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Diego Agudelo, Diego Amaya, Juliana Hincapié, Julián Múnera

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Universidad EAFIT

Attention-based vs information-based trading around announcements. Evidence from an emerging market

Diego Agudelo[*], Diego Amaya[†], Juliana Hincapié [‡], Julián Múnera [§]

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Abstract

We investigate who trades around new releases associate with large price changes in the Colombian Stock Exchange. We take advantage of two unique datasets: a transaction database with investor ids and a database of news reported to the regulator. We identify that both informed and attention-driven traders are two distinct groups of individuals. The former tend to hold larger and more diversified portfolios and trade more actively than the latter. Individuals do most of the liquidity providing around events. We report some evidence of momentum trading by Institutions after those large price changes. No significant participation of foreign investors around the events was found. These results highlight the critical role of retail investors and the need to improve the information environment and institutions' sophistication in a small Emerging Market.

1 Introduction

In a perfectly efficient market, prices should reflect fundamental information of the firms. News releases when conveying material information might change both private valuations and trading prices. In such market, no investor would have an edge predicting unexpected information, and trading in anticipation of news would be pointless[1]. Moreover, prices should reflect instantaneously and unbiasedly the price-relevant information of the announcement, without consistent drifts or corrections afterwards. This rules out as sensible any momentum or contrarian strategy following news releases.

However, there is enough empirical evidence against those theoretical implications. For instance, there is evidence on informed trading before announcements in U.S. markets (e.g., Bernile, Hu, and Tang (2016); Christophe, Ferri, and Angel (2004); Hendershott, Livdan, and Schürhoff (2015)). Furthermore, public announcements stir active trading by investors who disagree on their interpretation of the news (Barron, Harris, & Stanford, 2005). On the other hand, to our knowledge, there are few studies reporting momentum and contrarian trading after large price changes (Barber

[*]Associate Professor of Finance at Universidad EAFIT, Colombia. E-mail: *dagudelo@eafit.edu.co*
[†]Assistant professor at Wilfrid Laurier University, Canada. E-mail: *damaya@wlu.ca*
[‡]MSc in Finance student at Universidad EAFIT, Colombia. E-mail: *sjhincapis@eafit.edu.co*
[§]MSc in Finance student at Universidad EAFIT, Colombia. E-mail: *dmunera3@eafit.edu.co*

[1]Even according to the theoretical model of Grossman and Stiglitz (1980) that acknowledges the impossibility of perfectly efficient markets, extra returns due to informed trading should be minimal and privy of the most sophisticated investors.

and Odean (2007); Lee, Li, and Wang (2010))[2]. In this study, we investigate both informed-and attention-based trading in anticipation and after news releases, respectively, in an emerging market.

This paper is placed in two strands of the literature. The first is the study of the trading behavior of institutions and individuals, which have mostly focused on developed markets (e.g., Bushee and Goodman (2007); Barber and Odean (2007); Kaniel, Liu, Saar, and Titman (2012); Hendershott et al. (2015)). On the contrary, there is scarce research on emerging markets, except for Korea, Taiwan and China, as mentioned below, possibly due to the lack of detailed data. Emerging markets are different to developed ones, not only in terms of development, but also in the proportion between the two local groups, with individuals having a larger share of the trading activity [3]. The previous findings might be limited using summarized data by types of investors, which potentially obscure any relationship between net buys and returns[4].

Second, this study also fits in the literature of who is better informed in an emerging market. The early literature have usually compared locals vs. foreigners (e.g., Huang and Shiu (2009) in Taiwan; Dvořák (2005) in Indonesia; Chan, Menkveld, and Yang (2008) in China and Choe et al. (2005) in Korea). However, a different set of papers such as Barber et al. (2008) and Lee, Liu, Roll, and Subrahmanyam (2004) in Taiwan, and Agudelo et al. (2017) in Colombia, highlight the importance of differentiate locals in the two groups: individuals and institutions. Overall, these studies find that local institutions tend to have better performance than foreigners, and the latter hold a somewhat better performance than local individuals. This agrees at large with the notion that institutions and foreigners are professional investors, with knowledge, resources, scale economies and incentives to outperform individuals, mostly composed by "amateur" traders. Although these results point that any information advantage of individuals is puzzling, Tsai (2014) in Taiwan, finds that a group of these investors behaves as informed traders around new releases.

While most of the related literature has focused on the overall performance, to our knowledge, only a few papers have examined the differential trading behavior by groups of traders around announcements (Park, Lee, & Song, 2014). Accordingly, we study the trading activity behavior of three types of investors: foreigners, local institutions and individuals around news releases in the Colombian stock market. We focus on announcement days with extreme positive or negative prices changes, as a signal of the incorporation of price-relevant information. This approach has been adopted by similar studies, such as Barber and Odean (2007) and Hendershott et al. (2015). Using an event-study methodology, we identify informed investors as those who significantly accumulate (decrease) inventory before positive (negative) events, compared with a non-event period. In the same way, we also identify the attention-driven traders, both momentum and contrarian, after positive events. In cross-sectional regressions, we characterize the successful informed and the attention-driven traders, in both the individual and institutional groups.

[2] Momentum trading is somewhat related to behaviors of "positive feedback trading" reported in studies such as Richards (2005) and Ng and Wu (2007)

[3] Local individuals have a 60-75% of the traded value in Korea Choe, Kho, and Stulz (2005), 90% in Taiwan (Barber, Lee, Liu, & Odean, 2008) and 36% in Colombia (Agudelo, Byder, & Yepes, 2017), but only 4% in U.S. (Kaniel et al., 2012).

[4] In the presence of aggregated data, there could be buyers and sellers for a specific stock within the same group of traders. For example, Tsai (2014) finds in Taiwan that individuals as a group are not informed, but the most aggressively of them appear to be so.

We take advantage of two unique databases. First, the proprietary transactional dataset of the Colombian Stock Exchange, Bolsa de Valores de Colombia (henceforth BVC). This database, going from January 2007 to November 2016, provides not only prices and volumes per trade, but also unique identifiers for both buyer and seller, along with their respective group (local individuals, foreigners and various types of local institutions). In this respect, we identify which is the active side in each trade by using a modified version of the tick test algorithm. Second, we use the database of firm announcements published by Superintendencia Financiera, the Colombian financial regulatory entity (henceforth SF). Colombian listed firms are required to report all relevant information to the SF in the first instance. The news is digitally reported to the SF, and then immediately published in its official webpage. Thus, by combining these two databases we can detect the announcements with a larger impact on stock prices, and identify which type of investor trade around those events.

We initially expect individuals are more informed before announcements than institutions (Lee et al., 2010). The latter should be limited by the size of their positions to take advantage from any short-term information. Furthermore, we expect that a group of individuals manage to exploit private information opportunities, since they trade smaller volumes, and are less constrained than professional portfolio managers by career concerns, agency trade-offs, and diversification requirements. To the extent that some of the informed trading is based on insider information, institutions are less likely to do it, not just for the size of their portfolios, but also for a larger legal exposure and binding governance codes[5]. This is in line with the results of Kaniel et al. (2012) for U.S., where individuals' intense directional trading before earning announcements predicts abnormal returns, due to the presence of private information. Likewise, similar evidence has been reported for China (Lee et al., 2010) and Finland (Vieru, Perttunen, & Schadewitz, 2006).

In turn, some individuals are expected to be both momentum and contrarian traders after public announcements. Barber and Odean (2007) find that individuals are more attention-buyers than institutions in highly visible events in U.S., including extreme one-day returns. Likewise, Lee et al. (2010) argue that individuals are stronger net buyers than institutions following return shocks in China. On the other hand, Kaniel et al. (2012) report individuals as contrarian traders in U.S. after earning announcements or large returns, consistent with profit taking. Conversely, Ng and Wu (2007) in China, find that institutions and wealthy (no wealthy) individuals tend to be momentum (contrarian) traders.

In contrast, we do not expect significant informed trading previous to news announcements by foreign investors. In Colombia, all foreigners are institutions (Agudelo et al., 2017), and they are not supposed to have much firm-specific information. On the other hand, we expect these investors act as momentum traders, as reported in Taiwan (Liao, Chou, & Chiu, 2013) and Finland (Grinblatt & Keloharju, 2000). Besides, some return-chasing has been evidenced for foreigners in emerging markets (Froot, O'connell, and Seasholes (2001); Richards (2005)).

We find that individuals do the most informed trading before positive events, mostly using passive orders. These investors appear to be also the most informed traders before negative events,

[5] However, Park et al. (2014) report in Korea that institutions are profitable traders around earning announcements, specially before negative surprises. Besides, Hendershott et al. (2015) find that institutions are informed on news releases in U.S., but they do not trade on "hype" unrelated to fundamentals.

followed by foreigners. Although institutions as a group have no significant effect around both events, Brokerage Firms and Long-Term institutions appear to be the most informed institutional investors before positive events, while the latter appear as the only significant group before negative events. The most active and largest investors are the most informed traders before both events. Besides, individuals, followed by institutions, appear to do the most momentum trading after both positive and negative events. Family Offices and Long-term institutions tend to be the most significant buyers after positive events, while Brokerage Firms after negative ones. Informed individuals are diversified, sophisticated and active traders. Finally, we find that individual and institutional momentum traders are small and less active, tend to invest in less volatile stocks and are not well diversified.

The contribution of this research is two-fold. First, whereas the consensus of the recent literature in emerging markets indicates that institutions are overall better informed and have a better performance than individuals (Barber et al. (2008); Lee et al. (2004); Agudelo et al. (2017)), there are few studies that compare their performance in specific events (Park et al. (2014); Hung (2014); Tsai (2014)). In stark contrast with that literature, we find that the most successful trades before news releases are heavily made up by some individual investors. On the other hand, a different group of individuals act as the main liquidity providers for those informed traders. Thus, it is still possible that the individuals' performance as a group lags behind that of institutions.

Second, to our knowledge, this is the first paper in studying the role of foreign investors around extreme returns with announcements. This is interesting as a test of whether foreigners compete in equal terms with both local groups in procuring and trading in advance of firm-specific information. Moreover, we go beyond previous studies by analyzing the behavior of different types of institutional investors during announcement days, and not simply taking them together as a homogeneous group. Differentiating the performance on large returns of short-term institutions, as Brokerage Firms, against that of long-term ones, such as Pension Funds, give us a better understanding of their contrasting investment styles.

