How do Institutions Trade around Corporate News?*

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Combining a comprehensive database of news releases during 2000 to 2010 with a large high-frequency database of institutional trades, we examine how institutions trade on the qualitative information embedded in public news releases. We find that institutions trade on the tone of news on the days of news releases but not around news arrivals. That institutions trade speedily on but do not predict qualitative information in corporate news suggests that institutions' informational advantage, if any, stems mostly from their ability to process information in a highly timely manner.

I. Introduction

There is a long tradition in the finance literature assuming that institutional investors as a group are so-called "informed" investors and enjoy an informational advantage relative to retail or uninformed investor (e.g., Grossman and Stiglitz 1980; Glosten and Milgrom 1985; Kyle 1985). Apart from indirect evidence that focuses on liquidity measures to support the dichotomy of informed and uninformed investors (e.g., Amihud and Mendelson 1986; Hasbrouck and Seppi 2001; Pastor and Stambaugh 2003), studies also directly suggest that institutions possess an informational advantage over other market participants (e.g., Cohen, Frazzini and Malloy 2007, Irvine, Lipson and Puckett 2007), and that they exhibit superior trading skills (e.g., Lakonishok, Shleifer, and Vishny 1992, Nofsinger and Sias 1999, Gompers and Metrick 2001, and Sias, Starks, and Titman 2001, Puckett and Yan 2011).

Yet ample evidence also shows that institutional investors overall do not generate returns higher than the market.[1] For example, it has long been recognized that mutual funds, arguably the most pervasive type of institutional investors, did not outperform the market in the past five decades. If institutional investors enjoy an informational or trading advantage, it remains puzzling why then this advantage does not translate into returns.

In this paper we offer a direct test to examine whether institutional investors exhibit trading advantage when they face uncertain arrivals of corporate news. We collect a large sample of corporate news releases. Our data are sufficiently general that allow us to examine how institutions trade around news releases, regardless of news types. Our data also provide the distinct time stamps of both trades and news, so that we can analyze institutions' trading timing on news. We analyze institutions' trading direction on the tone of news, and find that institutions trade on the tone of news on the days of news releases but not around news arrivals. Our results

[1] See, for example, popular textbook teachings such as Bodie, Kane, and Marcus (2010).

suggest that institutions trade speedily on but do not predict qualitative information embedded in corporate news.

Our findings add to the debate of whether and through what channels institutional investors possess informational advantage. In particular, our examination of institutional trading is related to a large literature on the trading behaviors of institutional investors, who have gradually emerged as the most dominant players in the equity market over the past half century.[2] There are two non-mutually exclusive views regarding the trading skills of institution investors. The first view is that institutions are able to gather private information and trade ahead of major news events. Supporting evidence of this view typically concerns a certain type of news. For example, Irvine, Lispon and Puckett (2007) show that institutions are able to anticipate the contents of analysts' initial buy recommendation by receiving tips from sell-side analysts; Larson (2008) finds that institutions trade before the public disclosure of accounting frauds; and Baker and Savasoglu (2010) find that mutual fund can forecast earnings surprises. A number of studies also show that institutions are likely to have private information of M&A and related activities. For example, acquirer-advisor-affiliated funds buy target firms before takeover announcements (Bodnaruk, Massa and Simonov 2009), and there is a significant inside information leakage from target brokerages (Jegadeesh and Tang 2010) or information leakage in buyout deals through corporate connections (Acharya and Johnson 2010).[3]

The second view of the trading skills of institution investors is their ability to quickly process publicly available information. A number of studies (e.g., Rubenstein 1993, Kim and

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[2] According to the Federal Reserve Board's Flow of Funds report, institutional ownership reached over 60% in 2005 from just 7% in 1950. Jegadeesh and Tang (2010) document that major institutions own about 73% of publicly traded stocks in the U.S.

[3] Acharya and Johnson (2010) find that stock price run-up prior to buyouts is positively related to the number of private equity participants, suggesting information leakage through corporate connections. This finding is in contrast with Griffin, Shu and Topaloglu (2013), who do not find evidence that investment bank clients take advantage of connections through takeover advising, IPO and SEO underwriting, or lending relationships.

Verrecchia 1994, Kandel and Pearson 1995) suggest that traders generate differential interpretations to the same public news. As such, public news releases leave room for investors with different information processing abilities to interpret the value-relevant information embedded in the news differently. For example, Griffin, Shu, and Topaloglu (2007) examine institutional trading around takeover and earnings announcements and find that aggregate institutional trading profits stem from their ability to quickly process publicly available information rather than from private information.

While our findings support institutions' superior information processing skills, they seem to contrast with the findings that institutions possess private information ahead of news. We note that we derive our findings from a large sample of news stories—we have over 2 million initial news stories over the period of 2000 to 2010. Although we screen out news around earnings announcements, our conclusions are robust to the inclusion of earnings announcements news. In addition, news around M&A announcements account for only about one percent of our final sample. We do find that, institutions' trading intensity is higher on news that is more informative about firms' fundamentals, such as news that are related to firm earnings. Our findings in general suggest that institutional investors' informational advantage stem mainly from their superior information processing skills.

Our paper is also related to the growing literature of textual analysis of public news. Unlike specific corporate news events such as earnings and M&A announcements that cover only a fraction of corporate news,[4] this literature examines all types of corporate news in mass

[4] There is a voluminous literature on the impact of specific corporate news events such as earnings announcements, mergers, and management turnover in the past few decades. For example, Kothari and Warner (2006) report that over the period 1974-2000, five major finance journals publish over 500 articles related to specific corporate events.

media to better measure the supply of public information for publicly listed firms.[5] This stream of literature has primarily focused on the price impacts of news stories and has shown that qualitative information embedded in news stories are return-relevant. A number of papers document that public news releases predict the cross-section of asset returns (e.g., Klibanoff et al. 1998, Tetlock, Saar-Tsechansky, and Macskassy 2008, Fang and Peress 2009, and Engelberg, Reed, and Ringenberg 2010). In particular, Tetlock et al. (2008) document that the fraction of negative words embedded in firm-specific news stories (hereafter "negative tone") can predict short-term returns. Studies also link news contents to return momentums (e.g., Chan 2003) and reversals (e.g., Tetlock 2007, Tetlock 2011), and earnings momentums (Tetlock et al. 2008, Engelberg 2008). Our study extends this line of research to institutional trading. Unlike previous studies that typically rely on single source of news provider such as the *Wall Street Journal* or Dow Jones news archive, our study features a large number of wired news stories from a wide array of sources from the major news sources in the Factiva database. Our large dataset of news enables us to capture the general supply of information to the public. Importantly, our use of wired news allows us to pin down the time stamp of news that institutions can trade on. We show that institutions' news-content-contingent trading is concentrated in the first 15 minutes of news arrival, which provides further support of the speed at which institutions react to news.

To arrive at our conclusions, we carry out a careful research design to address confounding effects. We examine whether institutions as a group net-buy or net-sell around the news announcement, contingent on the news content. We deal with multiple same-day news appearances, multiple-day consecutive news sequels, and potential confounding effects from earnings and M&A announcements. In addition to negative tone that is typically used in the news

[5] See, for example, Klibanoff et al. (1998), Chan (2003), Tetlock (2007), Tetlock et al. (2008), Fang and Peress (2009), Tetlock (2011), Tetlock et al. (2008),), Loughran and McDonald (2011), Engelberg (2008) and Engelberg et al. (2012).

literature, we use net negative tone (that is, negative tone net of positive tone). We also examine the news contents beyond its negative tone, such as news related to firm fundamentals of earnings or to firm major events of M&A, and examine the news tone in both the full text of news and in the forward-looking statements only. Our results show that institutions trade on the tone of news on the news day, but not around (before and after) the news day; and such pattern is more pronounced when news is more informative of firm fundamentals or signals major events.

This study contributes to the literature in the following ways. First, we contribute to an emerging literature on how market participants respond to public news. We construct a comprehensive public news dataset on all US firms during 2000 to 2010 to examine how institutional investors respond to the qualitative information embedded in the news. Using all types of corporate news enables us to sort the universe of trading days into those with and without news and to examine the differential trading activities of institutional investors surrounding news releases. Second, we shed light on an ongoing debate on whether institutional investors are informed traders or their trading advantage arises from the ability to process publicly available information. Public news release is one of the most important channels of information dissemination for public firms, yet institutions' trading patterns around public news releases have received limited attention in the literature. To the extent that institutional investors are informed, one possible hypothesis is that institutional investors not only trade based on the contents of the news, but also anticipate the news and trade accordingly prior to news releases. Our results show that institutions' trading advantage, if any, stems mostly from their ability to process information in a highly timely manner.

The remainder of this paper proceeds as follows. Section II describes the sample. Section III presents our analyses and findings. Section IV provides a discussion of our results, and Section V concludes.

II. Data and Sample Selection

This study relies on two major datasets. Our first dataset contains all public news stories in the U.S during 2000 to 2010 from Factiva; and our second dataset contains institutional trading data from ANcerno. In this section we describe our data sources and sample selection process.

2.1 The news events sample

We retrieve corporate news for all U.S firms from the Top Sources in the Factiva database between January 1, 2000 and December 31, 2010. We first follow Tetlock et al. (2008) by requiring that each news release contains at least fifty words in total and that the first twenty-five words should mention a company identity, which includes company name, trading ticker, URL and company name initials. We assign a news article to the firm that has the highest frequency of company-identity mentions in the article. When there are more than two firm names in the same news article, we compute the frequency of appearance of the two names. If the frequency of mentions of the second highest firm is less than 90% of that of the highest firm, we assign the news to the highest-frequency firm; otherwise we drop the news from the sample. We obtain nearly 2.2 million news releases that mention a company identity at least once. To minimize false identification of news to a particular company, we require that each news release contain at least three mentions of company identity. We also drop observations that we cannot match to a Compustat Gvkey. After these sample screens, we are left with a total of nearly 1.7 million news articles.

