Trading Aggressiveness and Market Efficiency*

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JEL classifications: G14, G18, G19

Keywords: Trading Aggressiveness, Market Efficiency, Crowded Trading, Intermarket Sweep Order, Earnings Announcement

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Trading Aggressiveness and Market Efficiency

Abstract

Stein (2009) shows that crowding by sophisticated traders can cause price overreaction. To test Stein's theory, this paper uses trading aggressiveness after earnings releases as a measure of crowding. With a large number of traders, their strong aggregate demand makes trade execution more difficult, and leads every individual investor to trade more aggressively. I find that prices of aggressively traded stocks overreact after good news, but not after bad news, except during the financial crisis. The asymmetry in observed results can be explained by differences in belief heterogeneity of investors and market attention during news releases.

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1 Introduction

The discussion about how speculative trading affects asset price dynamics dates back at least to Keynes (1936) and Hayek (1945). More recent theoretical models of Delong et al. (1990), Cutler, Poterba, and Summers (1990), Hong and Stein (1999) and Stein (2009) also challenge Friedman's (1953) famous statement that rational arbitrageurs make markets more efficient. Specifically, Stein (2009) emphasizes that the increased number of sophisticated traders on current financial markets, such as hedge funds, does not necessarily push prices closer to fundamentals, even if one assumes that they are fully rational and have access to an infinite amount of capital.

Stein's (2009) model is based on two main assumptions. First, sophisticated traders do not anchor their demand to a fundamental value of an asset. A real-world example is a post-earnings announcement drift (PEAD) strategy, when they buy if post-announcement returns are positive, and sell if returns are negative. Second, they do not know the exact number of their competitors who are currently trading in the same direction.[1] When news comes out, it can only be observed by another group of investors, so-called "newswatchers." They are assumed to initially underreact to the news, which provides sophisticated traders with a potentially profitable trading opportunity. Even though sophisticated traders do not observe the new fundamental value directly, they could infer it from prices, if they knew the current amount of their competitors' capital.[2] If the current amount of competitors' capital is not known, they have to condition their demand on the expected number of their competitors currently trading in the market. However, when this number turns out to be larger than expected, excessively high demand causes prices to overreact - a situation Stein (2009) describes as a "crowded-trade" effect.

[1]The second assumption is crucial and differentiates Stein's (2009) model from previous work by Hong and Stein (1999) and Abreu and Brunnermeier (2002, 2003).

[2]The price for an asset in the first time period, P_1, is a function of the fundamental F, underreaction parameter δ and the total arbitrage capacity, n. So, if δ and n are known, sophisticated investors can infer F from the price P_1.

In this paper, I empirically test Stein's (2009) "crowded-trade" theory in the periods immediately after earnings announcement releases, using high trading aggressiveness as a measure of crowded trading. In Stein (2009), when an unexpectedly large number of sophisticated traders shows up, their high aggregate demand makes prices move more for a given fundamental shock, i.e., observed returns are high. Therefore, their linear return-based strategy buys a larger quantity of shares in these states. However, it is exactly in these states when execution of larger trades is more difficult because of an already high aggregate demand, and thus should make sophisticated investors trade more aggressively to obtain execution of their order. Therefore, high trading aggressiveness after earnings releases should reflect periods when trading becomes crowded, with many competing investors submitting their orders in the news direction. Overall, larger quantities traded taken together with a higher than expected number of participants should result in subsequent price overreaction and trading losses during these periods.

I measure trading aggressiveness as the proportion of volume executed through intermarket sweep orders (ISOs), split across multiple exchanges. ISOs represent the most aggressive order type available on the US market, because they are executed more quickly than standard market orders. Therefore, they directly reflect investors' preferences to trade quickly, even at an inferior price. Further, submission of ISOs requires simultaneous monitoring of several market centers and their usage is essentially restricted to professional traders.[3] My data sample consists of earnings announcements released within trading hours between October 2007, when ISOs first become available, and December 2017. Earnings announcements are the natural choice for this study, because they represent the most common type of information release for any stock.

The details of my research design and main findings are as follows. First, I analyze the usage of ISOs both during normal trading periods and on announcement days. My

[3]Section 2 provides a short overview of ISOs. For a detailed overview, please refer to Chakravarty et al. (2012), who provide an excellent analysis of ISO characteristics and their usage on the current financial markets.

findings show that only around a third of ISO trades, which are executed across multiple exchanges, can be regarded as truly aggressive. Further, the proportion of multi-exchange ISO volume, traded in the news direction, significantly increases for up to two hours following an announcement release, suggesting their potential usage by sophisticated investors to trade quickly on new information. Based on this evidence, I use the proportion of multi-exchange ISOs, submitted in the news direction within the first two hours following an announcement release, as the benchmark measure of trading aggressiveness in my subsequent empirical analyses.[4]

Next, I test the overreaction hypothesis, using Hong, Kubik, and Fishman's (2012) two-step approach. In the first step, I analyze the initial price reaction, measured as the buy-and-hold return over days 0 and 1, *BHAR(0;1)*. I conduct difference-in-differences tests, both in a univariate and multivariate setup, using pre-announcement trading days as the control group. My findings show that high trading aggressiveness significantly increases initial abnormal returns by 1.4 percentage points (p.p.) after positive news and decreases them by 1.0 p.p. after negative news, compared to stocks with low trading aggressiveness on the announcement day. However, a larger initial price reaction is not sufficient to test for overreaction, because it could also be that high trading aggressiveness pushes the stock price in the direction of fundamentals. For this reason, I next turn to sharper tests of long-run post-announcement returns.

If high trading aggressiveness does lead to price overreaction on the announcement day, then prices for these announcements should reverse in the long run. A long-term price reversal is a strong test, because it goes against the PEAD, with good news usually being followed by positive returns and bad news by negative returns (Bernard and Thomas 1989, 1990). Consistent with the price overreaction hypothesis, initial abnormal returns of 8.0 p.p. for aggressively traded stocks after good news are offset by subsequent return reversals of

[4] I conduct several robustness checks with respect to the length of the time interval, but all main results continue to hold.

-8.6 p.p., resulting in an overall negative abnormal return of -1.3 p.p. Thus, my findings for good news strongly support the predictions of Stein's (2009) "crowded trade" theory.

Interestingly, I do not observe any overreaction after bad news. In contrast, long-run returns for aggressively traded stocks are negative, consistent with PEAD: initial abnormal returns of -7.5 p.p. are followed by the post-announcement drift of -3.8 p.p., resulting in an overall abnormal return of -11.0 p.p. Importantly, the post-announcement drift for aggressively traded stocks is lower in absolute terms, compared to the drift of -8.4 p.p. for stocks with low trading aggressiveness on the announcement day. Overall, the findings for the sample of bad news suggest that high sell-side trading aggressiveness actually reduces the PEAD drift, consistent with sophisticated aggressive traders pushing prices in the direction of the fundamental value after the announcement release.

I further analyze whether the effect of trading aggressiveness on long-term returns is different during the financial crisis of 2007-2008. Price overreaction after positive releases is observed both in crisis and non-crisis periods, but is more pronounced during crisis, which can be explained by larger market uncertainty about the news in this period. However, after bad news, the positive effect of high trading aggressiveness on the PEAD drift is only limited to the crisis period.

Stein's (2009) predictions are symmetrical for positive and negative news, but price overreaction is empirically observed only in the sample of good news. I test two potential explanations for the asymmetry in the observed findings. The first explanation, based on theoretical predictions of Hong and Stein (1999) and Stein (2009), is related to differences in belief heterogeneity of unsophisticated investors. In both models, unsophisticated investors, or "newswatchers", are assumed to underreact to the news because of slow diffusion of private information: different investors observe different subsets of information, their beliefs are more heterogeneous at the beginning and converge only gradually, as they observe more and more information over time. Thus, more heterogeneous beliefs about news should slow down information diffusion, which leads to stronger initial underreaction. Since the total amount of profits is shared between "newswatchers" and sophisticated investors, stronger initial underreaction by "newswatchers" implies potentially larger profits for sophisticated traders. As a result, the latter trade more aggressively, and their stronger aggregate demand leads to stronger price overreaction.

Empirically, the "newswatchers'" beliefs are likely to be more heterogeneous after positive news, because a greater fraction of news is already incorporated in stock prices prior to the official release. Therefore, it is more difficult for "newswatchers" to agree on the interpretation of the "residual" news. Kothari, Shu, and Wysocki (2009) provide empirical evidence that managers leak positive information before the official announcement release, but withhold negative news until the release. Further, margin trading is easier for opening long positions with insufficient capital than short selling with insufficient stock holding. Therefore, short-sale constraints also prevent negative information from being incorporated into prices before a negative announcement release (Diamond and Verrecchia 1987). Consequently, after positive news, greater heterogeneity in investors' beliefs should increase overcrowding and lead to stronger price overreaction. In contrast, after negative news, beliefs of unsophisticated investors are likely to be more homogeneous, which reduces the probability of overcrowding. I test this explanation, using different proxies of heterogeneity of investors' beliefs: stock return volatility, the VIX index, and large drops in the order imbalance on an announcement day, capturing higher divergence in investors' opinions about news. My findings show that the overreaction for aggressively traded stocks after good news is indeed more pronounced for announcements with greater investors' belief heterogeneity, whereas it does not seem to play an important role after negative earnings releases.

The second explanation relates to the degree of market participants' attention after news releases. DeHaan, Shevlin, and Thornock (2015) show that managers choose to strategically report good news in periods of higher market attention and bad news in periods of lower market attention. However, the effect of market attention on price efficiency is largely dependent on the composition of traders on an announcement day. If higher attention is driven by sophisticated investors with superior information processing skills, then it should facilitate incorporation of information into prices. However, if it is largely driven by uninformed sophisticated investors that engage in positive feedback trading, then higher attention rather facilitates overcrowding and price overreaction.

Following DeHaan, Shevlin, and Thornock (2015), I examine announcements released on non-Fridays and those released on non-"busy" reporting days, which are supposed to attract higher levels of market attention. Overall, my findings suggest that aggressive trading on days with high market attention stems from uninformed investors that engage in positive feedback trading. After good news, aggressive purchases on days with higher attention lead to stronger price overreaction. After bad news, aggressive sales on days with lower attention lead to the reduction in the PEAD drift, improving price efficiency. Thus, low market attention after bad news appears to be largely driven by sophisticated traders with superior information processing skills.

One potential concern might be that the increased use of ISOs after information releases is related to decreasing liquidity supply, as discussed by Chakravarty et al. (2011). To address this concern, I analyze the intraday determinants of ISO volume and show that, in contrast to ISOs executed on a single exchange, the proportion of multi-exchange ISO trades is not related to larger spreads on the announcement day. This finding excludes the previous concern at least for the multi-exchange ISO category, which is used as a benchmark measure of trading aggressiveness in overreaction tests. Overall, my findings on the intraday use of ISOs complement those of Chakravarty et al. (2011) and show that splitting ISO volume by exchange category helps to distinguish aggressive orders that represent traders' reactions to the news from those that are used because of drops in liquidity supply.

This paper contributes to the literature that investigates how speculative trading by sophisticated investors affects asset price dynamics. To the best of my knowledge, the closest papers to mine are Lou and Polk (2012), Sias, Turtle, and Zykaj (2016) and McInish, Upson, and Wood (2014). The first two papers also empirically test Stein's (2009) predictions. Lou and Polk (2012) propose a new measure of the total amount of arbitrage capital, invested in momentum strategies. In particular, they measure excess correlations in abnormal returns of typical momentum stocks, and dub this measure *comomentum.* They further show that when comomentum is high, long-run returns to a momentum strategy are negative. Hence, their paper provides empirical evidence for Stein's (2009) theory for a sample of momentum stocks. Sias, Turtle, and Zykaj (2016) use overlap of stocks in hedge fund portfolios as a measure of hedge fund crowding and, surprisingly, find that the overlap of hedge fund equity portfolios is remarkably low, inconsistent with hedge funds crowding into the same stocks. In contrast to previous studies, my approach is independent of any assumption about trading strategy. Further, high trading aggressiveness in post-announcement periods can be regarded as a more direct measure of crowded trading, because it is based on actual trading data and reflects traders' preferences for quicker execution of their orders directly at the time of their submission.

McInish, Upson, and Wood (2014) also analyze the role of ISO trading aggressiveness in market efficiency, but in a different setup. Specifically, they document a substantially higher use of ISOs during the Flash Crash on May 6, 2010, with over 65% of the sell volume during the crash period and about 53% of the buy volume during the recovery period coming from these aggressive orders. My findings complement their earlier results and show that the usage of ISOs can have destabilizing effects not only during crisis times, but also after regular quarterly earnings announcements for a broad sample of firms.

Building upon the pioneering work of Chakravarty et al. (2012), my paper also sheds light on the use and characteristics of intermarket sweep orders on the current financial markets. Like them, I find that ISO trades have a significantly larger information share relative to non-ISO trades. In addition, I separately analyze ISOs, executed on a single exchange, and those split across multiple exchanges, and show that multi-exchange ISOs are increasingly used by professional traders to trade in the news direction immediately after earnings releases.