The most related study is Tsai (2014), who examine the relationship between net buys by types of investors around earning announcements in Taiwan. He also identifies individual accounts and passive and aggressive trades. This author finds that although individuals as a group do not appear to be informed, the most aggressive of them tend to correctly anticipate price changes. Further, he reports that individuals' net buys predict future abnormal returns, beyond what can be explained by past returns or volumes. In this respect, we have some important differences. Our main objective is to study the trading activity and the associated performance by type of investor around abnormal returns with announcements, no the abnormal return itself. Moreover, we not only identify the investors that actively trade before news releases, but also the groups that significantly buy or sell afterwards, and characterize both groups. Furthermore, we study foreign investors and different types of local institutional traders.

The rest of this paper is organized as follows. Section 2 describes the two datasets. Section 3 presents the research method. Section 4 discusses the results, and finally Section 5 provides concluding remarks.

2 Data

We are interested in studying the trading activity of different groups of investors around announcements associated with extreme returns in the Colombian stock exchange. For this purpose, we use two unique databases. The first dataset is provided by the BVC. The data include a total of 11.727.756 intraday records of stock market transactions from January 2008 to November 2016. Each trade record contains in detail, all key elements of a stock transaction, including the nemo, the execution price, the number of shares traded, the date and time, the side of the the trade, the type of investor and the account identifier. We supplement the BVC database with daily data on returns (close-to-close returns based on closing prices) and market capitalization (number of shares outstanding) from Bloomberg. The analysis is focused on the 40 stocks that have composed the COLCAP, the main stock market index in Colombia, along the sample period. Figure 1 displays the number of transactions executed on each stock in the whole sample.

During this period, the agents executed 5.820.029 buys and 5.907.727 sales. Based on the account identifiers, 96.53% of the accounts belong to individual traders with 511.766 different investors. During our sample period, individuals made 2.505.863 buys with an average value of $32.938.783 and 3.116.337 sales with an average value of $30.065.152. Our institutional traders data include intraday trading records for 14.139 institutional traders (2.67% of the accounts). During the sample period, institutions made 2.174.590 purchases with an average value of $68.591.964 and 1.977.677 sales with an average value of $77.090.152. The remaining 0.8% accounts belong to foreigners (4.242 accounts). Foreign investors made 925.342 buys with an average value of $61.876.065 and 646.181 sales with an average value of $68.136.201.

Our second dataset contains the announcements reported by the companies to the SF for the same period. It includes 20.000 news releases of diverse nature. The data are hand-collected and each record in the database includes for each announcement date and time of publication, company's name, type of announcement and summary of the contents. The news releases include information regarding financial statements, operating reports, capital structure, restructuring, decisions of the board of directors, company appointments, risk ratings, etc. The table 1 and figure 2 provide an overview of the different announcements topics covered by the dataset and the distribution of news releases over time.

3 Methodology

3.1 Trade assignment classification

The BVC transactional database does not allow to identify whether a trade was initiated by the buyer or the seller. To do this we use a modified version of the Tick Test algorithm. The Tick Test algorithm is a standard procedure in the market microstructure literature that determines the direction of a trade by comparing its price with those of preceding trades (Lyons (1995); Sias and Starks (1997)). Essentially, this algorithm classifies each trade as a buy (sell) if its price is higher (lower) than the price of previous trade. If these prices are equal, the trade is classified as the previous one.

A modified version of the Tick Test is implemented because BVC's database does not have the timestamp of the trades beyond seconds, a necessary condition for this trade assignment technique. Thus, trades in the same second can be misclassified (see the Appendix A for more details).

In order to test the accuracy of the modified Tick Test, we use an intraday TAQ database from Bloomberg to implement this algorithm and the original Tick Test. The data include a total of 751.171 intraday records from January 2012 to December 2015. The coincidence percentage between both methods was 97.3%, which reflects a fairly high accuracy of the proposed algorithm.

The table 2 reports the number of transactions classified as aggressive, passive or undetermined for each investor group in the sample period.

3.2 Event study methodology

We are interested in studying the trading activity of groups of investors around news releases with extreme returns. For this purpose, we perform an event study methodology similar to Irvine, Lipson, and Puckett (2006) and McNally, Shkilko, and Smith (2015). We define positive (negative) events at stock level, as returns in days of announcements, above (below) the 95th (5th) percentile of the respective empirical distribution. Out of a total of 602 (540) positive (negative) events, we selected 266 (240) to avoid contamination of our measures by overlapping events. Figure 3 shows the events selected by stock.

We analyze the abnormal trading activity by type of investor in the selected event window (-10, +50 days around the event). For each day in the [-10, +10] window, we calculate buys, sells and trading volume, normalizing by shares outstanding by type of investor. To detect abnormal trading activity, we implemented a t-test analysis to evaluate the significance of any single day with the benchmark level of trading activity, which is calculated by taking the mean across daily averages in the post-event period (window +10,+50).

We assume that 10 days before each announcement is the time where investors with information advantage might trade in anticipation. A positive (negative) and significant value of the net buy or buy variable suggests that the group of investors are trading on the foreknowledge of the favorable (non-favorable) news. Traders whit significant sell (buy) activity before favorable (non-) news are taking the opposite side of the trade. Also, we assume that the momentum (contrarian) traders increase their buys or net buys (sells) in the period [+1, +10] after a positive announcement, or sells (buys) after a negative one.

Figures 4 and 5 reports the average turnover by type of investor around positive and negative events, in the [-10;+10] trading window. As shown in figure 4, individuals are the most aggressive investors, followed by institutions, while foreigners have a much lower participation. In addition, in the pre-event trading window there is some substantial trading activity, which might be the result of increasing positions by informed traders. Likewise, trading activity is stronger in the post-event window, especially from the first to the fifth day for both individual and institutional investors. This is suggestive of sizable attention-based trading after extreme positive returns. On the other hand, figure 5 shows that in presence of extreme negative returns with announcements, investors tend to react mostly at the day before the event. Any eventual informed-or attention-based trading appear concentrated in the [-2;+3] window. However, both individuals' and institutions' turnovers are larger in the post-event window.

Additionally, to evaluate the performance of the investors in each event, we construct a performance measure based on the one of Irvine et al. (2006) as follows:

$$Perf_{jit} = \frac{\sum_{x\in[-10,-1]} B_{jix}(P_{it} - PB_{jix}) - \sum_{x\in[-10,-1]} S_{jix}(P_{it} - PS_{jix})}{\left|\sum_{x\in[-10,-1]} B_{jix} - \sum_{x\in[-10,-1]} S_{jix}\right| P_{i,t-1}} \tag{1}$$

where j is the investor, i is the stock, t is the event day, B (S) is the amount of shares i purchased (sold) by the investor j at time x, P_{it} is the closing price of stock i in the event day and PB_{jix}, PS_{jix} are the prices at which the transactions were executed. This measure acknowledge all realized gains and losses during the trading window [-10, -1] at prices actually executed. It takes as the investment, the absolute value of investor's net position during the window before the event [-10, -1] to the price at the end of that period ($P_{i,t-1}$). This profit is expressed as a fraction of the position established at the end of the trading period.

3.3 Regressions Using Investor-Level Aggregation

To characterize the informed and momentum traders, we complement the research by estimating cross-sectional at investor-level regressions. Specifically, we attempt to find the relation between the performance or net buys and a set of variables that capture aspects of the investor's style of trading. The cross-sectional regressions are estimated for the average performance, and for the average net buys in the windows [-10;-1] and [+1,+10], for both individual and institutional investors. The cross-sectional regressions for $Perf_i$ and $Net\_Buy_{i,(-10,-1)}$ are employed to analyze what characteristics define a successful informed trader. The regression for $Net\_Buy_{i,(+1,+10)}$ allows us to examine the characteristics that define an attention-driven trader. We estimate the following equations, separating by institutional and individual investors:

$$Avg\_Perf_j = \beta_0 + \beta_1 X_j + \epsilon_j \tag{2}$$

$$Avg\_Net\_Buy_{j,(-10,-1)} = \beta_0 + \beta_1 X_j + \epsilon_j \tag{3}$$

$$Avg\_Net\_Buy_{j,(+1,+10)} = \beta_0 + \beta_1 X_j + \epsilon_j \tag{4}$$

where,
Avg_Perf_i = average performance (equally weighted or value weighted) of investor i;
$Avg\_Net\_Buy_{i,(-10,-1)}$ = average net buys of investor i in the [-10, -1] window across the events she trades on;
$Avg\_Net\_Buy_{i,(+1,+10)}$ = the average net buys of investor i in the [+1, +10] window across the events she trades on;
X_j = matrix of control variables. Includes variables like number of different stocks traded, number of events in which agent has traded, capitalization and trading activity indicators, average value

per operation, diversification indicators, transactions in stocks with low and high volatility. The detailed information of these variables is in the Appendix B, table 15.

4 Results

This section presents the main results obtained from the methodology defined in Section 3. First, using t-tests, we report evidence on which types of investors appear to be the informed-and attention-based traders. We then characterize the informed and momentum investors, using the results of the cross-sectional regressions.

4.1 Informed-based trading by type of investor

We are initially interested in finding out which type of investor has abnormal trading activity before extreme positive returns with announcements. We expect that informed investors have particularly large buying before the announcement day, so that they can take advantage of price appreciations. Table 3 reports daily trading activity measures by the three types of investors in the [-10;+10]-day window around the filtered 266 positive events. To test for statistical significance, we use the time-series mean and variance of scaled-trading activity measures in the post-event [+11;+50] trading window, following Irvine et al. (2006) and McNally et al. (2015).

The table indicates that all traders have statistically significant buys and sales during some days before the event (-8, -7, -2). Individuals have both the largest and most significant buys and sales before the event. Thus, it appears that in the individual group are both the successful informed traders, as well as most of the liquidity providers. In turn, institutions tend to be significant sellers, probably providing liquidity to individuals, and foreigners do not seem to have an atypical behavior around these kinds of events.

Similarly, we expect that informed investors sell all or part of their inventory before extreme negative returns, avoiding incurring large losses. Table 4 shows that for all traders the anticipation of negative events is not for so many days as for positive ones. One explanation might be the difficulty of doing short-sales in the Colombian stock market for several days, to take advantage of falls in stock prices. However, although the main effect is concentrated in the day before, these sales are much larger. In this respect, although individuals are net-buyers, the most informed of them appear to be significant selling one day before the negative event. Likewise, foreigners have also significant sales during the same day, but in a smaller amount than individuals.

