Are Institutions Informed About News?[*]

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Abstract

This paper combines daily non-public data on buy and sell volume by institutions from 2003 through 2005 for NYSE-listed stocks with all news announcements from Reuters. Natural language processing categorizes the sentiment associated with each news story. We use institutional order flow (buy volume minus sell volume) as a quantitative measure of net trading by institutions. We find evidence that institutional investors are informed: i) institutional trading volume predicts the occurrence of news announcements; ii) institutional order flow predicts the sentiment of the news; iii) institutional order flow predicts the stock market reaction on news announcement days; and iv) institutional order flow predicts earnings announcement surprises.

Introduction

Institutional trading is important because it constitutes the majority of daily trading volume and institutional investors are the largest owner of publicly traded stocks in the U.S.[1] It has been argued that institutional trading is, to a large extent, driven by superior information gathering and processing skills. Superior information by institutions could arise from access to more information and greater resources to process information.[2]

This paper combines daily non-public data on buy and sell volume by institutions from 2003 through 2005 for 1,700 NYSE-listed stocks with all news announcements from Reuters. Natural language processing categorizes the sentiment associated with each news story. We use institutional order flow (buy volume minus sell volume) as a quantitative measure of net trading by institutions. There is some evidence that institutional investors are informed, but studies examining institutional order flow around specific events provide mixed evidence. Using a comprehensive data set of institutional trading and news announcements we find that institutional trading predicts news announcements, the sentiment of the news, returns on the announcement day, and earnings announcement surprises.

To initially examine the question of whether institutions are informed about the news Section 2 examines institutional trading volume around news announcements. Event-study methodology shows that institutional trading volume increases a few days before new announcements. Calendar-time probit regressions show that institutional trading volume predicts whether or not a news announcement will occur after controlling for prior stock volatility and prior news announcements. This is consistent with institutions being informed about whether or not news announcements will occur, but does not establish that institutions are informed about the content of the news itself.

Section 3 analyzes whether institutions are informed about the contents of the news. We measure institutions' forecast of future informational arrival with their order flow (buy volume minus sell volume). Natural language processing measures the contents of the news itself. We also use stock market reaction on news days as a signal of the information contained in the news announcements. Event-study methodology shows that institutional order flow increases more than five days prior to the announcement of good news as measured by the natural language sentiment of the news; institutional order flow decreases more than five days prior to bad news announcements. Regressions show that institutional order flow predicts the sentiment of news announcements and the stock

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[1] See, for example, Boehmer and Kelly (2009) and Securities Industry Association Fact Book (2007).

[2] Unlike retail investors, institutions often directly communicate with publicly traded firms as well as brokerage firms through their investment banking, lending, and asset management divisions. Most mutual and hedge funds employ buy-side analysts and enjoy better relationship with sell-side analysts. Their economies of scale allow institutions to monitor many sources of information. Finally, institutions employ professionals and technologies with superior information processing skills.

return on announcement days after controlling for prior stock returns, news sentiment, and trading volume. Vector autoregressions which control for longer and more complex dynamics confirm these results. Finally, Section 4 shows that institutional order flow predicts the surprise component of earnings announcements.

Several studies provide support to the notion that institutions are informed. Badrinath, Kale, and Noe (1995) show that returns of stocks with high institutional ownership lead returns of stocks with low institutional ownership. Sias and Starks (1997) and Boehmer and Kelly (2009) show that higher institutional holdings are associated with more efficient pricing. Boehmer and Wu (2008) and Boulatov, Hendershott, and Livdan (2011) find that institutional trading predicts returns at the firm, industry, and market levels. Irvine, Lipson, and Puckett (2007) find a significant increase in institutional trading and profitable buying beginning five days prior to the public release of analysts' initial reports containing positive recommendations.[3]

In contrast, studies of institutional trading around specific public news events such as takeovers, earnings announcements, and research recommendations find little or no evidence that institutions are informed. Griffin, Shu, and Topaloglu (2011) use Nasdaq broker identifiers on trades and clearing records to categorize trades likely made by institutions from 1997-2002. They examine daily trading by eight types of individual and institutional investors ahead of the most common stock market events associated with information asymmetry: takeover and earnings announcements. They find that in the two, five, and ten days prior to takeover announcements, general institutional investors are not net buyers in target firms and their buying is not related to future earnings announcement returns. They do report that hedge funds and investors trading through the largest investment banks that service hedge funds are consistently selling stocks prior to negative earnings announcements. Finally, they find little evidence that brokerage houses' proprietary trading desks or their clients buy prior to takeovers or trade in the right direction prior to earnings announcements.

Jegadeesh and Tang (2010) analyze trading patterns and profitability of institutional trades around takeover announcements using Abel-Noser's institutional client trade data from 1998-2008. They report that institutions on average are marginally net sellers of the targets in the month prior to takeover announcements and that their trading strategy around the announcement does not yield significant abnormal returns. However, they do find that institutions whose main brokers are also the brokerage arms of investment banks advising the targets are significant net buyers of target shares prior to announcements. Using the same data, Busse, Green, and Jegadeesh (2010) examine the performance of buy-side institutional investor trades around sell-side analyst

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[3]Campbell, Ramadorai, and Schwartz (2009) infer institutional trading by linking quarterly changes in institutional holding from 13-F filings with daily trades by size category and a buy-sell classification algorithm. Their measure of institutional trading predicts firms' earnings surprises.

stock recommendations. They find that institutions are not able to differentiate between good recommendations and bad recommendations.

Finally, our paper relates to a growing literature on how different market participants respond to public news. Tetlock (2010) tests a theoretical model with asymmetric information and public news. He finds evidence that news resolve asymmetric information: There is positive impact of news on volume-induced return momentum and a temporary increase in the correlation between absolute returns and volume during news, particularly for earnings news and in small and illiquid stocks.

A separate strand of literature studies whether specific types of institutions such as mutual funds have stock-picking skills prior to public news events.[4] Baker et. al. (2011) examines the earnings announcement returns of stocks that mutual funds hold and trade. They find that the future earnings announcement returns on stocks that funds buy are, on average, higher than the future returns on stocks that they sell. The stocks that funds buy perform significantly better at future earnings announcements than stocks with similar characteristics, while the stocks that funds sell perform significantly worse than such stocks. Fund trades predict not just earnings announcement returns but EPS surprises as well. Fang, Peress, and Zheng (2011) examine the propensity by mutual funds to trade high media coverage stocks. They find that funds with a lower propensity to trade media stocks perform significantly better. This finding is robust to different risk adjustment models and prevails after controlling for other fund characteristics. Their result is consistent with the hypothesis (see Kacperczyk and Seru (2007)) that funds with informational advantage trade less in stocks with media coverage.

Several papers examine the relationship between individual trading and news announcements. Kaniel, Saar, and Titman (2010) provide evidence in support of informed trading showing that intense aggregate individual investor buying (selling) predicts large positive (negative) abnormal returns on and after earnings announcement dates. Kelley and Tetlock (2011) use retail brokers' trading data from 2003-2007 to provide support for the conclusions of Kaniel, Saar, and Titman (2010) that retail investors have some information for a broader set of news announcements. Kelley and Tetlock (2011) can separately identify market and limit orders and find that market order imbalances predict both returns and news, whereas limit order imbalances predict returns but not news.

Short selling is another type of trading thought to be informed (Senchack and Starks (1993), Asquith, Pathak and Ritter (2005), Boehmer, Jones, and Zhang (2008), and others)). Engelberg, Reed, and Ringgelberg (2010) combine data on short selling with news releases and show that short

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[4]Mutual fund data has the advantage of identifying individual funds and managers, but only does so at monthly horizons. The institutional trading literature combines trading across many institutions at higher frequencies.

sellers' trading advantage comes largely from their ability to analyze publicly available information. They find only weak evidence that short sellers anticipate news events. When they do find differences between the timing of short sellers' trades and the overall market they find that short selling tends to occur after news stories and more strongly after earnings news. They conclude that, on average, short sellers trade on publicly available information and do not anticipate information before it becomes public.

The remainder is organized as follows. Section 1 discusses the data sources and provides summary statistics. Section 2 examines institutional trading volume around news announcements. Section 3 analyzes whether institutions are informed about the contents of the news. Section 4 shows that institutional order flow predicts the surprise component of earnings announcements. Section 5 concludes.

1 Data

The data on trading by institutions is constructed from the NYSE's Consolidated Equity Audit Trail Data (CAUD) files that contain detailed information on all orders that execute on the exchange, both electronic and manual (those handled by floor brokers). One of the fields associated with the buyer and seller of each order, Account Type, specifies whether the order comes from an institutional investor. We exclude program trading and index arbitrage trading because these order types are for trading multiple securities simultaneously which are less likely related to news about individual stocks. A sample of the CAUD data was first provided to academics as part of the TORQ dataset constructed by Joel Hasbrouck. We complement the CAUD data with daily data on returns (close-to-close returns based on closing bid and ask quotes in TAQ), trading volume (CRSP), and market capitalization (number of shares outstanding times price from CRSP).

Our news data comes from the Reuters NewsScope Sentiment Engine (RNSE), which is a database of news releases on the Reuters Data Feed (RDF). For each news story RNSE reports time stamped computer generated measures for news sentiment and relevance. Each news story on the RDF typically consists of several news items. Table 1 provides an overview of the different news topics covered by the RDF ordered in descending order based on the total number of news items reported in the last column. All news stories are assigned to news categories describing the topic of the news content. The most frequent news releases are directly related to companies and concern corporate results (RES) with a total of $213,781$ news items, corporate results forecasts (RESF, $153,928$), major breaking news (NEWS, $112,740$), debt markets (DBT, $97,910$), stock markets (STX, $96,399$), mergers and acquisitions (MRG, $93,674$), corporate bonds (USC, $74,030$), hot

stocks (HOT, $39,769$), business activities (BACT, $36,754$), corporate analysis (CORA, $34,270$), new issues (ISU, $29,463$), broker research and recommendations (RCH, $27,364$), ratings (AAA, $22,868$), and management issues and policy (MNGISS, $18,689$). The remaining news releases constitute macroeconomic announcements, government policies and politics, society, environment, and other financial market news. Each day we average the sentiment for each story and then construct a daily weighted average of sentiment across stories using the relevance measure as weights.[5]

[insert Table 1]

We construct our sample by merging the CRSP, RNSE, and NYSE data from 2003 through 2005 and dropping a small number of observations (0.51%) for which some data is missing from one of the sources. We obtain a total of 756 trading days in $1,667$ stocks, yielding more than 1.1 million daily observations with complete data on stock return, volume, news, and institutional trading. Table 2, Panel A provides summary statistics for the number of news releases and the distribution of news stories across time and stocks. There are a total of $126,438$ days with news releases out of $1,101,788$ daily observations during our sample period. This implies 11.5% of stocks have news releases on any given day, with 24% of stocks in the news at the upper 1% tail of days. Consistent with prior papers using news data there is substantial cross-sectional variation in news coverage. The average firm has a 10.7% chance of being covered in a news report. While the median firm has a propensity of news coverage of once per month (4.6%), news coverage ranges from zero for the bottom 1% of firms to 88.6% for the top 1% of firms.