My paper proceeds as follows. Section 2 describes the institutional framework and provides details of the sample construction. Section 3 analyzes characteristics of aggressive orders in the base period and around earnings announcements. Section 4 investigates effects of trading aggressiveness on asset price dynamics, and Section 5 briefly concludes.

2 Institutional Setting and Sample Construction

2.1 Overview of Intermarket Sweep Orders

On August 29, 2005, the Securities and Exchange Commission (SEC) adopted a new set of rules, known as the Regulation National Market System (Reg NMS). The SEC designed the new regulation to modernize US equity markets and to promote their efficiency. Due to technical difficulties with the implementation of several changes required by this new regulation, markets achieved full compliance with Reg NMS first on October 8, 2007.[5]

The Order Protection Rule. The most important change introduced by Reg NMS is the adoption of the Order Protection Rule (Rule 611), which implements partial protection against trade-throughs on US markets. A trade-through occurs when the best available bid or offer quotation is ignored, or in other words, "traded-through". For example, assume there are only two trading venues, A and B. Table I shows the bid sides of visible limit order books in two venues. The first column shows the currently quoted bid prices, while the second and third columns indicate the number of shares available at each price for venues A and B, respectively. Prior to Reg NMS, a market order sent to exchange A would just walk down the limit order book of A until either the order was completely filled or the limit price of the order was reached. For instance, an order of 4,000 shares would be split into 500 shares executed at $10.75, an additional 2,000 shares at $10.70 and the remaining 1,500 shares at $10.67. The best bid of $10.73 at B is then ignored, or "traded-through".

[5] See Regulation NMS, SEC Release No. 34-51808.

Table I. Bid Side of Limit Order Book

Price	Shares A	Shares B
\$10.75	500	
\$10.73		500
\$10.70	2,000	600
\$10.67	3,500	

With the new Order Protection Rule, when a new market (or marketable limit) order arrives, the trading venue has to check whether the order (or its portion) would cause a trade-through of better quotes on other venues. Should other venues quote better prices, the order (or its corresponding portion) is automatically re-routed for execution to other venues.[6] To comply with the Order Protection Rule, venue A now re-routes 500 shares for execution at B before executing the remaining part of the order.[7]

The Order Protection Rule caters mainly to the interests of retail investors. The best-price execution guarantee increases the retail investors' confidence and decreases their search costs for the best available price. Further, protection of best-priced bid and ask quotes on each trading venue from potential trade-throughs encourages liquidity providers to post limit orders at best prices. Although appealing to retail investors with a long-term investment horizon, the Order Protection Rule is less attractive for short-term and institutional investors: re-routing takes time and the best bid can change while the order is being re-routed. Thus, the execution of large-sized orders under the Order Protection Rule takes longer and might end up at an inferior average price, compared to having the whole order executed at a single venue.

[6]However, the order protection is partial, because it is only limited to the top visible quotes in the book of each venue, referred to as the Best Bid and Offer (BBO). In the previous example, only 500 shares at \$10.75 on A and 500 shares at \$10.73 on B are protected quotes.

[7]Note that such execution would still result in a trade-through of 600 shares available at \$10.70 on B, but this quote is not considered "protected" and can therefore be ignored under the current rules.

ISO as an exemption to the Order Protection Rule. To avoid such situations, the Order Protection Rule makes an exemption for a specific order type, an intermarket sweep order (ISO). An ISO is a marketable limit order (Immediate-Or-Cancel) that provides an opportunity for institutional investors to trade large blocks quickly. Specifically, when an ISO arrives at a particular trading venue, it is executed as if this venue stands alone. Importantly, there is no re-routing requirement, even if some parts of the order cause trade-throughs of the protected quotes at other venues. However, to ensure compliance with the principles of the Order Protection Rule, an investor who submits an ISO is responsible for sending additional limit orders, also designated as ISOs, to other venues quoting the stock. The size of these additional ISOs should be sufficient to execute against the total number of shares available at protected quotes superior to the ISO limit price.[8] Therefore, an ISO represents a series of marketable limit orders sent across all trading venues quoting stock at the BBO that is superior to the ISO limit price.[9]

To illustrate, suppose that an institutional investor would like to use an ISO to sell 4,000 shares at the limit price of $10.67. To comply with the Order Protection Rule, the investor has to send two limit orders, marked as ISO, of at least 500 shares each with the limit price of $10.67 simultaneously to both venues. The investor has a choice about how to split the total order: either send 3,500 shares to A and 500 shares to B or 2,900 to A and 1,100 to B. In the latter case, the split is optimal, because the investor gets a better average execution price. However, some investors might choose to send a larger portion of their order to A because they believe that the speed of execution on A is faster. Since trading venues can recognize both orders as ISOs, they do not re-route either of them. Both venues instantaneously

[8]Paragraph (b)(30) of Rule 600 gives a formal definition of an intermarket sweep order as a limit order that satisfies the following requirements: (1) when routed to a trading venue, the limit order is identified as an intermarket sweep order; and (2) simultaneously with the routing of the limit order identified as an intermarket sweep order, one or more additional limit orders, as necessary, are routed to execute against the full displayed size of all protected quotations with a superior price.

[9]Note that ISOs represent liquidity-demanding orders, because the unexecuted part of the order is canceled, without being displayed in the limit order book (Immediate-or-Cancel orders).

execute ISOs against the outstanding orders and the new best price drops to \$10.70 in the case of the suboptimal ISO split and to \$10.67 in the case of the optimal split.[10]

In the previous example, under the assumption that the limit order book does not change between the time of order submission and its execution, a series of ISOs sent across exchanges will always execute at the average price that is at least as good as that for a standard limit order. So where is the tradeoff between the speed of execution and execution at a better price? In reality, the state of the book might change when the routing decision for ISO has already been taken. Suppose a new bid quote at \$10.75 for 1,000 shares appears on another venue C at the time when both an ISO and a non-ISO are already on their way to A. The ISO is executed exactly as before, whereas the additional 1,000 shares of the non-ISO are re-routed to C. The average execution price of the non-ISO is better overall in this case. However, this case is most likely to occur during a normal trading period when liquidity supply is not scarce and there are no upcoming information releases about the stock. By contrast, as liquidity supply drops around information releases and the fundamental value of the stock is expected to change, there is a higher probability that a better priced quote (in this case, 500 shares at \$10.73) is withdrawn by the time the re-routed order reaches exchange B. For example, after negative news, an immediate sell with an ISO will result in a better overall average execution price, as compared to the execution price of non-ISO orders. Therefore, in highly volatile markets, traders care more about the immediacy of execution rather than execution at a potentially better price.

2.2 Sample Construction and Summary Statistics

The data source for earnings announcements is the Institutional Brokers' Estimate System (I/B/E/S) database. I collect announcements that are made within the trading hours of US

[10] Prior to Reg NMS an ISO could be replicated as a series of smartly routed marketable orders. However, the speed of execution was the same for all orders in the market. Even though technological advancements might have increased the absolute speed of order execution post-Reg NMS, the Order Protection Rule "slowed down" the execution of standard market (or marketable limit) orders relative to ISOs, thus generating a relative difference in the speed of execution between ISOs and non-ISOs.

equity trading exchanges (9.30 - 16.00 EST) from October 2007, when intermarket sweep orders become available, until December 2017.[11] Each record has an exact date and time stamp (accurate within a minute). Further, I require that each firm exists in the intersection set of I/B/E/S and CRSP. Table 1 provides details of the sample construction.

[Insert Table 1 approximately here]

The initial sample consists of 10,140 announcements by 3,775 firms. I omit 631 announcements for which the stock is not traded on the announcement day, and another 1,587 announcements for which intraday transaction data are not available. I further lose 1,079 announcements by excluding stocks with a closing price of less than $2 two days prior to the announcement date and days with multiple announcements by the same firm. Omitting announcements with fewer than 40 days of previous trading data and those of active stocks with more than 10 trades per minute leaves 6,229 announcements by 2,481 firms, or around 60% of the initial sample.[12]

Table 2 presents summary statistics for the final sample of earnings announcements. Data on daily stock prices, holding period returns, volume traded, and shares outstanding are from CRSP. Using these data, I calculate market capitalization, *MCap*, average daily volume traded, *Volume*, annualized daily return volatility, *Volat*, and buy-and-hold abnormal returns (*BHARs*) around earnings announcement dates. BHARs are estimated with the market model, using the equally-weighted CRSP index as the market portfolio. The estimation period for the parameters is (-264, -64). I require the stock to have at least 100 observations in the estimation period. *Beta* is the slope from the market model and represents the systematic risk of the firm. Appendix A provides a detailed description of variable definitions.

[11] The focus of this study are announcements made within trading hours, because they allow for the analysis of the immediate reaction of traders to the news. Even though the majority of earnings announcements take place outside trading hours, the analysis of the immediate reaction is important to assess potential effects of trading aggressiveness after unexpected information releases. The final sample contains many well-known firms, such as Google, Coca-Cola, Toyota, SAP, Allianz, Expedia, and many others.

[12] Previous trading data is required to construct the control sample and the average levels of ISO volume in the pre-announcement period. Excluding the announcements of active stocks with more than 10 trades per minute is necessary to mitigate the bias in classification of ISOs across single- and multi-exchange categories, as discussed in the next section.

[Insert Table 2 approximately here]

I extract additional variables from two different databases. First, quarterly accounting data on the book value of equity (item *ceqq*) are obtained from Compustat. The market-to-book ratio, *MTB*, is calculated as the ratio of market capitalization two days prior to an announcement to the book value of equity at the end of the previous quarter. Second, I extract the quoted spread, $Qspr$; the daily order imbalance, OIB; the total depth at the national best bid and the best ask, $Depth$; and the realized variance over the five seconds before trade execution, $RealVar[-5s]$, from the NYSE TAQ database.$Qspr$ over a given time interval is calculated as the difference between the National Best Ask and the National Best Bid, scaled by their average. OIB is calculated as the absolute value of the difference between the purchase and sale volume on the announcement day, scaled by the total volume traded. $RealVar[-5s]$ is calculated as the sum of the squared high-frequency NBBO quote midpoint returns over five seconds before the transaction. Appendix B provides further information on TAQ data filtering. The statistics for all variables are generally comparable to those reported in previous studies analyzing long-term post-announcement returns, e.g. by Hong, Kubik, and Fishman (2012) and Hung, Li, and Wang (2014).

3 Trading with Aggressive Orders

3.1 Trading with Aggressive Orders in the Base Period

First, I examine the usage of intermarket sweep orders during normal trading periods. I extract the tick-by-tick data on the trading volume separately for ISOs and standard market orders (non-ISOs) from the NYSE Trade and Quote database (TAQ) from October 2007, with the introduction of ISOs to the market, until the end of my sample in December 2017. ISOs are marked with the code “F” in the condition field of the TAQ. The TAQ database does not record the size of an original ISO order, only the sizes of individual ISO transactions executed on a particular exchange. However, individual ISOs are often reported as a series of transactions that are executed in the same second. To reconstruct the size of an original ISO order, I thus aggregate all individual ISOs that occur in the same second and in the same direction and refer to aggregated ISOs as "ISO trades" in the remaining part of the paper.

The mean proportion of ISO volume in my sample is 34.78%, which shows that aggressive orders are widely used.[13] However, not all ISO trades appear to be truly aggressive, because very often they are executed on a single exchange. This is puzzling since the original purpose of ISO is to allow quick trading of large blocks across multiple exchanges. To investigate the issue further, I split ISO trades into four exchange-price categories: trades executed on 1) a single exchange at the same price *(SameEx-SamePrc);* 2) a single exchange at multiple prices *(SameEx-MultiPrc);* 3) multiple exchanges at the same price *(MultiEx-SamePrc),* and 4) multiple exchanges at multiple prices *(MultiEx-MultiPrc).* The exchange category is arguably more important than the price category, because the choice to submit an order to different exchanges is made by the trader, whereas execution at multiple prices can be endogenous and reflect execution against hidden orders. Therefore, I mainly concentrate on split by exchange category in the remainder of the paper.

Panel A of Table 3 reports cross-sectional averages of the proportion of ISO volume by four exchange-price categories in the pre-announcement period (days -40 to -2). The daily proportion of ISO volume within a given category is calculated as the ratio of the daily ISO volume traded within the category to the overall volume traded during the day.

[Insert Table 3 approximately here]

Surprisingly, around 66% of all ISO trades are executed on the same exchange (22.98% of 34.78%), and out of them, the vast majority are also executed at the same price. By contrast, only around 34% of ISOs (11.80% of 34.78%) are executed across multiple exchanges, which

[13] Chakravarty et al. (2012) also find that the use of ISO orders is non-trivial and amounts to 41% of trading volume in their sample.

implies that only a third of ISO trades seem to be used according to their original purpose and can be classified as truly aggressive.[14]

It could still be that single-exchange ISO trades are also used to execute large blocks, if their size is on average larger than that of comparable non-ISO trades. For this reason, I compare sizes of ISO and non-ISO trades across two exchange categories. For comparison purposes, I also aggregate all non-ISOs that occur in the same second and in the same direction, and split all non-ISO trades into single-exchange and multi-exchange trades. Panel B of Table 3 presents the comparison results, separately for purchases ($SizeBuy$) and sales ($SizeSell$). The first two columns report differences between ISO and non-ISO trades, executed on a single exchange. The third and fourth columns report differences between trades, executed on multiple exchanges, whereas the last column reports differences between ISO trades across two exchange categories. Importantly, the trade size of ISOs, executed on a single exchange, is significantly lower than that of comparable non-ISO trades: 208 versus 275 shares for purchases, and 221 versus 315 shares for sales. Sizes of multi-exchange ISO trades are significantly larger than those of their single-exchange counterparts by 418 for purchases and 435 for sales. However, they are still significantly lower than the sizes of the multi-exchange non-ISO trades.