Institutions as a group have no significant abnormal trading activity around positive or negative events. We might fail to detect such activity because of the multiple groups that fall in this category. Thus, we disaggregate institutions in the following: Brokerage Firms, Family Offices, Long-Term institutions (i.e., Pension Funds and Insurance Companies), Funds (i.e., Mutual Funds and other managed portfolios), and Others (i.e., Banks, Leasing Companies, ADRs, Cooperatives, Investment Companies, Fiduciary and Factoring Firms). Conducting the t-tests for each group, Table 5 reports that Brokerage Firms followed by Long-Term institutions, appear to be the most informed institutional investors before positive events, given the magnitude of their significant buys in the pre-event window. On the other hand, Long-Term institutions appear as the only significant group speculating around negative events (see Table 6).

Otherwise, we investigate whether the informed trading is related to the level of trading activity or size (capitalization) of the investors. In this regard, table 7 indicates that although there is some significant buying in the Less-active and Small investors as a group, the most active and largest traders execute most of the informed trading in the [-8;-7] window around positive events, compared to the results reported in Table 3, column 1. Likewise, the most active and largest investors do most of the informed selling one day before the negative events (see Table 8).

Finally, it is important to classify the trades direction given the private information they can signal. The faster the private information disappears, the more informed investors execute their operations through market orders (Rock, 1996). Thus, we analyze trading activity measures around positive events by both aggressive and passive orders. Table 9 and Table 10 show that individuals are the main significant buyers before positive events by both active and passive orders. However, the successful individual speculator prefers to accumulate inventory by passive buys, which is consistent with they acting as informed traders well in advance of the new release (Kaniel & Liu, 2006). Likewise, some individuals significantly buy two days before the event by aggressive buys, which is also related with some of these investors with a lower depreciation rate of insider information (Glosten, 1994).

4.2 Attention-based trading by type of investor

As mentioned above, there are some investors who trade significantly after public announcements associated to large returns. For instance, some attention-based traders might be buying (selling) a given stock after a positive (negative) event, acting as short-term momentum traders or "trend followers" (Barber and Odean (2007); Lee et al. (2010)). We can also find other attention-based investors who are interested in selling (buying) valued stocks after these extreme positive (negative) returns, due to contrarian style, rebalancing or profit taking incentives. In particular, we concentrate in studying momentum investors as a specific kind of attention-based traders.

Table 3 indicates that all types of traders react strongly after a positive event, both buying and selling. Although individuals as a group are net buyers in the [+1;+4] window, acting as possible momentum traders, some of them are significant sellers during this period. Institutions have also significant buys two days after, but they tend to be much smaller than individuals and overall net-sellers like foreigners. In the same way, individuals are the most important net-sellers one day after negative events, followed by institutions, who as a group are net-buyers but also have substantial significant sells.

The event-study by groups of institutions in Table 5 shows that although Family Offices are net-sellers after an extreme positive return, some of them are the strongest significant buyers during these episodes, 2 and 4 days after, followed by Long-term institutions. On the other hand, Table 6 indicates that Brokerage Firms act as the main institutional investor trading in momentum style after extreme negative returns, while other Brokerage Firms and Family Offices appear to be the liquidity providers. In turn, there is not much attention-based trading in Long-term investors.

As mentioned above, Table 7 and Table 8 report average trading activity measures for the least and most active, and the smallest and largest traders, around positive and negative events, respectively. The tables show that momentum investors are active and large traders, given their significant buys (sells) after a positive (negative) event. Likewise, classifying the trades (see Tables 9 and 10), we find that individuals when acting as momentum investors use both aggressive and passive buys, but they prefer to trade with the former for positive events.

4.3 Characterizing Informed and Momentum Investors

To examine what kind of characteristics define an informed trader, we first estimate cross-sectional regressions for both equally-and value-weighted performance measures and the net buys in the [-10;-1] window, for individuals and institutions investors separately. Table 11 shows that the successful individual speculator is a diversified trader, who invests in several stocks throughout the whole market and sample. In addition, informed individual traders are active, have a smaller average traded value, and invest on fixed-income assets. On the contrary, we do not find these features significantly related to the institutions' performance, probably because most of these investors tend to be well diversified. Finally, we do not report evidence about a different performance by institutional groups.

Likewise, Table 12 presents the results of regressing the net buys in the [-10;-1] window for individuals and institutions investors, against all descriptive variables defined in equation 3. This table shows that most active buyers before positive events are well diversified but specialized investors that invest in many different stocks but in a few number on the same day, during the whole sample. Both individual and institutional net-buyers are placed in the top decile of their respective size distribution. In contrast, the least active individuals are net-sellers on average in days before of positive events. Further, both successful individual and institutional net-buyers tend to trade less in the non-volatile stocks in the pre-event window. This agrees with the notion that speculators prefer more volatile stocks, due to their higher potential profit. Finally, we find that except for the "Other" group, the remaining four institutional ones tend to be more net-buyers than the Brokerage Firms (omitted group on the regression).

On the other hand, to examine the characteristics of momentum traders, we also estimate cross-sectional regressions for the net buys in the [+1;+10] window, for individuals and institutions investors, separately. In this regard, Table 13 shows that both individual and institutional momentum net-buyers are not well diversified, but tend to participate in a high number of positive events. Further, they are small and less-active investors, with a small average traded value during the whole sample. Besides, both groups invest more in less volatile stocks in the whole sample, and the momentum individuals tend to trade in many stocks on the same day. Subsequently, we find that Long-term institutional investors have larger net buys on the post-event window than Brokerage Firms (omitted group on the regression). This is an unexpected result, given that long-term institutions place higher funding restrictions to act in the short-term in response to large positive returns.

5 Conclusions

In this paper, we study informed-and attention-based trading by types of investors around extreme returns associated with announcements in the Colombian stock market. Our results show that individuals are both the successful informed traders and the most liquidity providers, followed by institutions, before positive events. The informed investors prefer using passive orders in anticipation to extreme positive returns associated to announcements. Individuals appear to be also the most informed traders before negative events, followed by foreigners, with smaller significant sales. Institutions as a group have no significant abnormal trading activity around positive or negative events. However, disaggregating the latter group, Brokerage Firms followed by Long-Term institutions, appear to be the most informed institutional investors before positive events, while the latter appear as the only significant group speculating around negative extreme negative returns related with news releases. The most active and largest investors are the most informed traders before both events.

Besides, we find that individuals, followed by institutions, appear to do the most momentum trading after both positive and negative events. Family Offices and Long-term institutions tend to be the most significant buyers after positive events, while Brokerage Firms appear to be the most important momentum trader after negative events. The evidence points that informed individuals are diversified, sophisticated and active traders, with small average traded value. On the other hand, the most active individual and institutional buyers before positive events, are large and tend to trade less in the non-volatile stocks. Finally, we find that individual and institutional momentum net-buyers are small and less active, tend to invest in less volatile stocks and are not well diversified.

In our opinion, these results might motivate regulators in small emerging markets, like Colombia, to better scrutinize suspicions trading, especially around dramatic announcements. We expect that some abnormal trading activity before announcements is due to insider trading, as reported in Vietman by Nguyen, Tran, and Zeckhauser (2017). Our results report evidence on abnormal buying (selling) before abnormal positive (negative) returns in the Colombian stock market. Although there is a regulation against insider trading in Colombia, we have not found any prosecution of insider trading in this market during the last 15 years[6]. The implications of our research are also reinforced with the theoretical model of Bhattacharya and Daouk (2009), where a non-enforced insider trading regulation is a worse outcome for the market quality and fairness even that the absence of this regulation.

[6]The last prosecuted case was in 2005 and was related to insider trading in Government Bonds with the announcement of inflation. Moreover, Leaño and Pedraza (2016) report that Pension Funds in Colombia appear to have insider information when trading the stocks of companies from their same economic group.

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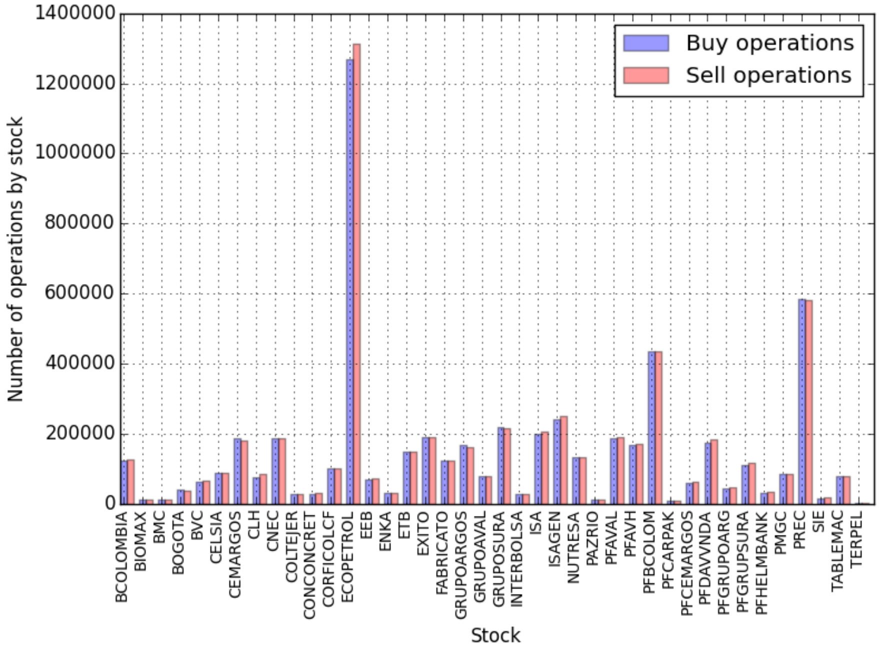
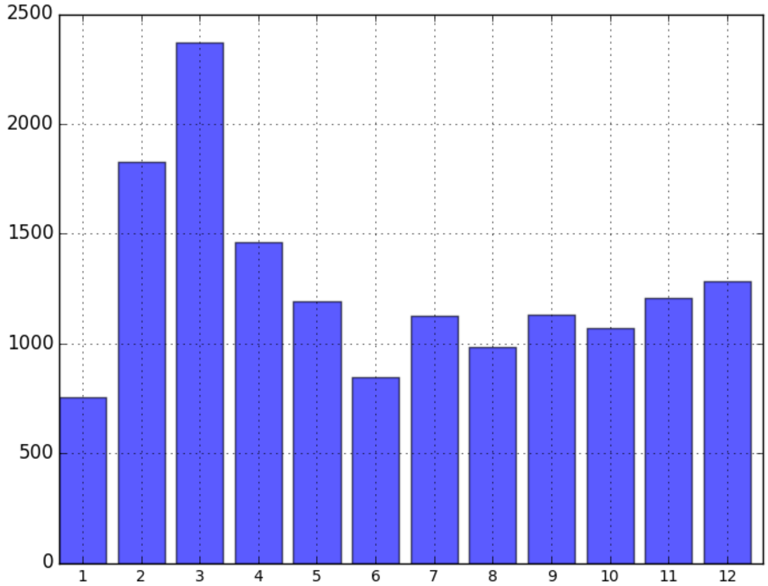
Figure 1: Operations by stock



The figure shows the number of sells and buys executed on 40 stocks that have composed the COLCAP index from January 2008 to November 2016. The most traded stock in the whole sample is ECOPETROL, followed by PREC and PFBCOLOMBIA, respectively.