The news sentiment measure used in this study is based on the analysis of the NewsScope news text released on the RDF. The Reuters algorithm determines how positive, neutral, or negative is the tone of the words used in the article and then puts it in the context by analyzing sentence structure, the proximity of particular words to one another, and other linguistics cues. Individual sentiment scores yield the positive, neutral, or negative sentiment score for the news item, ranging between -1 and 1. News items read from the RDF are also scored with respect to companies that are mentioned in the article to yield company-specific measures of relevance.

We compute the net sentiment of a news story as the relevance-weighted difference between the positive and negative score for each news item, ranging from -1 to 1. We then aggregate all news stories on a given day by relevance weighting the story-specific sentiment to obtain the daily sentiment in each stock. The net sentiment is set to zero on days without news stories. The last row in Table 2, Panel A provides summary statistics for daily sentiment. Sentiment ranges between -0.763 and 0.814 with mean and median close to zero and sizeable standard deviation of 0.419.

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[5]News items are either a new alert or new story take, where an alert is a single line of text and a story take has a headline and body. A story take is one in a series of updates to a particular story.

We calculate institutional purchases, $\text{IBuys}_{i,t}$, and sales, $\text{ISales}_{i,t}$, by aggregating all institutional buy and, correspondingly, sell orders for a firm i on day t and then normalizing these quantities by the firm's i market capitalization, MC, lagged by one year, i.e. we have

$$\text{IBuys}_{i,t} = \frac{\sum_{n=1}^{\# \text{ of Buys}_{i,t}} \text{Buys}_{i,t}^n}{\text{MC}_{i,t-250}}, \tag{1}$$

$$\text{ISales}_{i,t} = \frac{\sum_{n=1}^{\# \text{ of Sales}_{i,t}} \text{Sales}_{i,t}^n}{\text{MC}_{i,t-250}}.$$

We then define the institutional order flow, IOF, as the difference between institutional purchases, IBuys, and institutional sales, ISales. Institutional volume, IVol, is the sum of institutional purchases and sales.

[insert Table 2]

Table 2, Panel B provides summary statistics for the institutional trading volume and order flow imbalances across stocks in our sample. Institutional order flow imbalances are positive on average, consistent with the steady decline in direct individual stock ownership over time. Institutional order flow imbalances are distributed symmetrically about this mean, with significant negative left and positive right tail. This shows that despite the positive trend there are many days when institutions are net sellers and about the same portion of days when they are net buyers. Institutional order imbalances are small compared to overall institutional trading activity. On a typical day, roughly 83% of trading by institutions is among the institutions and only 15.5% of institutional volume is net purchases or sales from other investor groups, such as retail investors, market makers, and institutions trading baskets of stocks. Panel C of Table 2 reports summary statistics for stock returns and market-wide trading volume.

2 Institutional trading around news releases

First we test whether institutions adjust their overall trading ahead of future public news announcements and whether institutional trading predicts news announcements. Figure 1 graphically demonstrates this relation by plotting results from an event study. Panel A depicts institutional trading volume, IVol, in the $[-10, 10]$ window around the news announcement. Dashed lines represent standard errors adjusted for heteroskedasticity, contemporaneous correlation across stocks, and autocorrelation within stock (Petersen (2009)).

Institutional trading volume rises sharply before the news announcement day and declines sharply after the news has become public. These are consistent with the hypothesis that institutions are privately informed about future public news. An alternative story is that the rise in institutional trading leads to higher return volatility which in turn gets noticed by the news agencies which respond with news articles. Or simply put, news agencies track actively traded and volatile stocks and write news stories about them. We examine this hypothesis in Panel B of Figure 1 by plotting the absolute stock returns, |Return|, which proxy for return volatility, over ten days before and ten days after news announcements. As in the case of institutional trading volume, return volatility rises sharply before the announcement and then sharply declines after it. Next we study the joint relations among news announcements, institutional trading, and |Return| to analyze if institutional volume predicts news announcements over and above volatility.

[insert Figure 1]

Table 3 presents estimates from panel logit regressions with the dependent variable being zero or one depending on whether a news announcement involving firm i takes place on date t. Firm fixed effects are included in the specification to control for the cross-sectional heterogeneity in news announcement frequency. Column A reports the univariate regression with IVol as the explanatory variable. In agreement with the event study from Panel A of Figure 1 the regression coefficient on IVol is positive and statistically significant. Next, we use |Return| as the explanatory variable. The positive, statistically significant coefficient on |Return| in Column B of Table 3 is consistent with the event study where the return volatility increases prior to news announcements. Columns C and D of Table 3 report our results when the explanatory variables are an indicator variable for news announcements on the previous day, News day, and the absolute value of the prior news sentiment, |Sentiment|. If there are no news releases on the previous day news sentiment is set to its lagged value. Column C indicates that news announcements are persistent, i.e. clustered, as stocks previously in the news are more likely to be in the news again. However, the propensity of new news stories declines if the prior news story had more significant sentiment, as the coefficient on the lagged absolute sentiment is negative in column D. Panel E reports the results when all four variables are used together as explanatory variables. All of them remain statistically significant in the multivariate regression. Overall, our results on institutional trading volume and the occurrence of news announcements are consistent with the hypothesis that institutions have private information about future news.

[insert Table 3]

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3 Are institutions informed about public news?

While the previous section provides evidence that trading by institutions is related to future news releases, it does not establish that institutions are actually informed about contents of the news. To address this we study if institutional buying and selling predicts the sentiment of the news and the stock price reaction to the news. For institutions to be informed about the contents of the news more buying should predict news announcements with positive sentiment and positive price reactions; similarly more selling should predict negative news announcements and negative price reactions. Similar to our analysis of aggregate institutional trading volume and news in Figure 1 and Table 3 we examine event study and regression evidence.

3.1 Event-time evidence

To investigate the informativeness of institutional trading we examine whether trading predicts the announcement day abnormal return. To do so we calculate buy-and-hold abnormal stock returns ($BHAR$) for each news release per each firm. We also differentiate between different types of news by categorizing them as *Good* or *Bad* news. We define *Good* and *Bad* news as a function of the sentiment associated with the news release by dividing announcement sentiment into quintiles. *Good* are news releases associated with sentiment in the top quintile across all news announcements, Sentiment ≥ 0.374. Correspondingly, *Bad* news is when the news sentiment is in the bottom quintile, Sentiment ≤ -0.418. The results are not sensitive to the exact cutoff values. All $BHAR$'s are benchmarked against a control group of firms.

The buy-and-hold return in the $[t_0, t_1]$ window for an event-firm[6] $i \in (Good, Bad)$ is defined as:

$$BHR_i(t_0, t_1) = \prod_{t_0}^{t_1} R_{i,t},\qquad(2)$$

where $R_{i,t}$ is the gross return of firm i on date t. The mean abnormal buy-and-hold returns for good and bad news firms are:

$$BHAR(t_0, t_1) = \sum_i w_i BHR_i(t_0, t_1) - \sum_{Control} w_{Control} BHR_{Control}(t_0, t_1),\qquad(3)$$

w_i is firm i's market capitalization weight lagged by one year divided by the number of events so that $\sum_i w_i = 1$. The mean $BHAR$ is calculated as the value-weighted average of the individual event-firm BHRs benchmarked against the mean BHRs for all control firms. For simplicity, we take the value-weighted index of all firms in our sample as the control.

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[6]We account for each news event per firm.

If institutions are privately informed about news prior to the publication date, then one might not expect their trading to cause significant price run-up/run-down prior to the good/bad news. Alternatively, the sizable price movements in positive/negative direction could indicate that someone was privately informed about the news public prior to the announcement day or that past stock returns led to news and its sentiment. Similar to Figure 1 we calculate buy-and-hold abnormal returns starting at $t_0 = -10$ relative to the news release at date $t = 0$ and through the 10 trading days following the news. Panel A of Figure 2 reports our results for average buy-and-hold returns around good and bad news releases. The dotted lines correspond to 95% confidence bounds. Prices begin to drift in the direction of the news sentiment a few days before announcement day, consistent with models of private information prior to the public news announcement. The largest price run-up/run-down happens in the days immediately prior to the news announcement. This could be because informed traders, possibly institutions, start to trade more aggressively over time, as in Kyle (1985) and Back, Cao, and Willard (2000), or because traders become more informed about the news as the announcement day approaches.

Cumulative institutional order flows before an announcement provide a measure of institutional trading potentially driven by private information. Analogous to the $BHARs$ in Panel A of Figure 2, we calculate buy-and-hold institutional order flow for each firm experiencing a news release. $\text{IOF}_{i,t}$ is the institutional order flow of firm i on date t. The buy-and-hold institutional order flow in the $[t_0, t_1]$ window for an event-firm $i \in (Good, Bad)$ is defined as:

$$BHIOF_i(t_0, t_1) = \sum_{t_0}^{t_1} \text{IOF}_{i,t}. \tag{4}$$

Then similar to returns we compute the mean abnormal buy-and-hold institutional order flow for good and, respectively, bad news firms as in the case of buy-and-hold returns:

$$BHAIOF(t_0, t_1) = \sum_i w_i BHIOF_i(t_0, t_1) - \sum_{Control} w_{Control} BHIOF_{Control}(t_0, t_1). \tag{5}$$

As before we use the value-weighted index of all firms in our sample as the control.

Figure 2, Panel B summarizes the IOF results. The dotted lines correspond to 95% confidence bounds. Institutions start net buying at least two weeks before good news announcements and net selling before bad announcements. The order imbalances are largest during the last two days prior to the announcement corresponding to the larger returns on these days.

The event study in Figure 2 only considers IOF and news. However, returns, institutional trading, and sentiment are contemporaneously related in various ways. Multivariate regressions allow testing whether institutional order flow predicts announcement day returns and sentiment after controlling for the other market variables. Table 4 documents the predictability of news announcement returns (Panel A), news sentiment (Panel B), and institutional order flow on news days (Panel C). As in Table 3 estimates are from panel regressions with firm fixed effects. We examine volume, defined as the log of total trading volume, along with returns, sentiment, and institutional order flow. In addition, we split institutional order flow into its two components: institutional buys, IBuys, and sales, ISales. This decomposition helps test whether institutions are equally informed about both types of news, good and bad. All explanatory variables are measured on the day prior to the news announcement.

[insert Table 4]

Panel A of Table 4 shows that the institutional order flow imbalance and its individual components, IBuys and ISales, predict returns on news announcement days. Moreover, column F of panel A indicates that only IOF has power in predicting news announcement returns. To estimate the economic significance of this result we multiply the coefficient on the IOF, 0.632, by the standard deviation of the IOF from Table 2, 0.168, to obtain that on the news days institutions earn an average return of 10.6 basis points from trading with other investor groups. In column G IBuys and ISales are statistically significant. The positive coefficient on IBuys and negative coefficient on ISales shows that institutional buying and selling activity both predict announcement day returns.

Pane B of Table 4 shows that IOF, IBuys, and ISales predict news sentiment. A possible explanation for why IOF predicts the announcement day sentiment is that institutions communicate with the news agencies and influence the news in the direction of their past trading. This could also lead to sentiment being persistent as well as sentiment responding positively to past returns, i.e., higher returns in the past predict higher future sentiment. To find evidence consistent with institutions being privately informed Section 4 examines earnings announcements using only the announced earnings and not sentiment.