To analyze informativeness of single- and multi-exchange ISOs, I further compare their price impacts to price impacts of comparable non-ISO trades. The *price impact* of each trade after *s seconds* is defined as $PrcImp_{t,s} = 2\left|Q_{t+s} - Q_t\right|/Q_t \cdot 100\%,$ where Q_t is the midpoint price calculated as the average of the prevailing bid and ask quotes, $Q_t = (A_t + B_t)/2$, and Q_{t+s} represents the midpoint price after *s seconds.* The last two rows in Panel B of Table

[14] Aggregating ISO trades over each second can potentially lead to the overstatement of the multi-exchange ISO volume, if a series of single-exchange ISO trades are erroneously missclassified as one multi-exchange ISO trade. To mitigate the bias, I exclude trades of active stocks with more than 10 trades per minute. Even though the effect of this bias cannot be ruled out completely, classifying too many ISO transactions as multi-exchange ISO trades introduces more noise, and, if anything, should lead to underestimation of main effects in my paper. All main results continue to hold if I exclude trades of active stocks with more than 5 trades per minute (see robustness checks in Section 4.2).

3 present the initial one-second and the long-run one-minute (or 60-second) price impacts, with purchases and sales shown separately.

Regardless of the time horizon and exchange category, the price impact of ISO trades is significantly larger than that of corresponding non-ISO trades This finding is consistent with prior findings by Chakravarty et al. (2012), who also document a larger information share of ISO trades. It further suggests that ISOs might be used not only by institutional investors to escape complicated order re-routing, but also by more sophisticated investors, such as high-frequency traders (HFT), to trade quickly on the new information before it is incorporated in prices through trades of their competitors.[15]

Importantly, multi-exchange ISO trades appear to convey more information, because they have a significantly higher price impact than their single-exchange counterparts. Their higher initial one-second price impact can be partially attributed to their overall larger trade size. However, if all of it were mechanically related to the trade size, then it would dissipate shortly, after the order book is replenished with new limit orders. By contrast, the price impact of multi-exchange ISOs continues to stay significantly different from that of single-exchange ISOs even after one minute. Further, their one-minute price impact is also significantly higher than that of non-ISO trades with comparable trade sizes. Interestingly, whereas the price impact of multi-exchange ISO sales drops from 0.14% to 0.11% within one minute, the price impact of ISO purchases increases from 0.13% to 0.16%, signaling their relatively higher informativeness.

Overall, my findings in this section show that only around a third of ISO trades, which are executed across multiple exchanges, can be regarded as truly aggressive. The multi-exchange ISO trades have the highest one-minute price impacts, suggesting their potential usage by sophisticated investors to trade quickly on new information.

[15]Anecdotal evidence from practitioners suggests that HFTs do indeed use ISOs to gain first position in the execution queue. Chapter 3 of Bodek (2013) discusses the use of ISOs by high-frequency traders in more detail.

3.2 Trading with Aggressive Orders around Earnings Announcements

Next, I analyze trading with ISOs around earnings announcements. If sophisticated investors would like to trade quickly on the new information, I expect them to increase their trading aggressiveness in post-announcement periods. Panel A of Table 4 shows changes in the proportion of ISO volume ($\triangle ISOVol$) on the announcement day by four exchange-price categories. The change for each category is calculated as the difference between the proportion of ISO volume traded within the category on the announcement day and its mean in the base period.

[Insert Table 4 approximately here]

The results show that the total proportion of ISO volume increases significantly by 1.19%, which is consistent with earlier findings of Chakravarty et al. (2011).[16] Importantly, additional split by exchange categories shows that this increase in trading aggressiveness is almost exclusively driven by an increase in the proportion of truly aggressive multi-exchange ISO trades (1.22%), whereas the proportion of single-exchange trades practically does not change (-0.03%).

A total increase in the daily proportion of ISO volume of around 1% might not seem very significant economically. For this reason, I further examine changes in the proportion of ISO volume at the intraday level in Figure 1. The differences from the pre-announcement means are measured in 10-minute intervals relative to the 10-minute interval from an earnings announcement release (interval 0). Solid lines show changes in the proportions of single-exchange ISO trades and dashed lines those of multi-exchange ISO trades.

[Insert Figure 1 approximately here]

The intraday analysis shows a jump of around 4% in the proportion of multi-exchange ISO trades in the 10 minutes following the release, which is both economically and statistically

[16] McInish, Upson, and Wood (2014) also document a substantially higher use of ISOs during the Flash Crash on May 6, 2010, with 53% of the buy volume during the recovery period coming from these aggressive orders.

significant. It subsequently decreases, but remains significantly higher than in the pre-announcement period for around two hours after the release. In contrast, the proportion of single-exchange ISO trades drops by around 2% subsequent to an information release. Overall, these findings suggest that sophisticated investors increase their usage of multi-exchange ISOs immediately following an announcement release to quickly trade on new information.

To further test this prediction, I analyze the trade direction of multi-exchange ISOs on announcement days. If multi-exchange ISOs are indeed used by sophisticated traders, then I expect their proportion to increase more in the news direction. I split all earnings announcements into terciles of BHAR(0;1) and define the top 33% as good news, the bottom 33% as bad news, and the remainder as announcements with largely no news. Panel B of Table 4 shows that the proportion of multi-exchange ISO volume ($\triangle ISOVol_{MultiEx}$) increases more for announcements with greater news content: 1.90% for good news and 1.85% for bad news, as compared to 0.96% for no news. Importantly, the increase of ISO volume is larger in the direction of the news: the proportion of multi-exchange ISO buy volume increases by 2.71% after good news and that of ISO sell volume by 2.40% after bad news, which further confirms the increased usage of multi-exchange ISOs by sophisticated investors in post-announcement periods.[17]

3.3 Trading Aggressiveness as a Measure of Crowding

Two main underlying assumptions of Stein (2009) are that sophisticated traders do not anchor their strategies to the fundamental value and that they face uncertainty concerning the total number of their competitors taking the same position in the stock. Under these assumptions, their demand for an asset is linearly increasing in asset returns, causing them to behave as momentum traders. For example, they might engage in trading on the post-

[17] Even though the proportions against the news direction also increase, those in the news direction dominate: the difference between increases in ISO buy volume and ISO sell volume ($\triangle Buy - \triangle Sell$) is positive (negative) and statistically significant for good (bad) news, and practically zero for announcements with no news.

earnings announcement drift (PEAD), buying after positive returns and selling after negative returns.

Stein (2009) models aggregate risk tolerance of sophisticated traders as $n = N\theta$, where N represents the expected number of traders at a given point in time, and θ is a random variable with a mean of 1, distributed on the interval $[\theta_L, \theta_H]$, with $\theta_L \geq 0$. Thus, states with a low realization of θ correspond to a low number of sophisticated investors trading after the news. In these states, their aggregate demand is low, resulting in lower observed returns. Note that a trader following a linear return-based strategy will buy a lower quantity of shares when observed returns are low. Therefore, lower quantities demanded by every individual trader combined with a low overall number of sophisticated traders in the market lead to underreaction of prices to fundamentals and, consequently, small trading gains in low-θ states.

However, for the zero-profit condition to hold, the low-θ states that occur more frequently need to be balanced out by less frequent high-θ states, when an unexpectedly large number of sophisticated traders shows up. In a high-θ state, with a higher than expected demand, prices move more for a given fundamental shock, i.e., observed returns are high. Importantly, traders cannot differentiate whether these higher returns are due to a large fundamental news or due to trading by their competitors. Therefore, their linear momentum strategies buy a larger quantity of shares, which, taken together with a high overall number of sophisticated traders, causes price overreaction and subsequent trading losses - a situation described by Stein (2009) as a "crowded-trade" effect.

To test Stein's (2009) predictions empirically, I use high trading aggressiveness, measured as the proportion of multi-exchange ISO volume in post-announcement periods, as a signal of "crowded" trading. Aggressive trading in post-announcement periods should correspond to high-θ states in Stein's (2009) model: upon observing a larger return, a trader would like to buy a larger quantity of shares, which is even harder when aggregate demand is already very high, and thus makes him trade more aggressively in order to achieve the execution of his trade. Even though a trader cannot directly observe the exact number of his competitors, their large aggregate demand makes execution of large orders more difficult. Indeed, quick execution of large orders immediately after the news release might only be possible with aggressive multi-exchange ISO orders.

Based on results from Figure 1, I use the proportion of multi-exchange ISO volume traded in the news direction within two hours following an announcement release ($\%ISOVol_{MultiEx}$) as the benchmark measure of trading aggressiveness.[18] My findings so far provide supporting evidence that trading aggressiveness can indeed be regarded as a measure of "crowded-trade": the proportion of aggressive multi-exchange ISOs substantially increases in the period immediately following earnings announcement releases, especially for announcements with large absolute returns (see Table 4). Also, they are submitted predominantly in the news direction.

To provide further evidence that multi-exchange ISOs are increasingly used during periods of large aggregate demand, I investigate the intraday determinants of ISO trading volume in Table 5. The analysis is conducted separately for same-exchange and multi-exchange ISOs. Specifically, I estimate the following panel data OLS regressions with the proportion of ISO volume ($\%ISOVol$) split by exchange category as the dependent variable:

$$\begin{aligned}\%ISOVol_{i,t} &= \alpha + \beta_1 Volume_{i,t-1} + \beta_2 RealVar[-5s]_{i,t} + \beta_3 OIB_{i,t-1} + \\ &+ \beta_4 QSpr_{i,t} + \beta_5 Depth_{i,t} + DaytimeFE + DayFE + \varepsilon_t.\end{aligned}$$

One observation represents a 10-minute trading interval for a stock. Models (1) and (3) analyze the base period, which consists of 39 trading days before an announcement day, from day -40 to day -2. Models (2) and (4) analyze trading with ISOs on announcement days. The vector of explanatory variables consists of $Volume$, the total volume traded over the previous 10-minute interval; $RealVar\,[-5s]$, the average realized variance in the five seconds prior to ISO execution, averaged for all ISO trades within the 10-minute interval;

[18]I check that my results are robust with respect to the length of the post-announcement time interval (see Section 4.2).

OIB, order imbalance within the previous 10-minute interval; $QSpr$, the average prevailing NBBO relative spread at the time of ISO execution, calculated as $QSpr_t = (A_t - B_t)/Q_t$ and averaged for all ISO trades within the 10-minute interval; and $Depth$, the average sum of shares available at the best NBBO bid and the best NBBO ask at the time of execution.[19] All regressions include day-fixed effects and intraday dummies for each half-hour of the trading day, with standard errors double-clustered at the firm and day level.

[Insert Table 5 approximately here]

If sophisticated investors choose to trade more aggressively during periods of large aggregate demand, I expect the proportion of multi-exchange ISOs to increase with higher aggregate volume traded in the previous 10-minute interval. Indeed, the usage of multi-exchange ISOs increases significantly with the higher aggregate volume traded, both in the base period (Model 1) and on announcement dates (Model 2). By contrast, the proportion of single-exchange ISO volume significantly drops (Models 3 and 4), suggesting that traders prefer to submit multi-exchange ISOs in the periods of large aggregate demand. Further, the proportion of multi-exchange ISOs significantly increases after stronger price movements over the previous five seconds, as depicted by the coefficient on the realized variance. This finding further confirms that investors choose to trade more aggressively when they observe larger returns. Lower order imbalance in the previous period, which represents higher disagreement between traders, also predicts a significantly higher usage of multi-exchange ISOs within the next time interval. However, it is not significantly related to the proportion of single-exchange ISO orders.

I additionally control for liquidity of the stock, measured by the relative spread and the aggregate depth at NBBO, to account for another possible explanation of an increased usage of ISOs around earnings announcements. Prior findings by Chakravarty et al. (2011) suggest

[19] The realized variance, $RealVar\,[-5s]$, is calculated as the sum of the squared high-frequency NBBO midpoint returns over the five seconds before the transaction ($RealVar\,[-5s] = \sum_{t=-1}^{-5} (log\,Q_t - log\,Q_{t-1})^2$) and averaged for all ISO trades within each 10-minute interval.

that investors might trade more aggressively as a result of a decreased liquidity supply. In line with their findings, Models (3) and (4) show that the proportion of single-exchange ISO volume increases significantly with larger spreads and lower depth, suggesting that traders do indeed become more aggressive as liquidity supply drops. Importantly, the proportion of multi-exchange ISOs only increases with higher spreads and lower depth in the base period (Model 1) but no longer depends on either spreads or depth on announcement dates (Model 2). These results suggest that liquidity supply plays a smaller role for multi-exchange ISOs and their increased usage in post-announcement periods can be rather attributed to sophisticated investors trading quickly in the news direction. Overall, my findings complement the earlier results of Chakravarty et al. (2011) and show that splitting ISO volume by exchange category helps to distinguish aggressive orders that represent traders' reactions to the news from those that are used as a result of drops in liquidity supply.

