Institutional Trading around Corporate News: Evidence from Textual Analysis

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Abstract We examine institutional trading surrounding corporate news by combining a comprehensive database of newswire releases on U.S. firms with a high-frequency database of institutional trades. To identify the ability of institutions to predict or quickly interpret news, we form "news clusters" of related news about a particular firm that occurs in rapid succession. We find that institutions chiefly trade on the tone of news directly after the earliest news release in a cluster, and such news-motivated trading predicts returns over the following weeks. Our results suggest that institutional investors contribute to price efficiency by the speedy interpretation of public information. (*JEL* G11, G12, G14, G23, G39)

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Introduction

Institutional investors now own about two-thirds of U.S. corporate equities and account for an even greater proportion of trading volume.[1] Accordingly, institutions play a large role in the incorporation of new information into market prices; for example, Boehmer and Kelley (2009) find that institutional ownership is positively related to the relative informational efficiency of stock prices. A number of studies provide evidence in favor of institutions possessing an informational advantage over other market participants in various contexts, and exhibiting superior trading skills.[2] However, the mechanism of how institutional investors use information to trade, and how quickly their information-motivated trades are reflected in stock prices, is far from clear.

In this paper, we directly test whether institutional investors exhibit an informational advantage and superior trading skills, based on a large sample of corporate newswire releases from various major media news sources. We find that institutions react speedily to the initial news in a news sequel, and, to a much lesser (and mostly statistically insignificant) extent, on surrounding days. An increasingly negatively toned news article induces institutions to sell more heavily directly after (and on the same day as) the initial news release in a news sequel.

Our approach to testing the information-gathering skills of institutions is motivated by prior research that establishes that media releases account for a large amount of value-relevant information in the United States (e.g., Tetlock et al. 2008) and that we can precisely identify (using our comprehensive database) when the first news is released to the public about a newsworthy corporate topic. Specifically, we combine a sample of 2.2 million news articles with trades of over 1,000 institutions that total $40 trillion during 2000 to 2010. To our knowledge, our study is an examination of the most complete merger of high-frequency time-stamped news with time-stamped institutional trading to date.

[1] According to the Federal Reserve Board's Financial Accounts of the United States, issued on June 7, 2018, U.S. domestic institutions held $20.6 trillion in U.S. corporate equities at the end of 2017, representing 65.3% of U.S. publicly traded equities (https://www.federalreserve.gov/releases/z1/20180607/z1.pdf).
[2] See, among others, Nofsinger and Sias (1999), Irvine, Lipson, and Puckett (2007), Cohen, Frazzini, and Malloy (2008), Puckett and Yan (2011), and Hendershott, Livdan, and Schürhoff (2015).

When the timing of an impending news release is known, the literature indicates that institutions are able to predict and trade prior to this "anticipated news" (e.g., Campbell, Ramadorai, and Schwartz 2009; Baker et al. 2010).[3] In our study, we instead focus on "unanticipated news" by excluding news around earnings announcements (e.g., Rubin, Segal, and Segal 2017). We build on the idea that unanticipated news is difficult to predict—even if an institution monitors the firm closely every day—in part because of the Regulation Fair Disclosure's prohibition of selective corporate news releases to well-connected investors or analysts. By focusing on unanticipated news—consisting of the great majority of the vast daily stream of news—our study uniquely contributes to the question of how public corporate information becomes impounded into stock prices.

In conjunction with focusing on unanticipated news releases, a key contribution of our study is that our news data set captures the timeliness of the *initial* news release on a corporate topic more accurately than data used by prior researchers. As an example, some prior studies use the Dow Jones Archive, which contains only Dows Jones newswires and *Wall Street Journal* articles (e.g., Tetlock et al. 2008; Engelberg et al. 2012). We find that these data provide an incomplete view of news on a particular corporation. In our sample, only 27% of the earliest news releases of news sequels on a particular corporation are contained in Dow Jones News Service. Thus, our data allow a more robust set of tests of the interplay between the earliest release of *unanticipated* news on a corporation about a particular newsworthy issue and trading of its stock by institutional investors.

We condense successive news releases (both intraday and over consecutive days) into a single "news cluster" with a defined "first media release" time. Supporting this approach, we find that multiple newswire releases about a corporation on the same day, as well as news about that corporation over

[3] The vast majority of "anticipated" news releases (i.e., those news releases that have an ex ante known or highly predictable date and time of release) are related to quarterly earnings announcements.

consecutive days, are persistent in tone.[4] Such "news clustering" has the advantage of avoiding the complicated (and often impossible) task of sorting out the direction of causality when trading and news releases each occur repeatedly during a short-term period. Our approach, thus, focuses on the direction of causality between institutional trading prior to and directly following the *initial news* about an unanticipated news issue. That is, with our comprehensive news database, we precisely identify the initial news release in a cluster about a particular corporate newsworthy issue to establish whether institutions lead or follow the first news release in that cluster. By doing so, we avoid capturing trading that follows the first news release but precedes later (and related) news releases, that is, cases for which it is much more difficult to determine whether the trade is predictive of news content or follows news with a potentially skilled interpretation.

Our detailed empirical tests indicate that institutions trade speedily on, but not ahead of, the first news bulletin of a news cluster. An examination of clusters of *consecutive-day* news, which account for 22% of our news clusters, helps to explain the different inference of our study, relative to the literature reporting that institutions systematically possess private information and trade ahead of news (e.g., Hendershott, Livdan, and Schürhoff 2015). When we "uncluster" all (unanticipated) news and ignore the fact that some news releases follow other related news about a corporation, we find that institutions appear to trade ahead of news, on average. Consistent with Hendershott et al. (2015) who study a news dataset without discriminating between anticipated and unanticipated news, institutions show some ability to quickly interpret and/or to predict the incremental tone of the follow-up news releases.[5] However, schemes to set the news-cluster event day as the initial-news day change such predictability. We find that (1) using all news, clustered as described above, (2) using only the subset of consecutive-day news events (clustered),

[4] Following the literature on textual analysis (e.g., Tetlock et al. 2008; Loughran and McDonald 2011), we quantify the qualitative information embedded in each news article by calculating the frequency of "negative" and "positive" words and define the "tone" of the news as the net negative word ratio (the difference between negative and positive word counts, divided by the total number of words in the article).

[5] We note that a follow-up news release is much more "anticipated" in timing than the initial news release in our "unanticipated news clusters"; our finding that institutions trade in a way consistent with predicting follow-up news is consistent with our overall theme that institutions have superior skills in predicting the content of news with more predictable timing (e.g., Hendershott et al. 2015).

or (3) using only the initial day of consecutive-day news, all eliminate the predictive power of institutional trading for news tone, while still finding a speedy reaction of institutional trading to the initial news. Thus, although our study does not rule out that institutions are able to predict the (changing) tone of follow-up news (which would be consistent with our general theme that anticipated news is successfully predicted by institutions, while unanticipated news is not), it suggests that institutions chiefly trade on the tone of news after the earliest news release—at least for unanticipated news events—after which the timing and content of succeeding news become more predictable.

We also analyze the intraday timing of a news release versus the associated timing of institutional trading of a stock. Our study seeks to determine whether institutional investors chiefly predict or chiefly respond to news releases—a distinction of great importance in understanding the mechanism of the flow of information into stock prices—therefore, precise time-stamped data are crucial to identify both the first news release and pre- and post-news release trading. Using a minute-by-minute measurement of the interaction between newswire releases and institutional trades, we find that institutions react to news during the first 30 minutes after the newswire release time, but not at other surrounding time intervals. There is, however, an interesting distinction between the intraday reaction of institutions to "single-day news" (news of the firm that occurs all in one trading day) and consecutive-day news. For consecutive-day news, institutions significantly react to news during the first 30 minutes after the initial news release, but also significantly react exactly 24 hours after the initial news release. This finding of an "echo" in institutional trading reflects that consecutive-day news often has a rhythm of occurring one trading day apart (either before- or after-market), and is consistent with past studies (e.g., Hendershott et al. 2015) that find that news lags institutional trading by 1 day—meaning that institutions appear to predict news—which we find only occurs for follow-up news bulletins.[6]

News-driven institutional trades result in economically significant abnormal returns in the same direction as these trades. Specifically, a 1-standard-deviation increase in institutional trading results in an

[6] That is, corporate news most often occurs during pre- or post-NYSE hours; thus, institutional trading on consecutive-day news also exhibits this 1-trading-day periodicity.

abnormal return of 12.5 basis points (bps) over the 5 days following the news, incremental to the return predicted by news tone alone. This economic significance is about half of the annualized abnormal return of 20 to 26 bps of institutions' intraquarter trading skills estimated by Puckett and Yan (2011). We further partition institutional trades into news-contrarian (for trades opposite to the news direction) and news-reinforcing (for trades consistent with the news direction) and find that the incremental return predictability of trading comes mainly from reinforcing trades. Thus, while institutional trading predicts returns, the return predictability is mostly present when such trading is consistent with the news direction.

Our paper contributes to a growing literature on the textual analysis of public news. While most studies focus on a small fraction of news articles that cover specific corporate events, such as earnings announcements or M&A activities (e.g., Baker and Savasoglu 2002; Jegadeesh and Tang 2010), this new literature examines all types of corporate news in the mass media, to provide a much more robust measure of the supply of public information on publicly listed firms (e.g., Engelberg et al. 2012; Fang, Peress, and Zheng 2014; Hendershott et al. 2015; Wu 2017). The release of public news is one of the most important channels of information dissemination for public firms, yet institutional trading patterns around public news releases have received limited attention in the literature. Our study contributes to this recent literature by providing evidence of a substantial link among news tone, institutional trading, and the price reaction of stocks for unanticipated news releases. Unlike previous studies that typically rely on a single or limited news sources, such as the Dow Jones News Archive or Thomson Reuters News Analytics, our study features a large volume of wired news from a wide array of major news sources, which enables us to capture a larger supply of firm-specific public information and to more accurately identify the exact timing (the timestamp in our news database) of the first instance of related firm news (i.e., the first news bulletin among potentially multiple related news bulletins in a news cluster) for unanticipated news releases.

We also add to the literature by showing that institutions' prompt processing and interpretation of unanticipated public news contributes to the price discovery process for stocks to a greater degree than their ability to predict such news. Our finding that institutional trading is incrementally informative in the presence of news (i.e., a higher level of institutional trading for the same level of news tone more sharply predicts returns) offers a richer insight into the mechanism of the effect of news tone on stock returns documented by Tetlock et al. (2008), and provides one channel through which institutions make abnormal profits from their intraquarter trades, as documented by Puckett and Yan (2011). Our results suggest that prior studies that document an impact of news on stock returns are, at least in part, due to a quick reaction by institutional investors to the first release of such news.

1. Data and Sample Selection

This study relies on corporate news from Factiva and institutional trading data from ANcerno. In this section, we describe our data sources and sample selection process.

1.1 News sample

We retrieve corporate news for all U.S. firms between January 1, 2000 and December 31, 2010, from the Top Sources in the Factiva database. We obtain 2,187,720 corporate news that each contains at least fifty words in total, and that the first twenty-five words contain a company identity, which could be a company name, ticker symbol, URL, or company name initial. We are left with 1,714,336 news articles that we can match to Compustat for firm fundamentals. We are interested in whether institutional investors are able to predict and process news in a timely fashion, so we remove news from newspapers and magazines, which accounts for 7% of the news articles. We therefore solely focus on wired news, which we consider the timeliest source of publicly released information. Table A.1 discusses the sample selection procedure in detail.

The literature differentiates information flow that is anticipated, ex ante, from unanticipated information flow (e.g., Graham, Koski, and Loewenstein 2006). When the date of an impending news release is known ex ante ("anticipated news"), institutions may be able to gather information and forecast news and trade in advance on potential news content. In examining whether analysts predict news or possess skills in interpreting information, Rubin, Segal, and Segal (2017) treat 8-K reports outside [-3,3] days around earnings announcements as "unanticipated" material news that arrives at the market unexpectedly. As quarterly earnings announcement dates are typically preannounced, anticipation of earnings announcement news may lead to predictive trading. For example, Campbell, Ramadorai, and Schwartz (2009) and Baker et al. (2010) suggest that institutions anticipate both earnings surprises and post-earnings announcement drift, and trade accordingly. As we wish to focus on trading that is related to news releases, rather than trading that anticipates a corporate event even in the absence of news, we remove news [-3,3] trading days around earnings announcements, which reduces the number of news articles by around 25%, to 1.19 million.

One distinctive feature of our study is the large breadth of the news that we cover. Prior studies on public news typically focus on the Dow Jones Archive, which only contains Dow Jones Newswires and *Wall Street Journal* articles (e.g., Tetlock 2007, 2010; Tetlock et al. 2008; Engelberg et al. 2012). Panel A of Table 1 shows the coverage of our news stories by year and by news source. To compare with previous studies, we note that Dow Jones Newswire, Business Wire, and Press Release each supply about one-quarter of the total number of news stories in our sample, followed by the Associated Press (10.7%) and Reuters (4.3%). These five major newswires report 93.1% of the news releases in our sample. Our sample period also contains more than 100 other small news providers that each reports less than 1,000 news stories.

[Table 1 about here.]

Figure 1 provides the per-minute histogram of intraday news timestamps of the 1.19 million news stories. We observe that news is more frequently released in the premarket hours of 6:00 to 9:30 (Eastern Time), and in the after-hours of 16:00 to 17:00. One-third of the news stories are released during the market trading hours of [9:30, 16:00). We assign a news article to a particular trading day if the news is released on that day (including premarket hours), prior to the market close at 16:00, and to the next trading day if the news is released at or after 16:00, including news that is subsequently released on a nontrading day, such as a weekend or a holiday. Henceforth, "trading day" and "day" both refer to trading day.

[Figure 1 about here.]

1.2 News content measures and content persistence

Following prior research (e.g., Tetlock 2007; Tetlock et al. 2008; Loughran and McDonald 2011), we count the number of positive and negative words in each news article to construct its text tone. Our word lists are from Loughran and McDonald (2011). Our primary measure of news tone, Neg_net, is defined as total negative word occurrences (including those in the headline and body of the news) net of total positive word occurrences in each news article, divided by the number of total words in the news article. Because the literature typically emphasizes negative words (e.g., Tetlock et al. 2008), we also consider *Neg*, the ratio of negative word count to total number of words in the news article. *Neg_net* is bounded between minus one and one, whereas *Neg* is bounded between zero and one. The higher these two ratios, the more negative the news. Figure 2 shows the sample distribution of *Neg_net* and *Neg*. *Neg_net* has a mean of 0.002, indicating that the average news story has a slightly negative tone. About a quarter (23%) of our news stories have a *Neg* value of zero and thus contain no negative words.

[Figure 2 about here.]

A news event may receive continuous coverage, within the day or spanning multiple days. Because the press may exercise editorial control over the news content, articles by different sources covering the same event are unlikely to have exactly the same tone. This gives rise to both persistence and heterogeneity in news tone for the same-day and consecutive-day news stories, which we show below by examining the autocorrelation of news tone between the first and its subsequent news in the same news sequel.

We examine within-day news first. In the 1.19 million news stories, 29.7% involve multiple news releases about a given firm within a single day. We run the following regression:

$$Neg\_net_{i,t,1} = \alpha_k + \beta_k Neg\_net_{i,t,k} + \epsilon_{i,t,1} \quad (1)$$

for news of firm i at day t, where the subscripts 1 and k indicate, respectively, the first and k^{th} news during the day. Panel A of Table 2 shows that *Neg_net* of the first news has an autocorrelation coefficient of 0.59 (0.53) with the second (third) news on the same day, and of 0.52 with the last-but-second news of the day. Similar coefficients are observed if we use *Neg*. The magnitude of autocorrelations indicates that same-day news stories are highly correlated with each other. Yet these autocorrelations are far from 100%, suggesting that news agencies exercise editorial control giving rise to heterogeneity in news content. Given these high correlations, we combine multiple news articles for each firm in a given trading day into a single news day by taking the average of the news tone. Doing so also facilitates comparisons of our results with prior research that measures news on a daily basis. We keep the timestamp of the first news to improve the identification of the time sequencing of institutional trading in relation to news releases.