Panel C of Table 4 shows persistence in IOF as well as its individual components. It also indicates that institutions follow momentum strategies around news announcements as institutions increase purchases of past winners and sell more of past losers.

Overall we find that institutions trade in the right direction before a news announcement. IOF and IBuys predict positive announcement returns, positive sentiment, and more institutional buying

on news days. ISales predicts negative announcement returns, negative sentiment, and more selling on news days.

Since institutions tend to hold large market cap firms which also are in the news more often, one may have a concern that our results are driven by large firms. As a robustness check we sort all firms into three size terciles and then perform the same analysis within each size tercile as reported in Table 4. Table IA.1 reports our results. Panel A of Table IA.1 shows that the institutional order flow imbalance and its individual components, IBuys and ISales, predict returns on news announcement days across all terciles. The economic significance of the coefficient on IOF varies strongly across firm's size, with the coefficient for large firms being almost six times the coefficient on IOF for small firms. Moreover, columns A and C of panel A indicates that trading volume is statistically significant in predicting returns for small and medium firms.

Pane B of Table IA.1 shows that IOF, IBuys, and ISales predict news sentiment for small and large firms, but not for medium firms. A possible explanation for why IOF does not predicts the announcement day sentiment for medium firms but does predict it for small firms is that institutions do not influence media coverage for medium firms for whatever reason, while "bargain shopping" by the institutions puts small firms in the news.

Panel C of Table IA.1 shows results similar to those reported in Table 4.

3.2   Calendar-time evidence

An important question is whether institutional order flow imbalances predict returns only on news days or on any day. To test this we estimate return predictability from a panel regressions with firm fixed effects on the whole sample. Our empirical model reported in Table 5 shares all explanatory variables with the model from Table 4 as well as adding News day variable (column B) and its interaction with IOF (column C), and the rest of the explanatory variables (column D). News day is the contemporaneous news announcement indicator variable. We report our results for IBuys and ISales using identical specification in columns E to F.

Panel A of Table 5 shows that the institutional order flow imbalance and its individual components, IBuys and ISales, predict returns not just on news announcement days, but on all calendar days. To estimate the economic significance of this result we multiply the coefficient on the IOF, 0.361, by the standard deviation of the IOF from Table 2, 0.168, to obtain that on all days institutions earn an average return of 6.1 basis points from trading with other investor groups. The coefficient on the interaction term IOF*News day multiplied by the standard deviation of the IOF and equal to 6.0 basis points shows extra average return institutions earn on news days relative

to days without news. Interestingly, columns C and D indicate that once the interaction term is included into the specification, Sentiment gains power in predicting news announcement returns. Similar to results from Table 4, in columns E through H IBuys and ISales are statistically significant. The positive coefficient on IBuys and negative coefficient on ISales shows that institutional buying and selling activity both predict calendar day returns. Internet Appendix reports similar estimations using Fama-MacBeth regressions. All of our results survive.

To test the robustness of the regression results in Tables 4 and Table 5 we next account explicitly for the contemporaneous relation between returns, news sentiment, and institutional trading using panel vector autoregressions (VARs). Specifically, for each firm i and time t we combine these three variables into a 3X1 vector $\mathbf{y}_{it}$, $\mathbf{y}_{it} = (\text{IOF}_{it}, \text{Return}_{it}, \text{Sentiment}_{it})'$. Following Holtz-Eakin et al. (1988), we allow the individual components of $\mathbf{y}_{it}$ to be autocorrelated and jointly endogenously determined by specifying

$$\mathbf{y}_{it} = \boldsymbol{\alpha}_0 + \sum_{l=1}^{L} \boldsymbol{\lambda}_l \mathbf{y}_{it-l} + \boldsymbol{\alpha}_i + \boldsymbol{\varepsilon}_{it}, \tag{6}$$

where $\boldsymbol{\alpha}_0$ is a 3X1 vector of intercepts, $\boldsymbol{\lambda}_l$, $l = 1, ..., L$, are 3X3 coefficient matrices, $\boldsymbol{\alpha}_i$ is a 3X1 vector of unobserved individual (fixed) effects, and $\boldsymbol{\varepsilon}_{it}$ is a 3X1 vector of innovations.

The main advantage of the specification (6) is that it allows to relax the "pooling" constraint that the time series relationship of IOF_{it}, Return_{it}, and Sentiment_{it} is the same for each firm. One way to relax the pooling constraint is to allow for an individual specific intercept in equation (6). Changes in the intercept of a stationary VAR correspond to changes in the means of IOF_{it}, Return_{it}, and Sentiment_{it}. Instead, we set $\boldsymbol{\alpha}_0$ to be constant across firms and time[7] and account for the cross-sectional heterogeneity in the means by including unobserved individual fixed effects, $\boldsymbol{\alpha}_i$, in specification (6). In addition, we allow for individual heterogeneity by making variance of the innovation in equation (6) heteroskedastic across firms. Changes in the innovation variance of a VAR translates into changes in the variance of the variables, so that allowing for cross-section heteroskedasticity in the innovation variance allows for individual heterogeneity in the variability of IOF_{it}, Return_{it}, and Sentiment_{it}.

The fixed effects $\boldsymbol{\alpha}_i$ in equation (6) are correlated with the regressors due to lags of the dependent variables, leading to biased OLS estimates. However, the specification of equation (6) as a projection equation implies that the error term $\boldsymbol{\varepsilon}_{it}$ satisfies the orthogonality condition

$$\mathrm{E}[\mathbf{y}_{is} \odot \boldsymbol{\varepsilon}_{it}] = \mathrm{E}[\boldsymbol{\alpha}_i \odot \boldsymbol{\varepsilon}_{it}] = 0 \text{ for } s < t. \tag{7}$$

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[7]Making intercept time-dependent is most useful when the time series is fairly short and we have 756 observations per firm, which is quite long. Furthermore, we keep the stationarity constraint in equation (6) since all three components of the vector $\mathbf{y}$ are stationary.

These orthogonality conditions imply that lagged values of $\mathbf{y}$ qualify as instrumental variables for equation (6). In order to use the orthogonality conditions (7) to identify the parameters of equation (6), we must deal with the presence of the unobserved individual effect, $\boldsymbol{\alpha}_i$. It is well known that in models with lagged dependent variables it is inappropriate to treat individual fixed effects as constants to be estimated. Therefore, we apply the forward orthogonal deviations transformation, or Helmert transform, as in Arellano and Bover (1995), in equation (6) to eliminate individual fixed effects. This transformation preserves the orthogonality between transformed error terms and lagged regressors, so we can continue to use lagged regressors as instruments.

Let $\mathbf{y}_{it}^* = (\frac{T-t}{T-t+1})^{\frac{1}{2}}(\mathbf{y}_{it} - \frac{1}{T-t}\sum_{s=t+1}^{T}\mathbf{y}_{is})$ be the forward orthogonal deviation of $\mathbf{y}_{it}$. Then (6) reduces to

$$\mathbf{y}_{it}^* = \sum_{l=1}^{L}\boldsymbol{\lambda}_l\mathbf{y}_{it-l}^* + \boldsymbol{\varepsilon}_{it}^*, \tag{8}$$

where $\boldsymbol{\varepsilon}_{it}^* = (\frac{T-t}{T-t+1})^{\frac{1}{2}}(\boldsymbol{\varepsilon}_t - \frac{1}{T-t}\sum_{s=t+1}^{T}\boldsymbol{\varepsilon}_s)$ is the transformed error term. It immediately follows that moment conditions $\mathrm{E}[\mathbf{y}_{is}\boldsymbol{\varepsilon}_{it}] = 0$ imply $\mathrm{E}[\mathbf{y}_{is}\boldsymbol{\varepsilon}_{it}^*] = 0$ for $s \leq t$.

We estimate the coefficients in (8) by the system GMM with the lagged untransformed variables $\mathbf{y}_{is}$ for $s < t$ available as instruments (Holtz-Eakin et al. (1988)). For the just-identified system, the vector of instrumental variables to identify the parameters λ_l of equation (8) is $\mathbf{Z}_{it} = [\mathbf{1}, \mathbf{y}_{it-1}, ..., \mathbf{y}_{it-L}]$. With this set of instruments, the system GMM estimator is equivalent to equation-by-equation IV estimation on the forward demeaned $\mathbf{y}_{it}^*$ with instruments $\mathbf{Z}_{it}$.

Table 6 reports estimates from panel vector autoregressions with firm fixed effects. The estimates are obtained using GMM estimation as described in Holtz-Eakin et al. (1988).[8]

[insert Table 6]

Table 6's results are generally consistent with the event-time evidence from Table 4. Institutional order flow at one and two lags predict returns. Lag one returns negatively predict returns while lag one sentiment positively predicts returns. Regression coefficients on one-day lagged returns and sentiment have the same signs as in column F, Panel A of Table 4 but in Table 6 they are both statistically significant. These differences could arise from the VARs using both news and non-news days. The lag one return coefficient in Table 6 of -0.005 is smaller than the corresponding -0.011 coefficient in Table 4, but the VAR coefficient may be more precisely estimated due to the almost ten times larger sample size when non-news days are included. Both returns and sentiment lose their predictive power of future returns at a two-days horizon.

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[8]As in Hasbrouck (1991), we do not set the lag length optimally using the Akaike or Schwarz information criteria. Instead we choose $L = 2$ lags for all stocks because this lag structure is sufficient to eliminate all the serial correlation in the data (see Panel B). The Internet Appendix shows that the results that follow do not rely on this particular lag structure.

As in Table 4 institutional order flow is persistent. Positive returns today and yesterday both predict higher institutional order imbalances the following day. Sentiment today negatively predicts higher institutional order flow, as can be seen in column F of Table 4, Panel C. This effect is not present in Table 6. As before both lagged returns and lagged sentiment predict sentiment.

We apply a Cholesky decomposition to the residual variance-covariance matrix in order to obtain orthogonalized impulse responses. We vary the ordering of the variables, assigning contemporaneous correlation between the residuals to the variables that come earlier in the ordering. We then calculate standard errors for the impulse-response functions by Monte Carlo simulations, accounting for estimation error in the coefficients. Specifically, we randomly draw a set of coefficients from a Normal distribution centered around the point estimates for λ and with same error variance-covariance matrix. In each round, we re-calculate the impulse responses. We repeat this procedure 1,000 times to obtain confidence bounds on the impulse responses.

Figure 3 reports the impulse response functions (IRF) corresponding to the panel VAR estimated in Table 6. The dependent variables are ordered in the following sequence: sentiment, IOF, return. Error bands at 5% level for the impulse responses are generated using Monte-Carlo simulations with 1,000 draws. Figure IA.1 in the Internet Appendix contains all possible orderings for the variables showing impulse response functions consistent with Figure 3. The IRFs are generally consistent with the coefficient estimates in Table 6.