We next deal with news sources. Prior studies on public news typically focus on Dow Jones archive which contains all Dows Jones news and Wall Street Journal stories (e.g., Tetlock (2007), Tetlock et al. (2008), Tetlock (2010), Engelberg et al. (2012)). Our news dataset contains news stories from more than 150 sources included in the Top Sources of Factiva.[6] To tailor these news sources to our study, we first note that this paper examines institutional trading around news releases. A common perception is that institutional investors are able to process news efficiently and therefore are sensitive to the timeliness of news. We therefore remove news from newspapers and magazines, as news from these sources tends to be "stale."[7] Based on the amount of news stories, we identify five major news sources: Dow Jones Newswire, Press Release Newswire, Business Wire, Reuters Newswire, and the Associated Press Newswire. News releases from sources other than these five are grouped as "Others." This last group includes many small news providers; for example, more than one hundred sources release less than 1,000 news stories in our sample period. To compare with previous studies, we note that Dow Jones Newswire supplies about one-quarter of the total number of news in our sample.

Our next step of news-data processing addresses timing and clustering of news. We assign a news article to the same trading day if the news is released on the same day before the market close at 4:00 p.m.; and to the next trading day if the news is released on the trading day but after 4:00 p.m., or if the news is released on a non-trading day such as in a weekend and a holiday.[8] 26% of times in our sample a firm has at least two news releases on the same trading day. To address potential estimation biases arising from these multiple news on a same day, we combine multiple news releases for each firm in a given trading day into a single "composite"

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[6] There are five categories included in the Top Sources of Factiva: Dow Jones Newswires, Major News and Business Publications, Press Release Wires, Reuters Newswires and The Wall Street Journal.
[7] Only seven percent of news stories in our sample are from newspapers and magazines. Including these news stories does not change our conclusions.
[8] "Day" and "trading day" in this paper both refer to trading day throughout.

story. In this case, we take the average of the news content measures (to be elaborated subsequently), but keep the time stamp of the first news as the time of the news. At this step our news sample has around 1.1 million news articles for 15,540 firms.

We then intersect the news sample with institutional trading data from Abel Noser Solutions Co. Ltd., a.k.a. ANcerno data (to be discussed subsequently). We require that there is at least one ANcerno institutional trade of the firm on the trading day of news announcement. This reduces news stories to nearly half a million.[9] Panel A of Table I shows the coverage of these news stories by year and by news source. As previously mentioned, Dow Jones Newswire covers about one-quarter news stories. Business Wire and Press Release offer about the same percentage of news articles, followed by the Associated Press (about 10%) and Reuters (about 5%). These five major newswires provide about 90% of the new stories.

[Table I about here.]

We examine institutional trading around news releases on various samples constructed from the news stories from Panel A of Table I. In our primary final sample, we further enforce two screens. First, we remove news releases within [-3, 3] days around quarterly earnings announcements to avoid any compounding effect from earnings announcement.[10] Doing so reduces the news article number by about 20%. Second, it is not uncommon that the same event gets multiple days of media coverage. This will result in news "clustering," in the sense that the multiple days of media coverage may refer to the same news event. To address this issue, we

[9] This reduction in sample size indicates that there is no trading on many news stories. We suspect this is due to the portfolio holdings of the ANcerno institutions, the majority of which are plan sponsors and mutual funds. For these institutions, the "prudent man" rule typically prevents them from holding risky securities. Relaxing the requirement increases the number of news survived. For example, requiring that there is ANcerno institutional trading in any day within [-10, 10] days around the news announcement increases the surviving news to 720 thousand. Our results, however, are insensitive to how we cut the final sample.

[10] Griffin, Shu, and Topaloglu (2007) find that a certain groups of institutions are able to predict the information in the forthcoming quarterly earnings announcement. They argue that investors are able to predict the direction of earnings announcements by using information from past earnings and public reports.

group consecutive news of a firm (i.e., non-stopping news stories over a number of days) into a news cluster. We again average news properties within the cluster but keep the time stamp and source of the first news in the cluster as the event start time and news source. The cluster will be broken only when news coverage stops for at least one day. On average, a news cluster has 1.3 composite news stories. While the majority of news clusters have single-day coverage, over 10% of times firms get two or more days of consecutive news coverage. It should be noted that these clusters define our events, and that our event "window" has the duration of the cluster, which may not necessarily last for one day. We define pre- and post-event periods relative to the boundary of the cluster. Panel B of Table I shows the news source distribution of our primary sample. Again, around 90% of news stories are provided by the five major newswires. Our primary final sample consists of 306,280 news clusters covering 6,684 firms. See Appendix A for a description of our sample selection procedures.

We consider the following alternative samples revised from our primary final sample: i) adding back news around earnings announcements; ii) removing all news clusters that lasts more than one day, or iii) removing news around mergers and acquisitions announcements. Our conclusions remain robust to these alternative samples.

2.2 The ANcerno institutional trading data

Abel Noser Solutions collects its institutional clients' complete transaction records into the ANcerno database. ANcerno's clients include some large pension plan sponsors and mutual funds, such as the Commonwealth of Virginia and Massachusetts Financial Services. For each transaction, ANcerno provides, among other items, the unique code for each institution, the code of stock traded, the time of execution, the number of shared traded, the execution price, and whether the execution is a buy or sell.[11] A number of studies use the ANcerno database, such as Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2010), Puckett and Yan (2011). Puckett and Yan (2011) estimate that ANcerno institutions account for 8% of the CRSP trading volume and 10% of all institutional trading volume.

Following Goldstein, Irvine, and Puckett (2010) and Puckett and Yan (2011), we include only trades on common stocks. The most distinct advantage of the ANcerno data is that it provides to-the-minute high-frequency institutional trading, which allows us to accurately match with the time stamp of news. We include all of the before- and after-hours trading and align trades with news based on their respective time stamps. Trades and news may take place on the same day. In this case, if the trade happens before the news, the trade is categorized as a previous-event-day trading, otherwise it is treated as event-day trading.[12]

Panel A of Table II presents the overview of the ANcerno trading data for our sample period. During 2000 to 2010, ANcerno covers a total of 1,072 institutions, 386 of which are mutual funds and 686 pension plan sponsors. In total, these institutions traded 9,860 stocks and generated 40 trillion dollars of volume.

[Table II about here.]

Panel B of Table II shows the summary statistics of institutional trading on the news announcement dates only. Compared with Panel A, 1,060 out of 1,072 institutions trade on news announcements. Also compared with Panel A, on the news announcement dates institutions trade 2/3 of the stocks, make one tenth of the trades and trade about one sixth of the share and dollar

[11] Puckett and Yan (2011) provide a detailed description of the ANcerno data.
[12] ANcerno puts a time stamp of 16:20 for all after-hours trades executed after 4:20 p.m. If there are news releases after this time, we remove all of the ANcerno 16:20 trades since we cannot identify the precedence between news and trades in this case. This affects less than 0.1% of our sample.

volumes. This suggests that on news announcement dates, the average trading size of institutions is larger.

How large is institutions' trading size around new releases? Panel C of Table III provides a brief overview. On the announcement day of each news, an average institution trades 54,606 shares, with a dollar trading size of $1.6 million. These numbers roughly double when we expand the window to [-3, 3] days around news announcement. Again, these numbers confirm that institutions trade more heavily on news announcement days. Further, the median trade size is much smaller than the average trade size in both time windows, suggesting that the trade distribution is highly skewed towards large orders. This is consistent with Puckett and Yan (2011), who suggest that "institutional trade sizes are likely to be either very large or very small" (page 606).

2.2 Primary measures of news contents and institutional trading

Following prior research (e.g., Tetlock (2007), Tetlock et al. (2008), Loughran and McDonald (2011)), we measure the news contents by the degree of negativity of the news. As is standard in this strand of literature, we count the number of positive and negative words in each news article to examine the tone and sentiment of a text. Our word list is from Lougharn and Mcdonald (2011), who develop, among other types, a list of negative and positive words for the financial context. Lougharn and Mcdonald's (2011) list contains 2,349 unique negative words and 354 unique positive words. Our primary measure of news tone, Neg_net, is defined as the fraction of total negative-word count (including those in the headline and body of the news) net of total positive-word count in each news article, i.e.,

$$Neg\_net = \frac{\text{No. of negative word occurences} - \text{No. of positive word occurences}}{\text{No. of total words in the news}} \qquad (1)$$

Since the literature emphasizes negative words only (e.g., Tetlock et al. (2008)), we also consider Neg, the ratio of negative word count to total number of words in the news. Obviously, Neg is bounded below at zero.

Figure 1 shows the distribution of Neg_net and *Neg* in our primary sample. *Neg_net* has a mean (median) of -0.0007 (-0.0016), indicating that an average news story has a slightly positive tone. The distribution of *Neg_net* is rightly skewed—that is, when a news article is negative, the negative tone tends to be severe. Turning to *Neg*, we note that 23% of the times *Neg* has a value of zero; i.e., about a quarter of our news stories are purely positive news. The right-side distributions of Neg_net and *Neg* have approximately the same magnitudes, indicating that the more negative news contain few positive words. Lastly, the correlation between Neg_net and *Neg* is high at 0.85.

[Figure 1 about here.]

We next turn to institutional trading measures. ANcerno's buy and sell directions enable us to calculate not only the total institutional trading but also the net institutional trading of a stock for a given time. Following Irvine, Puckett and Lipson (2007), we first calculate the total number of shares traded regardless of trading direction and the net shares traded (i.e., shares purchased minus shares sold). We then scale these two values by the firm's total shares outstanding retrieved from the CRSP to facilitate cross-firm and institution comparison. For our primary results, we calculate these measures at the daily frequency (where "days" are defined relative to news). The former measure is the total institutional trading, and the latter is the trading imbalance by institutions.

Panel D of Table II compares the distribution of total institutional trading and trading imbalance between days around and days not news announcements. When aggregating trading by stock and trading day, our ANcerno sample gives 7.4 million stock-trading days. Out of the 7.4 million days, 2.1 million days or roughly 30% are within [-3, 3] days around news announcements. We note that days around news announcements have higher total trading but lower trading imbalance relative to days not around news announcements. Total institutional trading is 0.15% vs. 0.12% for around-news days vs. non-around-news days (with a *t*-statistic of the difference of 26.82), indicating that institutions trade more actively around news announcements. On average, institutions are net buyers, as the trading imbalances around news days and not around news days are both positive. However, the mean of trading imbalance between the two types of days is 0.002% vs. 0.004% (with a *t*-statistic of the difference of -5.70). This lower mean of around-news-day trading imbalance, coupled with its larger magnitude in both tails (25^{th} and 75^{th} percentiles), suggesting that institutions' opinions are more dispersed around news. Overall, these statistics show that institutions net-buy stocks, but net-buy less around news.