Next, we examine the tone persistence for news sequels spanning consecutive days, as it is likely that such closely spaced news articles are related. We group consecutive-day news about a firm (i.e., nonstopping news coverage over a number of consecutive days) into a news "cluster." A cluster ends when news coverage stops for at least 1 day. Left untabulated, the firm-news days yield 683,741 news clusters, with 14.3% of the news lasting for more than 1 day, the average cluster lasting for 1.22 days, and the 99th percentile of the cluster duration being 4 days. Panel B of Table 2 repeats the exercise of regression (1) for news clusters using the daily-averaged news. We observe that the autocorrelation between the first-day news and its *k*th subsequent-day news is about 10% lower than its within-day counterpart. However, the autocorrelation is still high; for example, *Neg_net* of the first-day news has an autocorrelation coefficient of 0.52 (0.41) with the second-day (fourth-day) news in the cluster.

Table 2 indicates that news tone exhibits an overall large degree of persistence within-day and across consecutive days. For a multiple-day news cluster, later-day trading may reflect both contemporaneous and earlier-day news, making distinction of a causal relationship between trading and news difficult. To ameliorate this confounding effect, we define news event by news cluster. We average news tone within the cluster and define pre- and post-event periods relative to the boundary of the news cluster. We use the timestamp of the first news in the cluster as the news start time. We note that our “event day” has the duration of the cluster, which may not necessarily last for only 1 day.

1.3 ANcerno institutional trading data and its intersection with the news sample

We intersect the news sample with institutional trading data from ANcerno Ltd. (formerly Abel Noser Solutions Corporation), which collects its institutional clients’ transaction records for which such clients use ANcerno’s trade cost analysis services. The vast majority of the ANcerno institutions are plan sponsors and mutual fund families. For each transaction, ANcerno provides, among other items, the unique client code for each institution, a unique code for each stock traded, the time of execution, the number of shares traded, the execution price, and whether the execution is a buy or sell. Hu et al. (2018) provide a detailed description and summary of the ANcerno data and estimate that ANcerno institutions account for 12% of all CRSP trading volume during 1999 to 2011. Following the literature (e.g., Puckett and Yan 2011), we include only trades of common stocks by plan sponsors and mutual funds. During 2000 and 2010, ANcerno covers a total of 1,072 institutions, with 386 money managers, 686 plan sponsors, and a total of $40.2 trillion in trading volume.

Panel A of Table 3 shows the summary statistics for the subset of institutional trades that occur on news release dates. Nearly all institutions (1,060 of 1,072) in the full ANcerno sample trade on at least one news release date. Compared with the full ANcerno sample, untabulated, on news release dates (that exclude earnings announcements), institutions trade about two-thirds of all of the stocks that they trade, execute about one-tenth of their total trades, and trade about one-sixth of their total shares and dollar volumes. In our news data set, an average (median) firm has 10 (5) days of news coverage per year, or about one news day every 25 (50) trading days. Institutions are thus much more likely to trade on a news day than on a “no-news” day. For each news story, an average institution trades 54,606 shares valued at about $1.6 million on the news release date.

[Table 3 about here.]

Next, we define institutional trading measures. Following the literature (e.g., Irvine, Lipson, and Puckett 2007), we calculate both the total number of shares traded regardless of trading direction (i.e., shares purchased plus shares sold, or total institutional trading) and the net shares traded (i.e., shares purchased minus shares sold, or trading imbalance). We then scale these two values by the firm's total shares outstanding from CRSP to facilitate cross-firm and cross-institution comparisons. Panel B of Table 3 compares the distribution of total institutional trading and trading imbalance across days surrounding news releases and other days. The full ANcerno sample contains around 7.4 million stock-trading days, roughly 30% of which are within [-3, 3] days surrounding news releases. Total *daily* institutional trading averages 0.15% of share turnover during this 7-day window surrounding the news announcement, whereas it is 0.12% on other days that institutions trade. Collectively, panels A and B of Table 3 show that institutions trade more actively on and around news releases.

In panel B of Table 3, the trading imbalance is 0.002% for around-news days versus 0.004% for not-around-news days, indicating less buying and/or more selling around news days than normal days. In both cases, the difference between around-news and not-around-news days is statistically significant at the 1% level. These statistics suggest that institutions net-buy less around news days. We normalize trading imbalance at the firm level by subtracting a firm's trading imbalance by its historical trading imbalance during days [-250, -20] (e.g., Irvine, Puckett, and Lipson 2007), to address the problem that some stocks may be more actively traded than others. This benchmark window roughly corresponds to the prior year's trading days, excluding the prior month. There are likely news arrivals in this benchmark window, which would otherwise add undesirable confounding effects. Accordingly, we remove [-3, 3] days around any news release event day from the benchmark window. We label this measure of abnormal trading imbalance *Abt*. Because institutions net-buy more on nonnews days, our abnormal trading imbalance measures will naturally be negative. This is corroborated in panel C of Table 3, which shows that the mean *Abt* on the news announcement day is -0.0065%, and the mean cumulative *Abt* over [-3, 3] days around news releases is -0.0271%.

We include all before- and after-hours trading and align trades with news based on their respective timestamps. For trades and news that take place on the same day, the trades are categorized as previous-day trading if they happen before the news; otherwise, they are treated as same-day trading. We require at least one institutional trade on the news day for each sample firm following the above news-trades alignment. This reduces the available firm news days by about half, from 834,274 news days to 394,708 news days covering 6,684 firms.[7] The reduction in sample size appears to be due to the preference of institutions for larger-capitalization stocks. The so-called "Prudent Man Rule" typically prevents plan sponsors or mutual funds—two major types of ANcerno institutions—from holding excessive positions in "risky securities," most likely small stocks. Accordingly, we find that stocks that appear in ANcerno have a median market capitalization of $1.98 billion and a median stock price of $24. In contrast, CRSP stocks that do not appear in ANcerno have a much smaller median market capitalization of $239 million and a median stock price of $11. After we cluster consecutive news days, the news-trading sample reduces to 306,280 news clusters. We refer to this sample as our "primary sample." News clusters that span more than 1 day compose 22% of our sample, and "clusters" that are actually stand-alone news days compose the remaining 78%.

Panels B and C of Table 1 show the news sources of the above ANcerno-Factiva intersection. Dow Jones consists of about one quarter in (a) the intersection itself (panel B) and (b) the initial sources of news clusters (panel C). These percentages are highly consistent with that of the entire wired news sample. Thus, our use of the Factiva data set captures, more accurately, the timestamp of the first news release in a given day or news cluster relative to the subsample of, for example, Dow Jones news. The Factiva news enables us to better pin down the timestamp of the first news release in a news sequel, and thus helps in determining the lead-lag relationships between news and institutional trading.

[7] Relaxing the requirement of institutional trading on news day substantially increases the news sample. Our results, however, are insensitive to whether we require the presence of institutional trading on news day at all or whether we require the presence of institutional trading in any day in the window of [-1, 1] days around news. These results are available on request.

2. Empirical Results of Institutional Trading around News Releases

We now examine whether, in our primary sample of clustered news, institutional trading exhibits systematic patterns prior to, on, or after the news event, contingent on the news tone. As discussed earlier, our "event day" has the duration of a news cluster, and the event day is identified as beginning from the initial news release about a particular firm to the end of the news cluster; we will refer to this event day as "news day" or "day 0," where appropriate. Day [-1] includes trades taking place during the previous trading day, as well as those same-day trades prior to the timestamp of the news if the news happens within the day. In this section, we carry out both simple univariate portfolio sorts and regression analyses, and also present evidence to reconcile with the past literature.

2.1 Portfolio analysis

Our primary objective is to investigate whether institutional trading is associated with news tone. We start by dividing the sample into quintile portfolios based on *Neg_net* and examine the abnormal trading imbalance in the event window of 10 days before to 10 days after the news cluster. Table 4 presents the results.

[Table 4 about here.]

Panel A of Table 4 shows that, on the news event day (day 0), *Abt* substantially decreases as a function of *Neg_net*, indicating that more negative news is associated with a higher amount of net-selling; the difference in *Abt* between the most negative news quintile portfolio (Q5) and the most positive news quintile portfolio (Q1) is highly significant (t-statistic = −4.36).[8] On the immediate surrounding days [-1] and [1], there is some evidence of higher selling in Q5 compared to Q1, but the difference in *Abt* between

[8] In untabulated results, we examine the difference in *Abt* between the top and bottom news tone portfolios using more extreme quantiles (such as the 10th or the 5th percentile) and find similarly that statistically significant differences in *Abt* only exist on the news day.

Q5 and Q1 is statistically insignificant on these 2 days.[9] Further, the difference in *Abt* between Q5 and Q1 is also statistically insignificant during any of the other 10 days prior to or after the news day. Panel A of Figure 3 plots the Q5-Q1 difference in *Abt* over these 21 days. We observe that the Q5-Q1 difference fluctuates around zero before and after news, but dips significantly on day 0. In panel B of Figure 3, we also plot the Q5-Q1 difference in *Abt*, where quintiles are based on the negative ratio, *Neg*. The pattern is similar.

[Figure 3 about here.]

The *Abt* pattern identified above could be possibly related to certain firm characteristics. We are guided by prior research that documents such characteristics. The size effect (that smaller firms comprise many return anomalies) exists in many empirical findings; media coverage affects investor preferences and stock returns (Fang and Peress 2009); and, abnormal trading imbalances may be driven by institutions' momentum trading (Griffin, Harris, and Topaloglu 2003). We carry out a double-sorting procedure to examine the impact of news tone on institutional trading, controlling for the firm characteristics of firm size, media coverage (as measured by the number of news stories on the firm in the prior year), or return momentum.

For each firm characteristic, we first sort our sample into terciles. Within each tercile, we further sort firms into quintile portfolios based on the ranked values of *Neg_net*. As with before, we examine the Q5-Q1 difference of *Abt* for each *Neg_net* quintile between the most negative news quintile portfolio (Q5) and the most positive news quintile portfolio (Q1) within each firm-characteristic tercile. Panel B of Table 4 presents the results for day 0 *Abt*. We observe that (a) the Q5-Q1 difference of *Abt* is negative for all subgroups sorted on size, media coverage, or return momentum; (b) the difference is statistically significant for medium and small firms, for firms with medium and low media coverage, and for all levels of return momentum; and (c) the magnitude of the difference is the largest for firms with the smallest size, the lowest media coverage, and the largest momentum. We also find (in untabulated results) that days [-1]

[9] This result is consistent with a subset of institutions having the ability to predict and trade ahead of the full set or a subset of impending news; we further explore this possibility in Sections 3.4 and 3.6.

and [1] exhibit an insignificant Q5-Q1 difference of *Abt* for all of these subsets of stocks. In sum, even though the day 0 institutional trading pattern on news is more pronounced in smaller and less-covered firms—those for which institutional investors are less likely to be able to, at low cost, monitor their investments to predict news events with an unanticipated timing—it exists across a wide spectrum of firms. In regression analyses that follow, we formally control for these firm characteristics to focus on the ability of institutions to predict or to react to news across all stocks.

Table 4 also suggests an asymmetric pattern in the reaction of institutions to positive and negative news: institutions appear to be net-sellers on negative news days, but not net-buyers on positive news days; that is, institutions appear to be much more sensitive to negative news. In Sections 3.5 and 5.1 we offer further analysis of the asymmetric impacts of news tone.

2.2 Regression analysis

The univariate analysis in the previous section indicates that institutions trade on news on the news event day (day 0), and, to a much weaker extent, immediately before and after day 0. To show that these results are not related to other firm and market factors, we next run the following regression analysis:

$$Abt_{i,t} = \alpha + \beta\ Neg\_net_{i,t} + \ \theta\ Controls_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where $\alpha, \beta,$ and θ are (vector of) coefficients. We follow Bennett, Sias, and Starks (2003), Griffin, Harris, and Topaloglu (2003), and Yan and Zhang (2009) to include the following control variables: (logged) size, firm age, dividend yield, book-to-market equity ratio, price, turnover, return volatility, whether the firm is a member of the S&P 500 index, short-term return momentum (past month abnormal stock return), and longer-term return momentum (past 1-year abnormal stock return). We measure each of the control variables, as described in Table A.2, during (or at the end of) time horizons before each time window's measurement of *Abt* to avoid look-ahead biases. In addition, we control for the degree and intensity of media coverage by adding two variables to our models: the logarithm of the number of news stories of the firm in the prior year (to measure degree of news coverage), and a dummy variable that indicates whether the news announcement day contains multiple news stories (to measure intensity). For consecutive-day news clusters whose event day spans multiple trading days, all variables in the cluster-event day are averaged across the corresponding trading days. We use firm and individual month fixed effects throughout our regression models to ameliorate the concern that our results may be driven by macro shocks and to address firm idiosyncrasies in news (e.g., a downward spiral of negative news about a particular firm may accelerate institutional selling, which might be counted multiple times in the absence of firm fixed effects).[10]

Table 5 reports the regression results for *Abt* of windows [-5, -3] (i.e., 3 to 5 days before the first news bulletin in a news cluster), [-2, -1], [0], [1, 2], and [3, 5]. The pre-event windows of [-5, -3] and [-2, -1] test whether institutions have predictive power and trade in advance of the news cluster, while the post-event windows of [1, 2] and [3, 5] test whether institutions continue to trade after the last day of the news cluster.

[Table 5 about here.]

Table 5 confirms the results from our prior univariate analysis. We find that the coefficient of *Neg_net* on *Abt* is significant only on the event day, with a coefficient of −0.103. Given a standard deviation of 0.0153 for *Neg_net* in our sample, a 1-standard-deviation increase in *Neg_net* leads to 0.1576 bps (= 0.0153 × 0.103%) of abnormal *1-day* net selling of total shares outstanding. Further, the sample mean (median) of shares outstanding is 349,707 (76,024) thousand, and the sample mean (median) of market equity is $11,664 (1,509) million. Thus, 0.1576 bps of abnormal net selling corresponds to a mean (median) of abnormal trading of 551 (120) thousand shares, or $18.38 ($2.38) million. However, the results show that institutional trading is not significantly related to the news tone for non-day-0 windows. In sum, the evidence indicates that institutions, as a group, trade on news tone only on the news day, and they do not substantially trade prior to or after the news day. This finding suggests that institutions react speedily to news, even though they do not appear to systematically predict initial news releases and trade accordingly.

[10] In untabulated tests, we also change month fixed effects to date fixed effects and find our results robust.

Regarding the control variables, we find that *Abt* is positively related to one-month return momentum, and negatively related to firm size and volatility. Thus, institutions are more likely to buy firms that experience short-term price momentum (consistent with Yan and Zhang 2009), and to sell firms with high volatility (consistent with Brandt et al. 2010).[11] Because we have controlled for firm fixed effects, we need to be cautious in interpreting the results of these firm characteristics. In untabulated regressions, we also remove all control variables and find our results robust, consistent with Table 4.

2.3 Effect of news clustering and alternative news sampling approaches

Our regression results, thus far, are based on clustering of consecutive-day news and news from multiple sources. We now show the effect of clustering as well as the robustness of our results to alternative news sampling approaches.

We first show the effect of news clustering. Given the within-cluster news persistence, causality between news and trading can be confounded by such persistence. For instance, in a persistent 2-day news sequel, day [1] trading may be related to the news tone of both days [1] and [2]. The latter association would imply predictive news trading, even if the trading is stimulated by day [1] news. Therefore, had we not clustered the news and instead run regressions on individual trading days, we might infer that institutions trade ahead of news for news articles that arrive subsequent to the initial news, when the trading may simply imply a delayed reaction between day [2] trading and day [1] news. Alternatively, an institution may observe the day [1] news in a cluster and have the ability to interpret it prior to further information arriving on day [2], which as we have shown, is likely to be predictive of the incremental news that arrives on day [2].

[11] One possible channel for the relation between news and institutional trading is the feedback effect, where return momentum positively drives trading (e.g., Nofsinger and Sias 1999) and, perhaps, news releases. Although we find a positive correlation between past-month return and institutional trading in our sample, the correlation between past-month return and news intensity is negative. This evidence indicates that the feedback effect is not likely to be large in our sample. In untabulated results, we remove 1-month return momentum from the control variables and find the results robust.