[insert Figure 3]

3.3 What types of news are institutions informed on?

Up to this point the analysis has grouped all news announcements together in trying to answer whether institutions are informed about news in the broadest context. Next we analyze the relations among IOF, news sentiment, and returns for the 14 news categories given in Table 1 using specification G in Table 4.[9]

[insert Table 7]

IBuys positively predicts news day returns and ISales negatively predicts news day returns for all news categories, although a number of the coefficients are not statistically significant. The coefficients for broker research and recommendations (RCH) are consistent the the tipping story

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[9]Because announcements in a number of categories occur in the same stock on the same day, the number of news days across all the categories sums to more than the number of news day observations in Table 4.

in Irvine, Lipson, and Puckett (2007). However, without additional evidence on information flow between institutions and brokers we can not rule out the possibility that institutions independently uncover information correlated with brokers' recommendations.

Consistent with Table 4 returns, sentiment, and volume do not generally statistically significantly predict returns. IBuys and ISales predict news day sentiment, although many coefficients lack statistical significance and in the ratings category (AAA) the coefficients have the wrong sign. Returns and sentiment both positively predict sentiment in all news categories.

4 Earnings announcement surprises

While the results showing institutional order flow predicting sentiment and returns in Figure 2 and Tables 4-7 are consistent with institutions having private information about the news, further evidence that institutions have private value-relevant information is useful in ruling out that they affect the news. Firms' earnings announcements fit this category of information. The corporate results category (RES) in Table 7 shows that IOF predicts the returns and sentiment associated with earnings. For further analysis we turn to the actual announced earnings.

If institutions are informed about corporate performance, institutional trading should have predictive power for analyst forecast errors around earnings days. The standardized unanticipated earnings, SUE, score is a commonly used measure to quantify the surprise in the marketplace. The SUE score measures the deviation of the announced earnings from the mean analyst estimate. We compute the standardized unanticipated earnings, SUE, score by aggregating the published earnings forecasts from the Thomson Reuters Institutional Brokers' Estimate System (I/B/E/S).

The SUE score measures the number of standard deviations the actual reported earnings differ from the I/B/E/S mean estimates for a company, for the current fiscal period. The SUE score for stock i on the announcement day is calculated as:

$$\text{SUE}_i = \frac{ER_i - \text{E}[\widehat{ER_i}]}{\sigma(\widehat{ER_i})},\tag{9}$$

where the surprise mean, $\text{E}[\widehat{ER_i}]$, is the arithmetic average of analysts' estimates on the release date of the quarterly earnings, ER_i. The surprise standard deviation, $\sigma(\widehat{ER_i})$, measures the dispersion in analysts' estimates at the time of the earnings announcement by the standard deviation of individual analyst estimates about the average estimate $\text{E}[\widehat{ER_i}]$. The narrower the range of estimates the more severe one expects a stock's reaction to an earnings surprise will be.

We obtain the SUE scores associated with each announcement from the I/B/E/S Summary History file. We winsorize the raw SUE scores at the top and bottom 1% to diminish the impact of extreme values. In addition, we require that the earnings release is covered in the Reuters news data.

Table 8 reports the determinants of SUE scores on the day of the earnings release. Panel A shows that returns and news sentiment are positively correlated with SUE. As in other tables estimates are from panel regressions with firm fixed effects and we include volume, defined as the log of total trading volume, as control in addition to returns, sentiment, and IOF or, alternatively, IBuys and ISales. All explanatory variables are measured on the day prior to the news announcement. The estimates show that institutional trading predicts the SUE score. Institutions trade in the right direction before a earnings announcement. IBuys predicts a positive earnings surprise while ISales predicts a negative surprise.

[insert Table 8]

5 Conclusion

This paper combines daily non-public data on buy and sell volume by institutions with news announcements from Reuters. Natural language processing categorizes the sentiment associated with each news story. We find that institutional trading predicts news announcements, the sentiment of the news, returns on announcement day, and earnings announcement surprises. These findings suggest that institutions are producing value relevant information for stocks and support the findings based on institutional holdings that institutions improve price efficiency (Badrinath, Kale, and Noe (1995), Sias and Starks (1997), and Boehmer and Kelly (2009)). Our results also provide direct evidence on Tetlock's (2010) finding that news reduce informational asymmetry.

Prior literature using other measures of institutional trading does not find evidence supporting institutions being informed (Griffin, Shu, and Topaloglu (2011), Jegadeesh and Tang (2010), Busse, Green, and Jegadeesh (2010)). One explanation is that our institutional data is comprehensive and possibly better measured. Further study of specific institutions' trading and information flows may help disentangle the sources of information. More generally, the relations between the media market and the stock market is critical for better understanding the informational efficiency of stock prices.

References

Areliano, M. and O. Bover (1995). "Another look at the instrumental variable estimation of error-components models," Journal of Econometrics, 68, 29-51.

Asquith, P., P. Pathak, J. Ritter (2005). "Short interest, institutional ownership, and stock returns," Journal of Financial Economics, 78, 243-276.

Baker, M., L. Litov, J. Wachter, and J. Wurgler (2011). "Can Mutual Fund Managers Pick Stocks? Evidence from Trades Prior to Earnings Announcements," Journal of Financial and Quantitative Analysis, forthcoming.

Badrinath, S., J. Kale, and T. Noe (1995). "Of Shepherds, Sheep, and the Cross-autocorrelations in Equity Returns," Review of Financial Studies, 8, 401-430.

Boehmer, E., and E. Kelley (2009). "Institutional investors and the informational efficiency of prices," Review of Financial Studies, 22, 3563-3594.

Boehmer, E., C. Jones, and X. Zhang (2008). "Which Shorts Are Informed?" Journal of Finance, 63, 491-527.

Boehmer, E., and J. Wu (2008). "Order flow and prices," working paper.

Boulatov, A., T. Hendershott, and D. Livdan (2011). "Informed Trading and Portfolio Returns," Review of Economic Studies, forthcoming.

Busse, J., N. Jegadeesh, N., and C. Greene (2010). "Buy-Side Trades and Sell-Side Recommendations: Interactions and Information Content," Journal of Financial Markets, forthcoming.

Campbell, J., T. Ramadorai, and A. Schwartz (2009). "Caught on tape: Institutional trading, stock returns, and earnings announcements," Journal of Financial Economics, 92, 66-91.

Back, K., C. H. Cao, and G. A. Willard (2000). "Imperfect competition among informed traders," *Journal of Finance* 55, 2117-2155.

Engelberg, J., A. Reed, and M. Ringgenberg (2010). "How are Shorts Informed? Short-Selling, News and Information Processing," working paper.

Fang, L., J. Peress, and L. Zhang (2011). "Media Coverage, Mutual Fund Trades, and Performance," INSEAD working paper.

Griffin, J., T. Shu, and S. Topaloglu (2011). "Examining the dark side of financial markets: Who trades ahead of major announcements?" University of Texas working paper.

Hasbrouck, J. (1991). "Measuring the Information Content of Stock Trades," Journal of Finance, 46, 179-207.

Holtz-Eakin, D., W. Newey, and H. Rosen (1988). "Estimating Vector Autoregression with Panel Data," Econometrica, 56, 1371-1395.

Irvine, P., M. Lipson, and A. Puckett (2007). "Tipping," Review Of Financial Studies, 20, 741-768.

Jegadeesh, N., and Y. Tang (2009). "Institutional trades around takeover announcements: Evidence of skill and information leakage," Working paper, Emory University.

Kaniel, R., S. Liu, G. Saar, and S. Titman (2011). "Individual investor trading and return patterns around earnings announcements," Journal of Finance, forthcoming.

Kacperczyk, M. and A. Seru (2007). "Fund Manager Use of Public Information: New Evidence on Managerial Skills," Journal of Finance, 62, 485-528.

Kelley, E., and P. Tetlock (2011). "How Wise Are Crowds? Insights from Retail Orders and Stock Returns," working paper.

Kyle, A. S. (1985). "Continuous auctions and informed trader trading," Econometrica, 53, 1315-1335.

Petersen, M. (2009). "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," Review of Financial Studies, 22, 435-480.

Sias, R.W., and L.T. Starks (1997). "Return autocorrelation and institutional investors," Journal of Financial Economics, 46, 103-131.

Tetlock, P. (2010). "Does public financial news resolve asymmetric information?" Review of Financial Studies, 23, 3520-3557.

Senchack, A., and L. Starks (1993), "Short-Sale Restrictions and Market Reaction to Short-Interest Announcement," Journal of Financial and Quantitative Analysis, 28, 177-194.

Table 1

Description of news categories

The table provide a brief description of the major news categories related to individual stocks in the RNSE data base. Additional news categories are listed with number of news items in parenthesis.

Topic code	Topic	Description	No. items
RES	Corporate Results	All corporate financial results; tabular and textual reports; dividends; accounts, annual reports	213,781
RESF	Corporate Results Forecasts	All forecasting of corporate financial results; tabular and textual reports	153,928
NEWS	Major breaking news	Top stories of major international impact (news that is likely to lead television or radio bulletins or to make the front pages of major international newspapers and web sites) - used on Reuters stories only	112,740
DBT	Debt Markets	All debt market news; including primary issuance and secondary trading of debt instruments; markets forecasts and analysis of debt markets	97,910
STX	Stock Markets	All news about equity markets operations, regulations and structure; additions and deletions from stock indices; all new listings; delistings; suspensions; stock markets (not used for news about individual companies, hot stocks or broker research)	96,399
MRG	Mergers and Acquisitions	All corporate stories about change of ownership; share stakes; mergers; acquisitions; buy-outs; share buy-backs; joint ventures; asset transfers; privatization	93,674
USC	US Corporate Bonds	All news about US corporate bonds, including issues, forecasts and analysis	74,030
HOT	Hot Stocks	News about stocks on the move	39,769
BACT	Business Activities	News relating to business activities	36,754
CORA	Corporate Analysis	Analysis about a company or group of companies	34,270
ISU	New Issues	All new government; supranational and corporate issues of debt and corporate issues of equity; all share issues	29,463
RCH	Broker Research and Recommendations	All news about broker research and recommendations	27,364
AAA	Ratings	All news about credit ratings	22,868
MNGISS	Management issues/policy	Management issues including executive pay, bonuses and corporate governance. Would also include accounting irregularities and auditor issues.	18,689

Additional categories (no. news items in parenthesis):

REGS (Regulatory Issues, 39,590), FUND (Fund Industry News, 34,028), WASH (Washington/US Government News, 32,580), LAW (Legislation, 27,381), JOB (Labor; Employment, Unemployment, 25,118), MTG (Mortgage Backed Debt, 25,091), DRV (Derivatives, 19,045), WWW (Internet/World Wide Web, 18,203), MUL (Multi-Industry, 15,645), POL (Domestic Politics, 14,255), INT (Interest Rates, 13,442), WIN (Reuters Exclusive News, 13,097), AGN (US Agencies, 12,753), GVD (Government and Sovereign debt, 12,257), DIV (Dividends, 11,023), TNC (Terms and Conditions – Bond Issues, 10,208), PRESS (Press Digests, 10,004), IPO (Initial Public Offerings, 9,613), CRIM (Crime, Law Enforcement, 9,551), LOA (Loans, 9,415), EUB (Eurobonds, 9,286), JUDIC (Judicial processes/court cases, 7,499), WHO (Wholesale, 7,202), WEA (Weather, 5,917), FRX (Forex Markets, 5,763), MMT (Money Markets, 5,561), BKRT (Bankruptcies & Corporate insolvencies, 5,286), TRD (International Trade, 5,146), ECI (Economic Indicators, 5,045), CDV (Credit Default Swaps, 4,696), DIS (Disasters, Accidents, Natural Catastrophes, 4,324), MCE (Macro-Economics, 4,203), IGD (Investment grade debt, 4,067), DIP (Diplomacy, International Relations, 3,396), FED (Federal Reserve Board, 3,022), LIF (Lifestyle, 2,899), EXCA (Exchange activities, 2,765), HYD (High-yield debt, 2,421), VIO (Civil unrest, 2,416), STIR (Short-term interest rates, 2,087), SECUR (National and international security, 1,918), RSUM (Reuters summits, 1,803), EQB (Equity-Linked bonds, 1,659), ABS (Asset-backed debt, 1,195), ODD (Human Interest, 820), REVS (State, Local Authority, Agency Debt, 681), HEDGE (Hedge Funds, 572), TAX (Tax, 414), VOTE (Elections, 369), REL (Religion, 279), BOMB (Bombings, 241), PLCY (Fiscal and Monetary Policy, 169), FES (Editorial special, analysis and future stories, 57), INSI (Technical Analysis, 55), INV (Investing, 44), CFIN (Corporate Finance, 22), RTM (Retirement, 18), PMI (Purchasing Managers Indices, 1)

Table 2
Descriptive statistics

The table reports descriptive statistics for the news data and the institutional trading data in our sample. News are aggregated by stock day. Sentiment is computed as the relevance weighted average of the difference between positive and negative sentiment scores. Institutional order flow IOF (institutional volume IVol) is defined as the difference between (sum of) institutional purchases IBuys and institutional sales ISales. All trade-related quantities are normalized by the firm's market capitalization lagged by one year and expressed in percent.