4 Trading Aggressiveness and Price Dynamics

In this section, I empirically test Stein's (2009) prediction that crowded trading - the situation of an unexpectedly large number of investors trading in the same direction - causes price overreaction, using high trading aggressiveness in post-announcement periods as a measure of crowding. Similar to Hong, Kubik, and Fishman (2012), I conduct testing for overreaction in two steps. In the first step, I analyze the initial price reaction: if high trading aggressiveness represents competitive trading by sophisticated investors in the news direction, I expect it to be associated with the higher initial reaction of prices in the direction of fundamentals. This higher initial reaction should occur irrespectively of whether prices subsequently overreact or not. In the second step, I directly test for potential price overreaction by examining long-run post-announcement returns: if high trading aggressiveness leads to price overreaction, I expect post-announcement returns to reverse in the long run. By contrast, if investors could infer the exact number of their competitors, e.g., as in Holden and Subrahmanyam (1992), high trading aggressiveness should bring prices more quickly towards fundamental values without causing any price overreaction.

4.1 Univariate Analysis

I start by testing the relation between trading aggressiveness and the initial price reaction, measured as the two-day buy-and-hold abnormal return over days 0 and 1, BHAR(0;1).[20] Since high trading aggressiveness should cause prices to react stronger initially, I expect larger abnormal returns in the direction of the news for the announcements followed by more aggressive trading.

I first test this prediction in a univariate setup, defining announcements in the top tercile of BHAR(0;1) as good news and in its bottom tercile as bad news. Within each news category, I match stocks with high trading aggressiveness ($HighTA$ stocks) and low trading aggressiveness ($LowTA$ stocks) both for announcement ($Event$) and non-announcement ($Non-Event$) days, using nearest neighbor propensity score matching. Specifically, for the good news sample, $HighTA$ stocks are defined as stocks, for which the proportion of multi-exchange ISO purchase volume within the first two hours of the announcement release is in the top 50% of its distribution.[21] The definition for the bad news sample is similar, but is based on the proportion of multi-exchange ISO sale volume. The matching factors include firm's market capitalization, *MCap*, stock's volatility, *Volat*, and its average daily trading volume, *Volume.* The pre-announcement trading days -20, -30 and -40 are used as a control group ($Non-Event$).[22] The classification of $HighTA$ and $LowTA$ stocks for the control group is based on the same two-hour time interval as for the corresponding announcement day. Table 6 presents the results of the propensity score matching analysis.

[20] All results continue to hold if I use BHAR(-1;1) to measure the initial price reaction (untabulated).

[21] I conduct robustness checks on the length of the time interval, used for the definition of high trading aggressiveness, in section 4.2.

[22] I use three equally-spread pre-announcement days as the control group to mitigate the effect of overlapping BHARs over longer time periods. Results are also robust if the control group consists of only one pre-announcement day (see Section 4.2).

[Insert Table 6 approximately here]

The upper panel reports the cross-sectional averages of $BHAR(0;1)$, separately for $HighTA$ and $LowTA$ stocks. Consistent with prior expectations, stocks with higher trading aggressiveness on the announcement day in the $Event$ group experience significantly stronger initial price reaction in the news direction. The first column shows results for the good news sample. Aggressive buying with multi-exchange ISOs within two hours of a positive earnings release significantly increases $BHAR(0;1)$ by 1.71 percentage points (p.p.). This represents a 28% increase relative to the average abnormal return of 6.19 p.p. for a stock with low aggressiveness in the good news sample. The difference of 1.71 p.p. is statistically significant at the 1% level, as suggested by the results of the t-test in the last row of the panel. The second column reports a lower corresponding difference of -0.21 p.p. for the $Non-Event$ control group. The third column ($Diff$) reports the differences between the $Event$ and $Non-Event$ groups. Importantly, the difference-in-differences equals 1.92 p.p. (= 1.71 p.p. + 0.21 p.p.) and is statistically significant at the 1% level. Similar results are observed for the bad news sample in the last three columns: $BHAR(0;1)$ is lower by 1.07 p.p. for $HighTA$ stocks on the event day relative to the control group and and the difference-in-differences is statistically significant at the 1% level.

The second step is testing for potential price overreaction by examining long-run post-announcement returns. If the price overreaction hypothesis holds, I expect returns to reverse in the long term for more aggressively traded stocks. The middle and the lower panel of Table 6 provide supporting evidence for this hypothesis in the sample of good news. Indeed, the middle panel shows that the long-term returns start to reverse for $HighTA$ stocks already after three months: $BHAR(2;64)$ after good news is negative and equals -2.74 p.p. The difference-in-differences constitutes -4.84 p.p., and is both economically and statistically significant. The reversal continues and is more pronounced after six months, as documented by the negative $BHAR(2;128)$ of -9.61 p.p. for $HighTA$ stocks and the negative difference-in-differences of -7.41 p.p. in the lower panel. Thus, consistent with Stein (2009), aggressive trading after positive news leads to significant price overreaction, with around a third of initial return dissipating over the first three months and even turning negative after six months.[23]

Interestingly, the long-term return reversal is not present in the sample of bad news. In contrast, consistent with PEAD, initial negative returns are followed by long-term negative returns for $HighTA$ stocks: $BHAR(2;64)$ and $BHAR(2;128)$ constitute -4.57 p.p. and -11.53 p.p., correspondingly. However, the long-term returns for $HighTA$ stocks are significantly higher than those for $LowTA$ stocks: the differences between the two groups of stocks equal 2.09 p.p. and 3.24 p.p. for $BHAR(2;64)$ and $BHAR(2;128)$, respectively. The corresponding difference-in-differences are also positive and statistically significant. Higher, but still negative, long-term returns imply the reduction in the PEAD drift for $HighTA$ stocks. Indeed, the ratio of $BHAR(0;1)$ to $BHAR(0;128)$ is around 42% for $HighTA$ stocks, compared to 33% for $LowTA$ stocks, consistent with a larger amount of information being priced in during the announcement window.[24] Overall, findings for the sample of bad news suggest that sophisticated investors are able to better process its content, with aggressive multi-exchange sell ISOs pushing prices closer to the new fundamental value after the announcement release.

Stein's (2009) predictions are symmetrical irrespective of the news direction, but price overreaction is only observed in the sample of good news. In section 4.3, I test two potential explanations for the asymmetry in the observed findings, related to heterogeneity in unsophisticated investors beliefs' and to the degree of market attention after the announcement release.

[23]The total initial reaction of 7.90 p.p. for $HighTA$ stocks and the subsequent drop of -9.61 p.p. imply overall negative abnormal returns of $(1 + 0.0790) * (1 - 0.0961) - 1 = -0.0247$ or -2.47%.

[24]For $HighTA$ stocks, $\frac{BHAR(0;1)}{BHAR(0;128)} = \frac{-0.0778}{(1-0.0778)(1-0.1153)-1} = 0.4228$ or 42.28%. For $LowTA$ stocks, this ratio equals $\frac{-0.0667}{-0.2045} = 0.3262$ or 32.62%.

4.2 Multivariate Analysis

I next check whether the previous findings hold in a multivariate setup, again using pre-announcement trading days -20, -30 and -40 as the control group. Specifically, I estimate the following regression, separately for positive and negative news:

$$
\begin{aligned}
BHAR(0;1)_{i,t} &= \alpha + \beta_1 Event + \beta_2 HighTA_{Buy/Sell i,t} + \beta_3 Event \cdot HighTA_{Buy/Sell i,t} \\
&+ \beta_4 LnMCap_{i,t} + \beta_5 MTB_{i,t} + \beta_6 Beta_{i,t} + \beta_7 BHAR(-23;-2)_{i,t} \\
&+ \beta_8 Volat_{i,t} + \beta_9 QSpr_{SPY} + \beta_{10} OIB_{SPY} + WeekdayFE \\
&+ Month - YearFE + \varepsilon_t.
\end{aligned}
$$

The dependent variable is BHAR(0;1). The first right-hand side variable, $Event$, equals 1 for earnings announcement days, and zero for non-announcement days that represent the control group. $HighTA_{Buy}$ ($HighTA_{Sell}$) for good (bad) news is a dummy variable that equals 1 for $HighTA$ stocks, following the same classification procedure as in the univariate analysis, and is zero otherwise. The main variable of interest is the interaction term between $Event$ and $HighTA_{Buy}$ ($HighTA_{Sell}$) that captures the differential sensitivity of $HighTA$ stocks after earnings releases, relative to $LowTA$ stocks. The vector of standardized control variables includes firm size, measured as the log of market capitalization two days before the announcement, $LnMcap$; the market-to-book ratio, MTB; the market model beta, $Beta$; one-month buy-and-hold abnormal returns before earnings announcements, $BHAR(-23;-2)$, and past volatility of daily returns, $Volat$. These control variables are standard in regressions explaining abnormal returns around earnings announcements.[25] I additionally control for market liquidity and market-wide order imbalances, because market-wide buying and selling pressure can potentially influence individual stock imbalances and returns. Specifically, I calculate daily market quoted spread, $Qspr_{SPY}$, as the average of rel-

[25] See, for example, a recent study on post-earnings announcement drift by Hung, Li, and Wang (2014).

ative quoted spread ($QSpr$) for SPDR S&P 500 ETF (ticker SPY) for each day. I calculate the daily market order imbalance, OIB_{SPY}, in a similar way, based on the order imbalance for SPDR S&P 500 ETF.[26] All regressions include weekday- and monthyear-fixed effects and allow standard errors to cluster at the firm and day level.[27]

[Insert Table 7 approximately here]

Model (1) of Panel A in Table 7 reports results for good news. β_1 implies that $LowTA$ stocks display a 6.6 p.p. higher $BHAR(0;1)$ after positive news releases relative to the benchmark group in the pre-announcement period. β_2 captures the relative difference in $BHAR(0;1)$ between $HighTA$ and $LowTA$ stocks in the pre-announcement period, which turns out to be insignificant. Importantly, β_3 implies that $HighTA$ stocks display a significantly higher $BHAR(0;1)$ of 1.4 p.p., compared to $LowTA$ stocks after the news release. Thus, the overall effect of having high buy-side trading aggressiveness after a positive announcement release can be computed as the sum of 6.6 p.p. and 1.4 p.p., or 8.0 p.p. Model (2) reports similar results after negative news: β_3 implies that high sell-side trading aggressiveness after a negative announcement release significantly decreases $BHAR(0;1)$ by 1 p.p., with the overall effect of -7.5 p.p. The economic significance of β_3 for both news directions is overall comparable to difference-in-differences from univariate results.

Currently, Models (1) and (2) suffer from a potential endogeneity problem. Ideally, I would like to control the abnormal return for true earnings surprise. Indeed, it could be the case that prices react more strongly to announcements with higher earnings surprises and traders choose to submit more aggressive orders in response to a higher earnings surprise. The most common proxy for the earnings surprise, used in the literature, is based on the difference between actual earnings and the median analyst forecast from I/B/E/S. However, only around 65% of firms in my sample are followed by analysts. Further, the I/B/E/S

[26] Table IA1 of the Internet Appendix reports the results for alternative controls of market factors, calculated as the value-weighted averages across all stocks in the TAQ universe. All results remain practically unchanged.

[27] I do not include firm-fixed effects since the median firm in my sample has only two announcements released within trading hours during the sample period.

surprise is based on forecasts of a handful of analysts and might itself be biased. I check my results for robustness with the news direction based on the I/B/E/S earnings surprise in Panel B of Table 7.

With no proper way to control for the true earnings surprise, the previous results for $BHAR(0;1)$ in Panel A only show the significant correlation between higher trading aggressiveness and larger initial price reaction. For this reason, I now turn to sharper tests of long-run post-announcement returns that no longer suffer from the omitted variable complications. Models (3) and (4) are similar to the previous specification, except that the dependent variable now is $BHAR(2;128)$.[28] Consistent with univariate results, β_3 in Model (3) is negative, suggesting that high buy-side trading aggressiveness after positive news leads to significantly lower subsequent returns of 7.1 p.p., compared to $LowTA$ stocks. As before, $BHAR(0;128)$ for $HighTA$ stocks is actually negative and constitutes -1.3 p.p., consistent with the predictions of Stein's (2009) price overreaction hypothesis.[29] β_3 for negative news in Model (4) is positive and significant at the 10% level, suggesting that stocks with high sell-side trading aggressiveness display higher abnormal returns of 4.6 p.p. in the long-run. However, given the constant of -0.128, $BHAR(2;128)$ remains overall negative and equals -0.128 + 0.044 + 0.046 = -0.038 or -3.8 p.p. Consistent with the univariate results, this result suggests that high sell-side trading aggressiveness after negative news actually reduces the PEAD drift.