For the sake of news-event study, we examine institutional trading 10 days before and after news announcement. As with the traditional event-study literature and related prior studies, we normalize trading imbalance at the firm level to ameliorate firm-specific idiosyncrasies, in particular, to ameliorate the problem that some firms may be more actively traded than others. In their investigation of institutional trading before the release of analysts' initial buy recommendations, Irvine, Puckett and Lipson (2007) calculate abnormal trading imbalance of each firm by adjusting for the firm's mean daily institutional trading imbalance during the benchmark window of [-60, -20] and [20, 60] days. In our case, there are likely news arrivals in any benchmark window that would impair its benchmarking purposes.[13] Accordingly, we take

[13] For example, in the benchmark window of [-60, -20] and [20, 60] days, there are on average 14 news announcements for each firm, and 75% of times a firm has more than five news announcements.

the days that are likely to be impacted by news out of the benchmark window; specifically, we remove [-3, 3] days around news announcement. In addition, we use [-250, -20] days (adjusted for news arrivals) as the benchmark to avoid look-ahead bias. This benchmark window roughly corresponds to prior year's trading days. Thus, our primary measure of abnormal trading imbalance, labeled as *Abt*, is net trading imbalance subtracted by the firm's normal trading imbalance over the window of [-250, -20] days. We use the window of [-60, -20] and [20, 60] days as a robustness check. Since institutions net-buy more in non-news days, our abnormal trading imbalance measures will necessarily be negative.

III. How do Institutions Trade around News?

In this section, we examine whether institutional trading shows systematic patterns prior to, on, and after news announcement contingent on new contents. We carry out both univariate and multivariate analyses, and also present robust evidence.

3.1 Portfolio Analysis

Our primary objective is to investigate whether institutional trading is associated with the tone of news. We start by univariate analysis where we divide the sample into quintile portfolios based on the ranked value of Neg_net and examine the abnormal trading imbalance 10 days before and after the news announcement. Panel A of Table III presents the results.

[Table III about here.]

The most striking result that we observe from Panel A of Table III is that institutions trade on the news tone only on the news announcement day but not the other days. Prior to news announcement, *Abt* does not display a monotonic pattern with *Neg_net*; and the difference of *Abt* between quintile 5-news (the most negative news) and quintile 1-news (the most positive news)

(“Q5-Q1” difference) is insignificant in any of the 10 days before news announcement. The results with the 10 days after news are similar—we do not find significance in the Q5-Q1 difference. In contrast, on the announcement day, *Abt* monotically decreases with *Neg_net*, indicating that more negative news incurs higher amount of net-selling, and the Q5-Q1 difference is highly significant (t-statistic = − 4.36). Panel (a) of Figure 2 plots the Q5-Q1 difference over these 21 days. We observe that the Q5-Q1 difference fluctuates around zero before and after news, but dips significantly at day 0. In Panel (b) of Figure 2, we also plot the Q5-Q1 difference contingent on the ratio of *Neg*. Again, the pattern is highly similar.

[Figure 2 about here.]

It is possible that the *Abt* pattern identified above may be caused by certain firm characteristics. We examine the firm characteristics of size, media coverage, and return momentum, due to the following considerations. The general size effect (that smaller firms drive empirical results) exists in many empirical findings. Fang and Peress (2009) show that media coverage affects investors’ preferences and stock returns. And lastly, abnormal trading imbalance may be driven by momentum trading by institutions (Griffin, Harris, and Topaloglu (2003)).

We carry out a double-sorting to examine the impact of firm characteristic. For each characteristic, we first sort our sample into tercile groups; and within each tercile sub-group, we further sort firms into quintile portfolios based on the ranked values of *Neg_net*. As with before, we examine of the Q5-Q1 difference of *Abt* for each quintile within each firm-characteristic tercile. For definitions and measurements of size, media coverage (the number of news stories of the firm in the prior year), and momentum, as well as other variables, refer to Appendix B, which provides a summary of variables used in this paper. Since Panel A of Table III shows that only day-0 *Abt* has a significant Q5-Q1 difference, we will focus on day-0 trading for these sub-portfolios. Panel B of Table III presents the results. We observe that i) the Q5-Q1 difference of *Abt* is negative for all sizes of firms, all levels of media coverage, and all levels of return momentum, ii) the difference is significant for medium and small firms (and marginally significant for large firms), significant for medium and low media coverage, and significant for all levels of return momentum, and iii) the magnitude of the difference is largest for smallest firms, for lowest media-coverage firms, and for highest momentum firms. In sum, even though the day-0 institutional trading pattern on news is more pronounced in smaller and less-covered firms, it exists in a wide spectrum of firms. In multivariate analyses that follow, we control for these firm characteristics.

3.2 Multivariate Regression Analysis

The portfolio analysis in the previous section indicates that institutions trade on news on the announcement day, but neither before nor after the announcement day. To show that these results are not caused by other confounding factors, we next run the following regression analysis:

$$Abt_t = \alpha + \beta Neg\_net + C * Controls_{t-1} + \epsilon \tag{2}$$

where the control variables are mostly based on Bennet, Sias, and Starks (2003), Griffin, Harris, and Topaloglu (2003), and Yan and Zhang (2009). The control variables include size, firm age, dividend yield, book-to-market equity, price, turnover, return volatility, whether the firm is included in the S&P 500 index, short-term return momentum (past month abnormal return), and longer-term return momentum (past one-year abnormal return). We measure all of the control variables at time horizons before the measurement of *Abt*, so that we do not have look-ahead biases in the determinants regression of *Abt*. In addition, we control for the degree of media coverage, as the literature suggests that media coverage affects investor choice and returns (Fang and Peress 2009; Zhao 2012). We include two media coverage variables, the logarithm of the number of news stories of the firm in the prior year, and a dummy variable (*multiple_dummy*) indicating whether there are more than one news stories during the news announcement day. We include the last control because the variable indicates news intensity, which is shown to affect stock returns (Zhao, 2012). We also control for year and 2-digit SIC industry dummies.

Table IV reports the pooled regressions results, where we cluster-adjust the standard errors a la Petersen (2009) at firm and trading day levels. We report the determinants of *Abt* of windows [-5, -3] (i.e., 3 to 5 days before news announcement), [-2, -1], [0], [1, 2], and [3, 5]. The pre-event windows of [-5, -3] and [-2, -1] test whether institutions has predictive power and trade in advance of news, and the post-event windows of [1, 2] and [3, 5] test whether institutions continue to trade after the release of the news.

[Table IV about here.]

Table IV confirms the results from the earlier portfolio analysis. After controlling for commonly used stock and media-coverage characteristics, the coefficient estimate of *Neg_net* on *Abt* is only significant on the event day, but not on the other windows. On the event day, the coefficient estimate of *Neg_net* is −0.079, indicating that as the negative tone of the news increases by one percent, institutions' (abnormal) net selling of the shares outstanding of the firm will increase by 0.079 basis points. However, the news tone is not significantly related to institutional trading imbalance in pre- and post-event windows. Collectively, the evidence points to that institutions trade on news but not around news. Institutions react speedily to news; but they do not predict news.

Interestingly, we also find similar results with the news intensity measure *multiple_dummy* (a dummy variable indicating whether there are multiple news articles on the news announcement day). The coefficient estimate on *multiple_dummy* is significantly negative on day 0 but not on other days, suggesting that institutions tend to net-sell when news are more intensive on day 0. In untabulated results, we also include an interaction term of *multiple_dummy* × *Neg_net*, and find that the coefficient estimate on this term is significantly negative on day 0. Thus, institutions' net-selling on day-0 on negative news is larger when the news is also more intense.

Regarding the control variables, we find that *Abt* is positively related to size and one-month return momentum and negatively related to price and volatility. These results indicate that institutions tend to buy large firms and firms that experience short-term price momentum (all consistent with Yan and Zhang 2009), and tend to sell firms with high volatility (consistent with Brandt et al. 2010). The negative sign on price looks puzzling at first sight; and we note that this is due to the compounding effect of other variables, in particular, that of firm size. When we remove firm size from the regression, price is on longer significant in predicting *Abt*, a result consistent with Yan and Zhang (2009). In sum, results on our control variables are consistent with the literature.

3.3 Robustness

Our results so far notably concern i) the net negative tone of news, ii) abnormal trading imbalance benchmarked against the estimation window of [-250, -20], and iii) consecutive news clustering. We now show that our results are robust to alternatives along these dimensions.

We first examine using the negative tone (*Neg*) instead of net negative tone of news. Panel A of Table V presents the results. We again observe that *Abt* is negatively related to *Neg* on day 0 only, reaffirming the results with *Neg_net* in Table IV. In addition, since there are many zero-value observations (about 20% of the sample) in *Neg*, we remove those observations. The second half of Panel A of Table V shows that our conclusions remain the same.

[Table V about here.]

Next we turn to abnormal trading imbalance using the estimation window of [-60, -20] and [20, 60] of Puckett and Yan (2011). The results are in Panel B Table V, which again confirm that institutions trade on news on day 0. Albeit somewhat weak, the results also show that institutions trade in the first two days post news announcement but there is no further delayed reaction to news —this is consistent with our theme that institutions do not predict news but react to news speedily.

Panel C of Table V takes on various schemes of news clustering: we either cluster all news articles that are within three days apart, or remove all of the news clusters that have coverage of more than one day. The former treats news articles within three days apart as a group. We carry out the latter, because when there are clusters of news, firms may have significant activities that are otherwise difficult to detect in machine parsing; and the trading pattern that we uncover may reflect only this part of news but not others. We therefore drop all clustered news (i.e., any news sequel that consists of two or more days of news articles). Lastly, in Panel C of Table V, we also remove news that is potentially related to M&A announcements. This is also due to the confounding-effect consideration. In our previous data screening, we filter out news surrounding earnings announcement days to remove the compounding effects of earnings announcements. Other significant firm activities include mergers and acquisitions (M&A). To address the confounding effects from M&A activities, we drop news articles that are three-days before and after M&A announcements.[14] Our results remain robust to these three alternatives.

