04	-4.99
<i>Thursday</i>					-0.046	-0.164
					-2.11	-6.25
<i>Friday</i>					-0.248	-0.329
					-11.27	-11.93
<i>P-RSQ</i>	7.19%	2.49%	4.89%	1.63%	0.26%	12.05%

Panel 2.B – LnAbnDSVI as a Dependent Variable

Variable	(1)	(2)	(3)	(4)	(5)	(6)
<i>LnNews t</i>	0.011					0.005
	6.16					2.69
<i>EarnAnnDum t</i>	0.017					0.000
	3.18					-0.08
<i>RecChngDum t</i>	0.017					0.011
	2.86					1.94
<i>AbsDgtw t</i>		0.004				0.004
		6.23				5.90
<i>AbnVol t</i>		0.004				0.003
		4.19				3.72
<i>HLtoH t</i>		-0.339				-0.039
		-3.94				-0.59
<i>52 High Dum t</i>		0.011				0.000
		3.36				-0.12
<i>52 Low Dum t</i>		0.000				-0.008
		0.05				-0.90
<i>LnSize</i>			0.007			0.005
			3.17			2.15
<i>LnBM</i>			0.003			0.002
			1.01			0.86
<i>SDRET</i>			-0.006			-0.007
			-3.57			-4.29
<i>InstHold</i>			0.000			0.004
			0.02			0.38
<i>LnNumEst</i>			-0.008			-0.009
			-1.71			-1.88
<i>AdvExpToSale</i>			-0.064			-0.076
			-0.70			-0.82
<i>AIA</i>				0.032		0.019
				9.77		7.29
<i>LnAbnEDGAR</i>				0.007		0.005
				5.10		3.24
<i>Tuesday</i>					0.008	0.007
					1.79	1.65
<i>Wednesday</i>					-0.001	-0.002
					-0.13	-0.32
<i>Thursday</i>					-0.007	-0.008
					-1.41	-1.61
<i>Friday</i>					-0.031	-0.030
					-6.13	-5.88
<i>Adj-RSQ</i>	0.08%	0.05%	0.12%	0.10%	0.11%	0.34%

Table 3 – Abnormal Institutional Attention, Abnormal Retail Attention and Abnormal Trading Volume

The table reports results of panel regressions of abnormal trading volume on abnormal institutional attention (“AIA”) (Panel A) and abnormal retail attention (“LnAbnDSVI”) (Panel B) controlling for Table 2’s attention determinants. “AIA” and “LnAbnDSVI” are defined in Table 1. We explore two samples of trading volume. The first is based on CRSP, where the CRSP’s daily abnormal trading volume (hereafter, “CRSP-AbnVol”) is calculated as the stock’s CRSP daily volume divided by the previous 8-week average trading volume. The second sample is obtained from Ancerno Ltd., and captures institutional investors’ trading volume. We calculate the abnormal institutional trading volume the same way as CRSP-AbnVol (hereafter, “Ancerno-AbnVol”). The Ancerno data are available until March 2013. After matching the CRSP and Ancerno samples and accounting for LnAbnDSVI’s data availability, Panel A (B) includes 1,314,755 (821,098) 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 2. For example, “Control Set 1” includes LnNews, EarnAnnDum and RecChngDum control variables. Note that we exclude abnormal volume from ControlSet 2 since 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-AbnVol-Diff” (“Ancerno-AbnVol-Diff”) is the difference in average abnormal volume of AIA=1 and AIA=0, where CRSP-AbnVol (Ancerno-AbnVol) is the dependent variable. “Diff-in-Diff” is the difference between the samples’ average differences, using the difference-in-difference regression approach. Panel B includes the same specifications. To employ the same methodology used in Panel A, we transform LnAbnDSVI into a dummy variable (DSVIDUM) that mimics AIA’s sample frequency. In particular, each day we rank LnAbnDSVI into ten deciles based on LnAbnDSVI values. Then, DSVIDUM received the value of 1 if LnAbnDSVI is in the top decile and 0 otherwise. Similar to Panel A, “CRSP-AbnVol-Diff” (“Ancerno-AbnVol-Diff”) is the difference between DSVIDUM=1 and DSVIDUM=0 where CRSP-AbnVol (Ancerno-AbnVol) is the dependent variable, and “Diff-in-Diff” is the difference using the difference-in-difference regression approach. Standard errors are clustered by stock and day. *t*-statistics are reported below the regression coefficients.

Panel 3.A – AIA and Abnormal Trading Volume

Variable	(1)	(2)	(3)	(4)	(5)	(6)
CRSP-AbnVol- Diff	0.650 17.78	0.461 11.47	0.263 9.31	0.235 8.98	0.230 8.53	0.240 8.6
Ancerno-AbnVol- Diff	0.763 20.51	0.547 14.57	0.333 12.19	0.315 11.96	0.308 11.09	0.318 11.12
Diff-In-Diff	0.114 3.98	0.086 3.77	0.070 2.61	0.081 3.39	0.078 3.23	0.079 3.14
<u>Table 2 Controls</u>						
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	0.73%	1.33%	4.37%	4.73%	4.77%	4.80%

Panel 3.B – LnAbnDSVI and Abnormal Trading Volume

Variable	(1)	(2)	(3)	(4)	(5)	(6)
<i>CRSP-AbnVol- Diff</i>	0.070 5.73	0.054 5.08	0.027 2.89	0.026 3.28	0.022 2.63	0.022 2.65
<i>Ancerno-AbnVol- Diff</i>	0.075 3.25	0.057 3.01	0.023 1.71	0.026 1.76	0.020 1.30	0.019 1.29
<i>Diff-In-Diff</i>	0.005 0.21	0.003 0.04	-0.004 0.052	-0.001 0.01	-0.002 0.03	-0.002 0.03
<i>Table 2 Controls</i>						
<i>Control Set 1</i>		Yes	Yes	Yes	Yes	Yes
<i>Control Set 2</i>			Yes	Yes	Yes	Yes
<i>Control Set 3</i>				Yes	Yes	Yes
<i>Control Set 4</i>					Yes	Yes
<i>Control Set5</i>						Yes
<i>Adj-RSQ</i>	0.05%	1.11%	4.23%	4.64%	4.75%	4.77%

Table 4 – Institutional Attention and Earnings Announcements Returns

The table reports results of panel regressions of earnings announcements' day-0 and cumulative day $t+1$ to $t+40$ DGTW risk adjusted returns on abnormal institutional attention and other explanatory variables. The sample includes 18,543 firm-quarter observations (see Table 1). In Panels A and B, we presents results using *AIA* and unexpected *AIA*, respectively. In Panel C, we focus on a reduced sample of earnings announcements that occur between 4:00pm-12:00am of day $t-1$. The reduced sample includes 9,308 stock-quarter observations.