Panel A of Table 6 shows the regression results using daily news but without clustering of consecutive-day news. In the left part of the panel, we use all news days; in the right part, we use only news about a firm that persists over consecutive days (but, without any clustering applied). In both cases, we observe that *Neg_net* is significant on *Abt* of days [-2, -1], [0], and [1, 2]; that is, there appears to be trading prediction of news, and also an immediate and a delayed trading reaction to news. We note that the trading prediction results are consistent with results from the extant literature; see, for example, Hendershott et al. (2015), who, absent news clustering, find that institutions trade ahead of the news by a day for a sample of news from Thomson Reuters News Analytics. As expected, the coefficient estimates for the consecutive-day-news-only sample are substantially larger than those of the full-sample, highlighting the confounding effect of consecutive-day news.

[Table 6 about here.]

Returning to our clustered-news sample approach, it is possible that our baseline results are driven only by either consecutive-day news clusters or single-day news clusters. We, hence, break our primary sample into single-day and consecutive-day news cluster subsamples, and repeat the regressions. Panel B of Table 6 presents the results. As with our baseline results, we continue to observe the significance of *Neg_net* on *Abt* on only day 0 for both subsamples (readers should note that panel B uses clusters, whereas panel A does not). Importantly, both the predictive and delayed trading results of panel A now disappear because of our clustering procedure, which (in panel B) identifies the timestamp of the first occurrence of a news bulletin for a particular firm and applies that time to the entire cluster to identify the starting time of "day 0." Note that the coefficient estimate of *Neg_net* on *Abt* on day 0 in the consecutive-day news sample is more than 4 times that in the single-day news sample. In untabulated results, the standard deviations of *Neg_net* across single- and consecutive-day news clusters are about the same (both are around 0.015). Thus, if we measure the economic significance by coefficient estimate times standard deviation, consecutive-day news has a much larger impact on day 0 *Abt*, consistent with consecutive day news occurring for more value-relevant news stories.

To further show that our clustering procedure dramatically changes results (and inference about the time sequence of institutional trades and news releases), we examine only the initial-news day in each consecutive-day news cluster. Continuing with the earlier example (consecutive news on days [1,2]), if we instead use only the initial news days, day [2] news (and also day [2] trading) is dropped from the sample, thus removing the potential association between day [1] trading and day [2] news. This approach is similar to clustering of consecutive-day news in panel B, in that trading of days [1] and [2] are grouped into a single event, aligned with day [1]'s time. Using this alternative approach, the right-most columns of panel B show that *Neg_net* is significant on *Abt* on days 0 and [1,2], but not on days [-2,-1]. The delayed reaction on days [1,2] highlights the significance of initial-day news.

In panel C of Table 6, we further demonstrate the effect of initial news by using only the initial day of *all* news clusters (note that, for single-day news, the initial day equals the news cluster, by definition), or by using only the very first news bulletin for each news cluster. The former measures *Neg_net* using all the news of the initial day, whereas the latter measures *Neg_net* using the very first news bulletin (only) of the news cluster. Both schemes attempt to separate initial (or initial day) news from follow-up news. The results in panel C confirm those in panel B: *Neg_net* is only significantly related to *Abt*[0], but not to *Abt* of other days. These findings further corroborate that institutions do not trade in advance of news at the beginning of a news sequel, at least for our sample of unanticipated news events.

Panels A to C of Table 6 suggest that sequences of news are complicated phenomena. Institutional trading prior to follow-up news may be an interpretation of the initial news, which might, in part, successfully predict the incremental news that is contained in the follow-up story. The imperfect (but significant) correlation between adjacent sequential news stories helps us to reconcile our findings with those of Hendershott et al. (2015) and others: with a more complete news data set, we find that institutions do not systematically predict the initial news release, but do appear to show some ability to quickly interpret and/or predict the incremental tone of the follow-up news release. As expected, institutions are more sensitive in their trading to consecutive-day news than to single-day news.

In the remainder of Table 6, we carry out regressions for a number of alternative news samplings using the clustering approach. Earlier, in Table 5, we presented trading results of [-5, 5] days around news announcements for news clusters with a stopping interval of 1 day. It is possible that correlated news about a firm may start and stop, then start again with a delay of 1 day or more. For example, there could be a news release about a particular corporation on day [-2] that is related to a news release about that same corporation on day 0, with no releases between these 2 days. Assuming that adjacent news has a high degree of tone persistence (as shown in Table 2), this example would most likely lead to a spurious association between *Abt* on days [-2] or [-1] and news on day 0 and thus bias findings toward significant trading ahead of (and in the same direction as) news.

To test whether our clustering procedure still allows such a potentially spurious result, in panel D of Table 6, we change the news clustering stopping interval to 3 and 5 days, respectively, and reconstruct our news clusters. Note that, with a stopping interval of 5 days (meaning that there is no news about a particular firm for 5 consecutive days before a cluster is "stopped"), we ensure that there is no other news in the windows of [-5, 5] days, except the day 0 news cluster. Given that 78% of news stories in our sample are single day news, a stopping interval of 1 day incorporates most of the news sequels, that is, widening the stopping interval does not significantly reduce the number of news clusters. For example, the number of observations, when we use a 3-day stopping interval to terminate a news cluster, is 80% of that using a 1-day stopping interval. Consistent with the results of Table 5, the coefficient on *Neg_net* continues to be negative and statistically significant, with a similar magnitude, for *Abt* at day 0 (and insignificant for other surrounding days), whether using a 3- or 5-day stopping interval for news clustering. Thus, our cluster stopping interval of 1 day appears to be adequate to capture similar news about the same corporation.

Our news data set is more comprehensive than comparable data sets used in previous research. We obtain our data set by aggregating news and press releases from different sources. As such, our news can be either firm or press initiated. Following Bushee et al. (2010) and Bushee and Miller (2012), who also use news on Factiva, we classify all news released through press release wires (Press Release Newswire, Business Wire, Federal Filings Newswire, and a few other smaller news wire services) as "firm-initiated news." Firm-initiated news stories account for about 50% of our news sample. News by all other news services, such as Dow Jones, Associated Press, and Reuters, is classified as "press initiated." Press-initiated news typically exercises editorial control over the news content and adds color to firm-initiated news on a firm's true information environment (Bushee et al. 2010). Because firms tend to withhold negative information (e.g., Kothari, Shu, and Wysocki 2009), firm-initiated news may be optimistically biased and, thus, may stimulate less trading by institutions. The sentiment between firm-initiated and press-initiated news is highly (but not perfectly) correlated: the correlation of *Neg_net* (*Neg*) in news clusters between firm-initiated and press-initiated news is 0.475 (0.541).[12]

Panel E of Table 6 presents the institutional trading results of press- versus firm-initiated news clusters by only including either press- or firm-initiated news and re-forming news clusters accordingly. We find that, for both types of news, the results are similar to our main conclusions using our primary sample of news. Contrary to the idea that institutions are less sensitive to firm-initiated news, we find that the sensitivity of *Abt*[0] to *Neg_net* of firm-initiated news is somewhat larger than that of press-initiated news. We believe that this reflects the fact that (a) firm-initiated news often leads press-initiated news and is hence more likely to be the initial news in the overall news cluster, which stimulates more trading as shown previously, and (b) institutions actively choose news to trade on, so they tend to trade on impactful firm-initiated news (because panel E includes only news bulletins with same-day nonmissing *Abt*[0]).

Our news comes from a multitude of sources that constitute the "Top Sources" in Factiva. Previous work often focuses on news from either Dow Jones (e.g., Tetlock et al. 2008; Engelberg et al. 2012) or Reuters (e.g., Hendershott et al. 2015). Earlier, we showed that Dow Jones (Reuters) accounts for about one quarter (4.3%) of our news sample. In panel F of Table 6, we separately run regressions for the Dow Jones or Reuters news sample only, where we redefine our news clusters by using news from either Dow

[12] Of course, this may reflect that firms are more truthful with news that they expect to be independently covered by the press, relative to news that the press does not cover with editorial interpretation (because this correlation is only measured over clusters having both types of news bulletins present). Our next test in panel F indicates that this concern is not particularly important, because panel F includes clusters coming from only one source of news.

Jones or Reuters. We observe that *Neg_net* is significantly negative on *Abt*[0] for Dow Jones news, and marginally significant on *Abt*[0] for Reuters news. In both cases, *Neg_net* is far from being significant on *Abt*[-2,-1]. Thus, our sample of a more robust number of news sources is crucial for the precision of our empirical tests of the interplay between news releases and institutional trading.

In sum, Table 6 shows that our results are robust to a number of alternative news samplings. In particular, we show that clustering of news helps tease out the causality between trading and news content for multiple-day news. Institutions react speedily to news, regardless whether it is press- or firm-initiated news.

2.4 Institutional heterogeneity

In Section 3.3, we showed that our results are robust to news samplings. This section further shows that our results robustly exist across a number of different types of institutions. Given that the literature shows that some subset of institutions may trade ahead of news—for example, Wu (2017) extends Hendershott et al. (2015) by showing that actively managed funds and skilled funds are better at predicting news—it is possible that our results may apply differently to specific types of institutions, relative to the all institutions.

We explore institutional heterogeneity using a number of approaches. Previous studies find that short-term (e.g., high-turnover) investors are more sensitive to information than long-term investors (e.g., Wermers 2000; Yan and Zhang 2009). Although ANcerno does not provide the security inventories of institutions for us to explicitly calculate the investment horizons of the institutions, it does group institutions into either plan sponsor or mutual fund families. The investment horizons of plan sponsors tend to be longer than those of mutual funds, as the former do not have frequent redemption pressures from investor flows (which can motivate mutual fund managers to react more strongly to short-term signals). We calculate abnormal trading imbalance for plan sponsors and mutual funds, respectively, and test their respective sensitivity to news tone. Panel A of Table 7 provides the results. Although we still observe that both types react to news on day 0, but not on other days, we note that mutual funds' sensitivity of trading to news is substantially higher, a finding consistent with the fact that mutual fund managers face a higher incentive for short-term performance from their investors.[13] In untabulated results, we further confirm that the difference of sensitivity between the two types is significant at the 1% level. Thus, mutual funds, or the type of institutions in our sample with shorter investment horizons and presumably more sensitivity to news, trade more heavily on news on day 0.

[Table 7 about here.]

Jame (2018) identifies a list of hedge funds from the universe of ANcerno institutions. Using a list of 82 hedge funds provided by Russell Jame,[14] the right-most columns in panel A of Table 7 show how these hedge funds trade on news. We find that trading by this group of hedge funds is more sensitive to news (whether before, on, or after a news announcement) based on the larger point coefficient estimates in the panel relative to those in Table 5, but that the noise in these estimates precludes us from making any strong inferences. We suspect that this result is due to two potential problems. First, hedge funds (including those in our sample), in general may trade on more complex strategies or strategies that are not based on public and widely disseminated news. For instance, Gargano, Rossi, and Wermers (2017) find that hedge funds trade on information that they obtain from the Food and Drug Administration through private requests submitted to the FDA through the Freedom of Information Act, for example, regarding results of clinical trials of new drugs. Second, there may be a selection bias issue. More highly skilled hedge fund managers may possibly be more sensitive about any disclosure to outside parties (ANcerno in this case) about their trades (including those managers who successfully predict or react to public news); if so, this sensitivity would dilute any evidence of skilled trading among our entire hedge fund sample (which may include both unskilled and skilled hedge fund managers). It is also possible that those hedge

[13] For evidence on the relative pressure of flows on mutual fund managers versus institutional fund managers, see, for example, Christoffersen, Musto, and Wermers (2014).

[14] Plan sponsors and mutual funds are identified by ANcerno's "clientcode," and Jame's (2018) list of hedge funds provided is identified by ANcerno's "managercode." See, for example, Hu et al. (2018) for an illustration of ANcerno's institutional identifiers.

funds that use ANcerno to evaluate their trade execution quality are more focused on providing liquidity to the market to achieve "alpha," relative to the general hedge fund universe.

The ANcerno data also allow us to distinguish institutions based on their trade patterns. The idea here is that funds that are quicker or more skilled in the execution of trades may be the same funds that are more skilled in their quick execution of trades in response to news bulletins. We provide two schemes of classification for institutions. In our first scheme, we classify institutions based on trader skill, following Henry and Koski (2017) who define an execution quality measure for trader skill:

$$\text{Execution Quality} = \frac{\text{Execution Price} - \text{Benchmark Price}}{\text{Benchmark Price}} \times (-1 \text{ if buy}, +1 \text{ if sell}).$$

Essentially, a buy (sell) execution that is lower (higher) than the benchmark price indicates execution quality skill. As with Henry and Koski (2017), we use the Hu (2009) volume-weighted-average-price of all institutions as the benchmark to estimate the execution quality. We calculate the execution quality of each trade, derive each institution's daily average execution quality using all its trades during the day as weighted by trading volume, and further calculate each institution's monthly execution quality using the monthly average of its daily execution quality. We sort institutions into deciles (e.g., Anand et al. 2012), based on previous-month execution quality, and classify institutions in the bottom three deciles as "less execution-skilled," and institutions in the top-three deciles as "more execution skilled."

Panel B of Table 7 presents the results for both types of funds. We find that neither type of institution is able to trade ahead of the news. Instead, more execution-skilled institutions exhibit trading that is insignificantly related to news during the entire window of [-2,2]; in contrast, less execution-skilled institutions significantly trade in the same direction as news over windows of days [0] and [1,2]. Thus, skills in the quality of execution appear to be unrelated to skills in interpreting and responding to news releases. This finding is consistent with that in Keim and Madhavan (1997) for "fundamental or value traders," who demand more immediate execution. In our case, institutions that are more skilled at interpreting news quickly also demand quick execution, which results in lower execution quality.

In panel C, we offer our second scheme of classification based on trading frequency. Using an institution's total number of trades in the previous year, we similarly sort institutions into the bottom-three, middle-four, and top-three deciles, respectively, as the least-active, median-active, and most-active traders, with the idea that the most active trading institutions may be those with the greatest skills in providing liquidity to the market. We find little evidence that such highly active traders are also skilled at speedy interpretation of news: panel C shows that the median-active traders react to news on day [0], but not on other days, and the least- and most-active traders do not trade on news over the window of [-2,2] despite a negative yet insignificant reaction to news on day [0]. Again, this result indicates that our sample includes some institutions that emphasize liquidity provision, which requires a higher level of trading activity each day, whereas others emphasize the interpretation of news, which requires trading immediacy on "news days."

2.5 Other robustness tests and discussion

Our results, thus far, are based on (a) the net negative tone of news and (b) defining unanticipated news by removing news around earnings announcements. We now show that our results are robust to alternative approaches along these dimensions. We also show, in this section, the effect of negative news and news content on institutional trading.

We first use the following alternative news tone measures: (a) the negative tone (*Neg*) instead of the net negative tone of news (*Neg_net*), (b) *Neg_net* and *Neg* based on forward-looking statements following Li (2010), and (c) the standardized *Neg_net* following Tetlock et al. (2008) (i.e., *Neg_net* minus its past-year mean and then divided by its past-year standard deviation at the firm level). Panel A of Table 8 presents the results. We observe that these alternative tone measures are negatively related to *Abt* on day 0 only, reaffirming our main results of speedy and nonpredictive trading to news in Table 5.[15]

[Table 8 about here.]

[15] The coefficient estimate of *Neg* is about twice as large as that of *Neg_net*; this is because the range of *Neg* is about half of that of *Neg_net* (because *Neg*'s lower bound is zero).

Earlier, Table 4 suggested that institutions are more sensitive to negative news. In panel B of Table 8, we further confirm this asymmetry. Here, we partition the news sample into positive, neutral, and negative news, based on the tercile values of *Neg_net*, then run our baseline trading regression, separately, for each news tercile. While we reaffirm that institutional trading does not predict news for each sentiment type of the news, we further observe that day 0 trading of news takes place for neutral and negative news, but not for positive news; moreover, trading is the most sensitive to negative news, as indicated by the magnitude of coefficient estimates. In untabulated results, we find that the economic significance of *Neg_net* on *Abt*[0]—defined as the standard deviation of *Neg_net* multiplied by its coefficient estimate—is larger for negative news than for neutral news.