In Panel D, we consider the effect of the recent financial crisis. One of the common observations from the recent financial crisis is that there was an elevated demand for liquidity across board. If so, negative news-driven selling may be aggravated in the financial crisis, because it is understood that liquidity is in short supply. We create a dummy variable for the NBER crisis period (Dec. 2007 to June 2009) and interact the dummy variable with *Neg_net.* As expected, the interaction term is significantly negative for *Abt* on day 0 (but not on other days), indicating that institutions are more sensitive to news contents during the financial crisis. Importantly, the coefficient estimate on *Neg_net* is still significantly negative on day 0 and not significant on other days, confirming our overall conclusion.

Lastly, Panel E considers an alternative tone measure developed from the General Inquirer's Harvard-IV-4 classification dictionary. Earlier studies use this dictionary for various contexts (e.g., Tetlock 2007, Engelberg 2008). Lougharn and Mcdonald (2011) find that about 73.8% of the negative words in the Harvard-IV-4 dictionary do not convey negative information in the financial context. For completeness, we calculate the measure of *Neg_net* based on the word list from the Harvard-IV-4 dictionary and repeat the regression in Table IV. The results are again robust.

IV. Discussion

4.1 Other informative news contents

[14] The M&A announcement dates are from the SDC Platinum. We include all M&A announcement days relating to target, acquirer, and if there is any, target and acquirer parent companies. About 1% of our news sample is [-3, 3] days around M&A announcement dates.

So far we examined how institutions trade on the negative tone of news. News stories contain a heterogeneity of information other than sentiment. Arguably, news related to firm fundamentals or firm major events has a larger impact than news of "regular" firm events. We identify two types of news that are related to firm fundamentals and major events: i) news that contains the word root "earn" , and ii) news on M&A.[15] The first type of news follows the approach in Tetlock, Saar-Tsechansky, and Macskassy (2008), who show that negative words in news stories that mention the word stem "earn" contain more information about firms' fundamentals than other stories. The second type of news signals a potential M&A activity, one of the most important corporate events. In our primary sample of news (i.e., the sample that does not include news articles in [-3, 3] days around news announcements), more than three-quarters of news articles do not contain the word "earn," and the same is true for the M&A related words. Collectively, 28% of the news articles have at least one occurrence of the key words on "earn" or M&A.

To examine whether these two types of news indeed have a larger impact on institutional trading, we run the following regression:

$$Abt_t = \alpha + \beta Neg\_net + \gamma Neg\_net * ContentDummy + C * Controls_{t-1} + \epsilon \qquad (2)$$

where *ContentDummy* is a dummy variable if the new story contains at least once the word stem of "earn" or the key words related to M&A. Table VI reports the regression results of Equation (2). We first note that the coefficient estimate of Neg_net on day-0 *Abt* is significantly negative, confirming our previous results. As expected, the coefficient estimate on the interaction term of $Neg\_net * ContentDummy$ is not only significantly negative, but also much larger than the coefficient estimate of Neg_net. The results are similar when *Neg* is used in lieu of Neg_net. In

[15] To identify M&A in the news, we search for the following key words and their stemming in the news: merger, acquisition, M&A.

sum, the evidence in Table VI supports the notion that institutions trade more heavily on more informative news. Institutions, however, do not trade in advance of more informative news.

[Table VI about here.]

News could also be more informative when they are issued as forward-looking statements. As such, we examine the tone of the forward-looking statements. Panel A of Table VII shows the distribution statistics of the number of forward-looking sentences in our news sample. In total, more than 90% of the news articles have at least one sentence of forward-looking statements. We calculate *Neg_net* and *Neg* from the forward-looking statements only and repeat the baseline regression with these ratios in lieu of the ratios calculated from the full text. Panel B of Table VII shows that the results using these ratios are highly similar to our baseline results.

[Table VII about here.]

4.2 A Possible reconciliation with the literature

A number of previous studies propose that institutions have the ability to trade in advance of news. Notably, Griffin, Shu, and Topaloglu (2007) find that a certain group of institutional investors are able to anticipate the information in the forthcoming quarterly earnings announcement based on information from past earnings and public reports. And using NYSE institutional trading data of NYSE stocks from 2003 to 2005 and news announcements from Reuters, Hendershott, Livdan and Schurhoff (2011) find that institutional order flow predicts the sentiment of the news.[16] Our results, however, are in stark contrast with these studies. In this section, we offer a potential reconciliation with these studies by showing that the compounding

[16] These authors also report that institutional order flow predicts stock return and earnings announcement surprises, similar to Tetlock et al. (2008). We find that institutional trading on news is clustered in day 0; an issue that is not discussed in Hendershott, Livdan and Schurhoff (2011). Our paper is also different by discussing how institutions trade post news announcements.

effects of earnings announcements may explain the differences of our study from the previous ones.

One of the differences of our sample is that we exclude news that is around earnings announcements. Panel A of Table VIII shows the results when we instead include these news stories. What we observe now is that while Neg_net and *Neg* are still significantly related to *Abt* of day 0, Neg_net is marginally significantly and negatively and *Neg* is significantly and negatively related to *Abt* of days [-2, -1]. In other words, institutions are able to predict the tone of news, in particular, the negative tone of news, and trade one to two days in advance.

[Table VIII about here.]

Clearly, the addition of the sample [-3, 3] days around earnings announcement leads to the different results in Panel A of Table VIII. In order to examine institutions' predictive trading ability in detail, we further examine separately the pre-, on, and post-earnings announcement periods by breaking the [-3, 3] days around earnings announcements to the periods of [-3, -1) (i.e., pre-earnings announcement and not inclusive of the earnings announcement day), 0 (earnings announcement day), and (1,3] (post earnings announcement days). Panel B of Table VIII shows that i) on and pre-earnings announcement, *Abt* of days [-2, -1] is not significantly related to either Neg_net or *Neg*; ii) *Abt* of days [-2, -1] is only significantly related to Neg_net and *Neg* post-earnings-announcement.[17] Therefore, the seemingly predictive power of institutions in our sample is driven by advance trading on post-earnings-announcement news—these trades may well dwell on the after-effects of the earnings announcement. In contrast, on and pre-earnings announcement, institutions do not advance-trade. Overall, the results are

[17] In untabulated robustness check, we can report that these results are robust to the additional control of earnings surprise on the earnings announcement day.

consistent with the conclusion that institutions trade on but not around news, and they do not predict the contents of news and trade accordingly.

4.3 What happens on Day 0?

Our previous results indicate that institution trading is clustered on day 0. We now further show that the day-0 trading is concentrated in a short period of time. As with the portfolio analysis, we partition news stories into quintiles based on the ranked value of *Neg_net* and examine the minute-by-minute trading of the quintile portfolios.[18] Figure 3 plots the trading imbalance and abnormal trading imbalance of the most positive and negative news 360 minutes before and after the news announcement. We group trading into 15-minute bins relative to the news time stamp, with the first trading bin (the first 15 minutes) defined as five minutes prior to and 10 minutes post the news time. From Figure 3, we observe that for the most positive news (Quintile 1 of *Neg_net*), there is a spike of net-buying and total trading volume in the first 15 minutes; similarly, total trading volume and net-selling spikes for the most negative news (Quintile 5 of *Neg_net*) in the first 15 minutes. The net-buy and net-sell around news are non-symmetrical: For the most positive news, institutions are more likely to be net-sellers 360 minutes before and after the news; and for the most negative news, institutions are very likely to be net-sellers 360 minutes before and after the news. These results are consistent with earlier observation that institutions are net sellers around news (Panel D of Table II).

[Figure 3 about here.]

Table IX further presents the net trading of quintile portfolios sorted on *Neg_net*. We examine the significance of the net trading difference between Quintiles 5 and 1. We benchmark the difference against the average net trading 12 hours to 4 hours before the news announcement

[18] In the minute-by-minute analysis, we use regular-hours trading only. We drop pre-hours and after-hours trades following the tradition of market microstructure research.

and 4 hours to 12 hours after the news announcement. Compared with the benchmark, none of the time bins before the news announcement has significant Quintiles 5 and 1 net trading difference. In contrast, the Quintiles 5 and 1 net trading difference is significantly negative in time bins 1 and 2 but not immediately afterwards, indicating that institutions react immediately to news contents. In sum, the evidence suggests that institutions react to news without delay.

[Table IX about here.]

V. Conclusion

We offer a direct test of whether institutional investors exhibit trading advantage when they face uncertain arrivals of corporate news. We match a comprehensive sample of corporate news of US firms from the major news sources from 2000 to 2010 with a large database of high-frequency institutional trades, and examine how institutional investors trade on the qualitative information embedded in public news releases. We find that the abnormal institutional trading imbalance is significantly negatively related to the negative tone of news stories on the news-announcement day but not on other days. Our results indicate that institutions trade speedily on but do not predict qualitative information in corporate news. To the extent that institutions may be informed investors, our findings suggest that institutions' informational advantage stems mostly from their ability to process information in a highly timely manner.

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Appendix A News Filtering and Sample Selection

We retrieve corporate news for all U.S firms from the Top Sources in the Factiva database between January 1, 2000 and December 31, 2010. We first follow Tetlock et al. (2008) by requiring that each news release contains at least fifty words in total and that the first twenty five words should mention a company identity, which includes company name, trading ticker, URL and company name initials. We assign a news article to a particular firm that has the highest frequency of company identity mentions in the news article. When there are more than two firm names in the same news article, we compute the frequency of appearance of the two names. If the frequency of the second highest-frequency firm is less than 90% of that of the highest-frequency firm, we assign the news to the highest-frequency firm; otherwise we drop the news from the sample. We obtain nearly 2.2 million news releases that mention a company identity at least once. To minimize false identification of news to a particular company, we require each news article mentions at least three times of the firm identity. We also drop observations that we can not match to a Compustat Gvkey.