In Panel A, “*AIA*” is our Abnormal Institutional Attention measure. “*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, that interaction between *SUE* and *AIA* measures the additional sensitivity of the *AIA* equals 1 group. “*LnNews*” is the log of 1 plus the number of news articles published on the Dow Jones newswire during the day, provided by RavenPack. “*EDGAR*” is the daily number of unique requests for firm filings on the SEC EDGAR server (Loughran and McDonald, 2015). “*LnAbnEDGAR*” is the natural log of the ratio of *EDGAR* on day t to the average of *EDGAR* over the previous month. “*LnAbnDSVI*” is the natural log of the ratio of *DSVI* on day t to the average of *DSVI* over the previous month (see Table 2 for Pontiff and Woodgate’s (2008) missing values approach). “*AbnVol*” is 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. “*HLtoH*” is the ratio between the stock’s daily high-and-low price difference and the daily high price. “*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. “*SDRET*” is the standard deviation of daily return from day $t-27$ to $t-6$. “*LnSize*” is the log of the stock’s average size in millions of dollars from day $t-27$ to $t-6$. “*LnBM*” is the firm natural logarithm of the firm book-to-market ratio, rebalanced every June following Fama-French (1992). “*InstHold*” is the percentage of shares held by institutional investors obtained from the Thomson Reuters CDA/Spectrum institutional holdings’ (S34) database. “*LnNumEst*” is the log of 1 plus the number of analysts covering the stock, using the most recent information.

In Panel B, we estimate a Probit model using the earnings announcement sample to predict the probability of being a firm with $AIA=1$ on earnings announcement days. The model includes the event day *AbnVol*, *LnAbnEDGAR*, *HLtoH* and *Spread* and also includes *LnSize* and *SDRET* firm characteristics. Using the model estimates, we spilt *AIA* into predicted and residual *AIA*. We then replace *AIA* with the residual part (hereafter, “*ResidAIA*”). For example, *SUE_ResidAIA*, is the interaction between *SUE* and *ResidAIA*. The other controls are identical to Panel A’s control variables.

In Panel C, *AIA* is estimated on day $t-1$ to match *SUE* timing (i.e., 4:00pm-12:00am). In a similar manner, *SUE t-1_AIA t-1* is the interaction between *SUE* and *AIA* on day $t-1$.

Standard errors are clustered by stock and day and each model includes quarter and day-of-week fixed effects. t -statistics are reported below the coefficient estimates.

Panel 4.A – AIA

Variables	<i>t</i>	<i>t+1</i> <i>t+1</i>	<i>t+1</i> <i>t+2</i>	<i>t+1</i> <i>t+3</i>	<i>t+1</i> <i>t+5</i>	<i>t+1</i> <i>t+10</i>	<i>t+1</i> <i>t+20</i>	<i>t+1</i> <i>t+30</i>	<i>t+1</i> <i>t+40</i>
<i>AIA t</i>	0.000	-0.001	0.000	-0.001	-0.001	-0.001	0.000	0.001	0.002
	-0.02	-1.11	-0.47	-1.11	-1.00	-0.72	0.12	0.24	0.76
<i>SUE t</i>	0.0046	0.0007	0.0009	0.0011	0.0011	0.0013	0.0017	0.0017	0.0020
	17.85	6.21	7.32	7.45	6.85	6.33	6.16	5.19	5.06
<i>SUE_AIA t</i>	0.0019	-0.0003	-0.0005	-0.0007	-0.0007	-0.0008	-0.0011	-0.0013	-0.0015
	5.59	-2.63	-2.96	-3.58	-3.09	-2.75	-2.91	-3.14	-3.02
<i>LnNews t</i>	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
	2.49	-0.41	-0.72	0.14	0.43	0.83	0.18	0.78	0.99
<i>LnAbnEDGAR t</i>	-0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000
	-1.01	0.77	0.73	-0.35	-0.43	1.10	0.04	0.85	0.15
<i>LnAbnDSVI t</i>	0.002	0.000	-0.001	0.000	0.001	0.001	0.003	0.004	0.003
	0.79	-0.05	-0.99	-0.22	0.64	0.61	1.17	1.31	0.93
<i>AbnVol t</i>	-0.001	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	-0.42	1.76	0.85	0.47	1.31	2.62	2.63	1.85	2.19
<i>HLtoH t</i>	-0.029	-0.030	-0.034	-0.020	-0.029	-0.043	-0.018	-0.006	-0.055
	-0.68	-3.36	-2.51	-1.31	-1.37	-1.76	-0.57	-0.18	-1.22
<i>Ret t-5_t-1</i>	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-5.40	0.17	0.54	0.81	0.98	0.74	-0.08	0.54	1.23
<i>Turnover t-5_t-1</i>	-0.325	0.010	0.016	0.042	0.058	0.002	-0.128	-0.223	-0.424
	-3.20	0.48	0.47	1.01	1.03	0.02	-1.12	-1.67	-2.75
<i>Spread t-5_t-1</i>	0.249	-0.007	0.178	0.246	0.302	0.668	0.806	0.759	3.150
	0.44	-0.01	0.37	0.42	0.43	0.71	0.60	0.49	1.32
<i>SDRET</i>	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003
	1.86	-0.64	0.25	-0.26	-0.34	-0.13	0.09	-0.18	0.63
<i>LnSize</i>	-0.003	0.000	0.000	0.000	-0.001	-0.001	-0.001	-0.002	-0.001
	-5.37	-1.84	-0.41	-0.84	-1.48	-1.98	-1.53	-1.68	-0.91
<i>LnBM</i>	-0.001	-0.001	-0.001	0.000	0.000	-0.001	-0.001	-0.002	-0.004
	-1.69	-1.60	-1.37	-0.30	-0.10	-0.69	-0.67	-1.51	-2.23
<i>InstHold</i>	0.004	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.002
	1.80	0.11	0.28	0.50	0.72	0.18	0.19	0.27	0.43
<i>LnNumEst</i>	0.002	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	-0.002
	1.81	0.40	-0.22	-0.19	-0.43	0.01	-0.04	-0.57	-0.77