	Mean	S.D.	1%	50%	99%
Panel A: News releases and sentiment (126,436 observations)					
News stocks per day	0.115	0.039	0.000	0.111	0.240
News days per company	0.107	0.166	0.000	0.046	0.886
Sentiment	0.005	0.419	-0.763	0.040	0.814
Panel B: Institutional trading (1,101,788 observations)					
IOF	0.004	0.168	-0.425	0.002	0.450
IVol	0.829	1.642	0.006	0.430	6.653
|IOF|/IVol	0.155	0.170	0.001	0.102	1.000
IBuys	0.416	0.828	0.001	0.215	3.347
ISales	0.413	0.823	0.001	0.212	3.332
Panel C: Return and volume (1,101,788 observations)					
Return	0.094	1.948	-5.451	0.035	6.232
Volume	0.880	1.600	0.013	0.499	6.599

Table 3
Predicting public news announcements

Estimates are from panel logit regressions with firm fixed effects. The dependent variable indicates a news announcement on date t in firm i. IVol is institutional volume, |Return| is the absolute daily return, and News day is the lagged news announcement indicator variable. The observations are value weighted. The number of observations is 1,101,788. In Panel A, we report odds ratios. Standard errors are robust to heteroskedasticity and clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(A)	(B)	(C)	(D)	(E)
		Panel A: News days			
IVol	1.025***				1.017***
	(0.000)				(0.000)
|Return|		1.108***			1.020***
		(0.000)			(0.000)
News day			2.427***		6.283***
			(0.000)		(0.000)
|Sentiment|				2.557***	0.448***
				(0.000)	(0.000)
Log-likelihood	-2.393	-2.392	-2.335	-2.379	-2.369
		Panel B: No. news stories			
IVol	0.066***				0.043***
	(0.000)				(0.000)
|Return|		0.074***			0.056***
		(0.000)			(0.000)
News day			0.889***		0.999***
			(0.000)		(0.000)
|Sentiment|				0.438***	-0.402***
				(0.000)	(0.000)
Log-likelihood	-9.944	-9.941	-9.757	-9.931	-9.736

Table 4
Returns, news sentiment, and institutional trading on announcement days

The table documents the predictability of news announcement returns (Panel A), news sentiment (Panel B), and institutional order flow on news days (Panel C). Estimates are from panel regressions with firm fixed effects. IOF denotes institutional order flow, IBuys (ISales) are institutional purchases (sales), and Volume is the log of total trading volume. All explanatory variables are measured on the day prior to the news announcement. The sample contains news days only and observations are value weighted. The number of observations is 126,436. Standard errors are robust to heteroskedasticity and clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(A)	(B)	(C)	(D)	(E)	(F)	(G)
			Panel A: Return				
IOF	0.632***					0.674***	
	(0.169)					(0.183)	
IBuys		0.611***					0.647***
		(0.169)					(0.183)
ISales		-0.671***					-0.711***
		(0.172)					(0.185)
Return			-0.013			-0.015	-0.016
			(0.014)			(0.015)	(0.015)
Sentiment				0.024		0.028	0.028
				(0.025)		(0.026)	(0.026)
ln(Volume)					-0.021	-0.022	0.003
					(0.030)	(0.030)	(0.036)
R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005
F	51.349	28.833	3.921	0.895	1.160	15.538	14.244
			Panel B: Sentiment				
IOF	0.076***					0.049**	
	(0.021)					(0.020)	
IBuys		0.068***					0.044*
		(0.021)					(0.020)
ISales		-0.091***					-0.057***
		(0.022)					(0.021)
Return			0.011***			0.009***	0.009***
			(0.001)			(0.001)	(0.001)
Sentiment				0.165***		0.162***	0.162***
				(0.010)		(0.010)	(0.010)
ln(Volume)					-0.015*	-0.013*	-0.008
					(0.008)	(0.007)	(0.008)
R^2	0.064	0.064	0.065	0.082	0.064	0.083	0.083
F	17.147	38.436	89.258	609.550	14.096	174.722	151.253
			Panel C: IOF				
IOF	0.257***					0.247***	
	(0.011)					(0.011)	
IBuys		0.259***					0.250***
		(0.011)					(0.011)
ISales		-0.254***					-0.243***
		(0.011)					(0.011)
Return			0.005***			0.004***	0.004***
			(0.000)			(0.000)	(0.000)
Sentiment				0.001		-0.001*	-0.001*
				(0.001)		(0.001)	(0.001)
ln(Volume)					0.003***	0.002**	-0.001
					(0.001)	(0.001)	(0.001)
R^2	0.075	0.075	0.033	0.020	0.020	0.084	0.084
F	1051.057	543.796	1084.337	1.753	28.262	516.891	420.616

Table 5
Returns, news, and institutional trading

The table documents the predictability of stock returns. Estimates are from panel regressions with firm fixed effects. IOF denotes institutional order flow, IBuys (ISales) are institutional purchases (sales), and Volume is the log of total trading volume. All explanatory variables are lagged by one day, except for News day. News day is the contemporaneous news announcement indicator variable. The observations are value weighted. The number of observations is 1,101,788. Standard errors are robust to heteroskedasticity and clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
IOF	0.361***	0.265***	0.291***	0.294***				
	(0.071)	(0.050)	(0.061)	(0.061)				
IOF * News day		0.358**	0.385***	0.376**				
		(0.143)	(0.148)	(0.152)				
IBuys					0.355***	0.259***	0.285***	0.294***
					(0.072)	(0.051)	(0.063)	(0.062)
ISales					-0.374***	-0.275***	-0.300***	-0.293***
					(0.072)	(0.050)	(0.061)	(0.061)
IBuys * News day						0.354**	0.380**	0.352**
						(0.143)	(0.148)	(0.152)
ISales * News day						-0.368**	-0.395***	-0.410***
						(0.145)	(0.149)	(0.153)
News day		0.015	0.015	0.086		0.020	0.019	0.237**
		(0.021)	(0.021)	(0.077)		(0.023)	(0.022)	(0.119)
Return			-0.017	-0.018			-0.017	-0.018
			(0.013)	(0.013)			(0.013)	(0.013)
Sentiment			0.041**	0.067***			0.041**	0.067***
			(0.020)	(0.022)			(0.020)	(0.022)
ln(Volume)			-0.008	-0.014			0.001	-0.014
			(0.025)	(0.026)			(0.031)	(0.031)
Return * News day				0.004				0.004
				(0.008)				(0.008)
Sentiment * News day				-0.037				-0.037
				(0.033)				(0.033)
ln(Volume) * News day				0.013				0.038*
				(0.014)				(0.021)
R^2	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
F	159.504	60.302	37.384	28.944	81.284	37.216	28.874	24.264

Table 6

Vector autoregressions of returns, news sentiment, and institutional trading

The table reports estimates from panel vector autoregressions with firm fixed effects. The estimates are obtained using system GMM estimation as described in Section 3.2. The dependent variables are institutional order flow (IOF), stock returns, and news sentiment. We set lag length $L = 2$. The number of observations is 1,101,788. Standard errors are reported in parenthesis and p-values in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

		IOF	Return	Sentiment
		Panel A: Estimates		
IOF	$t-1$	0.240***	0.169***	0.003***
		(0.008)	(0.016)	(0.001)
	$t-2$	0.077***	0.032**	-0.001
		(0.006)	(0.016)	(0.001)
Return	$t-1$	0.003***	-0.005***	0.001***
		(0.000)	(0.001)	(0.000)
	$t-2$	0.000***	0.000	0.000
		(0.000)	(0.001)	(0.000)
Sentiment	$t-1$	0.000	0.090***	0.098***
		(0.001)	(0.014)	(0.002)
	$t-2$	-0.001	0.019	0.030***
		(0.001)	(0.013)	(0.002)
		Panel B: Diagnostics		
AIC (BIC)			-6.270 (-6.270)	
MSE		0.161	1.945	0.139
Residual AC		-0.001	-0.002	0.007
		[0.238]	[0.125]	[0.000]
Residual cross-correlation:				
IOF		1.000	0.056	0.000
		[0.000]	[0.000]	[0.991]
Return			1.000	0.050
			[0.000]	[0.000]
Sentiment				1.000
				[0.000]

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Table 7
Returns, news sentiment, and institutional trading on announcement days

The table documents the predictability of news announcement returns (Panel A), news sentiment (Panel B), and institutional order flow on news days (Panel C). Estimates are from panel regressions with firm fixed effects. IOF denotes institutional order flow, IBuys (ISales) are institutional purchases (sales), and Volume is the log of total trading volume. Institutional purchases and sales are aggregated over the five trading days preceding the news announcement. The sample contains news days only and observations are value weighted. Standard errors are robust to heteroskedasticity and clustering. $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$.