	# of news stories	# of firms
News stories retrieved from Factiva between Jan. 1, 2000 and Dec. 31, 2010	2,187,720	
Subtract:		
Non-matched gvkey, and firm identify occurrences less than 3 times	(473,384)	
Total firm-specific news stories	1,714,336	15,650
Wired news (including Federal Filings Newswires)	1,594,284	15,540
Combine news released on the same trading day for a given firm	(506,106)	0
Total composite news stories	1,088,178	15,540
Traded by ANcerno institutions on the day of news announcement	505,352	6,956
Remove [-3,+3] days around quarterly earnings announcements	394,708	6,684
Cluster consecutive news to a single cluster	306,280	6,684

Appendix B Variable Definitions

Variable	Definition
Abt	Abnormal institutional trading imbalance. The primary measure of abnormal trading balance is the net trading imbalance (buy minus sell), measured as volume turnover, relative to the average net trading imbalance of the benchmark window [-250, -20] days of news announcement. In the benchmark window, all days that are [-3, 3] days around any news announcement are removed. Day-0 *Abt* refers to the abnormal trading imbalance on the news day; and *Abt* of a specific day range, such as *Abt*[-2, -1], refers to the cumulative *Abt* of the day range.
Neg_net	The fraction of total negative word count net of total positive word count relative to the total number of words in a news article, based on the word list of Loughran and McDonald (2011).
Neg	The fraction of total negative word count relative to the total number of words in a news article, based on the word list of Loughran and McDonald (2011).
lnme	The logarithm of market capitalization at the end of the previous quarter, or at the end of the previous two quarters if the end of the previous quarter is less than 10 days away from the news.
age	The logarithm of the number of months that a stock has appeared in the CRSP.
dy	The annualized dividend yield of the past 12 months (past 12-month dividend / beginning-of-the-month price).
bm	Book value of equity divided by the market value of equity, at the end of the previous quarter, or at the end of the previous two quarters if the end of the previous quarter is less than 10 days away from the news.
prc	The logarithm of the average stock price over the days of -27 to -6 (roughly corresponding to past month) relative to news.
turnover	The average daily market stock turnover ratio (overall CRSP market trading volume / shares outstanding) over the days of -27 to -6 relative to news.
volatility	The standard deviation of stock returns over the days of -27 to -6 relative to news.
sp	A dummy variable that equals one if the stock is included in the S&P 500 index.
ff4abret[-27, -6]	Cumulative abnormal returns relative to Fama-French four factors of market, size, book to market and momentum over the days of -27 to -6 (roughly corresponding to past month).
ff4abret[-252, -31]	Cumulative abnormal returns relative to Fama-French four factors of market, size, book to market and momentum over the days of -252 to -31 (roughly corresponding to past year).
log_media	The logarithm of one plus the number of articles mentioning the firm in the prior calendar year. For the first year of the sample (year 2000), this variable refers to the same year.
multiple_dummy	A dummy variable that equals one if there are more than one news story written on the firm on the same day.
crisis	A dummy variable that equals one if the time falls in the NBER financial crisis period (Dec. 2007 to June 2009).

Table I   Summary Statistics of Wired News

This table presents the summary statistics of the sample wired news from the following sources: Dow Jones Archive Newswire ("Dow Jones"), Press Release Newswire ("Press Release"), Business Newswire, Reuters Newswire ("Reuters"), Associated Press Newswire ("Associated Press"), and all other sources ("Others"). In Panel A, news at each day is treated independently and is not grouped. In Panels B and C, we group each non-stopping, consecutive-days news-sequel into a news "cluster."

Panel A: News that are accompanied by ANcerno trading on the news announcement day

Year	All News Sources	Dow Jones	Press Release	Business Newswires	Reuters	Associated Press	Others
2000	36,268	8,961	8,589	9,888	1,487	3,086	4,257
2001	40,735	10,482	9,285	11,074	1,677	3,458	4,759
2002	48,376	12,710	10,949	12,716	2,012	4,322	5,667
2003	27,819	7,299	6,681	6,935	1,151	2,558	3,195
2004	16,996	4,456	3,996	4,415	739	1,507	1,883
2005	21,898	5,844	4,792	5,704	953	1,959	2,646
2006	41,411	11,598	8,921	10,194	1,835	4,150	4,713
2007	42,011	12,012	9,135	9,862	2,060	4,165	4,777
2008	43,299	12,387	9,726	10,060	2,003	4,257	4,866
2009	37,409	10,394	8,030	8,786	1,690	3,921	4,588
2010	38,486	10,781	7,981	8,985	1,765	4,306	4,668
Total	394,708	106,924	88,085	98,619	17,372	37,689	46,019

Panel B: Initial Sources of news clusters

Year	All News Sources	Dow Jones	Press Release	Business Newswires	Reuters	Associated Press	Others
2000	28,654	7,064	6,776	7,793	1,173	2,486	3,362
2001	31,492	8,135	7,174	8,433	1,299	2,695	3,756
2002	35,991	9,498	8,113	9,400	1,510	3,216	4,254
2003	22,309	5,751	5,211	5,670	902	2,124	2,651
2004	13,270	3,519	3,030	3,421	614	1,187	1,499
2005	17,027	4,533	3,754	4,305	776	1,579	2,080
2006	32,107	9,055	6,810	7,739	1,441	3,336	3,726
2007	33,165	9,478	7,124	7,783	1,575	3,397	3,808
2008	33,385	9,448	7,409	7,755	1,565	3,374	3,834
2009	29,202	8,084	6,297	6,781	1,313	3,097	3,630
2010	29,678	8,382	6,185	6,760	1,372	3,313	3,666
Total	306,280	82,947	67,883	75,840	13,540	29,804	36,266

Table II Summary Statistics of the ANcerno Institutional Trading Data

This table includes ANcerno institutional trading of common stocks (those with a share code of 10 or 11 in CRSP). Panel B shows institutional trading on the news announcement days only. In Panel C, "Day 0" refers to the news announcement day, and "Days [-3, 3]" refers to the period three days before and three days after the earnings announcement. In Panel D, "News-day" is defined as [-3, 3] days around news announcement. *t*-statistics are two-way cluster-adjusted and are in parentheses.

Panel A: The full ANcerno sample, 2000-2010

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
No. of institutions	373	400	427	404	406	376	399	377	334	317	308	1,072
Mutual funds	44	65	82	86	119	132	157	157	152	144	139	386
Plan sponsors	329	335	345	318	287	244	242	220	182	173	169	686
# of stocks traded	6,347	5,474	5,196	5,751	6,128	5,891	5,854	5,774	5,331	5,199	4,559	9,860
No. of trades (million)	3.14	3.48	4.37	4.65	6.03	5.40	6.86	7.11	8.15	7.52	7.03	63.73
# of shares traded (billion)	74.6	100.0	133.8	109.3	147.8	121.2	135.6	134.8	160.1	152.4	116.1	1,385.7
Trading volume ($trillion)	3.22	3.03	3.23	2.70	4.20	3.80	4.37	4.77	4.57	3.25	3.06	40.20

Panel B: Institutional trading on news days only

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
No. of institutions	368	397	424	403	405	374	397	374	330	315	303	1,060
# of stocks traded	4,061	3,647	3,603	3,126	2,744	3,033	3,644	3,717	3,406	3,116	3,042	6,739
No. of trades (million)	0.33	0.42	0.60	0.40	0.37	0.39	0.77	0.74	0.89	0.77	0.73	6.42
# of shares traded (billion)	11.3	16.9	29.8	15.2	15.9	15.0	23.7	20.4	26.8	25.1	18.1	218.1
Trading volume ($trillion)	0.55	0.51	0.67	0.37	0.48	0.49	0.74	0.73	0.75	0.51	0.48	6.27

Panel C: Trading per institution per news around news announcement

	Day 0					Days [-3, 3]				
	Mean	std	p25	Median	p75	Mean	std	p25	Median	p75
Shares	54,606.1	419,816	675	3,197	17,100	113,280.1	911,935	1,200	5,800	30,400
Dollars (thousand)	1,583.3	11,035.4	20.7	98.9	520.3	3,330.0	25,691.4	36.0	176.9	920.1

Panel D: Total trade and trade imbalance of news vs. non-news days (% turnover) (news-day defined as [-3,3] days around news announcement)

	News-day					Non-news-day					Mean	
	trade days	Mean	p25	median	p75	trade days	Mean	p25	Median	p75	diff.	*t*-stat.
Total inst. trading	2,104,270	0.151	0.017	0.061	0.170	5,332,704	0.120	0.011	0.043	0.133	0.031	(26.82)
trade imbalance	2,104,270	0.002	-0.031	0.0011	0.037	5,332,704	0.004	-0.023	0.0013	0.031	-0.002	(-5.70)

Table III Institutional Trading and Negative Tone: Portfolio Analysis

Panel A shows the abnormal trading imbalance of quintile portfolios sorted on *Neg_net*. Panel B shows the abnormal trading imbalance of portfolios first sorted on a certain firm characteristic then on *Neg_net*. The firm characteristics include: market capitalization, media coverage, and the past-month return momentum. *t*-statistics are two-way cluster-adjusted and are in parentheses.

Panel A: Abnormal trading imbalance around news announcement

	Neg_net Quitile					Difference	
Day	1	2	3	4	5	5-1	t-stat.
-10	-0.0030	-0.0027	-0.0032	-0.0029	-0.0032	-0.0002	(-0.13)
-9	-0.0043	-0.0026	-0.0023	-0.0043	-0.0038	0.0005	(0.39)
-8	-0.0022	-0.0034	-0.0025	-0.0048	-0.0025	-0.0003	(-0.22)
-7	-0.0046	-0.0021	-0.0018	-0.0031	-0.0027	0.0019	(1.48)
-6	-0.0044	-0.0025	-0.0019	-0.0030	-0.0024	0.0020	(1.41)
-5	-0.0028	-0.0033	-0.0026	-0.0037	-0.0029	0.0000	(-0.01)
-4	-0.0038	-0.0019	-0.0027	-0.0040	-0.0032	0.0007	(0.52)
-3	-0.0039	-0.0030	-0.0033	-0.0032	-0.0032	0.0007	(0.55)
-2	-0.0040	-0.0043	-0.0029	-0.0035	-0.0044	-0.0004	(-0.29)
-1	-0.0043	-0.0038	-0.0025	-0.0039	-0.0064	-0.0021	(-1.35)
0	-0.0053	-0.0049	-0.0037	-0.0060	-0.0125	-0.0072	(-4.36)
1	-0.0033	-0.0040	-0.0032	-0.0034	-0.0056	-0.0022	(-1.50)
2	-0.0039	-0.0036	-0.0039	-0.0031	-0.0047	-0.0008	(-0.57)
3	-0.0057	-0.0028	-0.0038	-0.0046	-0.0050	0.0007	(0.50)
4	-0.0051	-0.0034	-0.0048	-0.0046	-0.0050	0.0001	(0.06)
5	-0.0051	-0.0047	-0.0044	-0.0038	-0.0035	0.0016	(1.24)
6	-0.0039	-0.0043	-0.0058	-0.0040	-0.0051	-0.0012	(-0.87)
7	-0.0037	-0.0034	-0.0041	-0.0035	-0.0047	-0.0010	(-0.78)
8	-0.0047	-0.0048	-0.0055	-0.0039	-0.0038	0.0008	(0.61)
9	-0.0049	-0.0049	-0.0048	-0.0038	-0.0036	0.0013	(0.96)
10	-0.0052	-0.0051	-0.0048	-0.0033	-0.0035	0.0017	(1.25)