In our previous data screening, we filtered out anticipated news surrounding earnings announcements to focus on unanticipated news bulletins. Other significant firm activities for which the timing of news may be anticipated include mergers and acquisitions (M&A) (e.g., through predetermined court dates or leakage of information to the press about M&A negotiations). Accordingly, we further remove news articles that are in the window starting 3 days before and ending 3 days after M&A announcements from our primary sample.[16] Panel C of Table 8 shows that our results remain robust with this more restrictive sample.

We align news and trades by the time-stamped minute that they take place, and end our day at 16:00, the end of the trading day. One problem with this alignment is that intraday news will experience less than a full day of trading, leading to a partial-day problem. As shown earlier in Figure 1, roughly one third of our news articles have intraday timestamps. The partial day problem may bias our coefficient on *Abt* systematically toward zero, relative to, for example, *Abt* measured after a 9:30 a.m. news announcement during a full 390-minute (NYSE) trading day. In panel D of Table 8, we add, to our regressions, the additional control variable of the logarithm of intraday trading minutes after news (for before and after-market news, this variable has the maximum value of log(390)). We find our prior results

[16] The population of M&A announcement dates comes from SDC Platinum. We include all M&A announcement days relating to the target, acquirer, and, if any, target and acquirer parent companies. Notably, only about 1% of our news sample is [-3, 3] days around the M&A announcement dates.

robust to this additional time duration control. In untabulated results, we also remove those single-day news clusters that start at an intraday time. If the partial-day problem biases our results, its effect would be most severe among these single-day news clusters. We again find our results robust.

So far, we have examined how institutions trade on the news tone. However, news stories contain heterogeneous information other than simply their overall tone. Arguably, news related to firm fundamentals or firm major events has a larger impact than other news. We identify two types of news that are related to firm fundamentals and major events: (a) news that contains the word root "earn" following Tetlock et al. (2008), who argue that news stories with the word stem "earn" contain more information about firm fundamentals than other stories, and (b) news that contains M&A-related words.[17] In our primary sample of news, 28% of the news articles contain the key words of "earn" or M&A, or both. To examine whether these two types of news indeed have a larger impact on institutional trading, we add to the regressions a content dummy variable that equals one if the news story contains the word stem of "earn" or key words related to M&A, as well as interacting the dummy variable with the news tone. Panel E of Table 8 reports the regression results. As expected, the coefficient estimate of the interaction term is significantly negative on day 0; it is, however, not significant on other days. The evidence supports the notion that institutions trade more heavily on more informative news; it does not, however, support the notion that institutions trade in advance of more informative news.[18]

2.6 Further reconciliation with the literature and limited evidence of news predictability

We further consider the robustness of our results in the regression framework of Hendershott et al. (2015). These authors specifically examine, in our context, whether *Abt* of day [-1] is related to *Neg_net* of day 0

[17] To identify M&A in the news, we search for the following keywords and their stems in the news: merger, acquisition, and M&A.

[18] The significant negative coefficient on the content dummy variable for *Abt*[-2,-1], when using *Neg_net* as the news tone measure, may be driven by some institutions selling (due to risk aversion) prior to major news events. However, this result is much weaker when we use *Neg* as the news tone measure. In the next section we offer evidence of when institutions might be able to predict news.

(panel B of table 4, p. 260 of their paper). We replicate these results and show similarly that news clustering subdues trading prediction of news, if any.

We first regress *Neg_net* of day 0 on *Abt* of day [-1] using the sample of nonclustered news, with news during [-3, 3] days around earnings announcements removed.[19] Table 9 reports the regression results. In Model (1) that uses the full sample of nonclustered news, we observe that *Abt[-1]* is significantly and negatively related to *Neg_net*, consistent with Hendershott et al.'s (2015) findings that institutional trading predicts the next-day news tone.

[Table 9 about here.]

We then separate nonclustered news into single-day news (i.e., news days without adjacent same firm news days before or afterward) and consecutive-day news and repeat the regression of Model (1). Models (2) and (3) in Table 9 show a significant coefficient of *Abt[-1]* for the consecutive-day news sample, but not for the single-day news sample. In the consecutive-day news sample, the coefficient estimate on *Abt[-1]* is much larger in magnitude than in Model (1). These results suggest that the trading prediction of news of Model (1) is concentrated in the consecutive-day news subsample.

We further apply the news clustering approach that we adopted earlier to nonclustered news and repeat the regressions using clustered news. Models (4)–(6) of Table 9 present the results. We no longer observe significance of *Abt[-1]* on *Neg_net* for the full sample or for the clustered news sample that consists of only consecutive-day news coverage. In sum, our replication of Hendershott et al.'s (2015) results of *Abt[-1]* on *Neg_net* is highly consistent with our results in Tables 5 and 6, supporting our theme that institutions do not predict the initial news story in a news cluster in their trading, although we note that they may be able to predict the tone of follow-up news stories.

[19] We note that adding back earnings announcement windows does not change the conclusion that institutional trading's precedence over news only takes place in consecutive-news in our sample. Our results are also robust if we use only the control variables used in Hendershott et al. (2015).

In the Internet Appendix, we also test the robustness of our results using the NYSE's Consolidated Equity Audit Trail Data (CAUD) adopted in Hendershott et al. (2015), a more complete cross-sectional representation of institutions than our ANcerno data, albeit on a daily granularity (rather than intraday) and covering only the period of 2003-2005 (inclusive). We replicate our results by matching the CAUD trading data with our Factiva news data, and find that the results are consistent with our baseline findings (using ANcerno data) that institutions react speedily to unanticipated news. Thus, the difference in the completeness of trading data sets used by Hendershott et al. (2015) versus our study does not explain the differences (between the two studies) in inferred trading patterns relative to news, that is, the question of whether institutional trading predicts news. Our analysis using the CAUD data set still indicates that institutions do not significantly predict the tone of news, at least across the entirety of institutional trading as represented by the CAUD data set (and using our robust Factiva news sample and our news-clustering methodology versus the more-limited Thomson Reuters News Analytics sample used by Hendershott et al. 2015). Nevertheless, we agree with Hendershott et al. (2015): empirical evidence indicates that there are nontrivial cases in which institutions are able to predict the news tone. We will provide our own evidence of this next.

To be specific, we identify a subset of news that institutions may predict (as inferred through their prenews trades). Motivated by the literature that 8-K filing intensity is related to future returns (Zhao 2017), we examine the ability of institutions to predict "intensive" versus "nonintensive" news, where we define intensive news as news clusters that have at least three news articles on the first news day; 8.5% of the news clusters are intensive news, so defined. The left half of panel F of Table 8 shows that, for intensive news, *Neg_net* is significantly and negatively related to *Abt*[-2,-1], suggesting that institutions are able to trade ahead of intensive news. In the right half, we further examine the subset of intensive news clusters that span across multiple days: these account for about 3% of our sample and are even more intensive. The results show a stronger *Abt*[-2,-1] effect (as evidenced by the coefficient estimate of *Neg_net*). In either case, we do not find evidence that institutions predict news more than 2 days in advance. Yet it is important to state that the predictive results of Hendershott et al. (2015) appear to hold when a corporate news event is more intensive, that is, when an event receives elevated media attention and coverage.

Panel F of Table 8 offers an explanation for why *Abt*[-2,-1] is on the margin of significance in some cases that we examined (e.g., the univariate tests in Table 4). In offering this explanation, we must caution that even these results of marginally significant predictive trading may be an artifact of news sample incompleteness, even with our robust sample of news. Given that our sample uses the Top Sources of news in Factiva, an event first reported by a non-Top Sources news agency (for instance, a local news agency) would either be missed by our sample, or would be associated with a delayed timestamp, if that event were later picked up by an agency in the Top Sources. The latter is more likely for intensive news. In other words, we cannot rule out the possibility that predictive trading on intensive news in panel F of Table 8 is a result of delayed coverage of a news event by our sample news agencies.[20] Our findings of nonpredictive trading of news over the (much larger) full sample and across many other settings offer comfort that such data incompleteness is limited.

3. Intraday Results of Trading Reaction to News

3.1 Speedy reaction to intraday news

To add further evidence to our central theme that institutional trades quickly follow (and do not precede) news bulletins, we now investigate day 0 trading during much more granular time periods around the time that a news bulletin is released. Our use of an extensive set of news sources helps in the identification of news timestamps and, therefore, allows an intraday analysis.

To explore institutions' intraday reaction to news, we first examine trading during the window starting three hours before and ending 3 hours after the timestamp of each news story. ANcerno's order placement

[20] Indeed, this is a major challenge to all the broad literature that employs publicly released information; that is, it is nearly impossible to know the initial release of (public) information to investors, given the incomplete information available in archival databases of public news releases.

and execution timestamps, for each trade, are provided by its clients; if the client does not provide these timestamps, based on ANcerno's representation to us, ANcerno sets the placement time to 9:30 and the execution time to 16:00. Because the client has the ability to "not report" and many elect this option, there is a large percentage of order placement times that are, by default, time-stamped at market open (9:30) and order execution times that are time-stamped at market close (16:00) (e.g., Choi et al. 2017). Panel A of Figure 4 shows the trend of the percentage of trades in ANcerno that are "placed" (according to their timestamp) at market open. The ratio starts at over 80% at the beginning of our sample period, decreasing to about 40% by the end. The full-sample percentage of trades "placed" at market open is 52%. Although not reported, we find similar proportions and trends in the timestamp for the order execution time at 16:00.

[Figure 4 about here.]

Panel B of Figure 4 shows the intraday distribution of order placement time for the remaining 48% of trades (premarket trade placement timestamps do not appear in the ANcerno database; thus, we believe that ANcerno also sets any such timestamps—if reported by a client—to 9:30). Notably, however, we do not find abnormal spikes in other intraday timestamps, with the exception of some "top-of-the-hour" spikes during NYSE open market hours.[21] Including all after-market trades, the timestamps indicate that the highest frequency of non-9:30 order placement occurs at 9:31 and accounts for only 0.31% of trades. These patterns indicate that the ANcerno timestamps are reliable when reported by the client to ANcerno (see also Hu et al. 2018).[22]

Next, we match order placement timestamps with news timestamps for each stock-day. The focus of this section is to examine the speediness of intraday reaction to news, so the news is *unclustered*. As a conservative measure, in our intraday analysis, we remove all orders placed at 9:30 and 16:00 (we note that only 0.07% of trades have a placement timestamp of "16:00"). As with the portfolio analysis of Table

[21] We note that news releases by corporations are often timed to occur at the "top-of-the-hour," as shown in Figure 1, which likely explains these trading spikes.

[22] ANcerno's personnel indicated that they believe that clients either nonreport or report an accurate timestamp. Indeed, the fact that a client can elect to nonreport the timestamp indicates that there is no incentive to report a misleading timestamp. Of course, our evidence does not rule out random errors in reporting timestamps by clients.

5, we partition news stories into quintiles based on the ranked value of *Neg_net*, and examine the trading of each quintile portfolio during each 15-minute interval, with trading bin 0 (the first 15 minutes) defined as (0, 15] minutes post the news time.

Table 10 presents the value of *Abt* for quintile portfolios sorted on *Neg_net*, 3 (trading) hours before to 3 hours after the news timestamp. We examine the significance of the *Abt* difference between Quintiles 5 (the most negative news) and 1 (the most positive news). None of the time bins prior to the initial news announcement have a significant *Abt* difference. In contrast, the *Abt* difference is significantly negative in time bins 0 and 1 (the first 30 minutes), but not afterward.[23] In sum, the intraday analysis suggests that institutions react to news speedily, with trading concentrated in the first 30 minutes after the news release.[24]

[Table 10 about here.]

3.2 Twenty-four-hour periodicity

While the results of Section 4.1 indicate that institutions react to each news speedily intraday, we further test whether intraday trading of consecutive-day related news stories helps to reconcile our results with those of Hendershott et al. (2015). It should be noted that institutions react to follow-up news in addition to the initial news story, consistent with further information content being revealed as follow-up news occurs. As evidence, in this section we show a trading spike—for news that carries over to consecutive days—at a periodicity of 24 hours; that is, we find trading spikes at the same time the next day. We show that it is only the confounding consecutive news that drives the subsequent trading spike.

To illustrate the above results, we extend the trading window of Section 4.1 from three to 12 hours on each side of a news bulletin timestamp. Figure 5 compares the intraday trading responsiveness to single-

[23] In untabulated results, we examine the second half of our sample period, when ANcerno clients provide timestamps to a greater degree, and find results similar to those for the full sample.
[24] We note that this pattern overall reinforces that the ANcerno timestamps are accurate; otherwise, we would find only random patterns in trading around news timestamps.

day versus consecutive-day news based on the difference of *Abt* between quintiles 5 and 1 of *Neg_net* news over 15-minute time bins. For single-day news (panel A), we observe that the *Abt* difference is noticeably more negative at time bins 0, 1, and 2 (i.e., for the first 45 minutes), but not at other times. Most notably, the *Abt* difference is sharply negatively at time bin 0. This evidence is highly consistent with our main theme that institutions react speedily to the release of news.

[Figure 5 about here.]

In panel B of Figure 5, we plot the difference of *Abt* for consecutive-day news. Not only do we observe a sharp negative *Abt* difference at time bin 0, we also observe a conspicuously negative value of *Abt* difference at time bins [-26] and [26], which are exactly one trading day (390 minutes) before and after the time of the news in question. The majority of news stories take place before- and after-market, as we have documented earlier; hence, if two news articles are 1 day apart, it is most likely that their time distance is 390 (trading) minutes. Therefore, panel B indicates that, for consecutive-day news events, institutions react to contemporaneous news, but also to 1-day-apart news. This continued reaction can be attributed to the continuation of similar news content, as we have shown earlier that intracluster news tone is persistent.

Lastly, in panel C of Figure 5, we use only the initial news day in the consecutive-day news sample (by dropping other days in consecutive-day news). We find that the downward peaks at time bins [-26] and [26] in panel B no longer exist. Rather, institutions' reaction to the initial-day news in consecutive-day news clusters is similar to that of single-day only news; that is, a strong reaction to news takes place only in a short period of time that follows the news release, rather than occurring in advance. In unreported results, we can show that (a) by using only the very first news bulletin (and dropping all other news in a consecutive-day news cluster) and (b) by excluding news stories outside trading hours (and using only intraday news), both yield results similar to those in panel C of Figure 5. In sum, the evidence in Figure 5 further confirms the difference in trading reaction to single-day versus consecutive-day news, and shows that, without clustering, consecutive-day news has confounding effects on trading prediction, at a periodicity of 24 hours.

4. Return Predictability of Institutional Trading

Our earlier results show that institutions trade speedily on news tone. We now further examine whether this speedy reaction gives rise to abnormal profitability for these institutional trades. Our investigation of the profitability of the news-driven institutional trading is related to two results established in the literature: (a) negative news content predicts 1-day stock returns for S&P 500 firms (Tetlock et al. 2008), and (b) institutions' intraquarter trades are profitable (Puckett and Yan 2011). These findings naturally lead to the question of whether institutional trading on news tone is profitable. We examine the following three aspects of returns: whether news tone predicts returns in our sample, whether institutional trading predicts returns over and above the predictability of news tone, and whether these effects reinforce each other.

4.1 News tone, institutional trading, and return prediction

We first examine the stand-alone predictive power of news tone on stock returns. We focus on examining whether news-driven institutional trades are profitable, so we measure stock returns starting after the end day of each news cluster. We adjust returns by the daily DGTW characteristic-based return benchmark following Daniel et al. (1997). We further adjust for future news arrivals to accommodate the possibility that longer horizon returns due to a given news article may be simultaneously driven by other news. Using the practice that we applied when forming a benchmark window for calculating the abnormal trading imbalance, we remove returns of [-3, 3] days around any other news release days when calculating future returns.[25] Because this will often cause the actual number of days of return accumulation to be different from the stated horizon, we use the average daily return over the return horizon as our return

[25] We enforce this filter only for returns after day five. We confirm, in untabulated tests, however, that our results remain qualitatively the same if we use (a) all of the return days in the entire return horizon and (b) only the return days that occur prior to the next news cluster, if any, during the return horizon (i.e., the return window stops before the first day of the next cluster).

measure. As we have documented that only the event-day 0 abnormal institutional trading is significantly related to news content, we only consider the predictive power of *Abt[0]* (day 0 *Abt* of each news cluster).