	RES	RESF	DBT	STX	NEWS	MRG	USC	HOT	BACT	CORA	ISU	RCH	AAA	MNGISS
N	32,059	33,419	28,147	27,401	26,584	23,819	25,052	14,463	16,796	16,184	9,127	10,154	9,577	7,296
							Panel A: Return							
IBuys	0.978*	1.302**	0.988*	1.320**	0.696	0.991*	1.605***	1.117*	0.897	0.867	1.002	3.997***	1.315**	0.291
	(0.528)	(0.539)	(0.530)	(0.554)	(0.571)	(0.557)	(0.616)	(0.641)	(0.691)	(0.711)	(0.831)	(0.899)	(0.626)	(0.858)
ISales	-1.012**	-1.280**	-1.016*	-1.310**	-0.692	-1.037*	-1.615***	-1.111*	-0.805	-0.791	-1.120	-3.748***	-1.387**	-0.419
	(0.515)	(0.533)	(0.539)	(0.557)	(0.580)	(0.568)	(0.614)	(0.619)	(0.708)	(0.731)	(0.852)	(0.858)	(0.633)	(0.895)
Return	-0.026	-0.016	-0.002	0.004	-0.003	-0.027	-0.002	0.012	0.005	0.006	-0.037	0.006	-0.019	-0.007
	(0.019)	(0.017)	(0.018)	(0.020)	(0.016)	(0.018)	(0.020)	(0.025)	(0.029)	(0.029)	(0.024)	(0.030)	(0.028)	(0.018)
Sentiment	-0.052	0.012	0.094*	0.011	0.033	0.010	0.062	-0.032	0.011	0.020	0.082	-0.061	0.250*	0.061
	(0.054)	(0.053)	(0.049)	(0.064)	(0.053)	(0.054)	(0.075)	(0.097)	(0.040)	(0.045)	(0.062)	(0.103)	(0.130)	(0.119)
Volume	-0.065	-0.076	-0.078*	-0.023	-0.033	-0.052	-0.100*	-0.084	0.031	0.039	0.008	-0.116	-0.083	-0.016
	(0.058)	(0.047)	(0.047)	(0.048)	(0.044)	(0.045)	(0.057)	(0.083)	(0.075)	(0.082)	(0.064)	(0.117)	(0.089)	(0.079)
R^2	0.020	0.016	0.016	0.014	0.013	0.014	0.017	0.035	0.014	0.015	0.036	0.050	0.053	0.040
F	2.505	2.544	2.568	2.075	0.658	2.728	3.933	0.972	0.799	0.774	1.375	7.435	2.331	0.334
							Panel B: Sentiment							
IBuys	0.158**	0.219***	0.029	0.140**	0.199**	0.209**	0.174**	0.184**	0.078	0.080	0.063	0.509***	0.031	0.224
	(0.070)	(0.071)	(0.085)	(0.069)	(0.084)	(0.086)	(0.085)	(0.088)	(0.058)	(0.054)	(0.098)	(0.134)	(0.122)	(0.187)
ISales	-0.144**	-0.206***	-0.032	-0.131**	-0.212***	-0.216**	-0.183***	-0.183***	-0.075	-0.077	-0.068	-0.469***	-0.041	-0.315*
	(0.068)	(0.075)	(0.085)	(0.067)	(0.082)	(0.092)	(0.087)	(0.086)	(0.064)	(0.061)	(0.094)	(0.132)	(0.122)	(0.191)
Return	0.015***	0.013***	0.011***	0.014***	0.011***	0.007***	0.011***	0.020***	0.007***	0.008***	-0.000	0.018***	0.013***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)
Sentiment	0.126***	0.152***	0.178***	0.131***	0.180***	0.146***	0.182***	0.136***	0.074***	0.065***	0.171***	0.099***	0.189***	0.192***
	(0.020)	(0.020)	(0.017)	(0.012)	(0.017)	(0.011)	(0.020)	(0.027)	(0.009)	(0.011)	(0.020)	(0.020)	(0.021)	(0.021)
Volume	-0.023***	-0.025***	-0.031***	-0.038***	-0.008	-0.022*	-0.024*	-0.033***	-0.025***	-0.031***	-0.017	-0.046***	-0.049***	0.012
	(0.008)	(0.009)	(0.011)	(0.010)	(0.009)	(0.013)	(0.013)	(0.011)	(0.007)	(0.007)	(0.012)	(0.013)	(0.016)	(0.019)
R^2	0.113	0.107	0.131	0.122	0.128	0.124	0.141	0.143	0.148	0.168	0.123	0.119	0.292	0.198
F	36.238	53.200	62.506	66.880	74.785	36.380	52.539	37.940	18.272	21.301	20.551	18.707	21.981	21.279
							Panel C: IOF							
IBuys	0.384***	0.375***	0.362***	0.389***	0.378***	0.383***	0.369***	0.348***	0.440***	0.441***	0.314***	0.421***	0.352***	0.452***
	(0.025)	(0.023)	(0.024)	(0.037)	(0.024)	(0.029)	(0.027)	(0.034)	(0.054)	(0.055)	(0.044)	(0.024)	(0.041)	(0.041)
ISales	-0.381***	-0.376***	-0.353***	-0.386***	-0.370***	-0.375***	-0.363***	-0.335***	-0.443***	-0.443***	-0.305***	-0.416***	-0.353***	-0.449***
	(0.027)	(0.023)	(0.024)	(0.038)	(0.025)	(0.030)	(0.027)	(0.033)	(0.055)	(0.056)	(0.045)	(0.027)	(0.041)	(0.044)
Return	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.005***	0.005***	0.004***	0.005***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sentiment	-0.003***	-0.003***	-0.003***	-0.002	-0.002*	-0.001	-0.002**	-0.003*	-0.001	-0.001	-0.002	-0.005*	-0.005**	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)
Volume	0.003	0.003*	0.002	0.003*	0.002	0.002	0.004**	-0.000	0.003*	0.003	0.004*	0.005*	0.003	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
R^2	0.079	0.083	0.105	0.107	0.109	0.115	0.110	0.128	0.161	0.162	0.193	0.136	0.168	0.182
F	81.657	85.223	78.056	89.768	97.814	78.494	59.251	36.406	70.622	68.224	45.717	39.325	22.211	23.581

Table 8
Institutional trading and earnings surprises

The table documents the predictability of earnings surprises by institutional order flow. Estimates are from panel regressions with firm fixed effects. Earnings surprises are measured by the standardized unanticipated earnings, SUE, score. The SUE score is calculated as follows:

$$\text{SUE}_i = \frac{ER_i - \text{E}[\widehat{ER_i}]}{\sigma(\widehat{ER_i})},$$

where the surprise mean, $\text{E}[\widehat{ER_i}]$, is the arithmetic average of analysts' estimates on the release date of the quarterly earnings, ER_i, and $\sigma(\widehat{ER_i})$ is the standard deviation of individual analyst estimates about the average estimate. IOF denotes institutional order flow, IBuys (ISales) are institutional purchases (sales), and Volume is the log of total trading volume. All explanatory variables are measured on the day prior to the news announcement. The sample contains earnings announcement days only and observations are value weighted. The number of observations is 9,126. Standard errors are robust to heteroskedasticity and clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Correlations

	IOF	Return	Sentiment
SUE	-0.038	0.338	0.211
	[0.000]	[0.000]	[0.000]

Panel B: Estimates

|	(A)	(B)	(C)	(D)	(E)	(F)	(G)
IOF	0.980**					0.838*	
	(0.499)					(0.496)	
IBuys		1.058**					0.853*
		(0.503)					(0.505)
ISales		-0.980**					-0.837*
		(0.490)					(0.495)
Return			0.066***			0.059**	0.058**
			(0.025)			(0.025)	(0.025)
Sentiment				0.139		0.104	0.103
				(0.181)		(0.184)	(0.184)
Volume					0.074	0.066	0.058
					(0.169)	(0.167)	(0.221)
R^2	0.197	0.197	0.198	0.197	0.197	0.199	0.199
F	4.755	2.735	3.846	0.361	0.278	2.289	1.873

Figure 1

Figure 1
Institutional trading volume and stock return volatility around news announcements

The figure documents institutional trading volume and stock return volatility around news announcements. Panel A reports institutional volume between ten days before and ten days after a news announcement. Panel B reports absolute stock returns over the same time period. The mean values are calculated as the value-weighted average of the individual news day values. Standard errors are robust to heteroskedasticity and clustering.

Panel A: IVol

Panel B: |Return|

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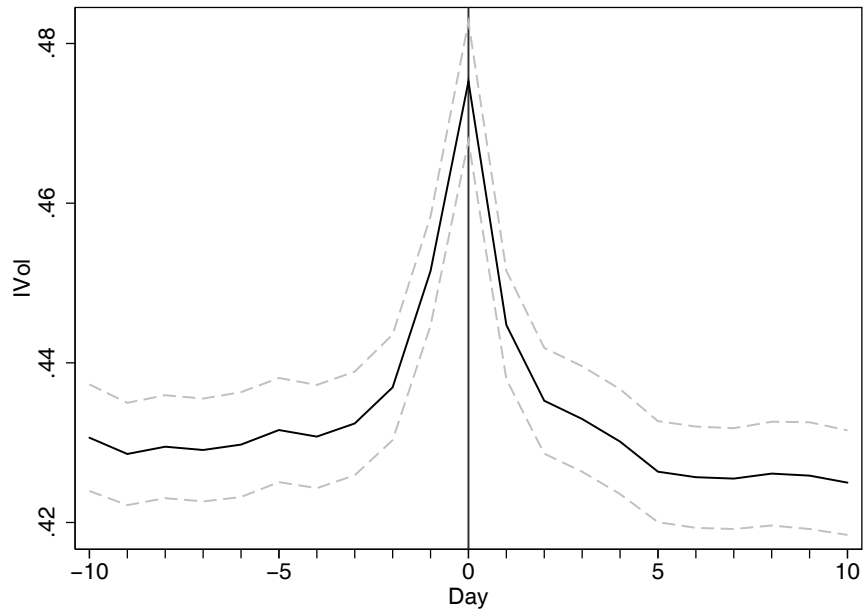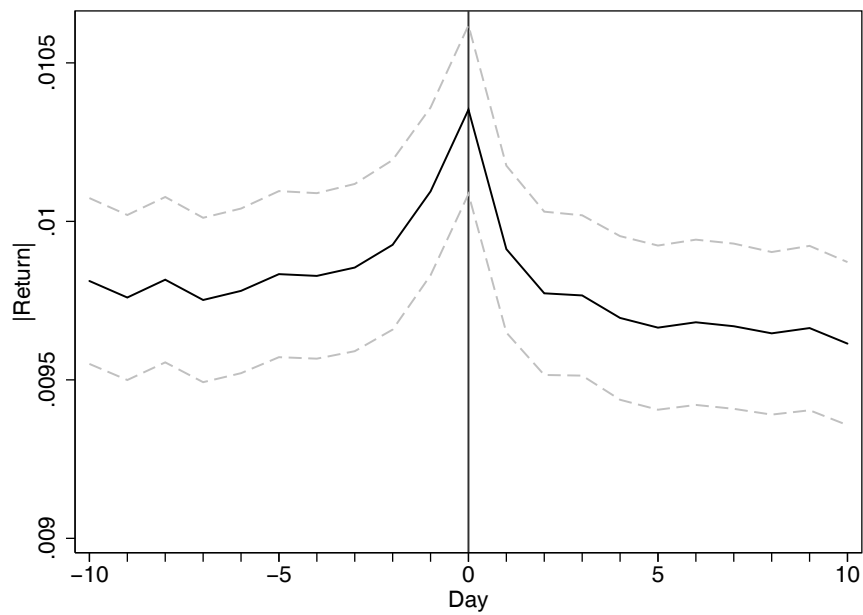
Figure 2
Institutional order flow and stock returns around news announcements