Figure 2: Distribution of news releases over time



The figure shows the number of announcements released by month in the whole sample. The announcements are concentrated mainly in February and March. From March, the news have a decreasing trend, reaching a minimum in June. In the second semester they increase again, reaching a maximum in December.

Table 1: Announcements topics

Topic	Percentage
Announcements published by the company	0.234
Decisions of the Board of Directors	0.074
Rating values	0.068
Financial situations of the issuer	0.067
Legal situations of the issuer	0.033
Financial statements	0.032
News in media of Securities Issuers	0.029
Reform of statutes	0.027
Utility or Lost Project to be presented to the Assembly	0.026
Profit or loss project approved by Assembly	0.026
Issuer rating	0.025
Quotation to Ordinary Assembly	0.024
Representation of Shareholders	0.024
Issuance of securities	0.022
Change of Board	0.022
Celebration, modification or termination of contracts	0.021
Extraordinary Assemblies	0.019
Good Government Codes	0.019
Investment in other companies	0.018
Acquisition and / or alienation of securities	0.014
Others	0.175

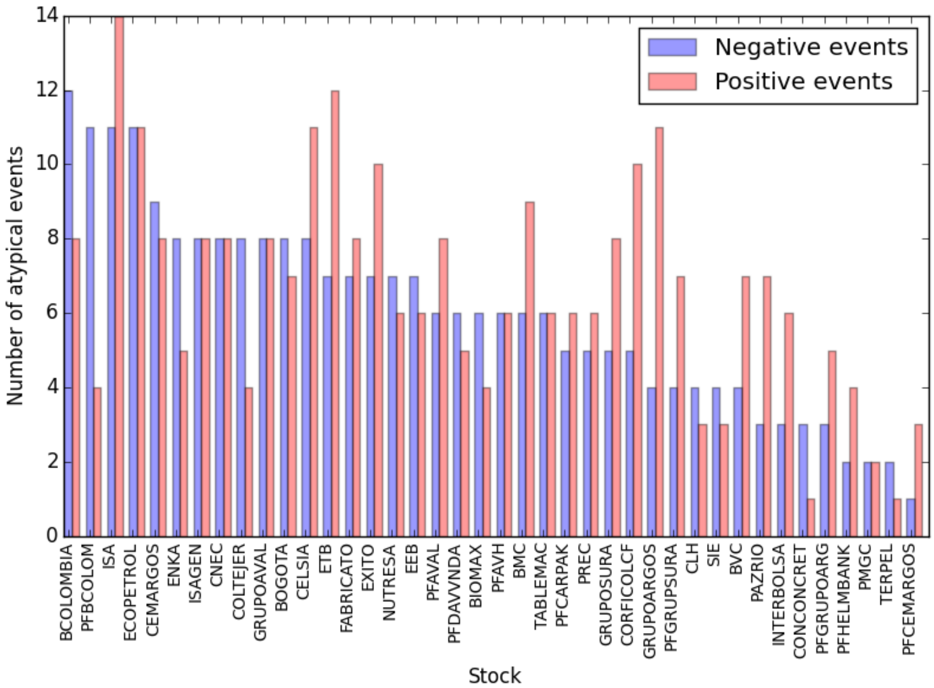
The table presents the main topics included in the announcements database. The news releases include information about financial statements, capital structure, investments risk ratings, etc. Around 30% of the news are concentrated on "announcements published by the company" and "decision of the board of directors".

Table 2: Trade assignment classification

	Individuals	**Institutions**	**Foreigners**
Types of Orders			
Active Orders	41.86%	45.14%	49.99%
Passive Orders	46%	44.32%	39.57%
Non-classifiable Orders	12.14%	10.54%	10.44%

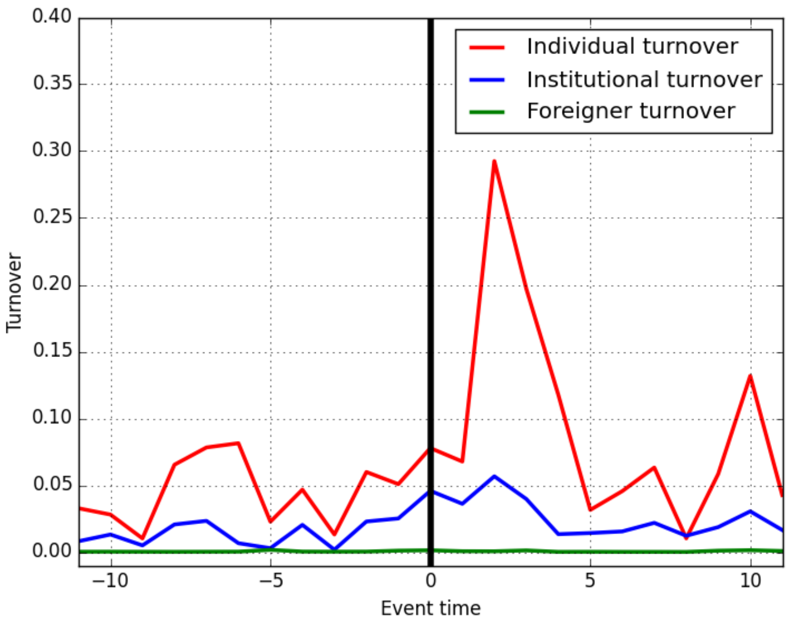
The table contains the trade assignment classification by type of investor. Individuals tend to have a greater proportion of passive orders than the other types of investors. Foreigners have a greater proportion of a active ders institutions have a balance between both, aggressive and passive orders.

Figure 3: Positive and negative events by stock



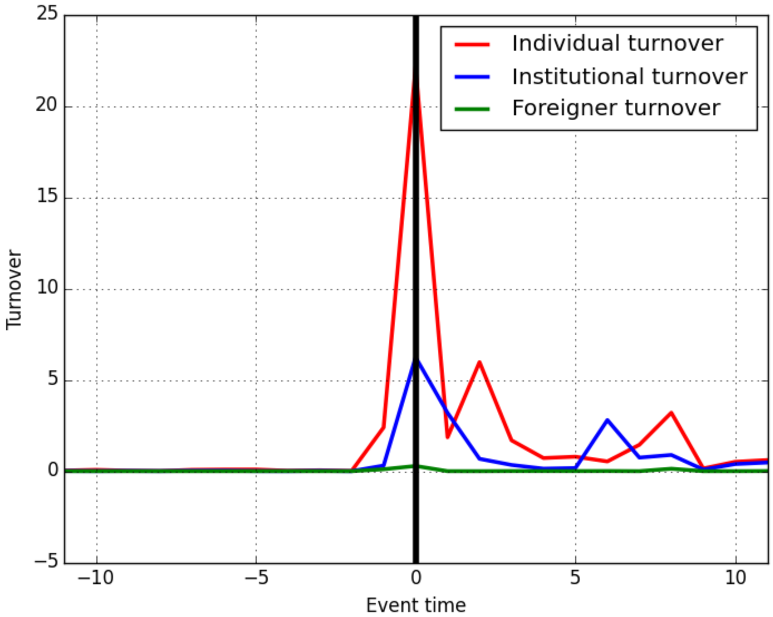
The figure shows the number of events selected by stock. We define positive (negative) events at stock level, as returns with announcements above (below) the 95th (5th) percentile of the respective empirical distribution. The data is presented in descending order of negative events.

Figure 4: Positive Events (Extreme positive returns with announcements)



This figure presents the turnover measure by type of investor around positive events. Turnover correspond to the sum of the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. We define positive events at stock level, as returns with announcements above the 95th percentile of the respective empirical distribution.

Figure 5: Negative Events (Extreme negative returns with announcements)



This figure presents the turnover measure by type of investor around negative events. Turnover correspond to the sum of the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. We define negative events at stock level, as returns with announcements below the 5th percentile of the respective empirical distribution.

Table 3: Trading Activity around positive events by Type of Investor

	All traders			**Individuals**			**Institutions**			**Foreigners**		
Time windows	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Buys	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*
-10	0.0208	0.0208	0.0417	0.0195	0.0086	0.0281	0.0012	0.0120	0.0132	0.0002	0.0002	0.0003
-9	0.0078	0.0078	0.0156	0.0067	0.0036	0.0103	0.0009	0.0041	0.0050	0.0002	0.0001	0.0003
-8	0.0432*	0.0432*	0.0864*	0.0353**	0.0301*	0.0654*	0.0078	0.0129*	0.0207	0.0001	0.0001	0.0003
-7	0.0510***	0.0510***	0.1020***	0.0444***	0.0340**	0.0783***	0.0065	0.0169***	0.0234**	0.0002	0.0001	0.0003
-6	0.0443*	0.0443*	0.0885*	0.0386**	0.0429***	0.0815***	0.0055	0.0012	0.0067	0.0002	0.0002	0.0004
-5	0.0137	0.0137	0.0274	0.0114	0.0114	0.0228	0.0022	0.0007	0.0029	0.0001	0.0016***	0.0017***
-4	0.0338	0.0338	0.0676	0.0313	0.0155	0.0468	0.0024	0.0180***	0.0204	0.0001	0.0003	0.0004
-3	0.0077	0.0077	0.0154	0.0067	0.0065	0.0132	0.0008	0.0010	0.0018	0.0002	0.0002	0.0004
-2	0.0417*	0.0417*	0.0833*	0.0355**	0.0245	0.0600	0.0060	0.0169***	0.0229**	0.0002	0.0002	0.0004
-1	0.0386	0.0386	0.0772	0.0347*	0.0161	0.0509	0.0031	0.0221***	0.0252***	0.0008	0.0003	0.0011
0	0.0626***	0.0626***	0.1252***	0.0423***	0.0356**	0.0778***	0.0197***	0.0262***	0.0459***	0.0006	0.0008***	0.0014**
+1	0.0523***	0.0523***	0.1047***	0.0479***	0.0199	0.0678**	0.0038	0.0324***	0.0362***	0.0006	0.0001	0.0007
+2	0.1750***	0.1750***	0.3500***	0.1619***	0.1307***	0.2926***	0.0129***	0.0438***	0.0567***	0.0002	0.0004***	0.0006
+3	0.1190***	0.1190***	0.2380***	0.1116***	0.0854***	0.1970***	0.0065	0.0332***	0.0397***	0.0009	0.0004**	0.0013*
+4	0.0657***	0.0657***	0.1314***	0.0570***	0.0608***	0.1178***	0.0086	0.0049	0.0134	0.0001	0.0001	0.0002
+5	0.0231	0.0231	0.0462	0.0196	0.0120	0.0316	0.0033	0.0110	0.0143	0.0002	0.0001	0.0003
+6	0.0307	0.0307	0.0614	0.0236	0.0220	0.0457	0.0069	0.0086	0.0155	0.0001	0.0001	0.0002
+7	0.0427*	0.0427*	0.0855*	0.0286	0.0347**	0.0633*	0.0140***	0.0080	0.0219*	0.0001	0.0001	0.0002
+8	0.0114	0.0114	0.0228	0.0054	0.0049	0.0103	0.0058	0.0064	0.0122	0.0001	0.0001	0.0002
+9	0.0392	0.0392	0.0784	0.0324*	0.0262	0.0586	0.0064	0.0123	0.0187	0.0004	0.0006***	0.0011
+10	0.0819***	0.0819***	0.1638***	0.0574***	0.0745***	0.1319***	0.0235***	0.0071	0.0305***	0.0011**	0.0004**	0.0014**
+11, +50	0.0301	0.0301	0.0601	0.0224	0.0202	0.0427	0.0070	0.0095	0.0165	0.0006	0.0003	0.0009