Models (1)–(4) of Table 11 present the return predictive power of news tone (in the absence of *Abt[0]*) for the stocks traded by institutions in our sample. In the table, we regress future DGTW-adjusted returns on *Neg_net* over horizons from the next day of the end of the news cluster (day 1) to the end of days 1, 5, 10, and 20, respectively. The control variables are based on Tetlock et al. (2008) and Zhao (2017). Specifically, we control for Fama-French 4-factor adjusted abnormal returns over past windows of day [0], [-1], [-2], [-30, -3], and [-252, -31],[26] firm size, book to market, the prior quarter's standardized unexpected earnings, turnover, volatility, historical media coverage, and news intensity on the news announcement days. Controlling for day 0 returns ameliorates the concern that institutions may be more likely to trade on more important news, which, in turn, is followed by larger future return drifts that may be completely explained by more intense news (with no significant role for institutional trading). The results show that the signs of the coefficient estimates for the control variables are largely consistent with those of Tetlock et al. (2008) and Zhao (2017).[27]

[Table 11 about here.]

Most importantly, we observe that *Neg_net* is negatively related to future returns over all of the horizons that we include, indicating that, for the set of news traded by institutions, news content predicts returns over short to medium horizons of 1 to 20 trading days. We note that our results are robust to using other return horizons within day 1 to day 20; for example, using returns of day 1 to either day 2 or 3 produces similar results. In sum, in Models (1) to (4) in Table 11, we show that (a) news content is related

[26] We follow Tetlock et al. (2008) to use abnormal returns as past return control variables. We can report, however, that our results are robust to using DGTW-adjusted past returns in lieu of the Fama-French 4-factor-adjusted abnormal past returns.

[27] We find that, consistent with days [-1] and [-2], the day 0 return is negatively related to future returns, contrary to Tetlock et al. (2008), who interpret the relation as return momentum due to day 0 news. Different from Tetlock et al. (2008), who use all news days for S&P 500 firms, we examine only returns on news of all firms that are also accompanied by institutional trading. Overall, our sample correlation between day 0 return and *Neg_net* is -0.06 (significant at 1%), indicating that news sentiment and day 0 return have a consistent sign.

to future returns in a sample that includes all U.S. firm-news releases accompanied by institutional trading and (b) the relation between news tone and returns extends to longer time periods than 1 day. Our somewhat stronger results than those in Tetlock et al. (2008) are perhaps due to our sample choice: we have a larger sample of news, with institutional trading, and use only wired news that emphasizes information timeliness; and we also include non-S&P 500 firms, which arguably are subject to a higher degree of information asymmetry, thus, leaving more room for profitable trading.

Earlier, we showed that institutions trade more heavily on negative news. In untabulated results, we further find that the return predictability by news tone is more pronounced for neutral than for positive news, and most pronounced for negative news. This finding is largely consistent with the literature that negative news, but not positive news predicts returns (e.g., Tetlock et al. 2008). The stronger return predictability of negative news is also consistent with institutions trading more heavily on negative news than on positive news.

Next, we examine whether institutional trading incrementally exhibits power in predicting returns, beyond the impact of news tone. We regress future returns over various time horizons on *Abt[0]*, after simultaneously controlling for *Neg_net* of day 0. Models (5) to (8) of Table 11 show the results. We continue to find that *Neg_net* predicts future returns up to 20 days, with estimated coefficients very similar to their counterparts in Models (1) to (4). More importantly, *Abt[0]* is significantly and positively related to returns of days [1], [1, 5] and [1,10], indicating that institutional trading predicts returns in addition to news tone for up to 10 days, post news release. These results suggest that institutional trading is an important short-term source of institutional returns that directly follows news bulletins.

We use the return impact of *Abt[0]* over days [1] and [1, 5] to gauge the economic significance of institutional trading. The coefficient estimates of *Abt[0]* is 0.106 on day [1] return and 0.042 on days [1,5] average-daily returns in Table 11. The standard deviation of *Abt[0]* is 0.206 over the full sample. Thus, a 1-standard-deviation change in *Abt[0]* predicts 2.2 bps of abnormal return over the next day (i.e., 0.206 × 0.106% = 0.022%), or 4.3 bps over 5 days (i.e., 0.206 × 0.042% × 5 = 0.043%). In our sample, firms, on average, have 4.36 news clusters per quarter, thus the annualized abnormal return from day 0 abnormal trading on news can be estimated to be 38 bps (= 2.2 × 4.36 × 4) over 1 day or 75 bps over 5 days. The directional *Abt*[0]-return relation also allows us to estimate the actual trading profit of institutional trading, which can be estimated as the returns induced by the magnitude of *Abt*[0]. The sample mean—or magnitude—of positive (negative) *Abt*[0] is 0.105 (-0.117). Following the same calculation, we estimate that the actual trading profit, as measured above, caused by a positive (negative) *Abt*[0] is 19 (22) bps over 1 day or 38 (43) bps over 5 days. These magnitudes are all about half of those calculated based on the standard deviation of *Abt*[0].

To contextualize the above economic significance, we note that (a) institutions subscribing to Abel Noser's services often compete for savings of only a few basis points on each trade (Hu et al. 2018), and (b) Puckett and Yan (2011) document that intraquarter trading skills of ANcerno institutions contribute between 20 and 26 bps per year to the average fund's abnormal performance. Earlier we reported that institutions trade about one-sixth of their total trading volume on news days. This one-sixth of trading thus results in an estimated annualized abnormal return of 6.5 bps (= 38/6) over 1 day, or 12.5 bps over 5 days, attributable to the response to news. Therefore, trading by institutions after the initial news bulletin is released is economically significant: the (annualized) subsequent 5-day period of a 1-standard-deviation increase in *Abt[0]* is about half of the annualized intraquarter profits documented by Puckett and Yan (2011).

4.2 Reinforcement effect of institutional trading to news tone in return predictions

We now examine the interplay between institutional trading on the news event day and news content for return predictability. Institutional trading and news content could reinforce or weaken each other. We illustrate this point through the following parsimonious partition of news and institutional trading:

	Institutions buy	Institutions sell
Negative news	Quadrant 1: Contrarian trades	Quadrant 2: Reinforcing trades
Positive news	Quadrant 3: Reinforcing trades	Quadrant 4: Contrarian trades

We call trades in quadrants 1 and 4 "contrarian" trades, as in these two quadrants, trades and news are in opposite directions (e.g., good news but sell trades). In contrast, we call trades in quadrants 2 and 3 "reinforcing" trades, as these trades move in the "same direction" as news. If *Abt[0]* incrementally predicts returns on top of *Neg_net*, or if the two influences provide complementary information to the market, then we should observe a stronger effect of such prediction for reinforcing trades.

To show this potential reinforcement effect, we first run the return prediction regressions separately for contrarian and reinforcing trades. We partition the sample by the median values of *Neg_net* and *Abt[0]* to form the above quadrants. Panel A of Table 12 shows the results. We observe that, for contrarian trades, *Abt[0]* no longer predicts returns; and for reinforcing trades, *Abt[0]* predicts returns up to 10 days after controlling for the effect of *Neg_net*. Compared to the case of using all trades (Table 11), the predictive power of *Abt[0]* on returns for reinforcing trades is larger: the coefficient estimates of *Abt[0]* over these return horizons are about twice as large in magnitude.[28]

[Table 12 about here.]

Next, we test the reinforcement effect by creating a dummy variable, *Q23_dummy*, that equals one, if an observation falls into either quadrant 2 or quadrant 3 of the above partition, and examining whether the interaction term of *Q23_dummy×Abt[0]*, along with *Q23_dummy×Neg_net* as a control variable, is significant in return regressions that include the same control variables used in Table 11. *Q23_dummy×Abt[0]* separates those trades that are consistent with *Abt[0]* ("reinforcing") from those that are not ("contrarian"), and would thus be indicative of the reinforcement effect.[29] Panel B of Table 12 shows the results. We observe that *Q23_dummy×Abt[0]* is significant for returns over days [1], [1,5], and [1,10]. We also note that adding the interaction term eliminates the main effect of *Abt[0]:* the coefficient

[28] It is possible that, despite our controls of concurrent return and multiple-news dummy, reinforcing trades, or more generally, institutional trades that generate profits, are driven by trades on "important" news, such as more informative or intensive news, which, in turn, are more predictive of future returns. Regardless of the sources of these profits, we show that institutions derive substantial profits from trading on news.

[29] An (unconditional) interaction term between *Neg_net* and *Abt[0]* will not capture the impact of reinforcing trades in return regressions and, thus, will have an ambiguous interpretation. To see this, interacting sell trades with negative news and interacting buy trades with positive news—our sell versus buy reinforcing trades—will have the same negative sign, yet they have exactly opposite return implications.

on *Abt[0]* is now insignificant; that is, the unconditional impact of *Abt[0]* on returns is subsumed by the conditional impact of news-driven trading. Therefore, news-stimulated trading has the more impactful predictive power for future returns. These results are consistent with those in panel A of Table 12, which segregates contrarian from reinforcing trades.

In our above partition of the quadrants based on medians, reinforcing trades, by construction, have the same number of trades as contrarian trades. Given that institutions, on average, trade in the direction of news, this partition may underestimate the percentage of reinforcing trades. We test for robustness by redefining the *Q23_dummy*. We categorize a trade as contrarian only if *Neg_net* is below median and *Abt[0]* is within the first quartile (positive news and strong sell), or if *Neg_net* is above median and *Abt[0]* is within the fourth quartile (negative news and strong buy). This way, contrarian trades, by construction, account for one quarter of all trades, and the remaining three quarters of trades are categorized as reinforcing trades (this more restrictive partitioning focuses on the effect of stronger contrarian trades). Panel C of Table 12 shows the results using the redefined *Q23_dummy*. We note that the panel B results on *Q23_dummy×Abt[0]* are largely retained: this interaction term is significant on returns over all of the return horizons, with similar magnitudes of coefficient estimates.

In untabulated tests, we further test the robustness of the return regressions by dropping either quadrant 2 or 3 (but not both) from the regressions, or by replacing *Neg_net* with *Neg*, or *Abt[0]* with day 0 net trading imbalance. Our conclusions remain unchanged. In sum, Table 12 shows that institutional trading and news reinforce each other in driving stock returns in the following weeks, and that the reinforcement effect has a more substantive return-predictive power than just news or institutional trading.

5. Conclusions

There is an ongoing debate in the literature on whether and through which channels institutional investors possess informational advantage and trading skills. Although some studies show that institutional investors do not outperform the market overall (e.g., Carhart 1997; Busse, Goyal, and Wahal 2010), other studies find outperformance of institutional investors in various contexts (e.g., Cohen, Frazzini, and

Malloy 2008; Puckett and Yan 2011). Even for those studies that document superior performance of institutional investors, some studies attribute institutional outperformance to preferential access to information due to client relationship or other social connections (e.g., Ke and Petroni 2004; Bodnaruk, Massa, and Simonov 2009), whereas others suggest that institutional investors' superior trading skills stem from prediction of or speedy response to public information (e.g., Engelberg, Reed, and Ringgenberg 2012; Hendershott et al. 2015). One limitation of most of these studies is that they focus on announcements of specific corporate events, such as M&A and earnings announcements, or on a specific investor types, such as short sellers or hedge funds. The findings from these studies are often limited to the specific context underlying each study. Although recent studies argue that institutions systematically trade ahead of public news (e.g., Hendershott et al. 2015), the evidence is inconclusive.

Combining a comprehensive sample of corporate news of U.S. firms from the major news sources with a large database of institutional trades, we examine how institutional investors trade on the qualitative information embedded in public news releases. One distinctive feature of our study is the large breadth of the news that we cover. We filter out news anticipation by excluding news around earnings announcement (e.g., Rubin, Segal, and Segal 2017), and find that news tone is both persistent and heterogeneous over the same day and across multiple days in a string of news. Our results suggest that identifying the first news release is paramount to knowing whether other follow-up news releases might be anticipated by a sophisticated institutional investor. We ameliorate this potential confounding causality between trading and news in consecutive-day news by "clustering" news across days into a single news event and examine trading reaction to the entire cluster or to the initial news.

We find that institutions react speedily to but do not predictively trade on news clusters, whether the clusters consist of single day or consecutive day news. In consecutive-day news, institutions possess some ability to quickly interpret and/or predict follow-up news releases. However, clustering of all news or only the subset of consecutive-day news or using only the initial day of consecutive-day news, all subsumes institutions' trading prediction and results in only speedy reaction to news. Our results suggest that institutional investors do not predict qualitative information embedded in unexpected corporate news releases; instead, they trade speedily on news once the information becomes public. Our findings are supported in firm- or press-initiated news, by intraday analysis of the trading, and across a heterogeneity of institutional types. Overall, we find that institutions' trading advantages stem from their ability to process public information in a highly timely manner.

News-driven institutional trades result in economically significant abnormal returns. A 1-standard-deviation increase in institutional trading results in an annualized abnormal return of 12.5 bps over 5 days following the news on top of the return predicted by news tone. This economic significance can explain half of the documented annualized abnormal return of 20 to 26 bps from intraquarter trading skills by institutions (Puckett and Yan 2011). Institutional trading and news tone reinforce each other to predict returns over the next 2 weeks. Our findings imply that prompt incorporation of public information into stock prices is a possible channel for institutional investors to improve market efficiency. Overall, this paper sheds light on how public news interacts with institutional trades and hence how institutions resolve information asymmetry in the marketplace.

Appendix

Table A1. 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 50 words in total and that the first 25 words mention a company identity—the company name, trading ticker, URL, or company name initial (such as HP for Hewlett-Packard). We assign a news article to the 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 that news article 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 article mentions the firm identity at least 3 times. We also drop observations that we cannot match to a Compustat GVKEY. We remove all nonwired news (e.g., newspaper and magazine articles) to focus on the timely news. We remove [-3, 3] days around quarterly earnings announcements and then combine all same-day news stories. Lastly, we drop all news stories not accompanied by at least one same-day institutional trade and combine (cluster) all consecutive-day same-company news into a single news cluster.