The figure documents institutional trading and stock returns around news announcements. Panel A reports buy-and-hold cumulative stock returns between ten days before and ten days after a news announcement. Panel B reports buy-and-hold cumulative institutional order flow over the same time period. The mean values are calculated as the value-weighted average of the individual news day values. Standard errors are robust to heteroskedasticity and clustering.
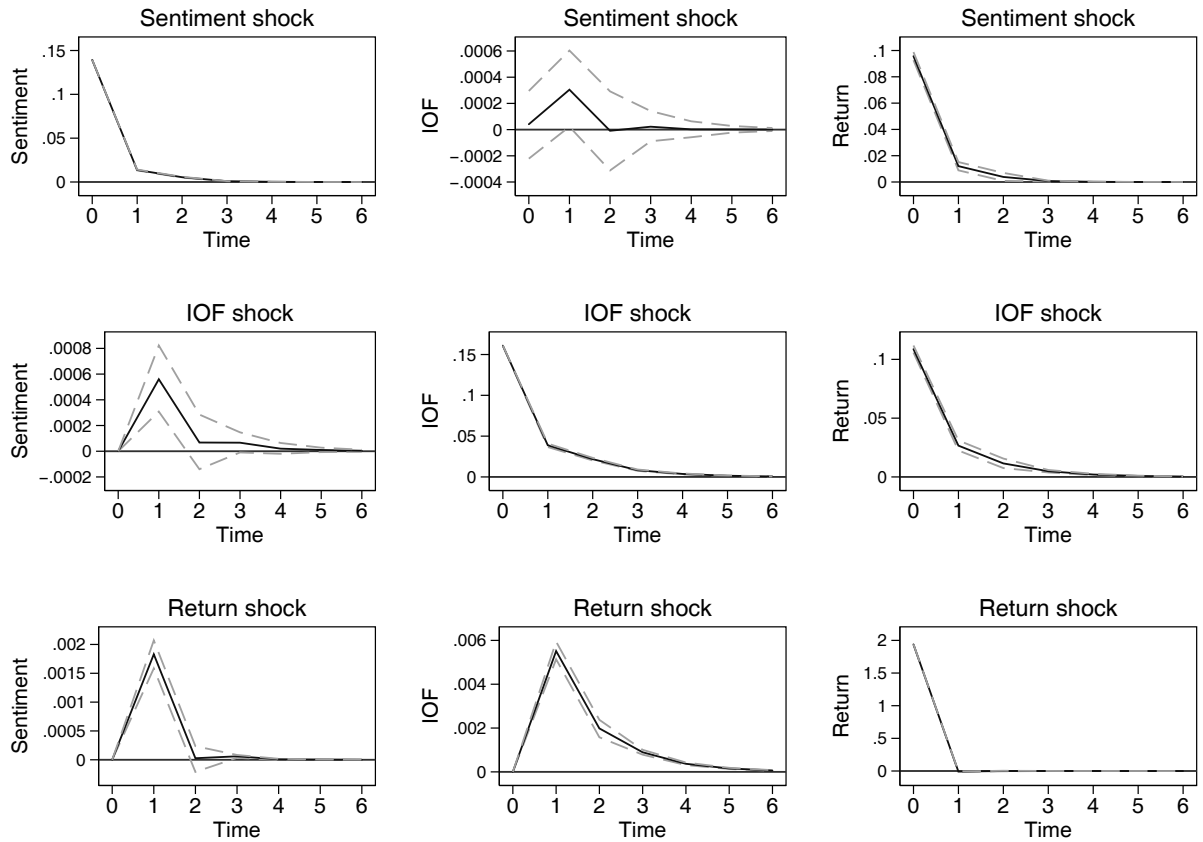
Panel A: Return
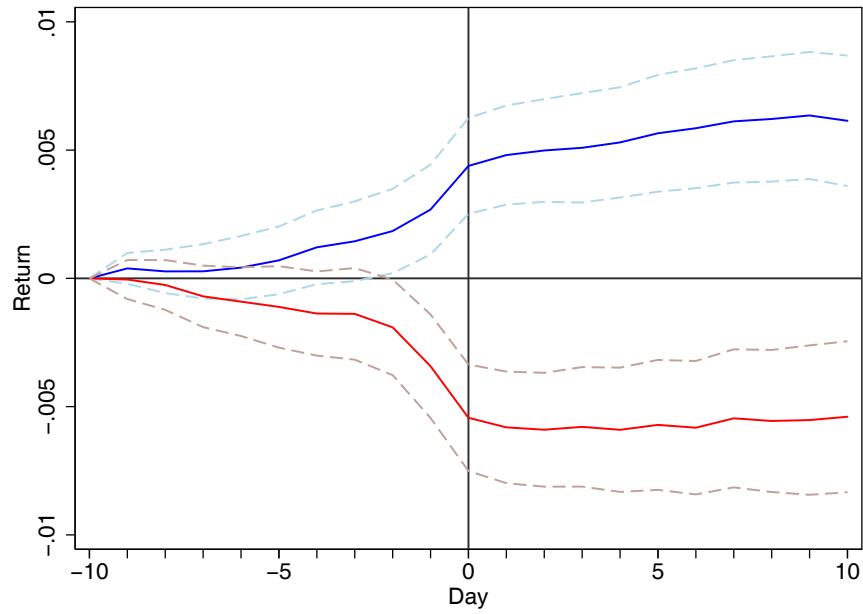
Panel B: IOF
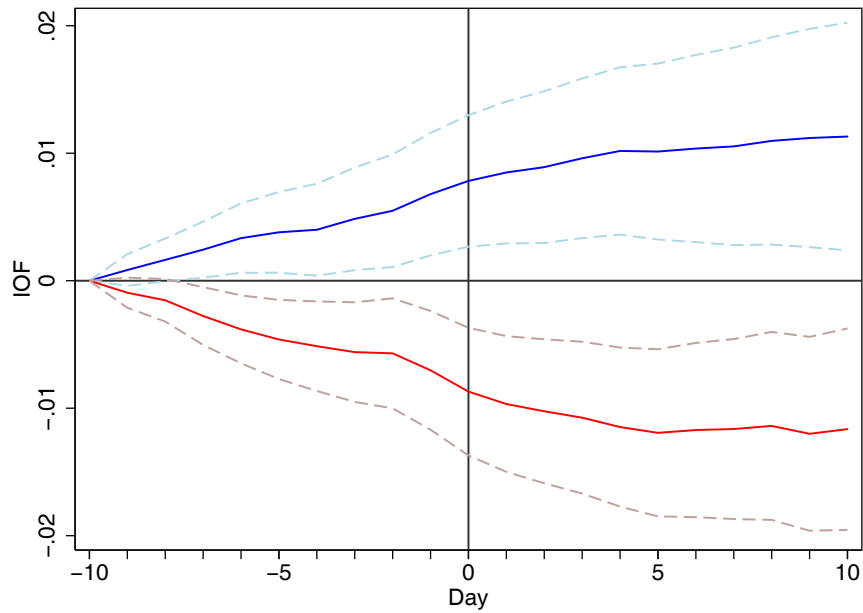
Figure 3
Impulse responses

The figure reports the impulse response functions corresponding to the panel VAR with lag length $L = 2$ reported in Table 6. The estimates in Table 6 are obtained using GMM estimation as described in Section 3.2. The dependent variables are ordered in the following sequence: sentiment, IOF, return. Impulse responses correspond to a one standard deviation shock. Error bands at 5% level for the impulse responses (dashed lines) are generated using Monte-Carlo simulations with 1,000 draws.

# Figure IA.1
Impulse responses

The figure reports the impulse response functions corresponding to the panel VAR with lag length $L = 2$ reported in Table 6. The estimates in Table 6 are obtained using GMM estimation as described in Section 3.2. Impulse responses correspond to a one standard deviation shock. Error bands at 5% level for the impulse responses (dashed lines) a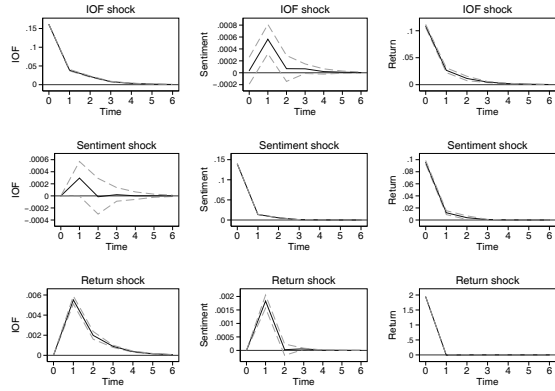re generated using Monte-Carlo simulations with 1,000 draws. Across panels, the dependent variables are ordered in varying sequences.
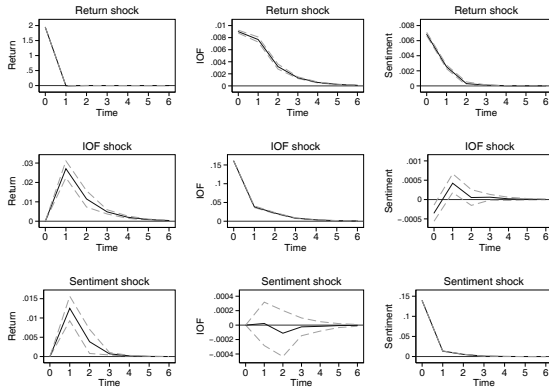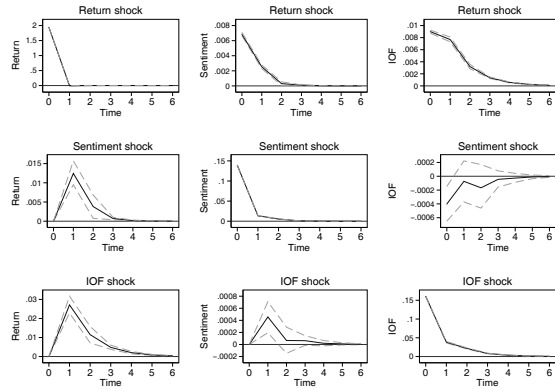
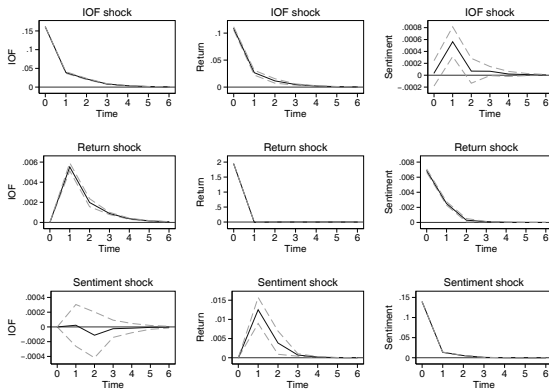Panel A: Sentiment, IOF, return
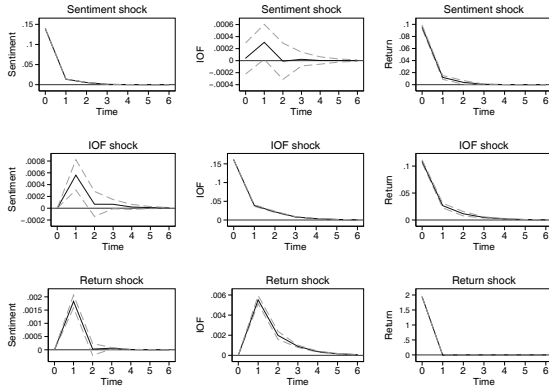
Panel B: IOF, Sentiment, return