Panel B of Table 7 reports similar results, with the news classification based on the I/B/E/S earnings surprise. I calculate it as the difference between actual earnings and the median analyst forecast from I/B/E/S, scaled by the price two days prior to the earnings announcement. As expected, using the I/B/E/S earnings surprise reduces the number of observations by around 50%, such that statistical significance is overall weaker. $BHAR(0;1)$

[28] Results for $BHAR(2;64)$, presented in the robustness section, also hold, but they are less significant economically and statistically. Results with shorter post-announcement event windows are not significant, which suggests that it takes the market at least three months to realize that the price has overreacted.

[29] The total initial reaction of 8.0 p.p. and the subsequent drop of -1.5 - 7.1 = -8.6 p.p. implies overall negative abnormal returns of $(1 + 0.08) * (1 - 0.086) - 1 = -0.013$ or -1.3 p.p.

for $HighTA$ stocks is still significantly higher by 1 p.p. after good news and lower by 1.4 p.p. after bad news. $BHAR(2;128)$ is significantly lower by 7.1 p.p. for stocks with high buy-side trading aggressiveness after good news. After bad news, β_3 is still positive and of comparable value of 4.6 p.p. to the previous results from Panel A, but is no longer statistically significant.

Since the direction of the I/B/E/S surprise and the direction of $BHAR(0;1)$ do not always match up, I also report results separately for the samples of matching (Models 1 and 2) and conflicting (Models 3 and 4) earnings signals in Table IA2 of Internet Appendix. The proportion of conflicts in direction of initial returns versus I/B/E/S surprise is around one-third of the number of observations with available I/B/E/S surprise. Importantly, the price overreaction after good news is observed only in the sample where both directions match up. Therefore, it is advisable for future studies to look at both initial returns and I/B/E/S surprise when classifying changes in the fundamental value of a stock.

Subsample splits. To analyze whether the effect of trading aggressiveness on long-run post-announcement returns is different during crises times, I split the sample into two periods: the financial crisis period of 2007-2008 and the non-crisis period, covering years 2009-2017. I repeat the analysis from Table 7 for $BHAR(2;128)$, separately for the two periods.[30] Models (1) and (2) of Table 8 present the results for the crisis period, whereas Models (3) and (4) report findings for the non-crisis period.

[Insert Table 8 approximately here]

Interestingly, the price overreaction after good news is more pronounced during the 2007-2008 financial crisis when the market uncertainty about the news is larger. However, β_3 is also negative and significant outside the crisis period. After bad news, β_3 is positive in both periods, but is only significant at the 10% level during the crisis period. Therefore, the effect of high sell-side trading aggressiveness on the PEAD drift is only limited to 2007-2008,

[30]For brevity, I do not report results for $BHAR(0;1)$. $HighTA_{Buy/Sell}$ is statistically significant at the 1% level for both types of news and in both periods, with effects being more pronounced in the crisis period.

suggesting that negative information gets quicker impounded into prices with aggressive orders during the crisis period.

Robustness checks. Panel A of Table 9 presents robustness checks of the main results for good news and Panel B for bad news. Model (1) follows the previous specification with $BHAR(2;64)$ as the dependent variable. As before, β_3 is statistically significant and negative after good news, but its economic significance is lower. Consistent with univariate results, the strongest effects of price overreaction in the sample of good news are only observed after six months. β_3 is no longer significant in the bad news sample, suggesting that there is no significant difference in the PEAD drifts between $LowTA$ and $HighTA$ stocks within the first three months after the announcement release.

[Insert Table 9 approximately here]

Models (2) and (3) report results for $BHAR(2;128)$, using alternative definitions of $HighTA_{Buy/Sell}$ that are based on the different time intervals on an announcement day: in the first hour of the announcement release for Model (2) and in the period following the first two hours after the announcement release until the end of the trading day in Model (3). The coefficient for $Event \cdot HighTA_{Buy}$ continues to be negative for both periods, but its economical magnitude and statistical significance are smaller in Model (3). The coefficient for $Event \cdot HighTA_{Sell}$ in Panel B is only significant in Model (2). Overall, these results suggest that the strongest effects can be attributed to the aggressive orders, submitted within the first two hours of an announcement release - used as a benchmark measure of trading aggressiveness in this study.

Model (4) shows results for $BHAR(2;128)$, excluding active stocks that have more than 5 trades per minute, and Model (5) the corresponding results, using only trading day -40 as the control group. Whereas the overall number of observations is lower in these models, both economic magnitude and statistical significance remain the same for β_3 after good news. After bad news, β_3 has even higher economic magnitudes compared to the benchmark specification in Model (4) of Table 7.

4.3 Heterogeneous Beliefs, Market Attention and Price Overreaction

In this section, I test two potential explanations for asymmetry in the observed results between positive and negative earnings releases. The first explanation, based on theoretical predictions of Hong and Stein (1999) and Stein (2009), is related to a greater heterogeneity in unsophisticated investors beliefs' after good news. The second explanation is based on the previous findings of DeHaan, Shevlin, and Thornock (2015) and relates to the degree of market participants' attention after positive and negative news releases.

In Hong and Stein (1999) and Stein (2009), unsophisticated investors, or "newswatchers", are assumed to underreact to the news because of slow diffusion of private information: individual agents can initially process just a subset of all available information and use it to form their current beliefs about the value of the stock. Since different investors observe different subsets of information, their beliefs are more heterogeneous at the beginning and converge only gradually, as they observe more and more information over time. Thus, more heterogeneous beliefs about news should signal slower information diffusion, and lead to stronger initial underreaction. In both models, the total amount of profits is shared between "newswatchers" and sophisticated investors. Consequently, stronger initial underreaction by "newswatchers" promises potentially larger profits for sophisticated investors, which causes the latter to trade more aggressively. However, since they do not know the exact fundamental value and the total number of their competitors in the market, their higher aggressiveness in this case leads to stronger aggregate demand and stronger subsequent price overreaction.

Theoretical predictions are symmetrical both for positive and negative news. However, heterogeneity in investors' beliefs, and hence the degree of underreaction by "newswatchers", is likely to be greater after positive news. The reasoning behind is that a greater fraction of news is incorporated in stock prices before a positive earnings release and it is more difficult for investors to agree on the interpretation of the "residual" news. Kothari, Shu, and Wysocki (2009) find that managers choose to disclose some of the positive information before the official announcement release, but do not leak any negative information. In addition, consistent with Diamond and Verrecchia (1987), short-sale constraints prevent informed investors, e.g. insiders, to trade on negative information before a public announcement release, whereas margin trading for opening long positions is easier. After positive news, greater heterogeneity in newswatchers' beliefs should therefore facilitate overcrowding and price overreaction. After negative news, investors' beliefs are likely to be more homogeneous - they underreact less and the probability of overcrowding is relatively low.

In the following, I explicitly test this explanation, using three proxies to measure heterogeneity of investors' beliefs: stock volatility, $Volat$, calculated as the annualized standard deviation of daily stock returns over the calendar month; market's expectation of the stock market volatility over the next 30 day period, captured by the VIX index; and $\triangle OIB$, the change in the absolute value of order imbalance on the announcement day relative to its mean in the base period. Earnings announcements of highly volatile stocks and in highly volatile market periods should be more difficult to interpret, and should thus cause more disagreement between unsophisticated investors. Lower values of $\triangle OIB$ mean that amounts of purchase and sale volumes become more equal on an announcement day, indicating higher divergence in investors' opinions about news. Appendix A provides a detailed definition of these variables.

I split the sample by the median measure of belief heterogeneity and report the results separately for announcements with the above ($High$) and below (Low) median heterogeneity of investor beliefs. I expect β_3 to be more negative for announcements that belong to *High Volat, High VIX* and *Low* $\triangle OIB$ samples.

[Insert Table 10 approximately here]

Panel A of Table 10 reports the results for good news. To conserve space, I only report the coefficients for main variables of interest, but all regressions also include the vector of previous control variables. Findings for all three measures of investors' belief heterogeneity are in line with prior expectations: high trading aggressiveness after announcements with greater belief heterogeneity in *High Volat, High VIX* and *Low* $\triangle OIB$ samples leads to stronger return reversals in the long run. The economic magnitude is larger for stocks with high past volatility (Model 1) and in highly volatile market periods (Model 3), as compared to the benchmark case in Model (3) of Table 7. For$\triangle OIB$ (Model 6), the economic magnitude is comparable to the benchmark case. After bad news, β_3 is only significant in *High VIX* sample, which is consistent with previous findings that the effect of high sell-side trading aggressiveness is only limited to the financial crisis period. Overall, the findings suggest that aggressive trading indeed leads to stronger price overreaction for announcements with greater belief heterogeneity in the sample of good news. After bad news, splitting the sample by different measures of belief heterogeneity does not play a big role, because unsophisticated investors' beliefs tend to be more homogeneous and the probability of overcrowding by aggressive traders is relatively low.

Another potential explanation of asymmetry in results is related to the degree of market participants' attention after positive and negative news releases. DeHaan, Shevlin, and Thornock (2015) show that managers choose to strategically report good news in periods of higher attention and bad news in periods of lower attention by market participants. However, it is not clear *ex ante* whether higher market attention is beneficial for price efficiency. If the majority of participating sophisticated traders have better information processing skills and anchor their trades to the new fundamental value, then higher attention from their side should benefit incorporation of information into prices, i.e. reduce the PEAD drift. In contrast, if higher market attention is to a large extent driven by uninformed sophisticated investors that engage in positive feedback trading, then it should rather facilitate overcrowding and price overreaction after earnings releases. By the same logic, low market attention can be either beneficial or detrimental to price efficiency, dependent on the composition of traders on the announcement day.

Following DeHaan, Shevlin, and Thornock (2015), I examine two specific times of earnings releases that are supposed to attract higher levels of market attention: announcements released on non-"busy" reporting days and those released on non-Fridays.[31] A reporting day is classified as "busy" if more than five other firms are releasing their earnings on the same day. Panel A of Table 11 reports the results for good news and Panel B for bad news. As before, I only report coefficients on main variables of interest to conserve space.

[Insert Table 11 approximately here]

Model (1) displays the results for announcements released on non-"busy" reporting days that are supposed to attract higher market attention. Model (2) presents the corresponding results for "busy" reporting days. After good news, β_3 is negative and significant only in the sample of non-"busy" days. Likewise, it is only significant in the sample of non-Friday announcements (Model 3), suggesting stronger price overreaction after good news on days with higher market attention. These findings are consistent with high market attention after good news being largely driven by uninformed investors that engage in positive feedback trading.

After bad news, β_3 is positive and significant for "busy" reporting days, consistent with reduction in the PEAD drift due to aggressive selling after the announcement release. Whereas market attention is generally lower on "busy" days, this finding suggests that aggressive selling on these days is largely driven by sophisticated investors with better information processing skills. Interestingly, β_3 is also weakly significant at the 10% level for non-Friday announcements that are supposed to attract higher levels of market attention. However, after explicit testing of both proxies, DeHaan, Shevlin, and Thornock (2015) report that attention appears to be the same on Fridays, compared to other weekdays, which questions the validity of this market attention measure.

Overall, aggressive trading on announcement days with high market attention can be rather attributed to uninformed sophisticated investors that engage in positive feedback trading. After good news, higher attention from their side leads to a more pronounced price

[31] I do not examine their third measure of market attention, based on announcements outside of trading hours, because my sample consists only of announcements released during the trading hours of US exchanges.

overreaction. After bad news, lower attention from their side is rather beneficial for price efficiency, resulting in a weaker PEAD drift.[32]

5 Conclusions

In this paper, I use trading aggressiveness in the periods immediately after earnings releases to empirically test predictions of Stein's (2009) "crowded-trade" theory. Specifically, I measure trading aggressiveness as the proportion of volume traded with intermarket sweep orders (ISOs) split across multiple exchanges, the most aggressive orders available on the US markets. ISOs represent an exemption from the Order Protection Rule of the Regulation National Market System and are executed more quickly than standard market orders.

Consistent with Stein's (2009) predictions, my findings suggest that high trading aggressiveness in post-announcement periods leads to price overreaction: a stronger initial price reaction of more aggressively traded stocks is offset by their long-term return reversals, signaling crowding of aggressive traders after earnings releases. Interestingly, price overreaction is only observed in the sample of good news. By contrast, after bad news, aggressive sale orders push prices in the direction of the fundamental value, reducing the PEAD drift.

The asymmetry in results can be explained by greater heterogeneity of unsophisticated investors' beliefs after good news. Since a greater fraction of previously available positive information is priced in before the announcement release, it is more difficult for unsophisticated investors to agree on the interpretation of the "residual" news. Therefore, their initial underreaction to positive news is likely to be stronger. In Stein (2009), stronger underreaction by "newswatchers" implies potentially larger profits for sophisticated traders, causing them to trade more aggressively. More aggressive sophisticated traders generate stronger aggregate demand and a stronger subsequent price overreaction. In support of this theoretical prediction, I show that price overreaction is stronger after positive announcements with greater

[32] Tables IA3 and IA4 of the Internet Appendix reproduce the analysis of two explanations for asymmetry in the observed results in Tables 10 and 11, using I/B/E/S earnings surprise for the news classification. The overall results are comparable to those using initial returns, but statistical significance is weaker.

heterogeneity in investors' beliefs, for which the initial underreaction by "newswatchers" is more likely.