	# of news stories	# of firms
News stories retrieved from Factiva between Jan. 1, 2000 and Dec. 31, 2010	2,187,720	
Subtract:		
Stories that cannot be matched to Compustat or firm identifier occurs less than 3 times	(473,384)	
Total firm-specific news stories	1,714,336	15,650
Remove newspaper and magazine news and keep only wired news	1,594,284	15,540
Remove [-3, 3] trading days around quarterly earnings announcements	1,186,538	14,097
Combine news released on the same trading day for a given firm	834,274	14,097
Total number of firms traded by ANcerno institutions		9,860
Traded by ANcerno institutions on the day of news announcement	394,708	6,684
Cluster consecutive-day news to a single cluster, with at least one day interval between two clusters (primary sample)	306,280	6,684

Table A2. 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 the percentage of 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 for the same company 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
DGTW return	Average daily returns within a given return horizon, adjusted for the DGTW characteristic-based return benchmark following Daniel et al. (1997)
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. The word list comes from Loughran and McDonald (2011)
Neg	The fraction of total negative word count relative to the total number of words in a news article. The word list is from 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 previous quarter-end 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 the news event day
turnover	The average daily stock turnover ratio (overall CRSP market trading volume / shares outstanding) over the days of -27 to -6 relative to the news event day
volatility	The standard deviation of stock returns over days -27 to -6, relative to the news event day
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 event days -27 to -6 (roughly corresponding to the past month). Other *ff4abret* horizons used are: [0] (the contemporaneous day), [-1] (the previous day), [-2] (2 days prior), [-30, -3] (days -30 to -3), [-252, -28], and [-252,-31]
sue	Standardized unexpected earnings of the most previous quarter, defined as the difference of earnings between the current quarter and the quarter of a year ago, scaled by standard deviation of earnings of the previous 12 quarters
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
ContentDummy	A dummy variable that equals one if the news story contains at least once the word stem of "earn" or the key words related to M&A
Q23_dummy	A dummy variable that equals to one if a trade falls to either (a) *Neg_net* above median and *Abt[0]* below median or (b) *Neg_net* below median and *Abt[0]* above median

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Table 1
Summary statistics of wired news

A. Entire wired news sample (1.19 million news stories)

Year	All news sources	Dow Jones	Business wire	Press release	Associated Press	Reuters	Others
2000	124,780	49,041	24,371	28,325	4,172	9,863	9,008
2001	130,211	41,161	37,955	32,136	5,561	5,537	7,861
2002	145,879	36,916	41,629	34,035	14,112	11,562	7,625
2003	90,974	30,488	23,421	12,388	15,027	5,419	4,231
2004	59,788	29,147	6,641	12,013	7,621	1,189	3,177
2005	68,238	30,596	9,179	11,482	10,030	2,894	4,057
2006	128,744	35,870	32,318	32,102	17,419	3,559	7,476
2007	124,890	26,181	33,698	31,321	20,528	3,276	9,886
2008	113,491	20,911	37,628	30,366	12,206	2,853	9,527
2009	96,868	18,736	31,219	24,661	10,502	2,375	9,375
2010	102,675	21,114	33,193	26,333	10,067	2,793	9,175
Total	1,186,538	340,161	311,252	275,162	127,245	51,320	81,398
%		28.7	26.2	23.2	10.7	4.3	6.9

B. Daily averaged news that are accompanied by ANcerno trading

	All news sources	Dow Jones	Business wire	Press release	Associated Press	Reuters	Others
Total	394,708	106,924	98,619	88,085	37,689	17,372	46,019
%		27.1	25.0	22.3	9.5	4.4	11.7

C. Initial sources of news clusters

	All news sources	Dow Jones	Business wire	Press release	Associated Press	Reuters	Others
Total	306,280	82,947	75,840	67,883	29,804	13,540	36,266
%		27.1	24.8	22.2	9.7	4.4	11.8

This table presents the summary statistics of the sample wired news from the following sources: Dow Jones Newswire ("Dow Jones"), Press Release Newswire ("Press Release"), Business Wire, Reuters Newswire ("Reuters"), Associated Press Newswire ("Associated Press"), and all other sources ("Others"). In panel A, the sample includes all news stories after those around earnings announcement are removed. In panel B, news stories accompanied by same-day ANcerno trading are grouped daily, with the news source attributed to the first news in the day. In panel C, we group each nonstopping, consecutive-day news-sequel into a news "cluster."

Table 2
Persistence of news

A. Persistence of news tone for within-day news

Autocorrelation between the first news and *k*th news during the day

	Neg_net				*Neg*			
	k = 2	*k* = 3	*k* = 4	Last, except *k* = 2	*k* = 2	*k* = 3	*k* = 4	Last, except *k* = 2
AR coefficient	0.59	0.53	0.50	0.52	0.62	0.54	0.50	0.53
N	201,014	70,414	31,287	70,414	201,014	70,414	31,287	70,414
R^2	.36	.30	.25	.28	.41	.33	.27	.31

B. Persistence of news tone for consecutive-day news within news clusters

Autocorrelation between the first-day news and k^{th} day news within the news cluster

	Neg_net				*Neg*			
	k = 2	*k* = 3	*k* = 4	Last, except *k* = 2	*k* = 2	*k* = 3	*k* = 4	Last, except *k* = 2
AR coefficient	0.52	0.42	0.41	0.41	0.51	0.38	0.39	0.37
N	98,088	25,470	10,098	25,470	98,088	25,470	10,098	25,470
R^2	.27	.18	.17	.17	.27	.15	.15	.14

In panel A we regress the news tone (either *Neg_net* or *Neg*) of the first news on the tone of the k^{th} news within the day, and in panel B, we regress the news tone of the first-day news on the tone of the k^{th}-day news within the news cluster (defined as news that lasts over multiple days without stopping). Each column in panels A and B represents a regression, and we report the autocorrelation ("AR") coefficient estimate of the news tone of the k^{th} news. All coefficient estimates are significant at the 1% level.

Table 3
ANcerno institutional trading and trading imbalance around news

A. Aggregate institutional trading on news release dates only

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
# 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	6,956
# 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

B. Total trading and trading imbalance of around-news versus not-around-news days (daily average, % of share turnover)

	[-3, 3] days around news releases					
	Trade days	Mean	SD	p25	Median	p75
Total inst. trading	2,104,270	0.151	0.242	0.017	0.061	0.170
Trading imbalance	2,104,270	0.002	0.170	-0.031	0.0011	0.037
	Other days					
Total inst. trading	5,332,704	0.120	0.207	0.011	0.043	0.133
Trading imbalance	5,332,704	0.004	0.152	-0.023	0.0013	0.031

C. Summary statistics of* Abt *of the final primary sample

	Trade days	Mean	Sd	p25	Median	p75
Abt on news announcement day	301,509	-0.0065	0.2058	-0.0496	-0.0005	0.0457
Cumulative *Abt* over [-3, 3] days of news	301,509	-0.0271	0.7557	-0.2880	-0.0025	0.2608

This table shows the total trading amount and the trading imbalance of ANcerno institutions on the news versus non-news days (excluding earnings announcement days). In panel B, "Total inst. trading" refers to institutions' aggregate trading amount of a firm, scaled by shares outstanding of the firm, and "Trading imbalance" refers to the net purchase of a firm, scaled by shares outstanding of the firm. In panel C, "*Abt*" refers to abnormal daily trading imbalance, relative to the benchmark window of [-250, -20].

Table 4
Institutional trading and negative tone: Portfolio analysis

A. Abnormal trading imbalance (% of abnormal share turnover) around news announcement

	Neg_net quintile					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)

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	-0.0021	-0.0046	-0.0086	-0.0047	-0.0054	-0.0050	-0.0031	-0.0031	-0.0087
5	-0.0022	-0.0134	-0.0225	-0.0056	-0.0118	-0.0184	-0.0115	-0.0086	-0.0156
5-1	-0.0001	-0.0088	-0.0140	-0.0009	-0.0064	-0.0134	-0.0084	-0.0055	-0.0069
	(-1.49)	(-3.12)	(-4.48)	(-0.30)	(-2.31)	(-5.04)	(-3.14)	(-2.48)	(-2.46)

Panel A shows the abnormal trading imbalance of quintile portfolios sorted on increasing values of *Neg_net*. Panel B shows the abnormal trading imbalance of portfolios first sorted on a certain firm characteristic and then on *Neg_net*. The firm characteristics include market capitalization, media coverage (measured by the number of news stories of the firm in the prior year), and return momentum (measured by prior-month stock return). *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses.

Table 5
Institutional trading and news tone: Regression analysis

	Abt at day(s)				
	[-5, -3]	[-2, -1]	0	[1, 2]	[3, 5]
Neg_net	0.055	-0.036	-0.103***	-0.043	0.017
	(0.93)	(-0.79)	(-3.25)	(-0.92)	(0.28)
lnme	-0.007*	-0.008**	-0.007***	-0.008**	-0.013***
	(-1.71)	(-2.18)	(-2.90)	(-2.23)	(-2.75)
age	0.002	-0.007	-0.001	0.001	-0.006
	(0.18)	(-0.97)	(-0.13)	(0.13)	(-0.63)
dy	0.167	0.188	0.006	-0.053	-0.105
	(0.98)	(1.37)	(0.09)	(-0.40)	(-0.60)
bm	-3.228	-4.162	-1.206	-1.656	-2.980
	(-0.93)	(-1.61)	(-0.74)	(-0.59)	(-0.79)
prc	-0.008*	-0.004	0.001	-0.002	-0.004
	(-1.75)	(-1.19)	(0.65)	(-0.70)	(-0.96)
turnover	0.213	-0.048	-0.144	-0.033	-0.311
	(0.85)	(-0.25)	(-1.21)	(-0.18)	(-1.25)
volatility	-0.378***	-0.199**	-0.063	-0.131*	-0.081
	(-3.80)	(-2.56)	(-1.30)	(-1.72)	(-0.79)
sp	0.015*	0.013**	0.007	0.011	0.017*
	(1.67)	(1.99)	(1.63)	(1.62)	(1.96)
ff4abret[-27, -6]	0.099***	0.042***	0.022***	0.028***	0.029***
	(12.79)	(7.18)	(5.97)	(4.95)	(3.90)
ff4abret[-252, -28]	0.004	0.002	0.003*	0.004	-0.000
	(1.13)	(0.63)	(1.73)	(1.38)	(-0.04)
log_media	-0.003	-0.003	-0.001	-0.001	-0.004
	(-1.08)	(-1.57)	(-0.87)	(-0.69)	(-1.26)
multiple_dummy	0.000	-0.000	-0.003**	0.001	0.001
	(0.12)	(-0.17)	(-2.49)	(0.85)	(0.60)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	260,459	258,658	268,028	258,706	260,428
R^2	.039	.038	.038	.037	.040

This table regresses abnormal institutional trading on the news tone measure of *Neg_net*. See Appendix A.2 for detailed variable definitions. All variables are winsorized at the 1st and 99th percentiles. All regressions include firm and month fixed effects. *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses. *p < .1; **p < .05; ***p < .01.

Table 6
Effect of news clustering and alternative news samplings

A. Regressions without news clustering

	Using all news days			Using only consecutive-day news		
	Abt at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2, -1]	0	[1, 2]
Neg_net	-0.104**	-0.108***	-0.076*	-0.239***	-0.163***	-0.116*
	(-2.39)	(-3.64)	(-1.75)	(-3.41)	(-3.38)	(-1.65)
Observations	317,686	327,064	317,491	115,748	117,835	115,308
R^2	.039	.036	.038	.097	.090	.101

Note: None of *Abt*[-5,-3] and *Abt*[3,5] are significant in this panel.

B. Single-day versus consecutive-day news clusters

	Single-day news clusters			Consecutive-day news clusters			Using only the initial day of consecutive-day news clusters		
	Abt at day(s)			*Abt* at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	-0.005	-0.061*	-0.027	-0.129	-0.278***	-0.042	-0.154	-0.225***	-0.208*
	(-0.10)	(-1.91)	(-0.53)	(-1.17)	(-3.58)	(-0.38)	(-1.53)	(-3.12)	(-1.95)
Observations	205,694	213,141	205,844	52,216	54,099	52,103	52,216	54,099	52,103
R^2	.041	.041	.041	.093	.103	.093	.114	.125	.120

C. Using all initial-day news or the very first news in a news cluster

	Using only the initial day of all news clusters			Using only the very first news of all news clusters		
	Abt at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2,-1]	0	[1,2]
Neg_net	-0.039	-0.128***	-0.069	-0.023	-0.053**	0.002
	(-0.91)	(-4.12)	(-1.56)	(-0.57)	(-1.98)	(0.06)
Observations	258,658	268,028	258,706	258,658	268,028	258,706
R^2	.039	.039	.039	.038	.038	.038

D. Alternative news-clustering schemes

	Clustering of consecutive news that are within 3 days apart			Clustering of consecutive news that are within 5 days apart		
	Abt at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2,-1]	0	[1,2]
Neg_net	-0.054	-0.095***	-0.053	-0.070	-0.089**	-0.028
	(-1.00)	(-2.61)	(-1.03)	(-1.19)	(-2.16)	(-0.49)
Observations	204,250	213,615	204,006	169,825	178,573	169,610
R^2	.040	.042	.039	.041	.044	.040

E. Press- versus firm-initiated news

	Press-initiated news			Firm-initiated news		
	Abt at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2,-1]	0	[1,2]
Neg_net	0.005	-0.090**	-0.032	-0.112	-0.111***	-0.044
	(0.08)	(-2.09)	(-0.50)	(-1.22)	(-2.70)	(-0.76)
Observations	130,503	135,221	130,414	140,017	144,980	139,893
R^2	.053	.054	.054	.050	.052	.051

F. Dow-Jones or Reuters news only

	Dow Jones news only			Reuters news only		
	Abt at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2, -1]	0	[1, 2]
Neg_net	0.025	-0.122**	-0.104	-0.001	-0.219	-0.237
	(0.31)	(-2.17)	(-1.27)	(-0.00)	(-1.61)	(-1.12)
Observations	74,473	77,023	74,392	12,133	12,513	12,138
R^2	.075	.076	.075	.197	.196	.195

We partition news with alternative schemes and define news clusters accordingly. This table presents the regression results with the same specifications of Table 5. In panel A, we use daily news but without clustering of consecutive-day news. For all the other panels, news clustering approach is applied. In panel B, "Single-day news" refers to news days without adjacent firm-news days before and after, and "Consecutive-day news" refers to firm-news days with consecutive news coverage. All regressions include firm and month fixed effects, with results for the control variables omitted for brevity. *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

Table 7
Institutional heterogeneity and news trading

A. Known institutional types

	Plan sponsors			Mutual funds			82 hedge funds		
	Abt at day(s)			*Abt* at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	0.021	-0.032**	0.003	-0.038	-0.071**	-0.011	0.392	-0.194	0.008
	(1.01)	(-2.26)	(0.16)	(-0.85)	(-2.24)	(-0.25)	(0.90)	(-0.41)	(0.02)
Observations	223,426	210,370	223,166	248,829	249,722	248,385	22,936	16,927	22,407
R^2	.095	.090	.096	.040	.040	.038	.110	.136	.123

B. Estimated institutional types based on execution quality (per Henry and Koski 2017)

	Less-skilled institutions			More-skilled institutions		
	Abt at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	-0.042	-0.057**	-0.033**	0.033	-0.001	0.013
	(-1.49)	(-2.35)	(-2.07)	(0.67)	(-0.08)	(0.45)
Observations	191,512	167,171	190,106	187,380	165,274	186,296
R^2	.088	.091	.090	.080	.081	.077

C. Estimated institutional types based on trading frequency

	Least-active traders			Median-active traders			Most-active traders		
	Abt at day(s)			*Abt* at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
Neg_net	-0.001	-0.021	0.003	-0.016	-0.040***	-0.009	0.003	-0.041	0.006
	(-0.03)	(-1.17)	(0.14)	(-0.87)	(-3.03)	(-0.48)	(0.08)	(-1.35)	(0.14)
Observations	64,629	50,982	64,386	154,950	132,172	154,414	253,933	258,940	253,526
R^2	.159	.174	.158	.127	.136	.127	.040	.039	.039

Each panel below presents coefficients of *Neg_net* using the baseline regression specification of Table 5 for different types of institutions. We calculate *Abt* for each type of institutions and run separate regressions. Results on all control variables are suppressed for brevity. In panel A, the 82 hedge funds list is provided by Jame (2018). In panel B, skilled institutions are defined per Hu (2009) and Henry and Koski (2017). In panel C, trading frequency refers to the number of trades by the institution in the previous year. All regressions include firm and month fixed effects, with results for the control variables omitted for brevity. *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses. *p < .1; **p < .05; ***p < .01.