Panel 4.B – Residual AIA

Variables	<i>t</i>	<i>t+1</i> <i>t+1</i>	<i>t+1</i> <i>t+2</i>	<i>t+1</i> <i>t+3</i>	<i>t+1</i> <i>t+5</i>	<i>t+1</i> <i>t+10</i>	<i>t+1</i> <i>t+20</i>	<i>t+1</i> <i>t+30</i>	<i>t+1</i> <i>t+40</i>
<i>ResidAIA t</i>	0.000	-0.001	0.000	-0.001	-0.001	-0.001	0.000	0.001	0.002
	0.12	-1.08	-0.50	-1.12	-1.05	-0.77	0.24	0.41	0.97
<i>SUE t</i>	0.0056	0.0005	0.0007	0.0007	0.0007	0.0009	0.0011	0.0010	0.0011
	29.87	8.12	7.81	7.46	6.30	5.95	5.78	4.81	4.30
<i>SUE_ResidAIA t</i>	0.0001	-0.0003	-0.0004	-0.0005	-0.0004	-0.0003	-0.0006	-0.0008	-0.0011
	0.29	-1.96	-1.97	-2.24	-1.42	-1.23	-1.54	-1.63	-2.04
<i>LnNews t</i>	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.001
	2.66	-0.47	-0.77	0.08	0.40	0.87	0.23	0.82	1.01
<i>LnAbnEDGAR t</i>	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000
	-0.77	0.69	0.65	-0.46	-0.51	0.91	0.02	0.88	0.17
<i>LnAbnDSVI t</i>	0.002	0.000	-0.001	0.000	0.001	0.001	0.003	0.004	0.003
	0.78	-0.05	-1.02	-0.24	0.70	0.58	1.15	1.33	0.93
<i>AbnVol t</i>	-0.001	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	-0.43	1.83	0.89	0.49	1.35	2.62	2.62	1.87	2.21
<i>HLtoH t</i>	-0.028	-0.032	-0.035	-0.023	-0.033	-0.046	-0.020	-0.009	-0.055
	-0.80	-3.56	-2.86	-1.52	-1.92	-2.18	-0.74	-0.26	-1.16
<i>Ret t-5_t-1</i>	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-6.04	0.20	0.35	0.81	1.01	0.74	-0.12	0.53	1.31
<i>Ave Turnover t-5_t-1</i>	-0.315	0.010	0.016	0.042	0.058	0.001	-0.129	-0.224	-0.423
	-3.06	0.48	0.49	1.09	1.12	0.01	-1.18	-1.74	-2.95
<i>Ave Spread t-5_t-1</i>	0.257	0.009	0.191	0.271	0.334	0.696	0.817	0.790	3.142
	0.45	0.02	0.40	0.46	0.47	0.73	0.62	0.51	1.30
<i>Daily SDRET t-1</i>	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003
	2.10	-0.66	0.24	-0.27	-0.34	-0.13	0.10	-0.18	0.63
<i>LnSize</i>	-0.003	-0.001	0.000	0.000	-0.001	-0.002	-0.002	-0.002	-0.001
	-5.54	-1.99	-0.59	-1.20	-1.92	-2.39	-1.83	-1.96	-0.91
<i>LnBM</i>	-0.001	-0.001	-0.001	0.000	0.000	-0.001	-0.001	-0.002	-0.004
	-1.87	-1.84	-1.59	-0.31	-0.10	-0.78	-0.75	-1.69	-2.41
<i>InstHold</i>	0.004	0.000	0.000	0.000	0.001	0.000	0.000	0.001	0.002
	1.71	-0.10	0.14	0.28	0.52	0.02	0.13	0.20	0.39
<i>LnNumEst</i>	0.002	0.000	0.000	0.000	-0.001	0.000	0.000	-0.001	-0.002
	1.96	0.07	-0.52	-0.58	-0.80	-0.20	-0.11	-0.67	-0.80