Another explanation relates to the degree of market participants' attention after the news release. DeHaan, Shevlin, and Thornock (2015) show that managers choose to strategically report good news in periods of higher attention and bad news in periods of lower attention by market participants. However, the effect of market attention on price efficiency depends on the composition of traders on an announcement day. Overall, my findings suggest that price overreaction after good news is stronger on days with higher market attention, consistent with higher market attention being largely driven by uninformed investors engaging in positive feedback trading. After bad news, lower attention from their side results in a weaker PEAD drift, improving price efficiency.

Importantly, earnings announcements are to a large extent scheduled and anticipated by the market. The destabilizing effects of aggressive trading on stock prices are likely to be even more pronounced during unexpected information releases when uncertainty and heterogeneity of investors' beliefs reach their peak levels. Therefore, better understanding of risks arising from an extensive usage of aggressive orders after information releases is important for regulators to ensure stability of financial markets.

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Appendix A

Variable Definitions

Variable	Description	Source
$\%ISOVol$	*Proportion of ISO volume*: the ratio of trading volume that is executed with intermarket sweep orders (ISOs) to the total trading volume within a given trading interval	TAQ
$\Delta ISOVol$	The change in the proportion of ISO volume within a given trading interval on the announcement day relative to its mean, calculated over the same interval in the base period	TAQ
$\%ISOBuy$ ($\%ISOSell$)	*Proportion of ISO purchase (sale) volume*: the ratio of purchase (sale) volume that is executed with intermarket sweep orders (ISOs) to the total purchase (sale) volume within a given trading interval	TAQ
$\Delta ISOBuy$ ($\Delta ISOSell$)	The change in the proportion of ISO purchase (sale) volume within a given trading interval on the announcement day relative to its mean, calculated over the same interval in the base period	TAQ
Beta	The systematic risk of the firm, estimated as the slope from the market model, using the equally-weighted CRSP index as the market portfolio. The estimation period for parameters is (-264, -64).	CRSP
BHAR(t;s)	Buy-and-hold abnormal return over event days t to s relative to the earnings announcement date. BHARs are estimated from the market model, using the equally-weighted CRSP index as the market portfolio. The estimation period for parameters is (-264, -64).	CRSP
Depth	Sum of shares available at the NBBO bid and NBBO ask (in hundreds of shares)	TAQ
Event	1 for earnings announcement dates, and zero otherwise	I/B/E/S

Variable	Description	Source
$HighTA_{Buy}$ ($HighTA_{Sell}$)	1, if the proportion of multi-exchange ISO purchase (sale) volume, traded within the first two hours following an announcement release, $\%ISOBuy_{MultiEx}$ ($\%ISOSell_{MultiEx}$), is above the median of the proportion of multi-exchange ISO purchase (sale) volume distribution for stocks in my sample, and zero otherwise	TAQ
LnMCap	Natural logarithm of market value two days before the announcement (in $ million)	CRSP
MCap	Market value of equity two days before the announcement (in $ million)	CRSP
MTB	Ratio of market value of equity two days before the announcement to book value of equity at the end of the previous quarter (item ceqq)	CRSP Compustat
OIB	Absolute value of order imbalance, calculated as $OIB = \frac{\lvert BuyVol - SellVol \rvert}{BuyVol + SellVol}$, where $BuyVol$ ($SellVol$) denotes purchase (sale) volume within a given trading interval	TAQ
ΔOIB	The change in the absolute value of order imbalance on an announcement day relative to its mean in the base period	TAQ
OIB_{SPY}	Daily market order imbalance, calculated as the OIB for SPDR S&P 500 ETF (ticker SPY) for each day.	TAQ
$PrcImpBuy_{+t \cdot s}$ ($PrcImpSell_{+t \cdot s}$)	Price impact of a buy (sell) trade, defined as $PrcImp_{+t \cdot s} = 2 \lvert Q_{t+s} - Q_t \rvert / Q_t$, where Q_{t+s} is the NBBO midpoint price of the stock after s seconds	TAQ
$RealVar\,[-5s]$	Realized variance over the five seconds prior to ISO execution, calculated as the sum of the squared high-frequency NBBO quote midpoint returns over five seconds before the transaction: $RealVar\,[-5s] = \sum_{t=-1}^{-5} (log\, Q_t - log\, Q_{t-1})^2$	TAQ
QSpr	The relative quoted spread, prevailing at the time of trade execution. Defined as the difference between the NBBO ask and the NBBO bid, scaled by their average; observations with *QSpr>0.5* are set to missing values.	TAQ

Variable	Description	Source
$QSpr_{SPY}$	Daily market quoted spread, calculated as the average of relative quoted spread (*QSpr*) for SPDR S&P 500 ETF (ticker SPY) for each day.	TAQ
SizeBuy (SizeSell)	Size of a purchase (sale) transaction (in shares)	TAQ
VIX	Chicago Board Options Exchange Market Volatility Index, a measure of the implied volatility of S&P 500 at-the-money options that represents the market's expectation of the stock market volatility over the next 30 day period	Chicago Board Options Exchange
Volat	Stock volatility, calculated as the annualized standard deviation of daily stock returns over the calendar month	CRSP
Volume	Total volume traded within a given trading interval (in thousands of shares)	TAQ

Appendix B

TAQ Data Processing

I use data filters to clean trade and quote data, as described by Holden and Jacobsen (2014). For each second, I calculate the National Best Bid and Offer (NBBO) with the help of Hasbrouck's (2010) algorithm.[33] First, the prevailing quote at the end of each second is identified for each exchange. Afterward, the best (maximum) bid (B_t) and the best (minimum) ask (A_t) is chosen across all exchange quotes. The midpoint price is calculated as the average of the prevailing bid and ask quotes: $Q_t = (A_t + B_t)/2$. If an abnormal quote enters the NBBO, the NBBO is set to missing. As recommended by Holden and Jacobsen (2014), NBBO quotes that are locked or crossed are deleted. I also record the total sum of shares available at the best bid and the best ask as well as the number of exchanges that quote the best bid and the best ask.

Trades are merged to the NBBO that prevails one second before the trade execution.[34] I use Lee and Ready's (1991) algorithm to identify the direction of a trade. Trades with the transaction price (P_t) above the midpoint price ($P_t > Q_t$) are identified as buyer-initiated transactions, and those with the transaction price below the midpoint price ($P_t < Q_t$) as seller-initiated transactions. If the transaction price is equal to the midpoint price, the current transaction price is compared with the previous transaction price. If $P_t < P_{t-1}$, I consider a trade to be seller-initiated; if $P_t > P_{t-1}$, I consider it to be buyer-initiated. Should the two prices be equal, the trade is left as unclassified. Papers by Odders-White (2000), Ellis, Michaely, and O'Hara (2000), and Theissen (2001) show that only 72%-85% of trades are correctly classified as buyer- or seller-initiated with Lee and Ready's (1991) algorithm. However, the missclassification is fairly symmetric and thus should not bias any results of this paper.

[33] I would like to thank Joel Hasbrouck for making the SAS code of his algorithm available at http://people.stern.nyu.edu/jhasbrou/

[34] Chakravarty et al. (2012) try 0, 10, 50, 500, 1,000 and 5,000 millisecond lags and find that the highest percentage of ISO and non-ISO trades occurs at the quotes if merged with a lag of 1,000 milliseconds.

Figure 1: **Changes in the Proportion of ISO volume on Earnings Announcement Dates.** This figure displays the mean percentage changes in the proportion of ISO volume throughout the announcement day, calculated as the differences between the proportion of ISO volume traded within the category on the announcement day and its mean in the base period. Changes are measured over 10-minute event intervals, with interval 0 representing the 10-minute interval following an earnings announcement release. The solid line shows the mean percentage changes in the proportion of ISO volume for single-exchange ISO trades, and the dashed line for multi-exchange ISO trades.

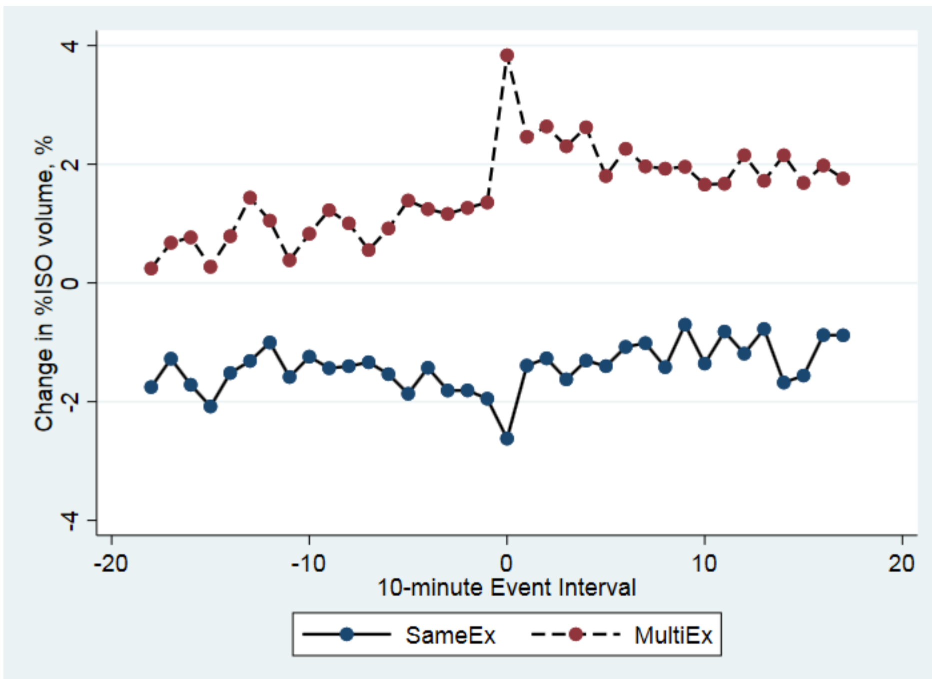

Table 1: **Sample Construction.** This table shows the sample selection of the US earnings announcements that take place within trading hours (9.30-16.00 EST) from October 1, 2007 to December 31, 2017. The data source for dates and times of the earnings announcements is the Institutional Brokers Estimate System (I/B/E/S). I require each firm to exist in the intersection set of I/B/E/S and CRSP.

Data Filters	**Events**	**Firms**
Initial sample	10,140	3,775
Stock traded on an announcement day	9,509	3,559
Intraday transaction data available on TAQ	7,922	3,042
Closing price not less than $2	6,870	2,745
Not more than one announcement of each firm per day	6,843	2,744
Trading data exists for previous 2 months	6,811	2,734
Exclude active stocks that have more than 10 trades per minute	6,229	2,481

Table 2: **Summary statistics.** This table presents summary statistics for the final sample of earnings announcements. Data on market capitalization, *MCap*, average daily volume traded (in thousands of shares), *Volume*, and annualized volatility of daily returns, *Volat*, are from CRSP. Quarterly data on the book value of equity, used to calculate the market-to-book ratio, *MTB*, are obtained from Compustat. Buy-and-hold abnormal returns around earnings announcement dates (*BHARs*) are estimated with the market model, using daily return data from CRSP and the equally-weighted CRSP market index as the market portfolio. The estimation period for the parameters is (-264, -64). The stock is required to have at least 100 observations in the estimation period. *Beta* is the slope from the market model. Daily averages of quoted spread, *Qspr,* the absolute value of order imbalance, *OIB*, total depth at the best bid and the best ask (in hundreds of shares), *Depth*, and realized variance over the five seconds before trade execution, $RealVar\,[-5s]$, are calculated from the NYSE TAQ database. See Appendix A for a detailed description of variable definitions.