Panel B: Abnormal trading imbalance of portfolios first sorted on a firm trait then on *Neg_net*

Neg_net	**Market cap**			**Media Coverage**			**Past-Month Ret. Momentum**		
quintile	Large	Medium	Small	High	Medium	Low	High	Medium	Low
1	-0.00207	-0.00465	-0.00856	-0.00471	-0.00544	-0.00497	-0.00310	-0.00308	-0.00865
5	-0.00221	-0.01342	-0.02255	-0.00559	-0.01179	-0.01840	-0.01148	-0.00858	-0.01557
5-1	-0.00013	-0.00877	-0.01399	-0.00088	-0.00635	-0.01343	-0.00837	-0.00549	-0.00692
	(-1.49)	(-3.12)	(-4.48)	(-0.30)	(-2.31)	(-5.04)	(-3.14)	(-2.48)	(-2.46)

Table IV Institutional Trading and News Tone

Abt = abnormal trading imbalance, Neg_net = fraction of negative words net of positive words in each news story, lnme = logarithm of market equity, age = logarithm of months the firm has appeared in CRSP, dy = annualized dividend yield, bm = book to market ratio, prc = average daily stock price of the past month, turnover = stock turnover of the past month, volatility = daily stock return volatility of the past month, sp = a dummy variable indicating whether a stock is included in the S&P500 index, ff4abret[-27, -6] = cumulative abnormal return relative to Fama-French four factors of the past 27 to 6 days, ff4abret[-252, -31] = cumulative abnormal return relative to Fama-French four factors of the past 252 to 31 days, log_media = one plus the number of articles mentioning the firm in the prior calendar year; and multiple_dummy = a dummy variable that equals one if there are more than one news story written on the firm on the same day. See Appendix B for detailed variable definitions. All variables are winsorized at 1% and 99% percentile. *t*-statistics are two-way cluster-adjusted and are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	[-5, -3]	[-2, -1]	0	[1, 2]	[3, 5]
Neg_net	0.087	-0.004	-0.079**	-0.025	0.070
	(1.38)	(-0.08)	(-2.42)	(-0.52)	(1.10)
lnme	0.002	0.002	0.001*	0.002*	0.003*
	(1.27)	(1.49)	(1.89)	(1.89)	(1.83)
age	0.002	0.001	0.001	0.001	0.001
	(1.02)	(0.70)	(0.63)	(0.76)	(0.74)
dy	0.072	0.115	0.001	0.051	0.038
	(0.69)	(1.47)	(0.03)	(0.68)	(0.37)
bm	-4.217	-5.540*	-1.378	-3.822	-4.968
	(-1.19)	(-1.69)	(-0.80)	(-1.25)	(-1.19)
prc	-0.008***	-0.006***	-0.002	-0.004**	-0.007***
	(-3.17)	(-3.15)	(-1.58)	(-2.26)	(-2.75)
turnover	0.023	-0.056	-0.122	-0.001	-0.216
	(0.10)	(-0.36)	(-1.21)	(-0.01)	(-1.01)
volatility	-0.432***	-0.282***	-0.123***	-0.205***	-0.239***
	(-5.10)	(-4.41)	(-3.14)	(-3.22)	(-2.83)
sp	0.004	0.003	0.001	0.001	0.003
	(0.92)	(0.98)	(0.66)	(0.25)	(0.55)
ff4abret[-27 -6]	0.104***	0.048***	0.027***	0.034***	0.038***
	(13.29)	(8.14)	(7.30)	(6.06)	(5.12)
ff4abretn[-252, -31]	0.002	-0.000	0.002	0.002	-0.002
	(0.50)	(-0.03)	(1.18)	(0.79)	(-0.54)
log_media	-0.002	-0.002	-0.001	-0.001	-0.003
	(-0.88)	(-1.39)	(-0.65)	(-1.11)	(-1.42)
multiple_dummy	-0.001	-0.001	-0.003***	0.000	0.000
	(-0.33)	(-0.56)	(-3.02)	(0.23)	(0.10)
Constant	0.032	0.030	-0.009	-0.006	0.040
	(0.97)	(1.36)	(-0.43)	(-0.20)	(0.99)
Year dummy	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes
Observations	264,862	262,689	272,561	262,439	264,850
R-squared	0.003	0.002	0.002	0.002	0.002

Table V Robustness of Institutional Trading on News Tone

Working from the baseline specification of Table III where we use *Neg_net* as the news tone proxy and the sample that is removed of news around earnings announcements, this table presents various robustness checks on this baseline specification. In each panel, we alter one dimension of the baseline regression, and run the full-model specification of Table III. Results on all control variables are suppressed for brevity. The left column indicates the news tone measure. In Panel E, "crisis" is a dummy variable that equals one for the recent financial crisis period as defined by NBER (from Dec. 2007 to June 2009). *t*-statistics are two-way cluster-adjusted and are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Using *Neg* instead of *Neg_net* as news tone measure

	Including all obs. *Abt* at day(s)			Removing zero-Neg obs. *Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg	-0.094	-0.196***	-0.094	-0.078	-0.213***	-0.077
	(-1.47)	(-4.73)	(-1.60)	(-1.19)	(-4.58)	(-1.19)

Panel B: Using abnormal trading imbalance derived using window of [-60, -20] and [20, 60]

	Abt at day(s)				
	[-5,-3]	[-2,-1]	0	[1, 2]	[3, 5]
Neg_net	-0.001	-0.063	-0.111***	-0.078*	-0.005
	(-0.01)	(-1.37)	(-3.60)	(-1.74)	(-0.09)

Panel C: Alternative news-clustering schemes and other confounding factors

	Clustering of consecutive news that are within 3 days apart *Abt* at day(s)			Removing all news clusters *Abt* at day(s)			Further removing M&A news *Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	-0.041	-0.095***	-0.054	-0.007	-0.076**	-0.028	-0.015	-0.082**	-0.026
	(-0.76)	(-2.64)	(-1.02)	(-0.14)	(-2.27)	(-0.57)	(-0.30)	(-2.54)	(-0.53)

Panel D: Financial Crisis

	Abt at day(s)		
	[-2,-1]	0	[1,2]
Neg_net	0.005	-0.065*	-0.066
	(0.10)	(-1.89)	(-1.32)
*Neg_net*crisis*	-0.136	-0.138*	0.204
	(-1.02)	(-1.70)	(1.61)

Panel E: Alterntaive news-tone measure (Harvard-IV-4 dictionary)

	Abt at day(s)		
	[-2,-1]	0	[1,2]
Neg_net	-0.025	-0.120***	-0.046
	(-0.59)	(-4.35)	(-1.11)

Table VI Institutional Trading on More Informative News Contents

ContentDummy is a dummy variable if the news article contains either the word stem "earn" or key words related to "M&A" at least one time. See Appendix B for all other variable definitions. *t*-statistics are two-way cluster-adjusted and are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Abt at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	-0.002	-0.049*	-0.022			
	(-0.03)	(-1.66)	(-0.43)			
Neg_net * ContentDummy	-0.066	-0.205***	-0.041			
	(-0.64)	(-2.91)	(-0.41)			
Neg				-0.068	-0.124***	-0.062
				(-1.14)	(-3.05)	(-1.05)
Neg * ContentDummy				-0.116	-0.312***	-0.138
				(-1.16)	(-4.37)	(-1.33)
lnme	0.001	0.001*	0.002*	0.001	0.001*	0.002*
	(1.23)	(1.66)	(1.68)	(1.27)	(1.75)	(1.71)
age	0.001	0.000	0.000	0.001	0.000	0.000
	(0.41)	(0.15)	(0.26)	(0.43)	(0.19)	(0.28)
dy	0.110	0.007	0.049	0.111	0.008	0.049
	(1.43)	(0.16)	(0.65)	(1.44)	(0.19)	(0.66)
bm	-2.595	-0.423	-0.606	-2.546	-0.357	-0.571
	(-0.84)	(-0.25)	(-0.23)	(-0.83)	(-0.21)	(-0.22)
prc	-0.005***	-0.001	-0.003*	-0.005***	-0.001	-0.003*
	(-2.72)	(-1.14)	(-1.65)	(-2.76)	(-1.18)	(-1.67)
turnover	-0.095	-0.134	-0.053	-0.092	-0.131	-0.051
	(-0.61)	(-1.32)	(-0.34)	(-0.59)	(-1.30)	(-0.32)
volatility	-0.271***	-0.117***	-0.179***	-0.270***	-0.116***	-0.178***
	(-4.24)	(-3.00)	(-2.81)	(-4.22)	(-2.98)	(-2.80)
sp	0.004	0.002	0.002	0.005	0.002	0.002
	(1.32)	(0.95)	(0.67)	(1.32)	(0.99)	(0.68)
ff4abret[-27,-6]	0.048***	0.027***	0.035***	0.048***	0.027***	0.035***
	(8.42)	(7.45)	(6.27)	(8.38)	(7.38)	(6.24)
ff4abret[-252,-31]	0.001	0.002	0.003	0.001	0.002	0.003
	(0.50)	(1.36)	(1.21)	(0.47)	(1.30)	(1.18)
log_media	-0.002	-0.000	-0.002	-0.002	-0.001	-0.002
	(-1.38)	(-0.49)	(-1.15)	(-1.41)	(-0.61)	(-1.18)
multiple_dummy	-0.000	-0.003***	0.001	-0.000	-0.003***	0.001
	(-0.30)	(-2.99)	(0.46)	(-0.10)	(-2.63)	(0.62)
Constant	0.030	-0.008	-0.007	0.031	-0.006	-0.006
	(1.39)	(-0.37)	(-0.22)	(1.41)	(-0.30)	(-0.20)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	258,733	268,443	258,492	258,733	268,443	258,492
R-squared	0.002	0.002	0.001	0.002	0.002	0.001