This table contains average trading activity measures around the filtered 266 positive events by type of investor. We define positive events at stock level, as returns with announcements above the 95th percentile of the respective empirical distribution. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 4: Trading Activity around negative events by Type of Investor

	All traders			Individuals			Institutions			Foreigners		
Time windows	(1) *Buys*	(2) *Sells*	(3) *Turnover*	(4) *Buys*	(5) *Sells*	(6) *Turnover*	(7) *Buys*	(8) *Sells*	(9) *Turnover*	(10) *Buys*	(11) *Sells*	(12) *Turnover*
-50, -11	0.0250	0.0250	0.0499	0.0194	0.0161	0.0356	0.0053	0.0087	0.0140	0.0002	0.0001	0.0003
-10	0.0395	0.0395	0.0791	0.0368	0.0360	0.0729	0.0025	0.0034	0.0059	0.0002	0.0001	0.0003
-9	0.0233	0.0233	0.0466	0.0218	0.0096	0.0314	0.0014	0.0136	0.0149	0.0001	0.0001	0.0002
-8	0.0087	0.0087	0.0173	0.0075	0.0040	0.0115	0.0010	0.0046	0.0056	0.0001	0.0001	0.0002
-7	0.0485	0.0485	0.0969	0.0395	0.0337	0.0732	0.0087	0.0146	0.0234	0.0002	0.0001	0.0002
-6	0.0571	0.0571	0.1141	0.0495	0.0379	0.0875	0.0073	0.0190	0.0262	0.0002	0.0001	0.0003
-5	0.0494	0.0494	0.0987	0.0430	0.0476	0.0906	0.0061	0.0017	0.0078	0.0002	0.0001	0.0003
-4	0.0156	0.0156	0.0312	0.0132	0.0128	0.0260	0.0023	0.0009	0.0032	0.0001	0.0018	0.0020
-3	0.0366	0.0366	0.0731	0.0341	0.0172	0.0513	0.0023	0.0193	0.0216	0.0001	0.0001	0.0002
-2	0.0081	0.0081	0.0162	0.0073	0.0073	0.0146	0.0007	0.0006	0.0013	0.0001	0.0002	0.0003
-1	1.4020***	1.4020***	2.8040***	1.2364***	1.1559***	2.3923***	0.1423	0.1638	0.3061	0.0233***	0.0823***	0.1055***
0	14.3383***	14.3383***	28.6766***	12.5483***	9.6104***	22.1586***	1.6011***	4.6331***	6.2342***	0.1889***	0.0946***	0.2835***
+1	2.5236***	2.5236***	5.0471***	0.7553***	1.0984***	1.8536***	1.7680***	1.4243***	3.1924***	0.0002	0.0008	0.0010
+2	3.3223***	3.3223***	6.6447***	3.0881***	2.8808***	5.9689***	0.2337	0.4413***	0.6750***	0.0005	0.0001	0.0006
+3	1.0183***	1.0183***	2.0366***	0.8452***	0.8437***	1.6889***	0.1729	0.1674	0.3404	0.0002	0.0070***	0.0072
+4	0.4308	0.4308	0.8617	0.3574***	0.3604	0.7178*	0.0726	0.0639	0.1365	0.0008	0.0065***	0.0073
+5	0.4828	0.4828	0.9656	0.3698***	0.4217	0.7914**	0.1129	0.0557	0.1686	0.0001	0.0053***	0.0054
+6	1.6704***	1.6704***	3.3407***	0.2476	0.2853	0.5329	1.4226***	1.3764***	2.7990***	0.0001	0.0086***	0.0087
+7	1.0938***	1.0938***	2.1875***	0.7504***	0.6931***	1.4435***	0.3432	0.3998***	0.7430***	0.0001	0.0008	0.0009
+8	2.1117***	2.1117***	4.2234***	1.7306***	1.4708***	3.2014***	0.3189	0.5694***	0.8884***	0.0621***	0.0715***	0.1335***
+9	0.1182	0.1182	0.2364	0.0622	0.0861	0.1483	0.0559	0.0319	0.0878	0.0001	0.0001	0.0003
+10	0.4517	0.4517	0.9034	0.1513	0.3611	0.5124	0.2998	0.0898	0.3896	0.0005	0.0007	0.0012
+11, +50	0.5439	0.5439	1.0878	0.2491	0.3590	0.6081	0.2894	0.1830	0.4724	0.0053	0.0019	0.0072

This table contains average trading activity measures around the filtered 240 negative events by type of investor. We define negative events at stock level, as returns with announcements below the 5th percentile of the respective empirical distribution. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 5: Trading Activity around positive events by types of Institutions

	Brokerage Firms			Family Offices			Long-Term institutions			Funds			Others		
Time windows	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Buys	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*
-50, -11	0.0007	0.0009	0.0015	0.0018	0.0022	0.0040	0.0001***	0.0001	0.0002	0.0001	0.0001	0.0002	0.0000	0.0022	0.0022
-10	0.0004	0.0010	0.0014	0.0003	0.0003	0.0006	0.0001***	0.0001	0.0002	0.0003	0.0001	0.0004	0.0000	0.0105***	0.0106***
-9	0.0002	0.0027	0.0030	0.0004	0.0003	0.0007	0.0002***	0.0001	0.0002***	0.0001	0.0000	0.0002	0.0000	0.0010	0.0010
-8	0.0046***	0.0012	0.0058***	0.0030	0.0035	0.0065	0.0001	0.0000	0.0001	0.0001	0.0000	0.0001	0.0000	0.0082***	0.0082***
-7	0.0011**	0.0044***	0.0055***	0.0052	0.0065*	0.0117	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0000	0.0059***	0.0059***
-6	0.0008	0.0002	0.0010	0.0045	0.0008	0.0052	0.0001	0.0001***	0.0002	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000
-5	0.0003	0.0003	0.0006	0.0017	0.0002	0.0020	0.0001	0.0001***	0.0002	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000
-4	0.0002	0.0020	0.0023	0.0017	0.0058	0.0075	0.0003***	0.0001*	0.0004***	0.0001	0.0001	0.0002	0.0000	0.0100***	0.0100***
-3	0.0003	0.0005	0.0008	0.0003	0.0003	0.0006	0.0002***	0.0002***	0.0003***	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
-2	0.0011**	0.0019	0.0030	0.0046	0.0003	0.0049	0.0001***	0.0001*	0.0002***	0.0001	0.0000	0.0001	0.0000	0.0147***	0.0147***
-1	0.0002	0.0004	0.0006	0.0025	0.0003	0.0029	0.0002***	0.0001	0.0003***	0.0001	0.0001	0.0002	0.0000	0.0212***	0.0212***
0	0.0007	0.0008	0.0015	0.0187***	0.0025	0.0212***	0.0001	0.0002***	0.0003***	0.0002	0.0002	0.0004	0.0000	0.0224***	0.0224***
+1	0.0002	0.0004	0.0007	0.0033	0.0023	0.0056	0.0001***	0.0002***	0.0003***	0.0001	0.0002	0.0003	0.0000	0.0293***	0.0293***
+2	0.0008	0.0014	0.0023	0.0116***	0.0165***	0.0281***	0.0003***	0.0001	0.0004***	0.0001	0.0002	0.0003	0.0000	0.0257***	0.0257***
+3	0.0002	0.0005	0.0007	0.0060	0.0068*	0.0128	0.0002***	0.0002***	0.0004***	0.0001	0.0001	0.0002	0.0000	0.0257***	0.0257***
+4	0.0002	0.0003	0.0005	0.0082***	0.0044	0.0126	0.0001	0.0001	0.0002	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000
+5	0.0003	0.0011	0.0015	0.0028	0.0096***	0.0124	0.0001***	0.0001	0.0002	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000
+6	0.0014***	0.0017	0.0031	0.0053	0.0067*	0.0120	0.0001	0.0001*	0.0002*	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000
+7	0.0002	0.0022	0.0024	0.0135***	0.0056	0.0191***	0.0001***	0.0001	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
+8	0.0001	0.0014	0.0016	0.0055	0.0049	0.0103	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
+9	0.0002	0.0011	0.0013	0.0061	0.0110***	0.0171***	0.0001	0.0001***	0.0002***	0.0000	0.0001	0.0001	0.0000	0.0000	0.0000
+10	0.0179***	0.0020	0.0199***	0.0054	0.0048	0.0102	0.0001	0.0001***	0.0002***	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
+11, +50	0.0006	0.0022	0.0028	0.0058	0.0048	0.0107	0.0001	0.0001	0.0002	0.0004	0.0005	0.0009	0.0001	0.0019	0.0020

This table contains average trading activity measures around the filtered 266 positive events by types of Institutions. We define positive events at stock level, as returns with announcements above the 95th percentile of the respective empirical distribution. Long-Term investors include: Pension Funds and Insurance Companies. Funds include: Collective Portfolios and Employees Funds. Other investors include: Banks, Leasing Companies, ADRs, Cooperatives, Investment Companies, Fiduciary and Factoring Firms. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 6: Trading Activity around negative events by types of Institutions