Panel 4.C – Earnings Announcements - After Market Hours

Variables	<i>t</i>	<i>t+1</i> <i>t+1</i>	<i>t+1</i> <i>t+2</i>	<i>t+1</i> <i>t+3</i>	<i>t+1</i> <i>t+5</i>	<i>t+1</i> <i>t+10</i>	<i>t+1</i> <i>t+20</i>	<i>t+1</i> <i>t+30</i>	<i>t+1</i> <i>t+40</i>
<i>AIA t-1</i>	0.000	-0.001	-0.001	-0.001	0.000	0.000	0.003	0.002	0.003
	0.13	-1.70	-0.96	-1.24	-0.15	0.11	1.09	0.81	0.67
<i>SUE t-1</i>	0.0054	0.0006	0.0007	0.0007	0.0008	0.0012	0.0012	0.0012	0.0013
	13.69	4.60	4.36	3.85	3.48	3.85	3.09	2.50	2.29
<i>SUE t-1</i> <i>AIA t-1</i>	0.0013	-0.0005	-0.0005	-0.0004	-0.0005	-0.0011	-0.0011	-0.0013	-0.0011
	2.47	-2.62	-2.00	-1.49	-1.55	-2.58	-2.08	-2.17	-1.85
<i>LnNews t</i>	0.002	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.002
	2.49	-0.09	-0.08	0.44	0.64	1.26	0.74	1.20	1.87
<i>LnAbnEDGAR t</i>	0.000	0.000	0.001	0.001	0.001	0.002	0.002	0.002	0.002
	-0.03	1.21	1.63	1.30	1.03	2.07	1.44	1.73	1.30
<i>LnAbnDSVI t</i>	0.002	0.001	0.001	0.002	0.003	0.003	0.005	0.006	0.004
	0.67	1.44	0.47	1.21	1.88	1.65	1.84	1.57	0.97
<i>AbnVol t</i>	-0.001	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	-0.35	2.15	1.18	0.22	1.13	2.45	1.82	0.98	1.69
<i>HLtoH t</i>	0.019	-0.036	-0.028	-0.016	-0.034	-0.063	-0.019	0.011	-0.050
	0.35	-2.78	-1.47	-0.74	-1.13	-1.74	-0.41	0.20	-0.76
<i>Ret t-5</i> <i>t-1</i>	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	-2.91	0.41	-0.33	0.02	0.37	0.32	0.44	0.89	0.64
<i>Turnover t-5</i> <i>t-1</i>	-0.342	0.012	0.021	0.067	0.095	0.061	0.014	-0.029	-0.300
	-2.37	0.52	0.57	1.32	1.28	0.56	0.10	-0.18	-1.54
<i>Spread t-5</i> <i>t-1</i>	0.928	-0.079	0.156	0.750	0.749	1.790	2.983	3.485	3.128
	0.82	-0.25	0.34	1.43	1.49	2.34	2.17	2.23	1.87
<i>SDRET</i>	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.000	0.006
	0.66	1.32	1.55	0.58	0.49	0.66	0.51	-0.08	0.86
<i>LnSize</i>	-0.002	-0.001	0.000	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
	-2.93	-1.94	-0.50	-1.22	-1.93	-2.38	-1.56	-1.44	-0.88
<i>LnBM</i>	-0.002	-0.001	-0.001	0.000	0.000	-0.001	0.000	-0.002	-0.004
	-2.18	-1.25	-1.48	-0.57	-0.41	-0.79	-0.28	-1.08	-1.88
<i>InstHold</i>	0.009	0.001	-0.001	0.000	0.001	0.003	0.004	0.002	0.000
	2.78	0.95	-0.34	-0.27	0.58	0.92	0.82	0.45	-0.03
<i>LnNumEst</i>	0.000	0.000	0.000	0.000	-0.001	0.001	0.000	-0.001	-0.003
	0.00	0.27	-0.37	-0.01	-0.41	0.50	-0.18	-0.36	-0.92

Table 5 – Institutional Attention and Change-in-Analyst-Recommendations Returns

The table reports results of panel regressions of change in analyst recommendations' day-0 and cumulative day $t+1$ to $t+10$ DGTW risk adjusted returns on institutional attention and other explanatory variables. In constructing the sample, we basically follow 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 who to have issued a recommendation for the stock and revised the recommendation within 180 calendar days; (4) require at least two analysts, other than the revising analyst, to have active recommendations for the stock as of the day before the revision; (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 these filters, we end up with 7,041 changes in recommendations.

Panel A (B) presents our main (robustness) model using *AIA* (unexpected *AIA*). In Panel A, “*AIA*” is our Abnormal Institutional Attention measure. “*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) (that is, a reverse scale). “*RecChng_AIA*” is the interaction between the *RecChng* and *AIA*. Similar to Table 4, since *AIA* is a dummy variable, that interaction measures the additional sensitivity of the *AIA* equals 1 group. “*LnNews*” is the log of 1 plus the number of news articles published on the Dow Jones newswire during the day, provided by RavenPack. “*EDGAR*” is the daily number of unique requests for firm filings on the SEC EDGAR server (Loughran and McDonald, 2015). “*LnAbnEDGAR*” is the natural log of the ratio of *EDGAR* on day t to the average of *EDGAR* over the previous month. “*LnAbnDSVI*” is the natural log of the ratio of *DSVI* on day t to the average of *DSVI* over the previous month (see Table 2 for Pontiff and Woodgate’s (2008) missing values approach). “*AbnVol*” is 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. “*HLtoH*” is the ratio between the stock’s daily high-and-low price difference and the daily high price. “*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. “*SDRET*” is the standard deviation of daily return from day $t-27$ to day $t-6$. “*LnSize*” is the log of the stock’s average size in millions of dollars from day $t-27$ to $t-6$. “*LnBM*” is the natural logarithm of the firm book-to-market ratio, rebalanced every June following Fama-French (1992). “*InstHold*” is the percentage of shares held by institutional investors obtained from the Thomson Reuters CDA/Spectrum institutional holdings’ (S34) database. “*LnNumEst*” is the log of 1 plus the number of analysts covering the stock, using the most recent information.

In Panel B, we estimate a Probit model using the earnings announcement sample to predict the probability of being a firm with *AIA* equals 1 on change in analyst recommendation days. The model includes the event day *AbnVol*, *LnAbnEDGAR*, *HLtoH* and *Spread* and also includes *LnSize* and *SDRET* firm characteristics. Using the model estimates, we split *AIA* into predicted and residual *AIA*. We then replace *AIA* with the unexpected part (hereafter, “*UnExpAIA*”). For example, *RecChng_UnExpAIA*, is the interaction between *RecChng* and *UnExpAIA*. The other controls are identical to Panel A’s control variables.

Standard errors are clustered by stock and day and each model includes quarter and day-of-week fixed effects. t -statistics are reported below the coefficient estimates.