Table VII Institutional Trading on the Tone of Forward-Looking-Statements

Neg_net and *Neg* in this table are defined from the forward-looking statements of each news article. *Neg_net* is the fraction of negative words, net of positive words, in total words in the forward-looking statements. *Neg* is the fraction of negative words in total words in the forward-looking statements. See Appendix B for all other variable definitions. *t*-statistics are two-way cluster-adjusted and are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Number of sentences of forward-looking statements per news

Mean	Std	10th percentile	Median	90th percentile
4.06	3.22	1	3.43	5.5

Panel B: Institutional trading on the tone of forward-looking statements

	Abt at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	-0.021	-0.053**	0.013			
	(-0.61)	(-2.28)	(0.40)			
Neg				-0.073	-0.124***	0.004
				(-1.50)	(-3.65)	(0.09)
lnme	0.001	0.001	0.002	0.001	0.001	0.002
	(1.10)	(1.46)	(1.43)	(1.12)	(1.50)	(1.44)
age	0.001	0.000	0.000	0.001	0.000	0.000
	(0.64)	(0.12)	(0.29)	(0.65)	(0.15)	(0.29)
dy	0.119	0.013	0.069	0.119	0.013	0.070
	(1.46)	(0.28)	(0.86)	(1.46)	(0.29)	(0.86)
bm	-3.131	-0.280	-0.699	-3.098	-0.237	-0.691
	(-1.12)	(-0.17)	(-0.27)	(-1.11)	(-0.14)	(-0.27)
prc	-0.005***	-0.001	-0.003	-0.005***	-0.001	-0.003
	(-2.85)	(-1.07)	(-1.53)	(-2.87)	(-1.13)	(-1.53)
turnover	-0.068	-0.149	-0.051	-0.066	-0.147	-0.051
	(-0.41)	(-1.40)	(-0.31)	(-0.40)	(-1.38)	(-0.31)
volatility	-0.271***	-0.123***	-0.176***	-0.270***	-0.121***	-0.176***
	(-4.05)	(-3.00)	(-2.66)	(-4.03)	(-2.97)	(-2.66)
sp	0.005	0.002	0.003	0.005	0.002	0.003
	(1.50)	(1.16)	(0.80)	(1.50)	(1.19)	(0.80)
ff4abret[-27,-6]	0.050***	0.028***	0.037***	0.050***	0.028***	0.037***
	(8.38)	(7.43)	(6.52)	(8.36)	(7.39)	(6.52)
ff4abret[-252,-31]	0.001	0.002	0.003	0.001	0.002	0.003
	(0.53)	(1.39)	(1.29)	(0.51)	(1.35)	(1.29)
log_media	-0.002	-0.000	-0.001	-0.002	-0.000	-0.001
	(-1.24)	(-0.27)	(-0.92)	(-1.24)	(-0.24)	(-0.93)
multiple_dummy	-0.000	-0.003***	0.000	-0.000	-0.003***	0.000
	(-0.12)	(-3.06)	(0.25)	(-0.05)	(-2.93)	(0.27)
Constant	0.037	-0.009	0.008	0.037	-0.008	0.008
	(1.34)	(-0.38)	(0.24)	(1.35)	(-0.35)	(0.24)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	235,679	244,451	235,480	235,679	244,451	235,480
R-squared	0.002	0.002	0.001	0.002	0.002	0.001

Table VIII Institutional Trading around News that Spans Earnings Announcements

In Panel A, the sample includes all of the news [-3, 3] days around earnings announcements. The dependent variable is abnormal trading imbalance (*Abt*) at various horizons. In Panel B, we regress only *Abt* of days [-2, -1] for the news sample [-3, 3] days around earnings announcements. See Appendix B for all other variable definitions. *t*-statistics are two-way cluster-adjusted and are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Institutional trading around news in the sample that includes earnings announcements

	[-5,-3]	[-2,-1]	0	[1, 2]	[-5,-3]	[-2,-1]	0	[1, 2]
Neg_net	0.088	-0.058	-0.119***	0.000				
	(1.55)	(-1.28)	(-3.88)	(0.00)				
Neg					0.092	-0.143***	-0.207***	-0.037
					(1.31)	(-2.60)	(-5.33)	(-0.70)
lnme	0.002*	0.002*	0.002**	0.003**	0.002*	0.002**	0.002**	0.003**
	(1.72)	(1.92)	(2.45)	(2.48)	(1.74)	(1.96)	(2.49)	(2.50)
age	0.003*	0.002	0.002*	0.002	0.003*	0.002	0.002**	0.002
	(1.85)	(1.31)	(1.94)	(1.27)	(1.85)	(1.33)	(1.97)	(1.28)
dy	0.061	0.081	-0.021	-0.009	0.062	0.081	-0.021	-0.008
	(0.64)	(1.13)	(-0.50)	(-0.12)	(0.65)	(1.14)	(-0.50)	(-0.12)
bm	-4.217	-5.190*	-0.882	-2.068	-4.189	-5.149	-0.858	-2.041
	(-1.23)	(-1.65)	(-0.53)	(-0.71)	(-1.23)	(-1.64)	(-0.52)	(-0.70)
prc	-0.009***	-0.007***	-0.002**	-0.004**	-0.009***	-0.007***	-0.002**	-0.004**
	(-3.82)	(-3.83)	(-2.05)	(-2.27)	(-3.81)	(-3.90)	(-2.17)	(-2.30)
turnover	-0.080	-0.146	-0.151	-0.022	-0.079	-0.143	-0.148	-0.021
	(-0.38)	(-0.97)	(-1.52)	(-0.15)	(-0.37)	(-0.94)	(-1.49)	(-0.14)
volatility	-0.384***	-0.249***	-0.110***	-0.179***	-0.384***	-0.247***	-0.109***	-0.178***
	(-4.92)	(-4.24)	(-2.95)	(-3.03)	(-4.92)	(-4.21)	(-2.91)	(-3.02)
sp	0.003	0.002	0.001	-0.000	0.003	0.002	0.001	-0.000
	(0.77)	(0.56)	(0.28)	(-0.03)	(0.75)	(0.58)	(0.34)	(-0.02)
ff4abret[-27,-6]	0.102***	0.045***	0.029***	0.034***	0.102***	0.045***	0.029***	0.034***
	(14.47)	(8.63)	(8.65)	(6.59)	(14.47)	(8.59)	(8.61)	(6.58)
ff4abret[-252,-31]	-0.001	-0.002	0.001	0.001	-0.001	-0.002	0.001	0.001
	(-0.38)	(-0.85)	(0.99)	(0.45)	(-0.38)	(-0.88)	(0.95)	(0.43)
log_media	-0.001	0.000	-0.000	-0.002	-0.001	0.000	-0.000	-0.002
	(-0.61)	(0.07)	(-0.22)	(-1.22)	(-0.63)	(0.09)	(-0.15)	(-1.22)
multiple_dummy	-0.005***	-0.005***	-0.004***	0.001	-0.005***	-0.005***	-0.004***	0.002
	(-3.11)	(-3.80)	(-4.14)	(1.09)	(-3.05)	(-3.61)	(-3.95)	(1.19)
Constant	0.018	0.027	-0.016	-0.033	0.017	0.028	-0.014	-0.033
	(0.57)	(1.29)	(-0.80)	(-1.12)	(0.54)	(1.33)	(-0.71)	(-1.11)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	338,526	335,522	349,382	335,795	338,526	335,522	349,382	335,795
R-squared	0.003	0.002	0.002	0.001	0.003	0.002	0.002	0.001

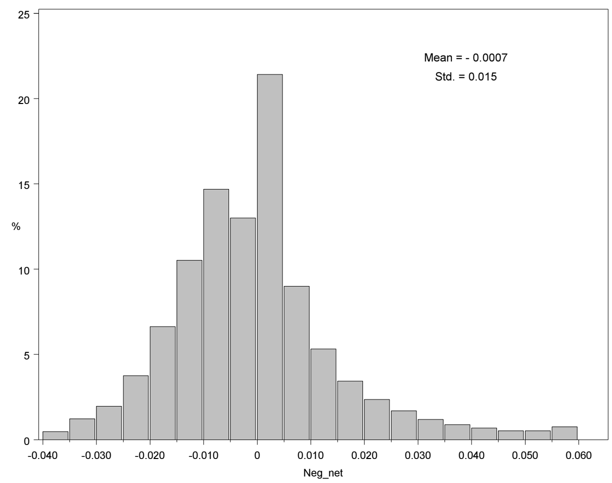
Panel B: *Abt*[-2, -1] around earnings announcement

	News occurring on day(s) relative to earnings announcement					
	[-3,-1]	[0]	[1,3]	[-3,-1]	[0]	[1,3]
Neg_net	0.002	0.073	-0.586***			
	(0.01)	(0.56)	(-2.87)			
Neg				-0.079	0.225	-0.812***
				(-0.33)	(1.33)	(-3.10)
lnme	0.008**	0.004*	0.002	0.008**	0.003	0.002
	(2.45)	(1.67)	(0.62)	(2.46)	(1.63)	(0.64)
age	0.006	0.002	0.009**	0.006	0.002	0.009**
	(1.55)	(0.87)	(2.39)	(1.55)	(0.82)	(2.39)
dy	-0.000	0.084	-0.238	0.001	0.080	-0.239
	(-0.00)	(0.73)	(-1.34)	(0.01)	(0.70)	(-1.35)
bm	-7.156	-8.344	9.971*	-7.115	-8.534	10.150*
	(-1.21)	(-1.45)	(1.82)	(-1.20)	(-1.48)	(1.85)
prc	-0.020***	-0.005*	-0.011**	-0.020***	-0.005	-0.011**
	(-4.03)	(-1.69)	(-2.34)	(-4.04)	(-1.54)	(-2.46)
turnover	-0.365	-0.768**	-0.742*	-0.360	-0.779***	-0.739*
	(-0.74)	(-2.56)	(-1.80)	(-0.73)	(-2.60)	(-1.80)
volatility	-0.109	-0.029	-0.365*	-0.107	-0.034	-0.358*
	(-0.56)	(-0.24)	(-1.83)	(-0.55)	(-0.27)	(-1.79)
sp	-0.012	-0.004	0.000	-0.012	-0.004	0.001
	(-1.40)	(-0.82)	(0.03)	(-1.40)	(-0.83)	(0.09)
ff4abret[-27,-6]	0.013	0.039***	0.048**	0.013	0.040***	0.048**
	(0.63)	(3.22)	(2.22)	(0.63)	(3.25)	(2.21)
ff4abret[-252,-31]	-0.001	-0.013***	-0.003	-0.001	-0.013***	-0.003
	(-0.15)	(-2.89)	(-0.40)	(-0.16)	(-2.86)	(-0.39)
log_media	-0.004	0.004*	0.005	-0.004	0.004*	0.006
	(-0.92)	(1.75)	(1.36)	(-0.92)	(1.72)	(1.43)
multiple_dummy	-0.005	-0.007**	-0.006	-0.004	-0.007**	-0.006
	(-0.73)	(-2.10)	(-1.11)	(-0.70)	(-2.15)	(-1.10)
Constant	-0.205	0.004	0.092	-0.205	0.002	0.100
	(-1.19)	(0.08)	(1.14)	(-1.19)	(0.04)	(1.23)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,054	38,048	21,254	14,054	38,048	21,254
R-squared	0.011	0.006	0.008	0.011	0.006	0.008