Time windows	Brokerage Firms			Family Offices			Long-Term institutions			Funds			Others		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Buys	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*
-50, -11	0.0007	0.0017	0.0024	0.0043	0.0038	0.0081	0.0001**	0.0001**	0.0002***	0.0001	0.0001	0.0002	0.0000	0.0031	0.0031
-10	0.0016	0.0011	0.0027	0.0007	0.0017	0.0024	0.0001	0.0001	0.0002	0.0001	0.0005	0.0006	0.0000	0.0000	0.0001
-9	0.0004	0.0013	0.0017	0.0005	0.0004	0.0009	0.0001	0.0001	0.0001	0.0003	0.0001	0.0005	0.0000	0.0117	0.0117
-8	0.0003	0.0030	0.0033	0.0005	0.0004	0.0009	0.0001***	0.0001	0.0002	0.0001	0.0001	0.0001	0.0000	0.0011	0.0011
-7	0.0051	0.0013	0.0064	0.0034	0.0041	0.0075	0.0001	0.0001***	0.0002	0.0001	0.0000	0.0002	0.0000	0.0091	0.0091
-6	0.0012	0.0050	0.0062	0.0058	0.0073	0.0131	0.0001***	0.0001***	0.0002***	0.0001	0.0001	0.0002	0.0000	0.0065	0.0065
-5	0.0009	0.0004	0.0013	0.0050	0.0010	0.0060	0.0002***	0.0001**	0.0003***	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000
-4	0.0002	0.0004	0.0007	0.0019	0.0003	0.0022	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
-3	0.0002	0.0017	0.0019	0.0019	0.0064	0.0083	0.0001***	0.0000	0.0002	0.0001	0.0001	0.0002	0.0000	0.0110	0.0110
-2	0.0002	0.0002	0.0005	0.0003	0.0002	0.0005	0.0001	0.0001	0.0002	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000
-1	0.0468**	0.0113	0.0581	0.0953	0.1361	0.2314	0.0001	0.0001***	0.0002	0.0001	0.0001	0.0002	0.0000	0.0162	0.0162
0	0.3403***	1.8094***	2.1497***	1.2097***	2.7910***	4.0007***	0.0508***	0.0001	0.0509***	0.0002	0.0091***	0.0093	0.0000	0.0235	0.0235
+1	0.1430***	1.0871***	1.2300***	1.6248***	0.3122***	1.9370***	0.0002***	0.0001***	0.0004***	0.0001	0.0001	0.0002	0.0000	0.0248	0.0248
+2	0.1216***	0.1786***	0.3001***	0.1119	0.2300***	0.3419	0.0001	0.0001***	0.0002**	0.0001	0.0001	0.0002	0.0000	0.0325	0.0325
+3	0.0011	0.0332**	0.0343	0.0786	0.0621	0.1407	0.0002***	0.0001	0.0003***	0.0931***	0.0436***	0.1367***	0.0000	0.0285	0.0285
+4	0.0002	0.0038	0.0040	0.0722	0.0315	0.1037	0.0001**	0.0001	0.0002	0.0001	0.0001	0.0001	0.0000	0.0285	0.0285
+5	0.0033	0.0034	0.0067	0.1094	0.0092	0.1186	0.0001	0.0431***	0.0431***	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
+6	0.1707***	0.0313**	0.2020***	1.2453***	1.3448***	2.5901***	0.0065***	0.0001	0.0066***	0.0000	0.0002	0.0003	0.0000	0.0000	0.0000
+7	0.0437**	0.0353**	0.0789***	0.2992	0.3643***	0.6636***	0.0003***	0.0001	0.0003***	0.0001	0.0001	0.0002	0.0000	0.0000	0.0000
+8	0.0869***	0.0202	0.1071***	0.2318	0.5490***	0.7808***	0.0002***	0.0001	0.0002***	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
+9	0.0003	0.0003	0.0006	0.0554	0.0313	0.0867	0.0002***	0.0001	0.0002***	0.0001	0.0001	0.0002	0.0000	0.0001	0.0001
+10	0.0003	0.0003	0.0006	0.2993	0.0891	0.3884	0.0001**	0.0002***	0.0004***	0.0001	0.0001	0.0001	0.0000	0.0000	0.0000
+11, +50	0.0268	0.0204	0.0471	0.2550	0.1337	0.3887	0.0001	0.0001	0.0002	0.0058	0.0015	0.0073	0.0017	0.0274	0.0291

This table contains average trading activity measures around the filtered 240 negative events by types of Institutions. We define negative events at stock level, as returns with announcements below the 5th percentile of the respective empirical distribution. Long-Term investors include: Pension Funds and Insurance Companies. Funds include: Collective Portfolios and Employees Funds. Other investors include: Banks, Leasing Companies, ADRs, Cooperatives, Investment Companies, Fiduciary and Factoring Firms. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 7: Trading Activity around positive events by Number of Trades and Portfolio Capitalization

Time windows	Number of Trades						Portfolio Capitalization					
	Less-active traders			Active traders			Small traders			Large traders		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Buys	Sells	Turnover	Buys	Sells	Turnover	Buys	Sells	Turnover	Buys	Sells	Turnover
-10	0.0000	0.0000	0.0000	0.0185	0.0182	0.0368	0.0000	0.0000	0.0000	0.0151	0.0038	0.0190
-9	0.0000	0.0000	0.0000	0.0045	0.0076	0.0121	0.0000	0.0000	0.0000	0.0029	0.0048	0.0078
-8	0.0002***	0.0006***	0.0008***	0.0341**	0.0331*	0.0672*	0.0002***	0.0007***	0.0009***	0.0290*	0.0249	0.0540*
-7	0.0000	0.0000	0.0000	0.0433***	0.0444***	0.0877***	0.0000	0.0000	0.0000	0.0402***	0.0339***	0.0741***
-6	0.0002***	0.0000	0.0002	0.0316	0.0334*	0.0650*	0.0023***	0.0023***	0.0047***	0.0257	0.0256	0.0513
-5	0.0000	0.0000	0.0000	0.0097	0.0100	0.0197	0.0000	0.0000	0.0000	0.0040	0.0071	0.0111
-4	0.0000	0.0000	0.0000	0.0223	0.0251	0.0474	0.0000	0.0000	0.0000	0.0115	0.0117	0.0231
-3	0.0000	0.0000	0.0000	0.0033	0.0037	0.0070	0.0000	0.0000	0.0000	0.0038	0.0035	0.0073
-2	0.0000	0.0020***	0.0020***	0.0278	0.0299	0.0578	0.0001***	0.0001**	0.0002***	0.0264	0.0124	0.0388
-1	0.0000	0.0000	0.0000	0.0234	0.0275	0.0508	0.0000	0.0000	0.0000	0.0153	0.0092	0.0244
0	0.0000	0.0000	0.0000	0.0522***	0.0525***	0.1046***	0.0005***	0.0002***	0.0006***	0.0440***	0.0174	0.0614**
+1	0.0001	0.0000	0.0001	0.0391***	0.0508***	0.0899***	0.0001***	0.0000	0.0001	0.0249	0.0153	0.0403
+2	0.0001	0.0000	0.0001	0.1253***	0.1336***	0.2589***	0.0021***	0.0023***	0.0044***	0.0714***	0.0627***	0.1340***
+3	0.0032***	0.0001	0.0033***	0.0762***	0.0866***	0.1628***	0.0000	0.0001***	0.0001	0.0491***	0.0345***	0.0836***
+4	0.0000	0.0000	0.0000	0.0295	0.0546***	0.0840***	0.0000	0.0004***	0.0004***	0.0398***	0.0505***	0.0903***
+5	0.0000	0.0000	0.0000	0.0187	0.0208	0.0395	0.0000	0.0000	0.0000	0.0146	0.0160	0.0307
+6	0.0000	0.0000	0.0000	0.0234	0.0286	0.0521	0.0000	0.0000	0.0000	0.0117	0.0196	0.0313
+7	0.0006***	0.0000	0.0006***	0.0268	0.0328	0.0596	0.0000	0.0000	0.0000	0.0244	0.0246	0.0490
+8	0.0000	0.0002***	0.0002	0.0076	0.0107	0.0183	0.0000	0.0002***	0.0002***	0.0047	0.0098	0.0145
+9	0.0000	0.0000	0.0000	0.0343**	0.0281	0.0624	0.0002***	0.0001	0.0002***	0.0310**	0.0200	0.0510
+10	0.0018***	0.0032***	0.0050***	0.0649***	0.0628***	0.1278***	0.0018***	0.0018***	0.0036***	0.0406***	0.0441***	0.0847***
+11, +50	0.0001	0.0001	0.0002	0.0229	0.0241	0.0471	0.0000	0.0000	0.0001	0.0204	0.0189	0.0393

This table contains average trading activity measures around the filtered 266 positive events by number of trades and portfolio capitalization. We define positive events at stock level, as returns with announcements above the 95th percentile of the respective empirical distribution. Less-active and Active traders correspond to those investors with a number of trades lower and higher than the 10th and 90th percentiles of the empirical distribution of all investors, respectively. Small and Large traders correspond to those investors with a portfolio capitalization lower and higher than the 10th and 90th percentiles of the empirical distribution of all investors, respectively. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 8: Trading activity around negative events by Number of Trades and Portfolio Capitalization