Panel 5.A – AIA

Variables	t	t+1	t+1	t+1									
		t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10		
<i>AIA t</i>	0.002	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	-0.001	-0.002		
	1.93	-0.17	-0.19	0.02	-0.04	0.09	1.13	0.69	-0.07	-0.59	-0.96		
<i>RecChng t</i>	0.0059	0.0016	0.0020	0.0018	0.0019	0.0024	0.0026	0.0029	0.0025	0.0027	0.0028		
	18.27	5.99	5.33	3.93	3.25	4.45	4.66	4.65	3.84	3.95	3.87		
<i>RecChng_AIA t</i>	0.0080	-0.0010	-0.0010	-0.0009	-0.0006	-0.0013	-0.0021	-0.0023	-0.0021	-0.0025	-0.0026		
	11.33	-2.53	-1.85	-1.52	-0.82	-1.54	-2.36	-2.37	-2.01	-2.19	-2.18		
<i>LnNews t</i>	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
	0.41	1.93	1.10	0.99	0.43	0.31	-0.05	0.31	0.23	0.21	0.26		
<i>LnAbnEDGAR t</i>	0.001	0.000	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000	0.00	0.00		
	0.87	0.47	-1.01	-0.14	-0.55	-0.79	-0.94	-0.16	0.08	0.20	0.12		
<i>LnAbnDSVI t</i>	0.001	0.001	0.000	0.001	0.002	0.000	0.000	-0.001	-0.001	0.00	0.00		
	0.66	1.12	0.34	0.63	1.23	0.16	0.09	-0.47	-0.66	-0.73	-0.54		
<i>AbnVol t</i>	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.001	0.001		
	0.09	0.51	0.88	0.78	0.65	1.21	0.90	0.73	1.00	1.08	1.09		
<i>HLtoH t</i>	-0.151	-0.008	-0.050	-0.035	0.054	0.024	0.012	0.000	0.012	0.036	0.024		
	-1.83	-0.29	-1.73	-0.76	0.52	0.29	0.14	0.00	0.14	0.40	0.28		
<i>Ret t-5_t-1</i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		
	0.69	1.21	1.88	0.50	-0.11	-0.12	-0.31	0.02	-0.12	-0.07	-0.11		
<i>Turnover t-5_t-1</i>	-0.122	-0.055	-0.069	-0.104	-0.133	-0.138	-0.136	-0.117	-0.151	-0.158	-0.144		
	-1.64	-2.16	-2.26	-2.98	-2.84	-2.48	-2.39	-1.98	-2.44	-2.42	-2.09		
<i>Spread t-5_t-1</i>	-0.822	0.743	1.663	0.885	2.790	3.163	1.523	1.055	0.605	2.401	2.702		
	-0.26	0.54	0.82	0.41	0.80	1.12	0.53	0.35	0.21	0.72	0.70		
<i>SDRET</i>	-0.002	-0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001		
	-2.20	-1.87	-1.43	-1.08	-0.14	-0.70	-1.19	-1.22	-1.38	-0.85	-0.83		
<i>LnSize</i>	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000		
	1.00	0.35	0.81	0.56	0.03	-0.12	-0.10	-0.16	-0.33	-0.46	-0.36		
<i>LnBM</i>	0.001	0.001	0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001		
	0.92	1.82	1.87	-0.30	-0.76	-0.84	-1.01	-1.11	-0.78	-0.73	-0.51		
<i>InstHold</i>	0.000	0.001	0.000	-0.001	0.002	0.004	0.005	0.004	0.003	0.006	0.005		
	-0.07	0.38	-0.19	-0.29	0.83	1.36	1.74	1.10	1.01	1.60	1.36		
<i>LnNumEst</i>	0.001	0.001	0.001	0.001	0.001	0.002	0.003	0.003	0.004	0.003	0.002		
	0.69	0.75	1.11	0.72	0.69	1.10	1.69	1.37	1.85	1.31	0.89		

Panel 5.B – Residual AIA

Variables	t	t+1	t+1										
		t+1	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10	t+10
<i>ResidAIA t</i>	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.001	0.000	-0.001	-0.002	
	0.88	-0.09	-0.23	0.01	-0.03	0.09	1.21	0.72	-0.04	-0.59	-1.03		
<i>RecChng t</i>	0.0094	0.0012	0.0016	0.0014	0.0016	0.0019	0.0017	0.0019	0.0016	0.0017	0.0016		
	29.15	6.18	6.29	4.50	4.02	4.60	3.97	4.02	3.18	3.13	2.88		
<i>RecChng_ResidAIA t</i>	0.0056	-0.0010	-0.0009	-0.0008	-0.0001	-0.0007	-0.0016	-0.0017	-0.0016	-0.0017	-0.0017	-0.0021	
	9.49	-2.31	-1.77	-1.22	-0.15	-0.84	-1.78	-1.68	-1.58	-1.67	-1.85		
<i>LnNews t</i>	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	0.65	1.88	1.05	0.94	0.38	0.27	-0.06	0.29	0.21	0.18	0.23		
<i>LnAbnEDGAR t</i>	0.001	0.000	0.000	0.000	0.000	-0.001	-0.001	0.000	0.000	0.00	0.00	0.00	
	0.95	0.49	-1.10	-0.13	-0.56	-0.77	-0.87	-0.12	0.08	0.17	0.08		
<i>LnAbnDSVI t</i>	0.001	0.001	0.000	0.001	0.002	0.000	0.000	-0.001	-0.001	-0.001	0.00	0.00	
	0.61	1.10	0.34	0.64	1.27	0.18	0.14	-0.48	-0.70	-0.76	-0.57		
<i>AbnVol t</i>	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	
	0.14	0.52	0.89	0.83	0.67	1.25	0.97	0.77	0.98	1.02	1.04		
<i>HLtoH t</i>	-0.148	-0.008	-0.050	-0.035	0.054	0.025	0.017	0.004	0.012	0.033	0.019	0.019	
	-1.78	-0.30	-1.73	-0.79	0.54	0.31	0.20	0.05	0.14	0.38	0.22		
<i>Ret t-5_t-1</i>	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	0.75	0.81	1.83	0.49	-0.11	-0.12	-0.31	0.02	-0.13	-0.08	-0.13		
<i>Turnover t-5_t-1</i>	-0.124	-0.055	-0.069	-0.104	-0.133	-0.138	-0.136	-0.117	-0.151	-0.158	-0.144	-0.144	
	-1.69	-2.28	-1.74	-2.48	-2.65	-2.54	-2.39	-1.79	-2.31	-2.30	-2.00		
<i>Spread t-5_t-1</i>	-1.000	0.765	1.683	0.900	2.794	3.174	1.522	1.065	0.638	2.456	2.779	2.779	
	-0.32	0.56	0.83	0.41	0.81	1.13	0.53	0.35	0.22	0.73	0.71		
<i>SDRET</i>	-0.002	-0.001	-0.001	-0.001	0.000	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	
	-2.14	-1.90	-1.46	-1.04	-0.14	-0.66	-1.08	-1.14	-1.43	-0.93	-0.94		
<i>LnSize</i>	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	
	0.84	0.38	0.85	0.57	0.04	-0.12	-0.13	-0.17	-0.30	-0.40	-0.28		
<i>LnBM</i>	0.001	0.001	0.001	0.000	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	
	0.84	1.67	1.67	-0.29	-0.79	-0.88	-1.06	-1.19	-0.88	-0.82	-0.58		
<i>InstHold</i>	0.000	0.001	0.000	-0.001	0.002	0.004	0.005	0.004	0.004	0.006	0.005	0.005	
	-0.17	0.39	-0.18	-0.29	0.79	1.37	1.73	1.11	1.06	1.67	1.46		
<i>LnNumEst</i>	0.001	0.001	0.001	0.001	0.001	0.002	0.003	0.003	0.004	0.003	0.002	0.002	
	0.86	0.78	1.06	0.70	0.68	1.12	1.81	1.43	1.99	1.38	0.89		