Table 8
Robustness of institutional trading on news tone

A. Alternative news tone measures

	Using negative-word ratio *Neg*			*Neg_net* based on forward-looking statements			Standardized *Neg_net*		
	Abt at day(s)			*Abt* at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
News tone	-0.118	-0.199***	-0.095	-0.033	-0.115**	-0.017	-0.000	-0.002***	-0.001
	(-1.44)	(-3.96)	(-1.38)	(-0.49)	(-2.72)	(-0.29)	(-0.86)	(-4.50)	(-1.40)

B. Degree of news negativity and trading

	Positive news			Neutral news			Negative news		
	Abt at day(s)			*Abt* at day(s)			*Abt* at day(s)		
	[-2, -1]	0	[1, 2]	[-2, -1]	0	[1, 2]	[-2, -1]	0	[1, 2]
Neg_net	0.058	0.024	-0.120	0.162	-0.139**	0.265	-0.093	-0.181***	-0.121
	(0.36)	(0.24)	(-0.73)	(0.39)	(-1.98)	(0.60)	(-1.18)	(-2.89)	(-1.39)

C. Further removing news [-3, 3] days around M&A announcements

	Neg_net as news tone measure		
	Abt at day(s)		
	[-2,-1]	0	[1,2]
Neg_net	-0.037	-0.096***	-0.034
	(-0.79)	(-3.02)	(-0.72)

D. Controlling for partial day in news-trading time alignment

	Neg_net as news tone measure		
	Abt at day(s)		
	[-2,-1]	0	[1,2]
Neg_net	-0.038	-0.102***	-0.044
	(-0.84)	(-3.21)	(-0.95)
Intraday trading minutes after news	-0.001	0.001	-0.001
	(-1.36)	(1.11)	(-0.89)

E. Trading on more informative news content

	Neg_net as news tone measure			*Neg* as news tone measure		
	Abt at day(s)			*Abt* at day(s)		
	[-2,-1]	0	[1,2]	[-2,-1]	0	[1,2]
News tone	-0.023	-0.027	-0.017	-0.104	-0.108***	-0.081
	(-0.47)	(-0.85)	(-0.34)	(-1.33)	(-3.51)	(-1.32)
ContentDummy	-0.003*	-0.005***	-0.001	-0.002	-0.001	-0.000
	(-1.83)	(-4.81)	(-0.53)	(-1.09)	(-1.13)	(-0.11)
News tone×*ContentDummy*	-0.047	-0.322***	-0.115	-0.040	-0.361**	-0.053
	(-0.50)	(-4.28)	(-1.15)	(-0.29)	(-2.27)	(-0.28)

F. News intensity and trading

	Intensive news					Intensive & multiple-day news				
	Abt at day(s)					*Abt* at day(s)				
	[-5, -3]	[-2, -1]	0	[1, 2]	[3, 5]	[-5, -3]	[-2, -1]	0	[1, 2]	[3, 5]
Neg_net	-0.111	-0.466***	-0.602***	-0.323**	-0.287	-0.220	-0.575**	-0.812***	-0.279	0.036
	(-0.55)	(-2.98)	(-4.55)	(-2.03)	(-1.45)	(-0.59)	(-1.97)	(-3.67)	(-1.02)	(0.10)
Observations	21,850	21,719	22,311	21,764	21,827	7,429	7,405	7,628	7,396	7,419
R^2	.137	.143	.171	.162	.150	.203	.214	.253	.212	.205

Working from the baseline regression specification of Table 5, this table presents various robustness checks. In each panel, we alter one dimension of the baseline regression, and run the full-model specification of Table 5. In panel B, we partition the news sample into positive, neutral, and negative news based on the tercile values of *Neg_net*. In panel D, we add the additional control variable of the logarithm of intraday trading minutes after news. In panel E, *ContentDummy* is a dummy variable that equals one if the news article contains either the word stem “earn” or key words related to M&A at least once. In panel F, we run the baseline regression of Table 5 for intensive news (with results of the control variables omitted for brevity), where intensive news is defined as new clusters that have at least three news articles on the first news day of the cluster. Results of all control variables are suppressed for brevity. *t*-statistics are two-way cluster-adjusted at the firm and news-date levels, and are in parentheses. *p < .1; **p < .05; ***p < .01.

Table 9
Trading precedence over news

Dependent variable: *Neg_net* of day 0						
	Nonclustered news			Clustered news		
	Full sample	Single-day news	Consecutive-day news	Full sample	Single-day news	Consecutive-day news
	(1)	(2)	(3)	(4)	(5)	(6)
Abt[-1]	-0.043***	0.013	-0.093***	-0.010	0.000	-0.030
	(-2.96)	(0.72)	(-4.32)	(-0.66)	(0.01)	(-1.14)
lnme	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.91)	(5.55)	(4.69)	(6.49)	(5.74)	(5.33)
age	-0.001***	-0.001***	-0.001***	0.001**	0.001**	0.001
	(-4.38)	(-4.70)	(-2.99)	(2.06)	(2.04)	(1.50)
dy	-0.001	-0.007	0.005	0.019***	0.014*	0.027***
	(-0.18)	(-0.89)	(0.46)	(2.60)	(1.80)	(2.98)
bm	0.575***	0.595***	0.486***	0.759***	0.760***	0.647***
	(4.48)	(4.74)	(2.84)	(5.95)	(5.43)	(3.92)
prc	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-9.58)	(-8.87)	(-7.86)	(-8.30)	(-7.52)	(-6.91)
turnover	0.079***	0.066***	0.085***	0.053***	0.048***	0.060***
	(8.40)	(6.92)	(7.24)	(6.17)	(4.94)	(5.84)
volatility	0.005	0.002	0.008	0.039***	0.034***	0.049***
	(1.24)	(0.41)	(1.63)	(9.69)	(7.61)	(9.33)
sp	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000
	(-0.90)	(-0.32)	(-0.99)	(-0.46)	(-0.19)	(-0.62)
ff4abret[-27, -6]	-0.003***	-0.003***	-0.004***	-0.002***	-0.002***	-0.002***
	(-13.60)	(-10.01)	(-10.31)	(-9.74)	(-7.54)	(-7.18)
ff4abret[-252, -28]	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-11.18)	(-9.20)	(-9.25)	(-7.03)	(-6.14)	(-5.39)
log_media	-0.001***	-0.001***	-0.001***	-0.000	-0.000	-0.000
	(-7.65)	(-8.37)	(-5.78)	(-1.21)	(-1.00)	(-1.45)
multiple_dummy	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(39.33)	(36.10)	(30.06)	(41.24)	(36.11)	(29.05)
Observations	379,101	198,116	180,402	246,177	156,092	89,405
R^2	.196	.196	.216	.229	.224	.272

This table reports the regression results of *Neg_net* on *Abt* of day [-1], following Hendershott et al. (2015). In the left panel ("nonclustered news"), we use the sample of all individual news days without news clustering; whereas in the right panel ("clustered news"), individual news days are clustered as in Table 5. "Single-day news" refers to news days without adjacent firm-news days before and after, and "Consecutive-day news" refers to firm-news days with consecutive news coverage. The "clustered news" sample also requires that the news day is accompanied by contemporaneous institutional trading, and, hence, the sample size of single-day news is smaller than its counterpart in "Nonclustered news." All regressions include firm and month fixed effects. *t*-statistics are two-way cluster-adjusted at the firm and news-date levels and are in parentheses. **p* < .1; ***p* < .05; ****p* < .01.

Table 10
Trading 3 hours before and 3 hours after the news announcement

	Neg_net quintile					Difference	
15-min bin	1	2	3	4	5	5-1	*t*-stat.
-12	-0.0028	-0.0033	-0.0029	-0.0035	-0.0031	-0.0003	(-0.18)
-11	-0.0029	-0.0035	-0.0044	-0.0037	-0.0059	-0.0030	(-1.55)
-10	-0.0005	-0.0011	-0.0010	-0.0018	-0.0029	-0.0024	(-1.23)
-9	-0.0005	-0.0027	-0.0033	-0.0042	-0.0029	-0.0024	(-1.44)
-8	-0.0016	-0.0027	-0.0036	-0.0034	-0.0046	-0.0030	(-1.44)
-7	-0.0015	-0.0034	-0.0037	-0.0034	-0.0033	-0.0018	(-0.98)
-6	-0.0009	-0.0021	-0.0014	-0.0033	-0.0034	-0.0025	(-1.43)
-5	-0.0002	-0.0011	-0.0028	-0.0031	-0.0010	-0.0008	(-0.48)
-4	-0.0005	-0.0014	-0.0023	-0.0012	-0.0017	-0.0011	(-0.53)
-3	-0.0010	-0.0022	-0.0036	-0.0023	-0.0024	-0.0015	(-0.81)
-2	0.0006	-0.0027	-0.0036	-0.0032	-0.0022	-0.0048	(-1.50)
-1	-0.0011	-0.0026	-0.0023	-0.0034	-0.0020	-0.0008	(-0.40)
0	**-0.0117**	**-0.0213**	**-0.0260**	**-0.0292**	**-0.0262**	**-0.0145**	**(-3.30)**
1	**-0.0093**	**-0.0120**	**-0.0169**	**-0.0204**	**-0.0183**	**-0.009**	**(-2.05)**
2	-0.0028	-0.0038	-0.0043	-0.0086	-0.0061	-0.0033	(-1.14)
3	-0.0022	-0.0022	-0.0012	-0.0070	-0.0056	-0.0034	(-1.36)
4	-0.0006	-0.0043	-0.0064	-0.0069	-0.0054	-0.0048*	(-1.73)
5	-0.0003	-0.0012	-0.0045	-0.0031	-0.0024	-0.0020	(-0.81)
6	-0.0007	-0.0049	-0.0050	-0.0038	-0.0037	-0.0030	(-1.34)
7	-0.0018	-0.0016	-0.0050	-0.0014	-0.0035	-0.0017	(-0.74)
8	-0.0006	-0.0032	-0.0019	-0.0031	-0.0027	-0.0020	(-0.91)
9	-0.0039	-0.0038	-0.0056	-0.0082	-0.0071	-0.0032	(-1.10)
10	0.0004	-0.0023	-0.0035	-0.0043	-0.0026	-0.0030	(-1.55)
11	-0.0028	-0.0042	-0.0027	-0.0039	-0.0043	-0.0015	(-0.80)

This table shows the level of *Abt* grouped by *Neg_net* quintile 3 hours before and 3 hours after the news announcement using order placement time. We drop all 9:30 and 16:00 hours trades. Each time bin represents 15 minutes, with bin 0 representing minutes (0, 15]. *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses.

Table 11
News tone, institutional trading, and return prediction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DGTW return over							
	[1]	[1, 5]	[1, 10]	[1, 20]	[1]	[1, 5]	[1, 10]	[1, 20]
Neg_net	-2.077***	-1.344***	-0.991***	-0.723***	-2.081***	-1.376***	-1.008***	-0.738***
	(-5.19)	(-6.68)	(-5.58)	(-4.91)	(-5.07)	(-6.69)	(-5.59)	(-4.97)
Abt[0]					0.106***	0.042**	0.031**	0.009
					(3.00)	(2.35)	(2.04)	(0.69)
ff4abret[0]	-1.193***	-0.473***	-0.397***	-0.289***	-1.267***	-0.487***	-0.400***	-0.277***
	(-4.63)	(-3.89)	(-3.90)	(-3.73)	(-4.88)	(-3.97)	(-3.90)	(-3.57)
ff4abret[-1]	-1.561***	-0.925***	-0.706***	-0.550***	-1.691***	-0.932***	-0.706***	-0.560***
	(-5.01)	(-6.02)	(-5.22)	(-5.15)	(-5.37)	(-5.91)	(-5.13)	(-5.17)
ff4abret[-2]	-0.970***	-0.723***	-0.542***	-0.354***	-0.953***	-0.693***	-0.511***	-0.331***
	(-3.45)	(-4.95)	(-4.43)	(-3.62)	(-3.36)	(-4.63)	(-4.08)	(-3.31)
ff4abret[-30,-3]	-0.197***	-0.185***	-0.155***	-0.146***	-0.193***	-0.188***	-0.156***	-0.146***
	(-3.69)	(-6.44)	(-6.28)	(-7.14)	(-3.59)	(-6.48)	(-6.25)	(-7.04)
ff4abret[-252,-31]	0.025	0.012	0.014	0.004	0.021	0.010	0.013	0.003
	(1.27)	(1.11)	(1.42)	(0.42)	(1.08)	(0.95)	(1.32)	(0.37)
lnme	-0.093***	-0.091***	-0.092***	-0.090***	-0.088***	-0.089***	-0.091***	-0.089***
	(-4.92)	(-8.95)	(-9.86)	(-11.38)	(-4.60)	(-8.41)	(-9.51)	(-11.09)
bm	17.095	-1.389	0.780	0.693	16.323	-3.241	-0.886	1.397
	(0.78)	(-0.11)	(0.08)	(0.08)	(0.71)	(-0.25)	(-0.08)	(0.15)
sue	0.016***	0.016***	0.015***	0.014***	0.016***	0.016***	0.014***	0.014***
	(2.99)	(5.66)	(6.12)	(6.57)	(2.93)	(5.47)	(5.88)	(6.31)
turnover	-4.107***	-2.423***	-2.149***	-2.021***	-4.307***	-2.683***	-2.316***	-2.124***
	(-3.39)	(-3.85)	(-3.85)	(-4.15)	(-3.47)	(-4.15)	(-4.04)	(-4.24)
volatility	0.143	0.375	0.295	0.394	0.280	0.466	0.370	0.486
	(0.17)	(0.83)	(0.76)	(1.21)	(0.32)	(1.01)	(0.94)	(1.47)
log_media	-0.007	-0.016**	-0.016***	-0.018***	-0.008	-0.015**	-0.015***	-0.017***
	(-0.57)	(-2.57)	(-2.93)	(-3.92)	(-0.60)	(-2.38)	(-2.74)	(-3.67)
multiple_dummy	0.012	0.004	0.001	0.003	0.013	0.004	0.002	0.003
	(0.92)	(0.61)	(0.24)	(0.60)	(0.95)	(0.64)	(0.31)	(0.70)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	261,434	261,497	261,547	261,692	252,098	252,160	252,209	252,352
R^2	.033	.033	.033	.037	.033	.033	.033	.038

The dependent variables are daily DGTW characteristic-adjusted returns (in percentage), averaged over an estimation window, ranging from 1 to 20 days. *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses. *p < .1; **p < .05; ***p < .01.

Table 12
Impact of news-driven institutional trading on returns

A. Returns of contrarian trades versus reinforcing trades

	DGTW return over							
	[1]	[1, 5]	[1, 10]	[1, 20]	[1]	[1, 5]	[1, 10]	[1, 20]
	Contrarian trades (Q14)				Reinforcing trades (Q23)			
Neg_net	-0.731	-0.626**	-0.452*	-0.288	-2.675***	-1.765***	-1.304***	-1.050***
	(-1.22)	(-2.07)	(-1.71)	(-1.34)	(-4.41)	(-5.68)	(-4.83)	(-4.81)
Abt[0]	0.019	-0.022	-0.017	-0.018	0.141***	0.084***	0.066***	0.020
	(0.35)	(-0.80)	(-0.73)	(-1.02)	(2.63)	(3.15)	(2.91)	(1.10)
Observations	125,982	126,015	126,044	126,107	125,451	125,481	125,501	125,582
R^2	.057	.054	.053	.056	.054	.055	.052	.055

B. Pooling regressions of contrarian and reinforcing trades

	DGTW return over			
	[1]	[1, 5]	[1, 10]	[1, 20]
Q23_dummy×Abt[0]	0.140*	0.109***	0.084***	0.038
	(1.90)	(2.92)	(2.70)	(1.63)
Q23_dummy×Neg_net	-1.635**	-1.067***	-0.830**	-0.727***
	(-2.10)	(-2.69)	(-2.40)	(-2.58)
Neg_net	-1.010*	-0.641**	-0.439*	-0.306
	(-1.77)	(-2.26)	(-1.75)	(-1.48)
Q23_dummy	-0.016	0.000	-0.002	-0.002
	(-1.48)	(0.05)	(-0.44)	(-0.56)
Abt[0]	0.012	-0.028	-0.023	-0.020
	(0.23)	(-1.05)	(-1.01)	(-1.17)
Observations	252,098	252,160	252,209	252,352
R^2	.033	.034	.033	.038

C. Return regressions using only a quarter of trades as contrarian trades

	DGTW return over			
	[1]	[1, 5]	[1, 10]	[1, 20]
Q23_dummy×Abt[0]	0.158**	0.120***	0.090***	0.044*
	(2.12)	(3.19)	(2.86)	(1.84)
Q23_dummy×Neg_net	-1.366	-0.895*	-0.606	-0.625*
	(-1.44)	(-1.78)	(-1.40)	(-1.81)
Neg_net	-0.794	-0.502	-0.402	-0.198
	(-0.90)	(-1.12)	(-1.03)	(-0.63)
Q23_dummy	-0.028**	-0.012*	-0.011**	-0.011**
	(-2.12)	(-1.75)	(-1.97)	(-2.27)
Abt[0]	0.006	-0.032	-0.024	-0.022
	(0.11)	(-1.16)	(-1.01)	(-1.22)
R^2	.033	.034	.033	.038

The dependent variables are daily DGTW characteristic-adjusted returns, averaged over an estimation window. In panel A, "Reinforcing trades" are those trades with *Neg_net* above median and *Abt[0]* below median, or those *Neg_net* below median and *Abt[0]* above median, and "Contrarian trades" are the rest of the trades. In panel B, *Q23_dummy* is a dummy variable that equals to one if a trade belongs to reinforcing trades. In panel C, a trade is redefined as contrarian only if *Neg_net* is below median and *Abt[0]* is below quartile one (positive news but strong sell), or if *Neg_net* is above median and *Abt[0]* is above quartile three (negative news but strong buy), and *Q23_dummy* is redefined accordingly. All regressions include firm and month fixed effects. The control variables are the same as in Table 11 and are omitted for brevity. *t*-statistics are two-way cluster-adjusted at the firm and news date levels and are in parentheses. *$p < .1$; **$p < .05$; ***$p < .01$.