Time windows	Number of Trades						Portfolio Capitalization					
	Less-active traders			Active traders			Small traders			Large traders		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Buys	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*
-50, -11	0.0001	0.0001	0.0002	0.0172	0.0189	0.0361	0.0004	0.0004	0.0008	0.0160	0.0141	0.0301
-10	0.0001	0.0000	0.0001	0.0241	0.0235	0.0476	0.0001	0.0000	0.0001	0.0198	0.0209	0.0407
-9	0.0000	0.0000	0.0000	0.0207	0.0205	0.0412	0.0000	0.0000	0.0000	0.0169	0.0045	0.0214
-8	0.0000	0.0000	0.0000	0.0050	0.0084	0.0134	0.0000	0.0000	0.0000	0.0032	0.0054	0.0086
-7	0.0003	0.0007	0.0009	0.0383	0.0372	0.0755	0.0002	0.0008	0.0010	0.0327	0.0281	0.0608
-6	0.0000	0.0000	0.0000	0.0484	0.0496	0.0980	0.0000	0.0000	0.0000	0.0449	0.0379	0.0829
-5	0.0002	0.0000	0.0003	0.0352	0.0373	0.0726	0.0026***	0.0026**	0.0052***	0.0286	0.0286	0.0572
-4	0.0000	0.0000	0.0000	0.0109	0.0114	0.0223	0.0000	0.0000	0.0000	0.0046	0.0081	0.0126
-3	0.0000	0.0000	0.0000	0.0240	0.0269	0.0509	0.0000	0.0000	0.0000	0.0120	0.0120	0.0240
-2	0.0000	0.0000	0.0000	0.0033	0.0036	0.0070	0.0000	0.0000	0.0000	0.0039	0.0034	0.0073
-1	0.0515***	0.0022	0.0538***	0.7458***	1.0489***	1.7946***	0.0015***	0.0001	0.0016	0.7533***	0.9984***	1.7517***
0	0.2501***	0.0245***	0.2746***	6.7280***	11.2436***	17.9716***	0.0860***	0.0120***	0.0980***	7.5243***	11.2758***	18.8001***
+1	0.0032	0.0162***	0.0194***	2.1825***	2.0523***	4.2348***	0.0017***	0.0002	0.0019	2.2221***	2.2086***	4.4307***
+2	0.0126***	0.0062**	0.0188***	2.8203***	1.5053***	4.3256***	0.0017***	0.0021	0.0038***	2.7211***	1.3030***	4.0241***
+3	0.0011	0.0025	0.0036	0.7932***	0.7661***	1.5593***	0.0028***	0.0049***	0.0076***	0.6045***	0.5532***	1.1577***
+4	0.0035	0.0001	0.0036	0.3071	0.2606	0.5677	0.0000	0.0001	0.0001	0.2965	0.0885	0.3850
+5	0.0000	0.0000	0.0000	0.3438	0.3768	0.7206	0.0015***	0.0035***	0.0050***	0.3722	0.2570	0.6293
+6	0.0000	0.0000	0.0000	1.5004***	1.5356***	3.0360***	0.0005	0.0026**	0.0032**	1.4695***	1.5001***	2.9696***
+7	0.0000	0.0000	0.0000	0.8887***	0.7048***	1.5935***	0.0000	0.0303***	0.0303***	0.7371***	0.7235***	1.4606***
+8	0.0223***	0.0000	0.0224***	1.4904***	1.5236***	3.0140***	0.0015***	0.0015	0.0030*	1.1791***	1.1133***	2.2924***
+9	0.0000	0.0008	0.0008	0.0745	0.0505	0.1251	0.0005	0.0002	0.0007	0.0822	0.0481	0.1303
+10	0.0000	0.0000	0.0000	0.2654	0.3036	0.5690	0.0002	0.0001	0.0003	0.2501	0.1122	0.3622
+11, +50	0.0023	0.0035	0.0058	0.4312	0.3453	0.7765	0.0005	0.0016	0.0021	0.4454	0.3230	0.7685

This table contains average trading activity measures around the filtered 240 negative events by number of trades and portfolio capitalization. We define negative events at stock level, as returns with announcements below the 5th percentile of the respective empirical distribution. Less-active and Active traders correspond to those investors with a number of trades lower and higher than the 10th and 90th percentiles of the empirical distribution of all investors, respectively. Small and Large traders correspond to those investors with a portfolio capitalization lower and higher than the 10th and 90th percentiles of the empirical distribution of all investors, respectively. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 9: Aggressive Trading Activity around positive events by Type of Investor

	All traders			**Individuals**			**Institutions**			**Foreigners**		
Time windows	(1) *Buys*	(2) *Sells*	(3) *Turnover*	(4) *Buys*	(5) *Sells*	(6) *Turnover*	(7) *Buys*	(8) *Sells*	(9) *Turnover*	(10) *Buys*	(11) *Sells*	(12) *Turnover*
-50, -11	0.0085	0.0095	0.0180	0.0072	0.0063	0.0135	0.0012	0.0031	0.0043	0.0001	0.0000	0.0001
-10	0.0158	0.0028	0.0186	0.0152	0.0020	0.0172	0.0005	0.0007	0.0013	0.0001	0.0001	0.0001
-9	0.0016	0.0050	0.0066	0.0011	0.0015	0.0026	0.0004	0.0035	0.0039	0.0001	0.0000	0.0001
-8	0.0170	0.0236***	0.0406**	0.0122	0.0172***	0.0294*	0.0047***	0.0064***	0.0111***	0.0001	0.0000	0.0001
-7	0.0085	0.0334***	0.0419**	0.0070	0.0212***	0.0283*	0.0014	0.0121***	0.0135***	0.0001	0.0000	0.0001
-6	0.0139	0.0201***	0.0340	0.0135	0.0192***	0.0327**	0.0003	0.0008	0.0011	0.0001	0.0000	0.0001
-5	0.0082	0.0038	0.0120	0.0064	0.0035	0.0099	0.0017	0.0003	0.0020	0.0000	0.0000	0.0001
-4	0.0080	0.0185***	0.0264	0.0077	0.0123***	0.0200	0.0002	0.0061**	0.0063	0.0001	0.0001	0.0001
-3	0.0020	0.0049	0.0069	0.0016	0.0044	0.0060	0.0003	0.0004	0.0007	0.0001	0.0000	0.0001
-2	0.0289***	0.0091	0.0380*	0.0239**	0.0024	0.0263	0.0049***	0.0067***	0.0116***	0.0001	0.0001	0.0001
-1	0.0059	0.0269***	0.0328	0.0055	0.0102*	0.0158	0.0003	0.0165***	0.0169***	0.0001	0.0001**	0.0002
0	0.0351***	0.0232***	0.0584***	0.0238**	0.0111**	0.0349**	0.0110***	0.0121***	0.0231***	0.0002	0.0001	0.0003
+1	0.0293***	0.0221***	0.0515***	0.0259***	0.0073	0.0331**	0.0032	0.0148***	0.0180***	0.0003	0.0000	0.0003
+2	0.1060***	0.0524***	0.1584***	0.0954***	0.0432***	0.1386***	0.0105***	0.0089***	0.0193***	0.0001	0.0004***	0.0005*
+3	0.0258**	0.0274***	0.0533***	0.0225**	0.0237***	0.0461***	0.0026	0.0035	0.0061	0.0007***	0.0002***	0.0010***
+4	0.0167	0.0430***	0.0597***	0.0163	0.0425***	0.0587***	0.0003	0.0005	0.0008	0.0001	0.0000	0.0001
+5	0.0108	0.0060	0.0168	0.0104	0.0056	0.0160	0.0004	0.0003	0.0007	0.0001	0.0000	0.0001
+6	0.0101	0.0112	0.0214	0.0093	0.0084	0.0176	0.0008	0.0028	0.0036	0.0000	0.0000	0.0001
+7	0.0080	0.0264***	0.0344	0.0069	0.0200***	0.0268	0.0010	0.0064***	0.0074	0.0001	0.0000	0.0001
+8	0.0019	0.0043	0.0061	0.0016	0.0032	0.0048	0.0002	0.0011	0.0013	0.0000	0.0000	0.0001
+9	0.0258**	0.0117	0.0375*	0.0235**	0.0059	0.0294*	0.0019	0.0052*	0.0072	0.0003	0.0006***	0.0010***
+10	0.0358***	0.0199***	0.0557***	0.0275***	0.0145***	0.0420***	0.0074***	0.0051*	0.0125***	0.0010***	0.0003***	0.0013***
+11, +50	0.0144	0.0116	0.0260	0.0117	0.0077	0.0194	0.0025	0.0038	0.0063	0.0002	0.0001	0.0003

This table contains average trading activity measures by aggressive orders around the filtered 266 positive events by type of investor. We define positive events at stock level, as returns with announcements above the 95th percentile of the respective empirical distribution. We use a modified tick test algorithm to infer the trades direction, as explained in subsection 3.1. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 10: Passive Trading Activity around positive events by Type of Investor

	All traders			Individuals			Institutions			Foreigners		
Time windows	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Buys	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*	*Buys*	*Sells*	*Turnover*
-50, -11	0.0095	0.0085	0.0180	0.0083	0.0067	0.0150	0.0011	0.0018	0.0029	0.0001	0.0000	0.0001
-10	0.0028	0.0158	0.0186	0.0022	0.0049	0.0071	0.0005	0.0109***	0.0114***	0.0001	0.0000	0.0001
-9	0.0050	0.0016	0.0066	0.0046	0.0011	0.0057	0.0004	0.0004	0.0008	0.0001	0.0001	0.0001
-8	0.0236***	0.0170	0.0406**	0.0206***	0.0105	0.0311**	0.0029	0.0064***	0.0094**	0.0000	0.0000	0.0001
-7	0.0334***	0.0085	0.0419**	0.0284***	0.0079	0.0363***	0.0049***	0.0005	0.0055	0.0001	0.0001	0.0001
-6	0.0201***	0.0139	0.0340	0.0184***	0.0136	0.0321**	0.0016	0.0002	0.0019	0.0000	0.0000	0.0001
-5	0.0038	0.0082	0.0120	0.0035	0.0064	0.0099	0.0003	0.0002	0.0005	0.0000	0.0016***	0.0016***
-4	0.0185***	0.0080	0.0264	0.0165***	0.0024	0.0190	0.0019	0.0055**	0.0074	0.0000	0.0001	0.0001
-3	0.0049	0.0020	0.0069	0.0045	0.0016	0.0061	0.0003	0.0003	0.0006	0.0001	0.0001	0.0001
-2	0.0091	0.0289***	0.0380*	0.0082	0.0187*	0.0269	0.0009	0.0101***	0.0110***	0.0000	0.0001	0.0001
-1	0.0269***	0.0059	0.0328	0.0243***	0.0054	0.0297*	0.0025	0.0004	0.0029	0.0001	0.0001	0.0002
0	0.0232***	0.0351***	0.0584***	0.0147***	0.0232***	0.0379***	0.0083***	0.0114***	0.0197***	0.0002	0.0005***	0.0007**
+1	0.0221***	0.0293***	0.0515***	0.0216***	0.0121	0.0337**	0.0004	0.0172***	0.0176***	0.0002	0.0001	0.0002
+2	0.0524***	0.1060***	0.1584***	0.0513***	0.0789***	0.1303***	0.0011	0.0270***	0.0280***	0.0001	0.0001	0.0001
+3	0.0274***	0.0258**	0.0533***	0.0236***	0.0188*	0.0425***	0.0037*	0.0068***	0.0105***	0.0001	0.0002	0.0003
+4	0.0430***	0.0167	0.0597***	0.0380***	0.0131	0.0510***	0.0050***	0.0036	0.0086**	0.0000	0.0000	0.0001
+5	0.0060	0.0108	0.0168	0.0056	0.0048	0.0104	0.0002	0.0060**	0.0063	0.0001	0.0000	0.0001
+6	0.0112	0.0101	0.0214	0.0087	0.0088	0.0176	0.0024	0.0013	0.0037	0.0000	0.0000	0.0001
+7	0.0264***	0.0080	0.0344	0.0165***	0.0068	0.0232	0.0098***	0.0012	0.0111***	0.0000	0.0000	0.0001
+8	0.0043	0.0019	0.0061	0.0032	0.0013	0.0045	0.0010	0.0006	0.0015	0.0000	0.0000	0.0001
+9	0.0117	0.0258**	0.0375*	0.0073	0.0190**	0.0264	0.0043***	0.0068***	0.0111***	0.0000	0.0000	0.0001
+10	0.0199***	0.0358***	0.0557***	0.0129**	0.0342***	0.0471***	0.0070***	0.0015	0.0085*	0.0001	0.0000	0.0001
+11, +50	0.0116	0.0144	0.0260	0.0086	0.0110	0.0196	0.0028	0.0032	0.0061	0.0002	0.0001	0.0003