Table 6 – Retail Attention and Earnings Announcement and Change-in-Analyst-Recommendation Returns

The table repeats Tables 4 and 5 analyses, where we replace *AIA* with the Da, Engelberg and Gao (2011) daily abnormal retail attention measure (*LnAbnDSVI*, defined in Table 1). In Panel A (B) we analyze the earnings announcements (change in analyst recommendations) sample. We standardized *LnAbnDSVI* to reflect the effect of 1 standard deviation on returns (“*StndLnAbnDSVI*”). In each panel, Specification 1 only includes *StndLnAbnDSVI* and Specification 2 also includes the interaction term with the relevant event variable (i.e., *SUE* or *RecChng*). For brevity, the panels do not report Table 4 and 5’s other control variables. Standard errors are clustered by stock and day and each model includes quarter and day-of-week fixed effects. *t*-statistics are reported below the coefficient estimates. Finally, due to daily SVI data availability, Panel A (B) includes 11,315, (4,954) event-stock observations.

Panel 6.A – Earnings Announcements

SPC	Variables	<i>t</i>	<i>t+1 t+1</i>	<i>t+1 t+2</i>	<i>t+1 t+3</i>	<i>t+1 t+5</i>	<i>t+1 t+10</i>	<i>t+1 t+20</i>	<i>t+1 t+30</i>	<i>t+1 t+40</i>
(1)	<i>StndLnAbnDSVI t</i>	0.0005	0.0000	-0.0003	-0.0001	0.0002	0.0003	0.0009	0.0014	0.0012
		0.71	0.04	-0.99	-0.33	0.60	0.52	1.06	1.27	0.96
	<i>SUE t</i>	0.0050	0.0005	0.0007	0.0007	0.0007	0.0007	0.0009	0.0007	0.0009
		15.88	5.21	5.81	5.80	4.90	4.28	3.54	2.44	2.58
(2)	<i>StndLnAbnDSVI t</i>	0.0001	0.0000	-0.0005	-0.0003	0.0001	0.0002	0.0007	0.0011	0.0010
		0.11	-0.03	-1.44	-0.79	0.29	0.26	0.80	1.03	0.81
	<i>SUE t</i>	0.0050	0.0005	0.0006	0.0007	0.0007	0.0007	0.0009	0.0007	0.0009
		15.82	5.26	5.78	5.74	4.85	4.22	3.49	2.38	2.54
	<i>SUE_StndLnAbnDSVI t</i>	0.0005	0.0000	0.0002	0.0002	0.0001	0.0002	0.0003	0.0003	0.0002
		2.13	0.29	2.34	2.46	1.84	1.56	1.60	1.52	1.24

Panel 6.B – Analyst Recommendation Changes

SPC	Variables	<i>t</i>	<i>t+1 t+1</i>	<i>t+1 t+2</i>	<i>t+1 t+3</i>	<i>t+1 t+4</i>	<i>t+1 t+5</i>	<i>t+1 t+6</i>	<i>t+1 t+7</i>	<i>t+1 t+8</i>	<i>t+1 t+9</i>	<i>t+1 t+10</i>
(1)	<i>StndLnAbnDSVI t</i>	0.0001	0.0002	0.0003	0.0004	0.0003	0.0000	0.0000	0.0001	0.0001	0.0001	0.0002
		0.08	0.56	0.63	0.66	0.40	-0.03	-0.06	0.12	0.07	0.07	0.21
	<i>RecChng t</i>	0.0085	0.0012	0.0013	0.0011	0.0011	0.0015	0.0015	0.0015	0.0012	0.0012	0.0010
		19.67	5.30	4.22	2.68	2.30	2.96	2.87	2.52	1.90	1.83	1.51
(2)	<i>StndLnAbnDSVI t</i>	0.0000	0.0002	0.0003	0.0004	0.0003	0.0000	-0.0001	0.0001	0.0000	0.0001	0.0002
		-0.03	0.54	0.62	0.62	0.37	-0.06	-0.09	0.10	0.05	0.06	0.20
	<i>RecChng t</i>	0.0082	0.0011	0.0013	0.0010	0.0011	0.0015	0.0014	0.0014	0.0011	0.0012	0.0010
		20.21	5.18	4.12	2.52	2.19	2.83	2.73	2.44	1.80	1.82	1.51
	<i>RecChng_StndLnAbnDSVI t</i>	0.0021	0.0002	0.0000	0.0005	0.0005	0.0005	0.0007	0.0004	0.0006	0.0002	0.0001
		2.76	0.62	0.12	1.41	0.97	0.95	1.14	0.67	0.88	0.25	0.14