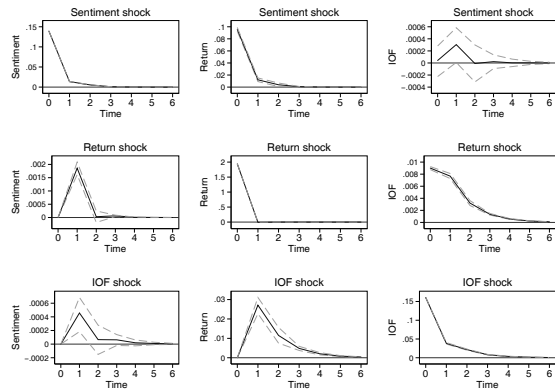Panel C: Return, IOF, sentiment

Panel D: Return, sentiment, IOF

Panel E: IOF, return, sentiment

Panel F: Sentiment, return, IOF

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Table IA.1
Returns, news sentiment, and institutional trading on announcement days sorted by size

The table documents the predictability of news announcement returns (Panel A), news sentiment (Panel B), and institutional order flow on news days (Panel C). Estimates are from panel regressions with firm fixed effects. IOF denotes institutional order flow, IBuys (ISales) are institutional purchases (sales), and Volume is the log of total trading volume. All explanatory variables are measured on the day prior to the news announcement. The sample contains news days only and observations are value weighted. We sort all firms into size terciles. The number of observations is 42,087 in each portfolio. Standard errors are robust to heteroskedasticity and clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Small		Medium		Large	
	(A)	(B)	(C)	(D)	(E)	(F)
Panel A: Return						
IOF	0.255***		0.417***		1.315***	
	(0.077)		(0.148)		(0.427)	
IBuys		0.243***		0.408***		1.248***
		(0.078)		(0.149)		(0.423)
ISales		-0.268***		-0.435***		-1.438***
		(0.078)		(0.148)		(0.443)
Return	0.011	0.011	-0.019	-0.019	-0.017	-0.018
	(0.012)	(0.012)	(0.014)	(0.014)	(0.016)	(0.016)
Sentiment	0.025	0.027	0.019	0.020	0.028	0.027
	(0.077)	(0.077)	(0.036)	(0.036)	(0.028)	(0.028)
ln(Volume)	-0.070**	-0.043	-0.055**	-0.035	-0.017	0.035
	(0.032)	(0.039)	(0.028)	(0.035)	(0.034)	(0.054)
R^2	0.024	0.024	0.010	0.010	0.004	0.004
F	6.439	5.510	6.783	5.457	9.782	8.458
Panel B: Sentiment						
IOF	0.031***		-0.003		0.125**	
	(0.011)		(0.020)		(0.050)	
IBuys		0.026**		-0.005		0.100**
		(0.011)		(0.021)		(0.050)
ISales		-0.037***		-0.001		-0.170***
		(0.011)		(0.020)		(0.054)
Return	0.011***	0.011***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sentiment	0.276***	0.277***	0.254***	0.254***	0.149***	0.149***
	(0.018)	(0.018)	(0.015)	(0.015)	(0.011)	(0.011)
ln(Volume)	0.000	0.012**	-0.010*	-0.006	-0.015*	0.004
	(0.004)	(0.005)	(0.006)	(0.007)	(0.009)	(0.011)
R^2	0.130	0.130	0.118	0.119	0.076	0.077
F	188.033	154.077	253.099	202.935	121.129	109.312
Panel C: IOF						
IOF	0.220***		0.272***		0.236***	
	(0.016)		(0.016)		(0.016)	
IBuys		0.224***		0.274***		0.239***
		(0.016)		(0.016)		(0.017)
ISales		-0.215***		-0.268***		-0.230***
		(0.016)		(0.017)		(0.016)
Return	0.005***	0.005***	0.005***	0.005***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Sentiment	0.011	0.010	-0.001	-0.001	-0.001*	-0.001*
	(0.007)	(0.007)	(0.002)	(0.002)	(0.001)	(0.001)
ln(Volume)	0.001	-0.008**	0.002	-0.002	0.002**	-0.001
	(0.003)	(0.004)	(0.002)	(0.003)	(0.001)	(0.001)
R^2	0.069	0.070	0.095	0.096	0.100	0.101
F	84.195	73.727	178.609	149.266	306.836	251.104

Table IA.2
Return predictability using Fama-MacBeth

The table documents the predictability of stock returns. Estimates are from Fama-MacBeth regressions. IOF denotes institutional order flow, IBuys (ISales) are institutional purchases (sales), and Volume is the log of total trading volume. Institutional purchases and sales are aggregated over the five trading days preceding the news announcement. All explanatory variables are lagged by one day, except for News day. News day is the contemporaneous news announcement indicator variable. The number of observations is 1,101,788. Standard errors are robust to heteroskedasticity and clustering. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
IOF	0.236***	0.205***	0.210***	0.210***				
	(0.032)	(0.032)	(0.030)	(0.030)				
IOF * News day		0.342***	0.348***	0.301**				
		(0.132)	(0.130)	(0.130)				
IBuys					0.253***	0.228***	0.207***	0.207***
					(0.032)	(0.032)	(0.030)	(0.030)
ISales					-0.210***	-0.186***	-0.222***	-0.224***
					(0.033)	(0.033)	(0.031)	(0.031)
IBuys * News day						0.323**	0.345**	0.295**
						(0.136)	(0.136)	(0.136)
ISales * News day						-0.307**	-0.336**	-0.257*
						(0.134)	(0.134)	(0.135)
News day		0.040***	0.061***	0.054***		0.032***	0.062***	0.033
		(0.010)	(0.009)	(0.012)		(0.012)	(0.011)	(0.021)
Return			-0.016***	-0.018***			-0.016***	-0.018***
			(0.003)	(0.003)			(0.003)	(0.003)
Sentiment			0.089***	0.111***			0.090***	0.111***
			(0.013)	(0.016)			(0.013)	(0.016)
ln(Volume)			0.036***	0.037***			0.042***	0.043***
			(0.006)	(0.006)			(0.005)	(0.005)
Size			-0.017***	-0.017***			-0.017***	-0.017***
			(0.004)	(0.004)			(0.004)	(0.004)
Return * News day				0.024***				0.023***
				(0.006)				(0.006)
Sentiment * News day				-0.059**				-0.063**
				(0.026)				(0.026)
ln(Volume) * News day				-0.013				-0.021
				(0.010)				(0.014)
R^2	0.001	0.004	0.027	0.030	0.010	0.014	0.031	0.034
F	54.343	24.724	30.546	23.928	35.204	17.618	28.591	22.149

Table IA.3

Vector autoregressions of returns, news sentiment, and institutional trading with four lags

The table reports estimates from panel vector autoregressions with firm fixed effects. The estimates are obtained using system GMM estimation as described in Section 3.2. The dependent variables are institutional order flow (IOF), stock returns, and news sentiment. Across columns, we vary the VAR lag length L from 1 to 4. The number of observations is 1,101,788. Standard errors are reported in parenthesis and p-values in brackets. $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$.

	L=1 IOF	L=1 Return	L=1 Sentiment	L=2 IOF	L=2 Return	L=2 Sentiment	L=3 IOF	L=3 Return	L=3 Sentiment	L=4 IOF	L=4 Return	L=4 Sentiment
Panel A: Estimates												
IOF $t-1$	10.259*** (0.007)	0.177*** (0.016)	0.003*** (0.001)	0.240*** (0.008)	0.169*** (0.016)	0.003*** (0.001)	0.236*** (0.008)	0.171*** (0.017)	0.003*** (0.001)	0.234*** (0.008)	0.170*** (0.017)	0.003*** (0.001)
$t-2$				0.077*** (0.006)	0.032** (0.016)	-0.001 (0.001)	0.065*** (0.006)	0.041** (0.016)	-0.001 (0.001)	0.063*** (0.006)	0.040** (0.016)	-0.001 (0.001)
$t-3$							0.055*** (0.005)	-0.022 (0.015)	0.001* (0.001)	0.047*** (0.005)	-0.027* (0.016)	0.001 (0.001)
$t-4$										0.035*** (0.004)	0.017 (0.016)	0.000 (0.001)
Return $t-1$	10.003*** (0.000)	-0.005*** (0.001)	0.001*** (0.000)	0.003*** (0.000)	-0.005*** (0.001)	0.001*** (0.000)	0.003*** (0.000)	-0.005*** (0.001)	0.001*** (0.000)	0.003*** (0.000)	-0.005*** (0.001)	0.001*** (0.000)
$t-2$				0.000*** (0.000)	0.000 (0.001)	0.000 (0.000)	0.000*** (0.000)	-0.002 (0.001)	0.000 (0.000)	0.000*** (0.000)	-0.002* (0.001)	0.000 (0.000)
$t-3$							-0.001*** (0.000)	-0.004*** (0.001)	0.000 (0.000)	-0.001*** (0.000)	-0.004*** (0.001)	0.000 (0.000)
$t-4$										0.000 (0.000)	0.000 (0.001)	0.000 (0.000)
Sentiment $t-1$	0.001 (0.001)	0.091*** (0.014)	0.101*** (0.002)	0.000 (0.001)	0.090*** (0.014)	0.098*** (0.002)	0.000 (0.001)	0.091*** (0.014)	0.097*** (0.002)	0.000 (0.001)	0.091*** (0.014)	0.097*** (0.002)
$t-2$				-0.001 (0.001)	0.019 (0.013)	0.030*** (0.002)	-0.001 (0.001)	0.021 (0.013)	0.027*** (0.002)	-0.001 (0.001)	0.022 (0.013)	0.026*** (0.002)
$t-3$							0.000 (0.001)	0.008 (0.013)	0.031*** (0.002)	-0.001 (0.001)	0.007 (0.013)	0.028*** (0.002)
$t-4$										0.000 (0.001)	0.005 (0.013)	0.026*** (0.002)
Panel B: Diagnostics												
AIC (BIC)		-6.268 (-6.268)			-6.270 (-6.270)			-6.273 (-6.272)			-6.272 (-6.272)	
MSE	0.161	1.945	0.139	0.161	1.945	0.139	0.161	1.943	0.139	0.161	1.942	0.139
Residual AC	-0.016 [0.000]	-0.001 [0.234]	0.005 [0.000]	-0.001 [0.238]	-0.002 [0.125]	0.007 [0.000]	0.001 [0.457]	-0.001 [0.222]	0.006 [0.000]	0.001 [0.162]	-0.002 [0.038]	0.006 [0.000]
Residual cross-correlation:												
IOF	1.000 [0.000]	0.056 [0.000]	0.000 [0.943]	1.000 [0.000]	0.056 [0.000]	0.000 [0.991]	1.000 [0.000]	0.056 [0.000]	0.000 [0.937]	1.000 [0.000]	0.056 [0.000]	0.000 [0.917]
Return		1.000 [0.000]	0.050 [0.000]		1.000 [0.000]	0.050 [0.000]		1.000 [0.000]	0.050 [0.000]		1.000 [0.000]	0.050 [0.000]
Sentiment			1.000 [0.000]			1.000 [0.000]			1.000 [0.000]			1.000 [0.000]