	N	Mean	Std	25%	50%	75%
MCap (in mln $)	6,229	1106	2822	81	260	888
Volume (in 000's)	6,229	254	400	13	72	315
Volat	6,229	.51	.32	.28	.43	.64
MTB	6,229	1.9	2.7	.44	1.2	2
Beta	5,952	.93	.61	.46	.92	1.3
BHAR(-23;-2)	5,952	-.0082	.13	-.069	-.0067	.05
BHAR(0;1)	5,952	-.00045	.072	-.03	-.000026	.03
BHAR(2;128)	5,952	-.081	.41	-.25	-.044	.14
QSpr	6,229	.014	.02	.0019	.0048	.016
OIB	6,229	.25	.27	.065	.16	.33
Depth	6,229	29	92	7	11	23
$RealVar\,[-5s]$	6,229	.058	.068	.014	.034	.073

Table 3: **Trading with Aggressive Orders in the Base Period.** Panel A of this table shows the split of the total proportion of ISO volume by four price-exchange categories in the base period, consisting of days [-40, -2]. I aggregate all ISOs that occur in the same second and in the same direction in one ISO trade, and further assign aggregated ISO trades to four categories: ISO trades executed on a single exchange at the same price (*SameEx-SamePrc);* on a single exchange at multiple prices (*SameEx-MultiPrc);* on multiple exchanges at the same price (*MultiEx-SamePrc);* and on multiple exchanges at multiple prices (*MultiEx-MultiPrc)*. The daily proportion of ISO volume within a given category is calculated as the ratio of the daily ISO volume traded within the category to the overall volume traded during the day (both with ISOs and non-ISOs). Panel B of this table summarizes differences in sizes and price impacts of ISO and non-ISO trades, separately for purchases and sales. The first two columns report differences between ISO and non-ISO trades executed on a single exchange (*SameEx*). The third and fourth columns report differences between trades executed at multiple exchanges (*MultiEx*). The last column reports differences between ISOs across two exchange categories. See Appendix A for a detailed description of variable definitions. The table also reports p-values of the t-test for the null-hypothesis that the difference in means equals zero. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: %ISO volume split

	SameEx	MultiEx	Total
SamePrc	20.66%	5.88%	26.54%
MultiPrc	2.32%	5.92%	8.24%
Total	22.98%	11.80%	34.78%

Panel B: Differences in ISO and non-ISO trades

	SameEx			MultiEx			MultiEx - SameEx	
	ISO	non-ISO		ISO	non-ISO		ΔISO	
SizeBuy	208	275	***	627	668	***	418	***
$PrcImpBuy_{+1s}$	0.09	0.06	***	0.13	0.11	***	0.039	***
$PrcImpBuy_{+60s}$	0.13	0.10	***	0.16	0.14	***	0.034	***
SizeSell	221	315	***	656	695	***	435	***
$PrcImpSell_{+1s}$	0.10	0.07	***	0.14	0.11	***	0.040	***
$PrcImpSell_{+60s}$	0.09	0.07	***	0.11	0.09	***	0.019	***

Table 4: **Trading Aggressiveness on Announcement Days.** Panel A of this table shows changes in the proportion of ISO volume ($\triangle ISOVol$) on an announcement day by four price-exchange categories. I aggregate all ISOs that occur in the same second and in the same direction in one ISO trade, and further assign aggregated ISO trades to four categories: ISO trades executed on a single exchange at the same price (*SameEx-SamePrc);* on a single exchange at multiple prices (*SameEx-MultiPrc);* on multiple exchanges at the same price (*MultiEx-SamePrc);* and on multiple exchanges at multiple prices (*MultiEx-MultiPrc).* The change for each category is calculated as the difference between the proportion of ISO volume traded within the category on an announcement day and its mean in the base period, consisting of days [-40, -2]. Panel B shows changes in the proportion of multi-exchange ISO volume ($\triangle ISOVol_{MultiEx}$) on announcement days by news direction. Announcements in the top 33% of BHAR(0; 1) distribution are defined as good news, those in the bottom 33% as bad news, and the remainder as those with largely no news. See Appendix A for a detailed description of variable definitions. The table also reports p-values of the t-test for the null-hypothesis that changes in $\triangle ISOVol_{MultiEx}$ equal zero. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Panel A: $\Delta ISOVol$ on Announcement Day

	SameEx		MultiEx		Total	
SamePrc	-0.49%	**	-0.26%	***	-0.75%	***
MultiPrc	0.46%	***	1.48%	***	1.94%	***
Total	-0.03%		1.22%	***	1.19%	***

Panel B: $\Delta ISOVol_{MultiEx}$ by News Direction

	Good		None		Bad	
$\triangle ISOVol$	1.90%	***	0.96%	***	1.85%	***
$\triangle ISOBuy$	2.71%	***	0.96%	***	1.09%	***
$\triangle ISOSell$	1.40%	***	0.95%	***	2.40%	***
$\triangle Buy - \triangle Sell$	1.31%	***	0.01%		-1.31%	***

Table 5: **Determinants of Intraday ISO Trading Volume.** This table reports results of panel data OLS regressions with the proportion of ISO volume ($\%ISOvol$) split by exchange category as the dependent variable. One observation represents a 10-minute trading interval for a stock. Models (1) and (3) analyze the base period, which consists of 39 trading days before an announcement day, from day -40 to day -2. Models (2) and (4) analyze trading with ISOs on announcement days. See Appendix A for a detailed description of variable definitions. All regressions include day-fixed effects and intraday dummies for each half-hour of the trading day. Standard errors allow for double-clustering at the firm and day level. T-statistics of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in parentheses below each coefficient. P-values of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in form of asterisks to the right of each coefficient. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. I also report the number of observations (N) and R^2 for each regression.

	$\%\text{ISOVol}_{\text{MultiEx}}$		$\%\text{ISOVol}_{\text{SameEx}}$	
	Base	Event	Base	Event
	(1)	(2)	(3)	(4)
L.Volume	0.2298 ***	0.1468 ***	-0.7593 ***	-0.3133 ***
	(7.62)	(6.45)	(-9.85)	(-6.18)
$RealVar\,[-5s]$	0.0114 ***	0.0161 ***	-0.0325 ***	-0.0288 ***
	(5.91)	(4.60)	(-15.86)	(-8.44)
L.OIB	-0.0027 ***	-0.0054 ***	0.0011	-0.0008
	(-4.68)	(-2.91)	(1.13)	(-0.38)
QSpr	1.0876 ***	0.2171	4.2372 ***	2.9204 ***
	(3.18)	(0.52)	(15.41)	(7.67)
Depth	-0.0004 ***	-0.0001	-0.0002 ***	-0.0001 **
	(-4.36)	(-1.45)	(-3.64)	(-2.04)
N	3,238,606	90,148	4,716,757	124,701
R-squared	0.02	0.09	0.05	0.12
Daytime FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Table 6: **Trading Aggressiveness and Price Dynamics: Propensity Score Matching.** This table presents results of propensity score matching analysis, with matching factors including market capitalization, *MCap*, stock's volatility, *Volat,* and average daily trading volume, *Volume*. Announcements in the top 33% of BHAR(0; 1) distribution are defined as good news and those in the bottom 33% as bad news. Within each news category, I match stocks with high trading aggressiveness (High TA stocks) and low trading aggressiveness (Low TA stocks) separately on announcement days (*Event*) and non-announcement days (*Non − Event*), using nearest-neighbor propensity score matching. High TA stocks for the good (bad) news sample are defined as stocks, for which the proportion of multi-exchange ISO purchase (sale) volume within the first two hours of the announcement release is in the top 50% of its distribution ($HighTA_{Buy/Sell} = 1$). Low TA stocks are the corresponding stocks in the bottom 50% of its distribution ($HighTA_{Buy/Sell} = 0$). The upper panel of this table reports the cross-sectional averages of BHAR(0;1) for High TA and Low TA samples, separately for good news and bad news. The middle panel reports the corresponding statistics for the three-month buy-and-hold abnormal return, BHAR(2;64), and the lower panel - for the six-month buy-and-hold abnormal return, BHAR(2;128). The t-statistics of the two-sided t-test on the equality of the means between High TA and Low TA stocks are reported in parentheses in the last row of each panel.

	Good News			**Bad News**		
BHAR(0;1)	Event	Non-Event	Diff	Event	Non-Event	Diff
High $\mathrm{TA_{Buy/Sell}}$	7.90%	-0.18%	8.08%	-7.78%	-0.15%	-7.63%
Low $\mathrm{TA_{Buy/Sell}}$	6.19%	0.03%	6.16%	-6.67%	-0.11%	-6.56%
Diff	1.71%	-0.21%	1.92%	-1.11%	-0.04%	-1.07%
t-stat	(4.54)	(-1.74)	(4.85)	(-3.69)	(-0.26)	(-3.20)

	Good News			**Bad News**		
BHAR(2;64)	Event	Non-Event	Diff	Event	Non-Event	Diff
High $\mathrm{TA_{Buy/Sell}}$	-2.74%	6.24%	-8.98%	-4.57%	-13.17%	8.60%
Low $\mathrm{TA_{Buy/Sell}}$	0.89%	5.03%	-4.14%	-6.66%	-11.59%	4.93%
Diff	-3.63%	1.21%	-4.84%	2.09%	-1.58%	3.67%
t-stat	(-2.78)	(1.24)	(-2.98)	(1.17)	(-1.83)	(1.86)

	Good News			**Bad News**		
BHAR(2;128)	Event	Non-Event	Diff	Event	Non-Event	Diff
High $\mathrm{TA_{Buy/Sell}}$	-9.61%	-0.83%	-8.78%	-11.53%	-21.73%	10.20%
Low $\mathrm{TA_{Buy/Sell}}$	-1.16%	0.21%	-1.37%	-14.77%	-17.82%	3.05%
Diff	-8.45%	-1.04%	-7.41%	3.24%	-3.91%	7.15%
t-stat	(-3.52)	(-0.65)	(-2.66)	(1.75)	(-2.36)	(2.88)

Table 7: **Trading Aggressiveness and Price Dynamics: Multivariate Analysis.** Models (1) and (2) of this table present results of panel OLS regressions with the two-day buy-and-hold abnormal return over days 0 and 1, *BHAR(0; 1)*, as the dependent variable. Models (3) and (4) report results with the six-month post-announcement return, *BHAR (2; 128),* as the dependent variable. The news classification in Panel A is based on *BHAR(0; 1).* In Panel B, the news classification is based on the I/B/E/S earnings surprise, which is calculated as the difference between the earnings and the consensus forecast, scaled by the price two days prior to the earnings announcement. All regressions include observations for non-earnings announcement days -40, -30 and -20 that represent the control group. See Appendix A for a detailed description of variable definitions. All explanatory variables are standardized. All regressions include weekday- and monthyear-fixed effects, with standard errors double-clustered at the firm and day level. T-statistics of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in parentheses below each coefficient.

Panel A: News Classification: BHAR(0;1)				
	BHAR(0;1)		BHAR(2;128)	
	Good	Bad	Good	Bad
	(1)	(2)	(3)	(4)
$Event$	0.066 ***	-0.065 ***	-0.015	0.044 **
	(23.74)	(-25.78)	(-0.93)	(2.46)
$HighTA_{\text{Buy}}$	-0.000		0.008	
	(-0.07)		(0.43)	
$Event \cdot HighTA_{\text{Buy}}$	0.014 ***		-0.071 ***	
	(3.08)		(-2.95)	
$HighTA_{\text{Sell}}$		-0.002		-0.017
		(-0.84)		(-0.91)
$Event \cdot HighTA_{\text{Sell}}$		-0.010 ***		0.046 *
		(-2.62)		(1.68)
$LnMCap$	-0.002	-0.002	-0.077 ***	-0.045 ***
	(-1.63)	(-1.21)	(-3.58)	(-2.94)
MTB	-0.000	0.000	-0.043 ***	-0.042 ***
	(-0.39)	(0.32)	(-3.08)	(-3.62)
$Beta$	0.003 **	-0.002	0.020	0.000
	(2.39)	(-1.36)	(1.09)	(0.02)
$BHAR(-23; -2)$	-0.003	-0.003 **	0.100 ***	0.110 ***
	(-1.64)	(-2.38)	(7.03)	(7.26)
$Volat$	0.011 ***	-0.002	-0.058 ***	-0.067 ***
	(3.32)	(-1.35)	(-2.81)	(-4.10)
$QSpr_{\text{SPY}}$	-0.002	0.011 **	-0.002	-0.007
	(-0.49)	(2.10)	(-0.07)	(-0.17)
OIB_{SPY}	-0.000	-0.000	0.003	-0.000
	(-0.44)	(-0.36)	(0.60)	(-0.08)
$Constant$	0.001	0.000	-0.005	-0.128 ***
	(0.56)	(0.04)	(-0.28)	(-4.94)
N	7,050	6,832	7,050	6,832
R-squared	0.23	0.20	0.14	0.15
Weekday FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes

Panel B: News Classification: IBES Earnings Surprise

	BHAR(0;1)		BHAR(2;128)	
	Good	Bad	Good	Bad
	(1)	(2)	(3)	(4)
$Event$	0.020 ***	-0.010 **	-0.006	0.003
	(7.08)	(-2.29)	(-0.27)	(0.13)
$HighTA_{\text{Buy}}$	-0.000		0.018	
	(-0.05)		(0.61)	
$Event \cdot HighTA_{\text{Buy}}$	0.010 **		-0.071 **	
	(2.20)		(-2.12)	
$HighTA_{\text{Sell}}$		0.002		-0.028
		(0.66)		(-1.18)
$Event \cdot HighTA_{\text{Sell}}$		-0.014 **		0.046
		(-2.15)		(1.26)
$LnMCap$	-0.001	-0.003	-0.083 ***	-0.022
	(-0.95)	(-1.61)	(-3.09)	(-0.90)
MTB	0.000	-0.003 **	-0.038 *	-0.046 **
	(0.13)	(-2.09)	(-1.71)	(-2.00)
$Beta$	0.001	-0.001	0.069 ***	-0.023
	(0.62)	(-0.36)	(3.01)	(-1.11)
$BHAR(-23;-2)$	-0.003 *	-0.001	0.116 ***	0.103 ***
	(-1.88)	(-0.58)	(6.59)	(6.05)
$Volat$	0.008 **	0.001	-0.027	0.005
	(2.34)	(0.18)	(-0.97)	(0.17)
$QSpr_{\text{SPY}}$	0.002	0.013	0.049	0.006
	(0.31)	(1.44)	(0.76)	(0.14)
OIB_{SPY}	0.000	0.000	0.001	-0.001
	(0.34)	(0.40)	(0.19)	(-0.12)
$Constant$	0.004	-0.001	0.009	-0.0841 ***
	(1.42)	(-0.14)	(0.32)	(-2.63)
N	3,577	3,037	3,577	3,037
R-squared	0.08	0.06	0.19	0.23
Weekday FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes

Table 8: **Trading Aggressiveness and Price Dynamics: Subsample Analysis.** This table presents results of panel OLS regressions with the six-month post-announcement return, *BHAR (2; 128)*, as the dependent variable. Good news is defined as the top 33% and bad news as the bottom 33% of *BHAR(0; 1)*. Models (1) and (2) present results for the financial crisis period of 2007-2008, whereas Models (3) and (4) present results for 2009-2017. All regressions include observations for non-earnings announcement days -40, -30 and -20 that represent the control group. See Appendix A for a detailed description of variable definitions. All explanatory variables are standardized. All regressions include weekday- and monthyear-fixed effects, with standard errors double-clustered at the firm and day level. T-statistics of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in parentheses below each coefficient.