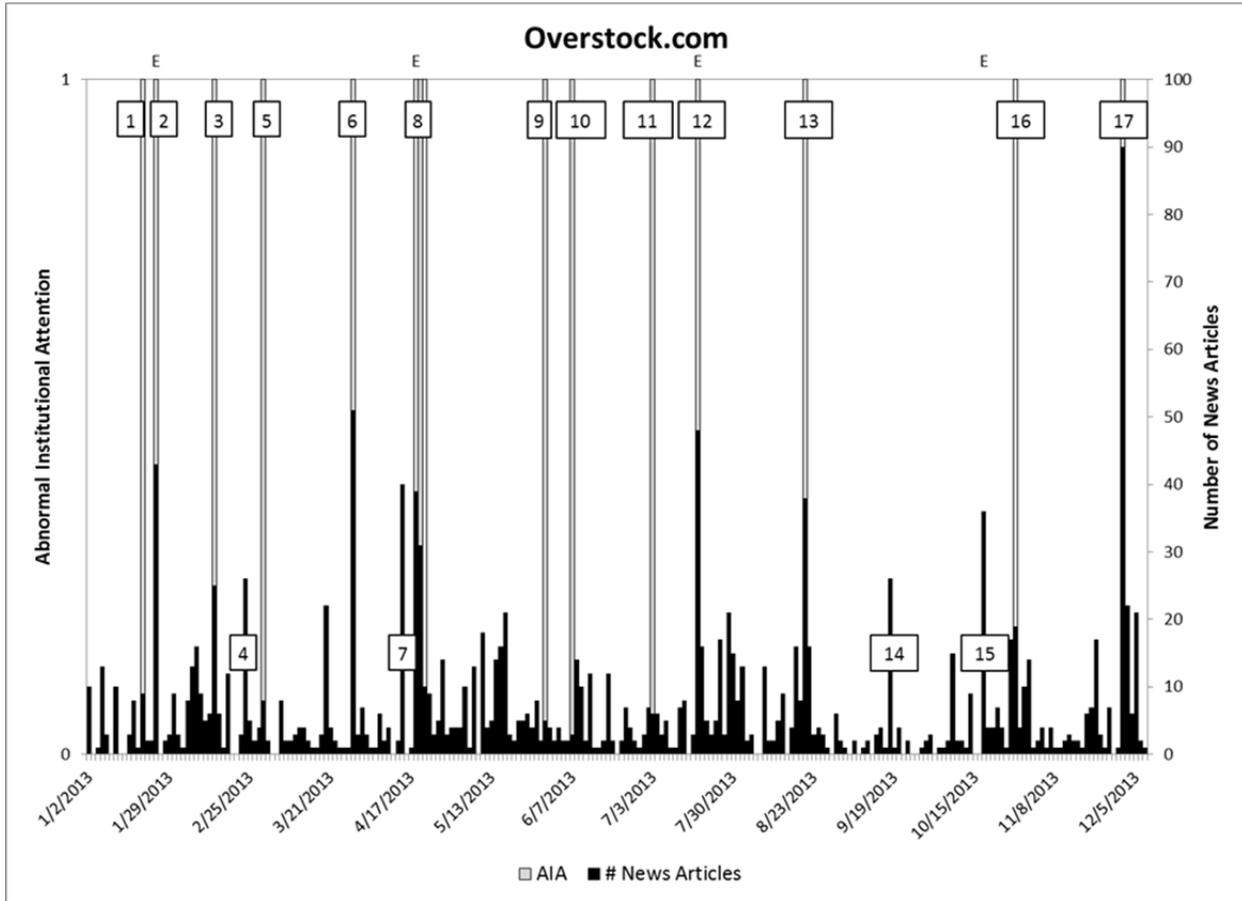
Table 7 – The Relation between Institutional and Abnormal Retail Attention around Information Events

The table explores the daily relation between Abnormal Institutional Attention measure (“*AIA*”) and the abnormal retail attention measure (“*LnAbnDSVI*,” defined in Table 1) around earnings announcements (“*EarnAnn*”) and change in analyst recommendations (“*RecChng*”) events. In particular, we pool together these events and estimate the lead-lag relation between *AIA* and *LnAbnDSVI*. We use Probit panel models when *AIA* is the dependent variable (Specifications 1-3) and OLS panel regressions when *LnAbnDSVI* is the dependent variable (Specifications 4-6). For each explanatory variable, the suffix *t-j* refers to the *j*th lag of the corresponding variable, where *j* is from 1 to 5. For example “*AIA t-1*”, is the first lag of *AIA*. “*EarnDum t*” is a dummy variable which receive the value of 1 for earnings announcements events and 0 otherwise. This captures the difference in attention between the two types of events. “*LnNumEvents t*” is the natural log of 1 plus the number of events on a given day. This captures the effect of multiple events on attention (Hirshleifer, Lim and Teoh, 2009). “*PSD/ADJ RSQ*” is the *Pseudo-RSQ (Adjusted-RSQ)* of the Probit panel models (OLS panel regressions). Standard errors are clustered by stock and day and each model includes quarter and day-of-week fixed effects. *t*-statistics are reported below the coefficient estimates.

Variable	AIA <i>t</i>			LnAbnDSVI <i>t</i>		
	Probit			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>AIA t-1</i>	0.884 24.06	0.783 21.66	0.754 20.97	0.015 3.08	0.009 1.92	0.008 1.77
<i>AIA t-2</i>		0.328 9.35	0.269 7.69		0.009 1.46	0.007 1.11
<i>AIA t-3</i>		0.431 12.31	0.318 8.92		0.017 2.61	0.013 2.05
<i>AIA t-5</i>			0.309 8.18			0.009 1.50
<i>AIA t-5</i>			0.364 9.93			0.013 1.95
<i>LnAbnDSVI t-1</i>	0.098 2.30	0.063 1.65	0.056 1.43	0.632 20.95	0.664 18.93	0.660 18.29
<i>LnAbnDSVI t-2</i>		0.004 0.08	0.001 0.02		-0.022 0.52	-0.019 0.43
<i>LnAbnDSVI t-3</i>		0.028 0.71	0.004 0.09		-0.040 1.20	-0.031 0.90
<i>LnAbnDSVI t-4</i>			0.019 0.51			-0.019 0.46
<i>LnAbnDSVI t-5</i>			0.007 0.17			-0.001 0.03
<i>EarnDum t</i>	0.607 9.84	0.704 11.65	0.748 12.43	0.029 3.05	0.031 3.19	0.032 3.20
<i>LnNumEvents t</i>	0.0246 0.91	0.0280 1.06	0.0299 1.14	-0.0073 1.75	-0.0076 1.83	-0.0072 1.71
<i>PSD/ADJ RSQ</i>	15.04%	16.94%	18.13%	42.18%	42.60%	42.08%

Figure 1 – Institutional Abnormal Attention, Earnings Announcements and News

The figure plots the daily AIA values for Overstock.com during 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. Additionally, sample headlines (from Factiva) for seventeen indicated events are listed below the figure.