This table contains average trading activity measures by passive orders around the filtered 266 positive events by type of investor. We define positive events at stock level, as returns with announcements above the 95th percentile of the respective empirical distribution. We use a modified tick test algorithm to infer the trades direction, as explained in subsection 3.1. Buys and Sells correspond to the average number of shares purchased and sold scaled by the number of outstanding shares of each stock. Turnover is the sum of the two previous measures. All trading activity variables are multiplied by 106. We use the time-series mean and variance of scaled-trading activity measures in the post-event trading window [+11,+50] to test for abnormal trading activity around the events, following Irvine et al. (2006) and McNally et al. (2015). ***, **, * denotes significance at the levels 1%, 5% and 10%, respectively.

Table 11: Performance by Type of Investor

	Individuals		Institutions	
	(1)	(2)	(3)	(4)
Dependent Variable:	EWA_Perf_j,t	VWA_Perf_j,t	EWA_Perf_j,t	VWA_Perf_j,t
num_ac_total	.0002636**	.0002295**	0.0001626	0.0000109
num_eve	-0.0000751	-0.000173	0.0000291	0.0000734
id_capit_total_dec==BOTTOM_DECIL	0.0001443	0.000505	-0.003732	-0.0041274
id_capit_total_dec==TOP_DECIL	0.0018043	.0024806*	0.0034408	0.0017885
id_act_total_dec==BOTTOM_DECIL	-.0057278***	-.0049438**	-0.005199	-0.0061357
id_act_total_dec==TOP_DECIL	.0038047**	0.0010318	0.0033805	0.0041955
value_op_wind	9.12E-13	-8.4E-12	4.57E-12	3.33E-12
value_op_total	-8.29e-11**	-7.23e-11**	-7.59E-12	-3.82E-12
op_fixed_instr	1.52e-06***	1.33e-06**	0.000000032	0.000000016
pro_stocks_total	-.0053643***	-.0050114***	-0.0003906	0.0012342
pro_op_volat_q4_wind	0.001714	-0.0009887	-0.0019663	-0.0049443
pro_op_volat_q1_wind	-.0016434*	-0.0011885	-0.0035393	-0.0027548
type_inv==fondos			0.0070691	0.0025423
type_inv==largo plazo			0.0141723	0.0121521
type_inv==otros			0.016745	0.0179167
type_inv==sector real			0.0152517	0.014133
Constant	0.0024806	0.0016574	-0.0165333	-0.0175604
R-squared	0.0028252	0.0015075	0.0043046	0.0045492
N. Obs	40296	40296	3920	3920

This table reports the results of regressing both equally-and value-weighted performance measures by individuals and institutions investors, against all variables defined in subsection 3.3., equation (2). ***, **, * denotes significance at the levels 0.1%, 1% and 5%, respectively.

Table 12: Net Buys before positive events by Type of Investor

Dependent Variable: $NET\_BUYS_{j,(-10,-1)}$	(1) Individuals	(2) Institutions
num_ac_total	1.73e-08*	-1.57E-08
num_eve	-1.51E-08	1.36E-08
id_capit_total_dec==BOTTOM_DECIL	-4.71e-07***	-0.00000221
id_capit_total_dec==TOP_DECIL	1.09e-06***	5.95e-06***
id_act_total_dec==BOTTOM_DECIL	-2.30e-07*	-0.00000184
id_act_total_dec==TOP_DECIL	-4.74E-09	-0.000000903
value_op_wind	-8.52E-16	1.04E-14
value_op_total	3.87E-15	1.14E-16
op_fixed_instr	5.14E-11	-4.11E-11
pro_stocks_total	-5.36e-07***	0.000000476
pro_op_volat_q4_wind	6.54e-07***	0.000000621
pro_op_volat_q1_wind	-6.46e-07***	-2.97e-06**
type_inv==fondos		.0000138*
type_inv==largo plazo		.0000213**
type_inv==otros		0.0000136
type_inv==sector real		.0000151*
Constant	6.75e-07***	-0.0000129
R-squared	0.0144261	0.0208318
N. Obs	41090	3989

This table reports the results of regressing the net buys by individuals and institutions investors during the pre-event trading window [-10,-1], against all variables defined in subsection 3.3., equation (3). ***, **, * denotes significance at the levels 0.1%, 1% and 5%, respectively.

Table 13: Net Buys after positive events by Type of Investor

Dependent Variable: $NET\_BUY_{j,(+1+10)}$	(1) Individuals	(2) Institutions
num_ac_total	-4.05e-07***	-1.67e-06***
num_eve	7.53e-08***	2.32e-07***
id_capit_total_dec==BOTTOM_DECIL	1.31e-06***	5.73e-06*
id_capit_total_dec==TOP_DECIL	4.27E-08	-0.00000157
id_act_total_dec==BOTTOM_DECIL	5.79e-07***	.0000112***
id_act_total_dec==TOP_DECIL	4.42E-08	0.00000355
value_op_wind	-4.65E-16	1.17e-14*
value_op_total	-1.49e-14***	-3.98e-14*
pro_op_volat_q4_total	-1.62e-06***	-0.00000438
pro_op_volat_q1_total	9.55e-07***	9.89e-06***
op_fixed_instr	1.09E-11	-1.35E-11
pro_stocks_total	8.69e-07***	0.000000958
type_inv==fondos		0.00000758
type_inv==largo plazo		.0000183*
type_inv==otros		0.0000103
type_inv==sector real		0.0000117
Constant	6.59e-06***	.0000181*
R-squared	0.1506511	0.1820044
N. Obs	40296	3920

This table reports the results of regressing the net buys by individuals and institutions investors during the post-event trading window [+1,+10], against all variables defined in subsection 3.3., equation (4). ***, **, * denotes significance at the levels 0.1%, 1% and 5%, respectively.

Appendix A: Modified Tick Test

We use a modified tick test algorithm that groups the transactions in the same second and applies the classification as specified below:

Stage one: The first transaction of the day per stock is not classifiable.
Stage two: Subsequent transactions at equal prices to the first one of the day are not classifiable, if:

$$\text{If } min(P_{R-1}) \leq min(P_R) \leq max(P_{R-1}) \text{ or,}$$
$$\text{if } min(P_{R-1}) \leq max(P_R) \leq max(P_{R-1})$$

Stage three:

$$\text{If } min(P_R) > max(P_{R-1}) \rightarrow clas_R = B$$
$$\text{If } max(P_R) < min(P_{R-1}) \rightarrow clas_R = S$$
$$\text{Else } clas_R = NC$$

Stage four:

$$\text{If } clas_R = NC \ \wedge \ clas_{R-1} \neq NC :$$
$$\text{If } clas_{R-1} = B \ \wedge \ min(P_R) \geq min(P_{R-1}) \rightarrow clas_R = B$$
$$\text{If } clas_{R-1} = S \ \wedge \ max(P_R) \leq max(P_{R-1}) \rightarrow clas_R = S$$

where R denotes a set of operations made in the same second, P_R are the prices of operations in the set R, B is a buy initiated trade and S a sell initiated trade. Finally, NC is the abbreviation of "Non Classifiable".

In order to test the accuracy of the modified Tick Test, we use an intraday TAQ database from Bloomberg to implement this algorithm and the original Tick Test. The data include a total of 751.171 intraday records from January 2012 to December 2015. The coincidence percentage between both methods was 97.3%, which reflects a fairly high accuracy of the proposed algorithm. The table 14 presents the detail of the percentage of coincidence after excluding the not classifiable trades from both techniques.

Table 14: Confusion matrix between the Original and Modified Tick Test

		Original Tick Test	
Modified	Buyer-initiated	49.71%	1.32%
Tick Test	Seller-initiated	1.39%	47.58%
		Coincidence level: 97.3%	

This table presents the confusion matrix between the Original and Modified tick tests. Both algorithms were executed into the Bloomberg's TAQ database, over the period January 2015 – December 2016. The estimates are obtained after excluding the not classifiable trades from both tests.

Appendix B: Control variables of regression analysis

Table 15: Control variables of regression analysis

Variable	Description
num_ac_total_i	Number of different stocks traded by agent i in the whole sample
num_eve_i	Number of events in which agent i has traded
id_capit_total_dec_i	Dummy variable that equals "Top decile" ("Bottom decile") if the capitalization of agent i is above (below) the 90th (10th) percentile of the respective empirical distribution
id_ac_total_dec_i	Dummy variable that equals "Top decile" ("Bottom decile") if the trading activity of agent i is above (below) the 90th (10th) percentile of the respective empirical distribution;
value_op_wind_i	Average value per operation of agent i in the window [-10,-1]
value_op_total_i	Average value per operation of agent i in the whole sample
op_fixed_instr_i	Numer of different fixed income instruments traded by agent i in the whole sample
pro_stocks_total_i	Average of different stocks traded in a day by the agent i
pro_op_volat_q4_wind_i	Proportions of operations in stocks with high volatility in the window [-10, -1]
pro_op_volat_q1_wind_i	Proportions of operations in stocks with low volatility in the window [-10, -1]
type_inv_i	Dummy variable that indicates the type of institutional investor. Apply only to regression of institutional traders

This table presents the description of the control variables considered in the regression analysis defined in section 3.3, equations (2), (3), (4). Stocks with high (low) volatility are those above (below) the 3rd (1st) quartile of the empirical distribution of standard deviations of returns. The institutional group is made up of Brokerage Firms, Family Offices, Long-Term Institutions, Funds and Others.