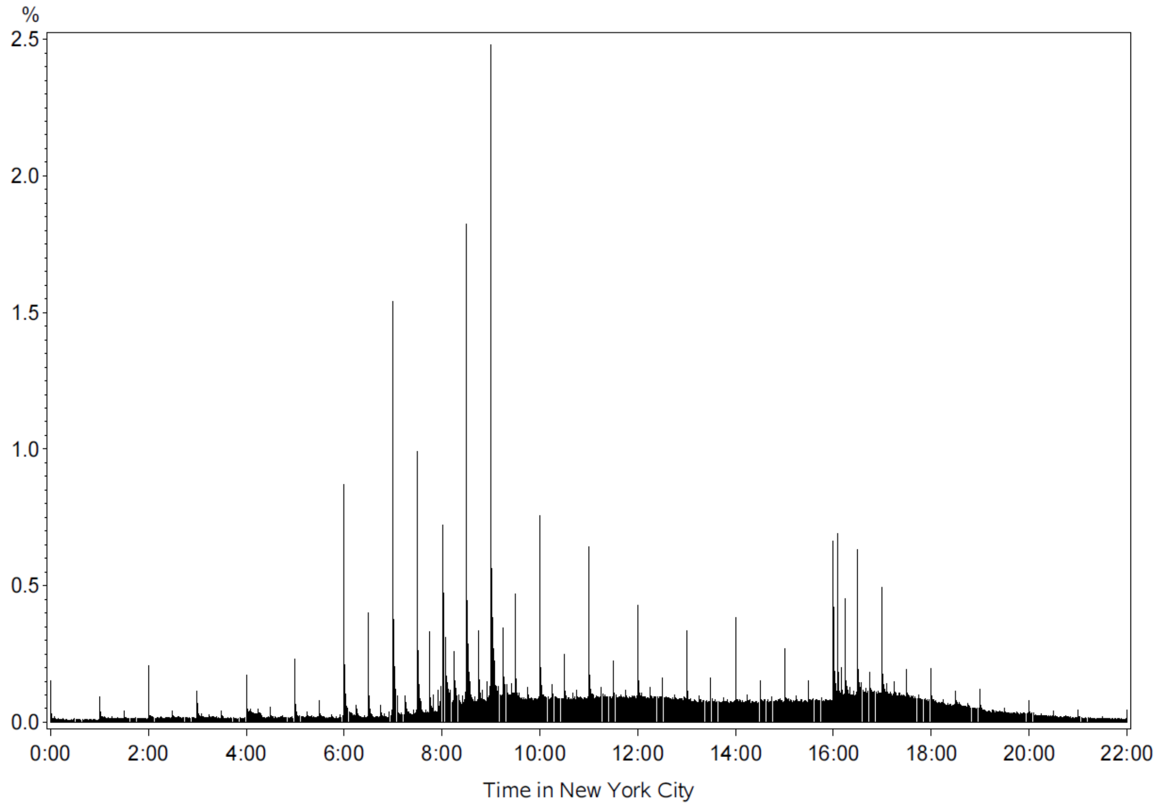
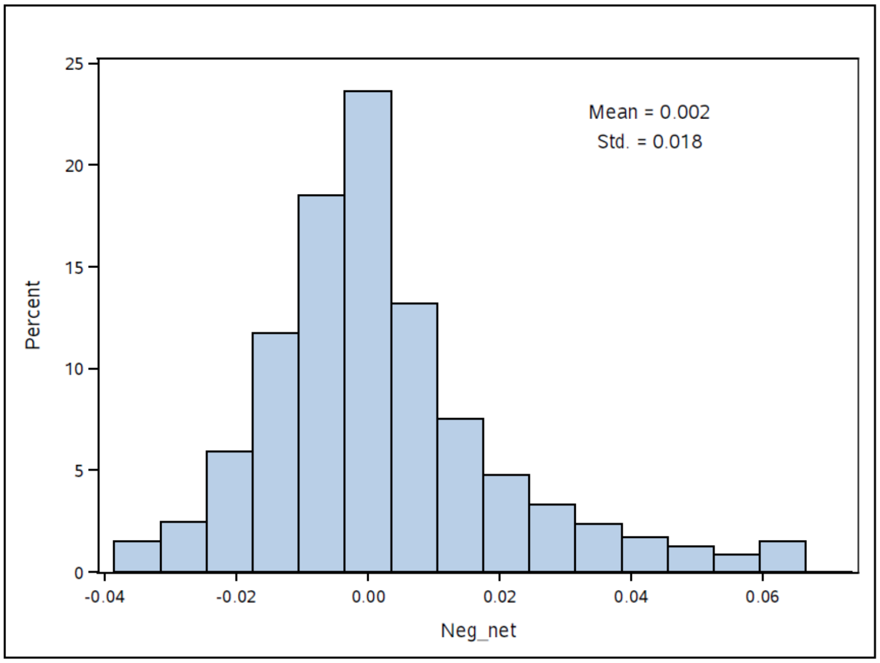
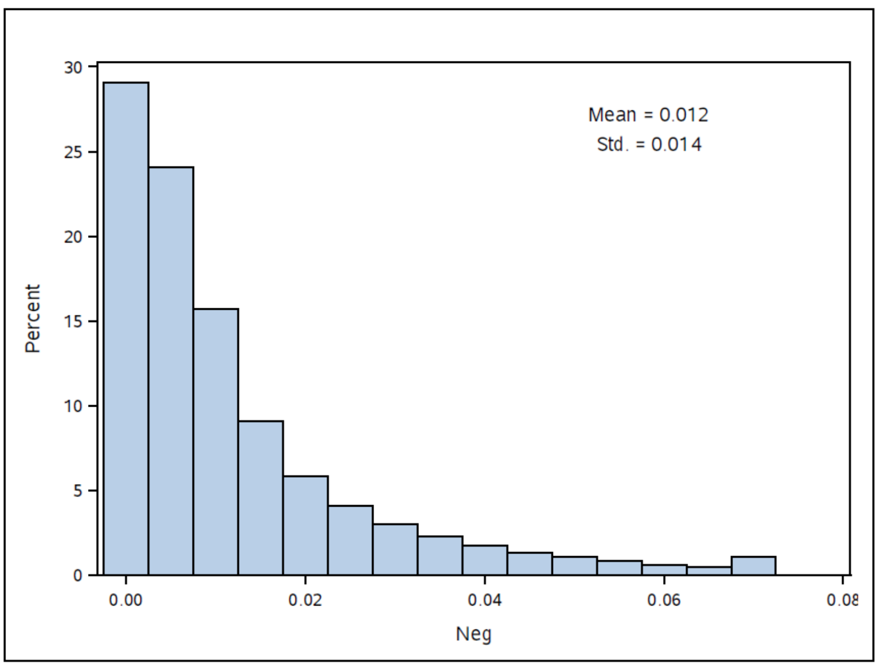


Figure 1: This figure shows the percentage histogram of the intra-day news time stamp, by minute, of the 1.19 million news articles.

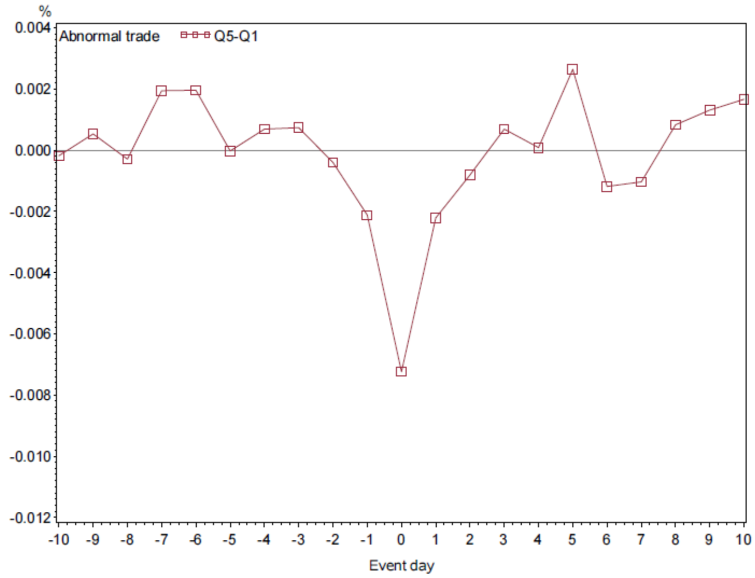


(a) Neg_net

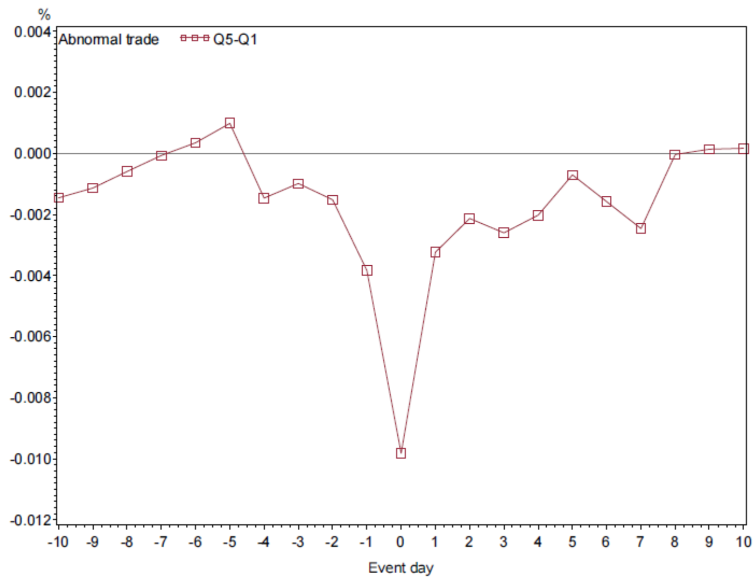


(b) Neg

Figure 2: This figure shows the percentage histogram of the variables Neg_net (Panel (a)) and Neg (Panel (b)). In Panel (b), the first bar shows that value of Neg between 0 and 0.005; the percentage of $Neg = 0$ is 23%.

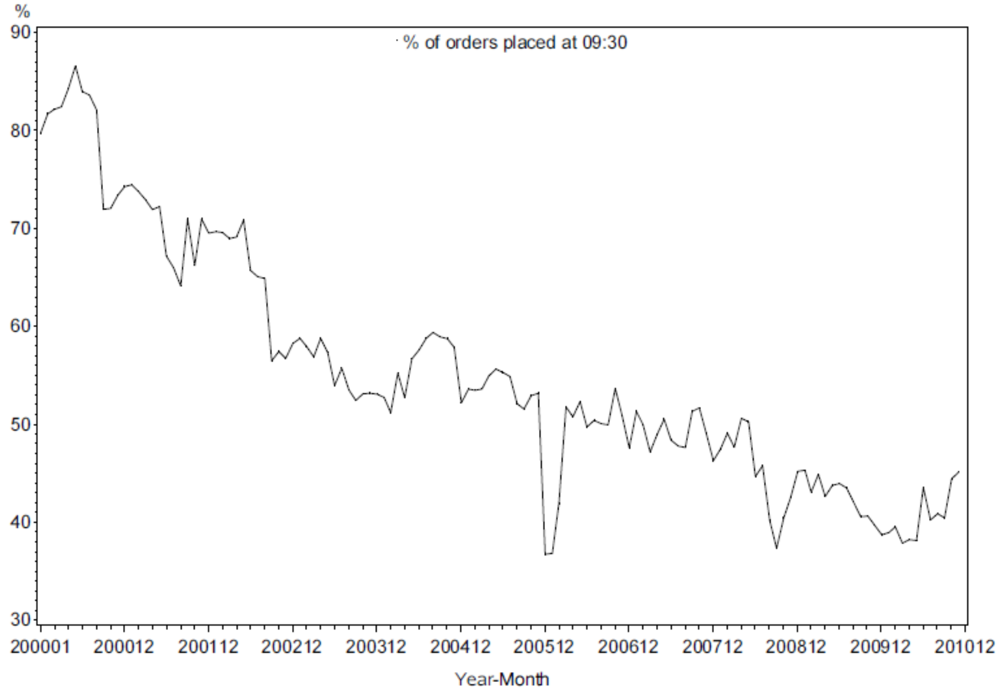


(a) Neg_net Q5–Q1 abnormal trade imbalance difference

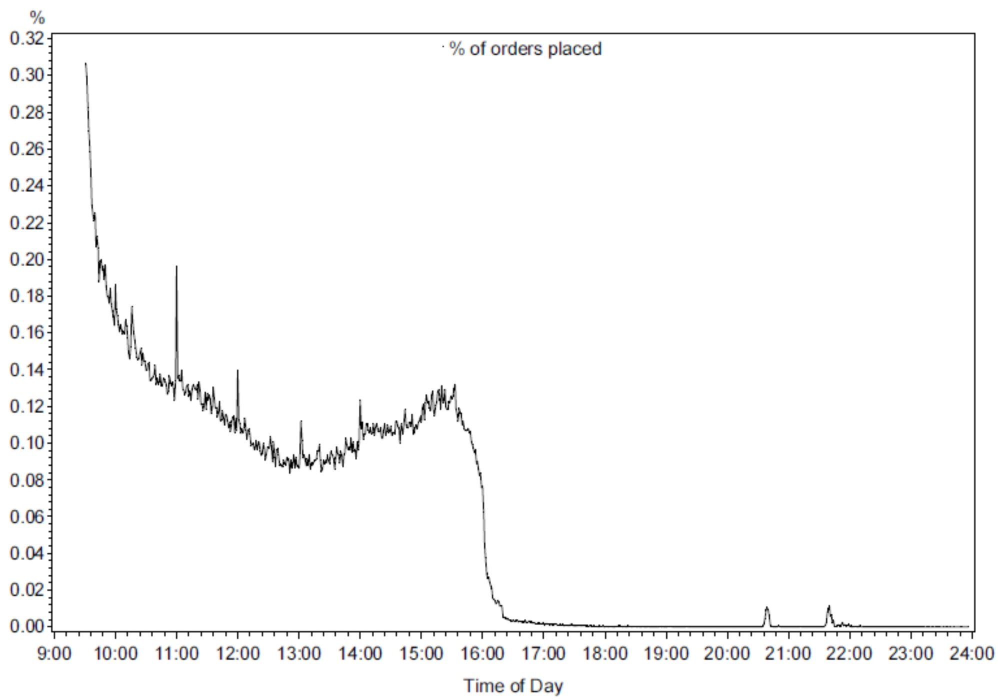


(b) Neg Q5–Q1 abnormal trade imbalance difference

Figure 3: Abnormal trade imbalance difference between news tone Quintiles 5 and 1.



(a) Percent of orders placed at 9:30, from 2000:01 to 2010:12



(b) Percent of orders placed at times other than 9:30

Figure 4: ANcerno data order placement time pattern.