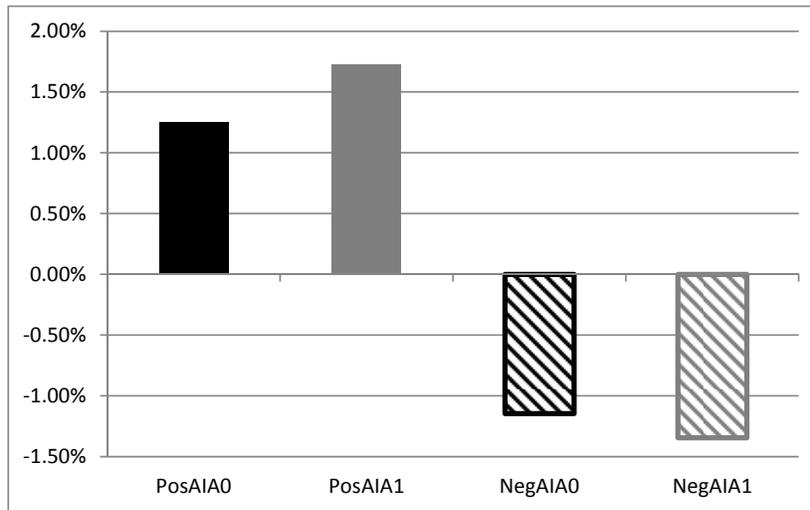


Event	Date	AIA	Sample Headline
1	1/18/2013	1	Airport police: Overstock CEO arrested for having gun in luggage
2	1/24/2013	1	Overstock.com 4Q EPS 37c
3	2/12/2013	1	Overstock.com CEO to Take Medical Leave of Absence
4	2/22/2013	0	Overstock.com Inc Announces President Change-Form 8-K
5	2/28/2013	1	Groupon 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 2 – Abnormal Institutional Attention and Earnings Announcements Returns

The figure plots the effect of *SUE* on earnings announcements' day-0 *DGTW* risk adjusted returns (Graph 2.A) and day $t+1$ to $t+40$ cumulative risk adjusted returns (Graph 2.B) for the following four cases: positive *SUE* with *AIA* equals 0 (“*PosAIA0*”); positive *SUE* with *AIA* equals 1 (“*PosAIA1*”); negative *SUE* with *AIA* equals 0 (“*NegAIA0*”); and negative *SUE* with *AIA* equals 1 (“*NegAIA1*”). In order to estimate the conditional returns, for each group, we multiply the group’s relevant *SUE* regression coefficient - estimated in Table 4.A - 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* equals 0, and use the sum of *SUE* and *SUE_AIA* regression coefficients for *AIA* equals 1.

Graph 2.A – Day-0 Returns



Graph 2.B – $t+1 - t+40$ Cumulative Returns

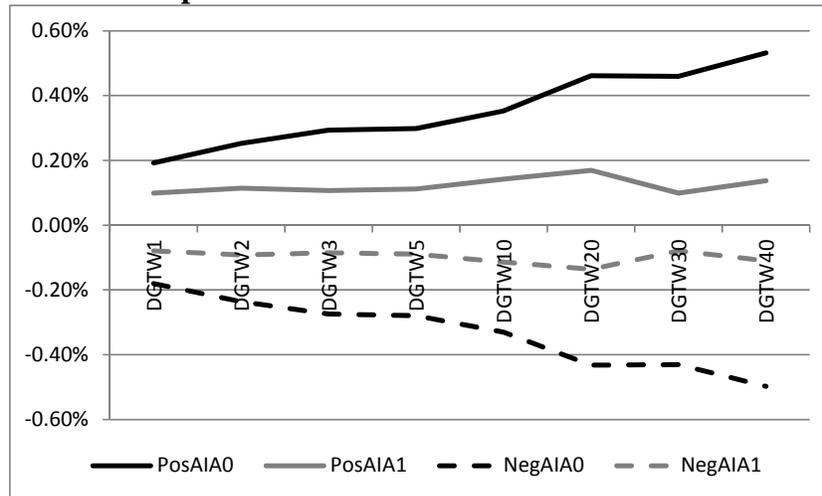
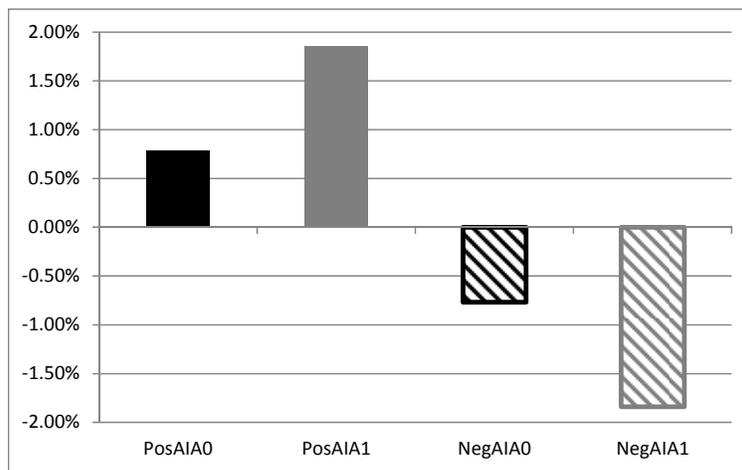


Figure 3 – Abnormal Institutional Attention and Change-in-Analyst-Recommendations Returns

The figure plots the effect of change in analyst recommendations (*RecChng*) on day-0 *DGTW* risk adjusted returns (Graph 3.A) and day *t+1* to *t+10* cumulative risk adjusted returns (Graph 3.B) for the following four cases: positive *RecChng* with *AIA* equals 0 (“*PosAIA0*”); positive *RecChng* with *AIA* equals 1 (“*PosAIA1*”); negative *RecChng* with *AIA* equals 0 (“*NegAIA0*”); and negative *RecChng* with *AIA* equals 1 (“*NegAIA1*”). In order to estimate the conditional returns, for each group, we multiply the group’s relevant *RecChng* regression coefficient - estimated in Table 5.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* equals 0, and use the sum of *RecChng* and *RecChng* *_AIA* regression coefficients for *AIA* equals 1.

Graph 3.A – Day-0 Returns



Graph 3.B – *t+1* – *t+10* Cumulative Returns