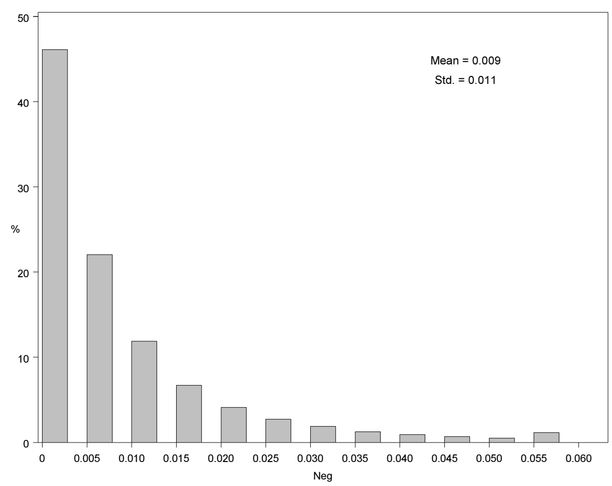
Table IX Trading Three Hours Before and After the News Announcement

This table shows the net institutional trading balance three hours before and three hours after the news announcement. Each time bin represents 15 minutes, and the time duration shown ranges from -12th time bin to 12th time bin. The robust P-value is from the test whether the difference between quintiles 5 and 1 is different from the benchmark, where the benchmark of each news announcement is defined as the average quintiles-5 and 1 difference of net trading 12 hours to 4 hours before the news announcement and 4 hours to 12 hours after the news announcement.

	Neg_net Quintile					Diff.	
15m bin	1	2	3	4	5	5-1	P-value
-12	-0.00024	-0.00010	-0.00054	-0.00103	-0.00091	-0.00067	[0.79]
-11	0.00017	-0.00021	-0.00049	-0.00066	-0.00099	-0.00116	[0.15]
-10	-0.00004	0.00020	-0.00084	-0.00065	-0.00057	-0.00053	[0.46]
-9	-0.00005	-0.00024	0.00004	-0.00051	-0.00119	-0.00114	[0.24]
-8	0.00013	-0.00042	0.00000	-0.00068	-0.00085	-0.00098	[0.45]
-7	-0.00016	-0.00002	0.00003	-0.00056	-0.00112	-0.00097	[0.49]
-6	-0.00001	-0.00021	-0.00038	-0.00062	-0.00090	-0.00090	[0.60]
-5	-0.00004	-0.00013	-0.00050	-0.00058	-0.00090	-0.00085	[0.68]
-4	0.00007	-0.00021	-0.00014	-0.00070	-0.00118	-0.00125	[0.18]
-3	-0.00012	0.00003	-0.00025	-0.00029	-0.00094	-0.00082	[0.82]
-2	-0.00001	-0.00017	-0.00059	-0.00068	-0.00084	-0.00083	[0.76]
-1	-0.00009	-0.00057	-0.00055	-0.00055	-0.00110	-0.00100	[0.41]
1	0.00091	0.00067	-0.00031	-0.00036	-0.00206	-0.00297	[<0.01]
2	-0.00026	-0.00025	-0.00046	-0.00130	-0.00154	-0.00129	[0.09]
3	-0.00022	-0.00062	-0.00036	-0.00097	-0.00094	-0.00072	[0.93]
4	-0.00031	-0.00026	-0.00065	-0.00104	-0.00081	-0.00051	[0.47]
5	-0.00030	-0.00038	-0.00064	-0.00117	-0.00127	-0.00098	[0.49]
6	0.00012	-0.00034	-0.00053	-0.00111	-0.00078	-0.00090	[0.62]
7	0.00002	-0.00013	-0.00068	-0.00053	-0.00107	-0.00109	[0.32]
8	0.00012	-0.00030	-0.00055	-0.00093	-0.00112	-0.00125	[0.10]
9	-0.00067	-0.00006	-0.00036	-0.00099	-0.00051	0.00016	[<0.01]
10	-0.00015	-0.00026	-0.00053	-0.00073	-0.00097	-0.00082	[0.82]
11	-0.00011	-0.00020	-0.00066	-0.00108	-0.00141	-0.00130	[0.57]
12	0.00001	0.00001	-0.00044	-0.00081	-0.00140	-0.00140	[0.07]

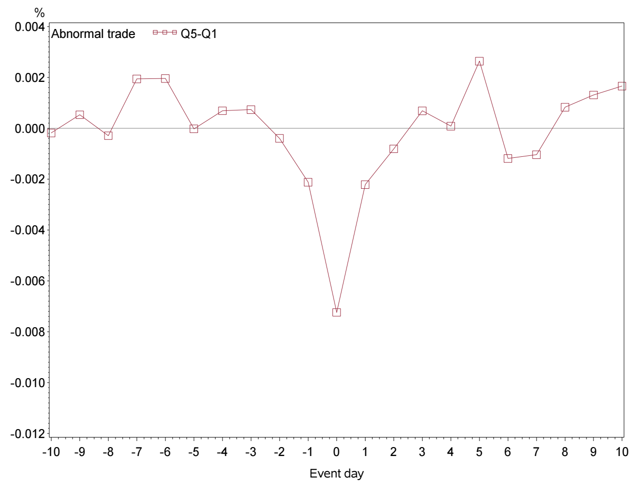


(a) Neg_net

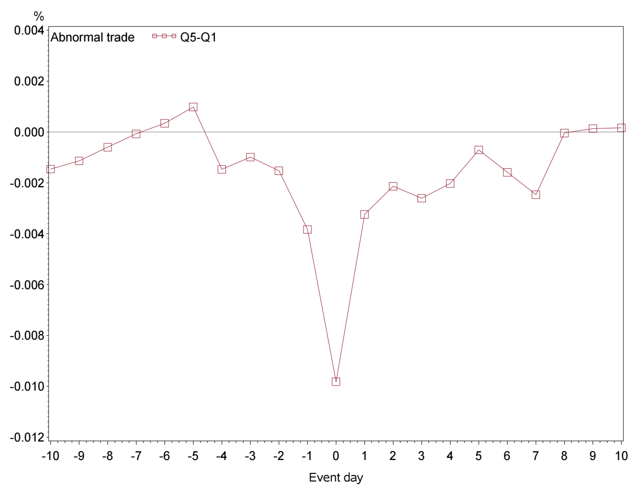


(b) Neg

Figure 1: Percentage histogram

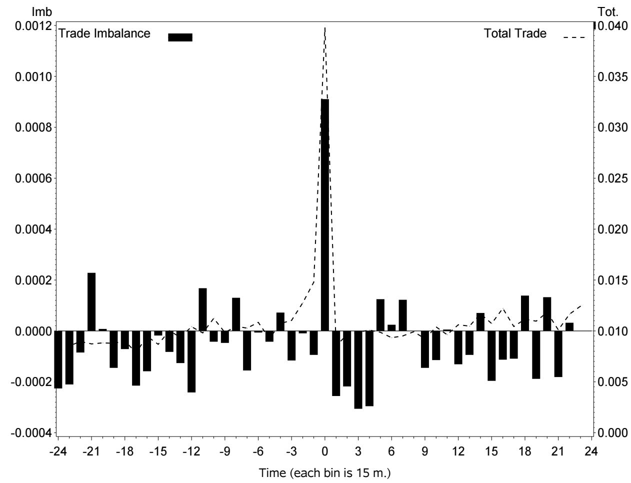


(a) *Neg_net* Q5–Q1 abnormal trade imbalance difference

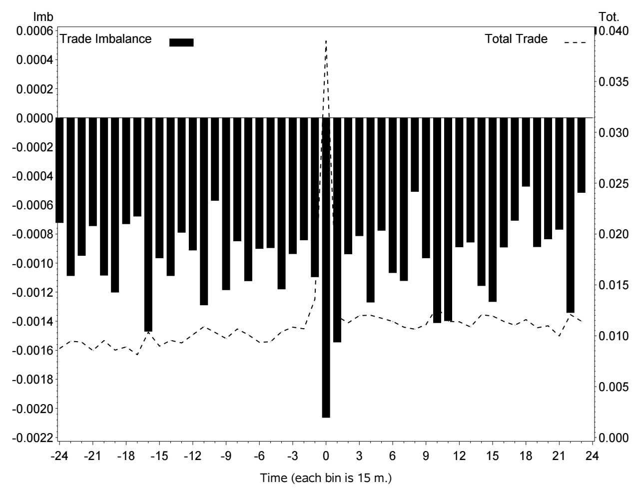


(b) *Neg* Q5–Q1 abnormal trade imbalance difference

Figure 2: Abnormal trading imbalance difference between news-tone Quintiles 5 and 1



(a) Most positive news: Quintile 1 of Neg_net



(b) Most negative news: Quintile 5 of Neg_net

Figure 3: Net trading imbalance and total trading 360 minutes before and after the news announcement. Each bin represents 15 minutes. The left vertical axis indicates net trading imbalance, and the right vertical axis indicates total trading.