BHAR(2;128)	Crisis: 2007-2008		Non-Crisis: 2009-2017	
	Good	Bad	Good	Bad
	(1)	(2)	(3)	(4)
$Event$	0.004	0.044 *	-0.023	0.042
	(0.18)	(1.95)	(-1.28)	(1.57)
$HighTA_{\text{Buy}}$	0.001		0.016	
	(0.02)		(0.91)	
$Event \cdot HighTA_{\text{Buy}}$	-0.111 **		-0.057 **	
	(-2.53)		(-2.26)	
$HighTA_{\text{Sell}}$		-0.018		-0.025
		(-0.61)		(-1.13)
$Event \cdot HighTA_{\text{Sell}}$		0.068 *		0.045
		(1.72)		(1.31)
$LnMCap$	-0.095 ***	-0.057 **	-0.082 ***	-0.059 ***
	(-2.72)	(-2.42)	(-4.38)	(-2.94)
MTB	-0.051 **	-0.057 ***	-0.036 **	-0.028 *
	(-2.30)	(-3.31)	(-2.52)	(-1.82)
$Beta$	0.022	-0.027	-0.006	-0.016
	(0.79)	(-1.07)	(-0.34)	(-0.63)
$BHAR(-23;-2)$	0.110 ***	0.109 ***	0.094 ***	0.117 ***
	(5.90)	(7.00)	(7.15)	(5.67)
$Volat$	-0.047 *	-0.049 **	-0.043 **	-0.075 ***
	(-1.92)	(-2.25)	(-2.24)	(-3.97)
$QSpr_{\text{SPY}}$	-0.018	-0.042	0.003	0.062
	(-0.41)	(-1.05)	(0.08)	(0.65)
OIB_{SPY}	0.009	0.004	0.001	-0.004
	(0.65)	(0.31)	(0.22)	(-0.66)
$Constant$	-0.050	-0.109 *	-0.005	-0.122 ***
	(-1.19)	(-1.94)	(-0.30)	(-2.76)
N	2,455	2,507	4,595	4,325
R-squared	0.11	0.15	0.15	0.18
Weekday FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes

Table 9: **Trading Aggressiveness and Price Dynamics: Robustness Checks.** This table presents robustness checks of main results for good news in Panel A and bad news in Panel B. The good news is defined as the top 33% and bad news as the bottom 33% of *BHAR(0; 1)*. Model (1) reports results with the three-month post-announcement return, *BHAR (2; 64)*, as the dependent variable. For the remaining models, the dependent variable is *BHAR (2; 128)*. Models (2) and (3) report results with alternative measures of $HighTA_{Buy}$ and $HighTA_{Sell}$: in model (2) it is based on the proportion of multi-exchange ISO volume traded within the first hour of the announcement release, [0;1]; in model (3) - on the proportion of multi-exchange ISO volume over the period following the first two hours after the announcement release until the end of the trading day, [3+]. Model (4) reports results for the sample of stocks that excludes active stocks with more than 5 trades per minute. Model (5) includes only the non-earnings announcement day -40 as the control group. See Appendix A for a detailed description of other variable definitions. All explanatory variables are standardized. All regressions include weekday- and monthyear-fixed effects, with standard errors double-clustered at the firm and day level. T-statistics of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in parentheses below each coefficient.

Panel A: Good News					
	BHAR(2;64)	Multi-Ex ISOVol		Exclude	Control
		[0;1]	[3+]	active5	day [-40]
	(1)	(2)	(3)	(4)	(5)
$Event$	-0.031 ***	-0.017	-0.033 **	-0.014	0.001
	(-2.64)	(-1.12)	(-2.42)	(-0.88)	(0.08)
$HighTA_{\text{Buy}}$	0.014	0.008	0.009	0.010	0.013
	(1.33)	(0.44)	(0.43)	(0.50)	(0.49)
$Event \cdot HighTA_{\text{Buy}}$	-0.041 ***	-0.064 ***	-0.042 *	-0.075 ***	-0.078 **
	(-2.63)	(-2.77)	(-1.81)	(-2.81)	(-2.44)
$LnMCap$	-0.048 ***	-0.077 ***	-0.079 ***	-0.087 ***	-0.078 ***
	(-4.28)	(-3.60)	(-3.74)	(-3.34)	(-3.46)
MTB	-0.019 ***	-0.043 ***	-0.043 ***	-0.035 **	-0.041 ***
	(-2.95)	(-3.09)	(-3.09)	(-2.23)	(-2.98)
$Beta$	0.028 ***	0.020	0.019	0.029	0.018
	(3.63)	(1.08)	(1.05)	(1.49)	(0.97)
$BHAR(-23;-2)$	0.041 ***	0.100 ***	0.101 ***	0.105 ***	0.093 ***
	(5.66)	(7.03)	(7.04)	(6.90)	(7.76)
$Volat$	-0.015	-0.058 ***	-0.058 ***	-0.057 ***	-0.070 ***
	(-1.58)	(-2.81)	(-2.82)	(-2.67)	(-3.49)
$QSpr_{\text{SPY}}$	0.027	-0.003	-0.000	-0.002	-0.006
	(1.05)	(-0.11)	(-0.01)	(-0.08)	(-0.14)
OIB_{SPY}	0.004	0.003	0.003	0.003	0.009
	(1.42)	(0.58)	(0.61)	(0.52)	(1.02)
$Constant$	0.028 ***	-0.005	-0.006	-0.011	-0.012
	(2.66)	(-0.30)	(-0.35)	(-0.58)	(-0.50)
N	7,050	7,050	7,050	6,311	3,636
R-squared	0.11	0.14	0.14	0.13	0.13
Weekday FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Bad News					
	BHAR(2;64)	Multi-Ex ISOVol		Exclude	Control
		[0;1]	[3+]	active5	day [-40]
	(1)	(2)	(3)	(4)	(5)
$Event$	0.061 ***	0.037 **	0.058 ***	0.042 **	0.021
	(4.10)	(2.00)	(3.98)	(2.27)	(1.00)
$HighTA_{\text{Sell}}$	-0.003	-0.023	-0.026	-0.015	-0.055 *
	(-0.36)	(-1.28)	(-1.03)	(-0.74)	(-1.89)
$Event \cdot HighTA_{\text{Sell}}$	0.020	0.065 **	0.018	0.053 *	0.079 **
	(1.19)	(2.27)	(0.66)	(1.78)	(2.38)
$LnMCap$	-0.020 **	-0.045 ***	-0.043 ***	-0.067 ***	-0.047 ***
	(-2.26)	(-2.90)	(-2.82)	(-3.53)	(-2.91)
MTB	-0.021 ***	-0.042 ***	-0.042 ***	-0.040 ***	-0.037 ***
	(-3.63)	(-3.63)	(-3.61)	(-3.12)	(-3.38)
$Beta$	-0.005	0.000	0.001	0.011	0.001
	(-0.61)	(0.02)	(0.05)	(0.60)	(0.04)
$BHAR(-23;-2)$	0.048 ***	0.110 ***	0.110 ***	0.120 ***	0.099 ***
	(6.60)	(7.26)	(7.26)	(7.31)	(6.91)
$Volat$	-0.014	-0.067 ***	-0.067 ***	-0.080 ***	-0.077 ***
	(-1.34)	(-4.10)	(-4.07)	(-4.82)	(-4.43)
$QSpr_{\text{SPY}}$	0.020	-0.006	-0.007	-0.001	0.059
	(0.88)	(-0.15)	(-0.18)	(-0.02)	(1.58)
OIB_{SPY}	-0.000	-0.001	-0.000	-0.003	0.004
	(-0.00)	(-0.12)	(-0.05)	(-0.51)	(0.48)
$Constant$	-0.100 ***	-0.127 ***	-0.128 ***	-0.134 ***	-0.099 ***
	(-7.15)	(-4.91)	(-5.04)	(-4.75)	(-2.83)
N	6,832	6,832	6,832	6,055	3,523
R-squared	0.12	0.16	0.15	0.16	0.14
Weekday FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes

Table 10: **Heterogeneous Beliefs and Price Overreaction.** This table presents results of panel OLS regressions with *BHAR(2; 128)* as the dependent variable. Good news (Panel A) is defined as the top 33% and bad news (Panel B) as the bottom 33% of *BHAR(0; 1)*. Models (1) and (2) estimate effects of trading aggressiveness conditional on stock volatility (*Volat*), Models (3) and (4) conditional on the VIX index (*VIX*), and Models (5) and (6) conditional on the change in absolute order imbalance on the announcement day ($\triangle OIB$). All regressions include observations for non-earnings announcement days -40, -30 and -20 that represent the control group. See Appendix A for a detailed description of variable definitions. All explanatory variables are standardized. All regressions include control variables $LnMcap$, MTB, $Beta$, $BHAR(-23;-2)$,$Volat$,$Qspr_{SPY}$ and OIB_{SPY} as well as weekday- and monthyear-fixed effects. Standard errors are double-clustered at the firm and day level. T-statistics of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in parentheses below each coefficient.

Panel A: Good News

	Volat		VIX		ΔOIB	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Event	-0.003	-0.030 **	-0.003	-0.046 **	0.023	-0.053 *
	(-0.11)	(-2.04)	(-0.12)	(-2.13)	(0.77)	(-1.87)
$HighTA_{\text{Buy}}$	0.022	-0.006	0.013	-0.004	0.001	0.020
	(0.70)	(-0.47)	(0.43)	(-0.19)	(0.04)	(0.77)
$Event \cdot HighTA_{\text{Buy}}$	-0.100 **	-0.040 **	-0.098 **	-0.031	-0.058 *	-0.073 **
	(-2.43)	(-2.06)	(-2.33)	(-1.06)	(-1.73)	(-1.99)
N	3,868	3,176	3,672	3,370	3,470	3,519
R-squared	0.15	0.23	0.13	0.19	0.16	0.14
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Bad News

	Volat		VIX		ΔOIB	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Event	0.039	0.071 ***	0.027	0.048 *	0.044	0.049 *
	(1.59)	(2.97)	(0.93)	(1.87)	(1.33)	(1.72)
$HighTA_{\text{Sell}}$	-0.011	-0.014	-0.047 **	0.004	-0.013	-0.017
	(-0.36)	(-0.96)	(-2.35)	(0.15)	(-0.52)	(-0.67)
$Event \cdot HighTA_{\text{Sell}}$	0.058	-0.008	0.084 **	0.010	0.039	0.044
	(1.38)	(-0.25)	(2.57)	(0.21)	(0.86)	(1.17)
N	4,054	2,773	3,755	3,070	3,402	3,358
R-squared	0.17	0.22	0.18	0.16	0.17	0.17
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: **Market Attention and Price Overreaction.** This table presents results of panel OLS regressions with *BHAR(2; 128)* as the dependent variable. Good news (Panel A) is defined as the top 33% and bad news (Panel B) as the bottom 33% of *BHAR(0; 1)*. Models (1) and (2) estimate effects of trading aggressiveness conditional on the "business" of the reporting day. A reporting day is classified as "busy" if there were more than five earnings announcements released on the same day, and as "non-busy" otherwise. Models (3) and (4) estimate effects of trading aggressiveness separately for Friday and non-Friday releases. All regressions include observations for non-earnings announcement days -40, -30 and -20 that represent the control group. See Appendix A for a detailed description of variable definitions. All explanatory variables are standardized. All regressions include control variables $LnMcap$, MTB, $Beta$, $BHAR(-23;-2)$,$Volat$,$Qspr_{SPY}$ and OIB_{SPY} as well as weekday- and monthyear-fixed effects. Standard errors are double-clustered at the firm and day level. T-statistics of the two-tailed t-test with the null-hypothesis of a coefficient equaling zero are reported in parentheses below each coefficient.

Panel A: Good News	Non-Busy Day	Busy Day	Non-Friday EA	Friday EA
	(1)	(2)	(3)	(4)
$Event$	0.003	-0.022	-0.022	-0.054
	(0.09)	(-1.18)	(-1.07)	(-0.27)
$HighTA_{\text{Buy}}$	0.031	-0.006	0.013	0.001
	(1.05)	(-0.26)	(0.69)	(0.03)
$Event \cdot HighTA_{\text{Buy}}$	-0.113 ***	-0.042	-0.080 ***	-0.078
	(-2.61)	(-1.54)	(-2.97)	(-1.37)
N	2,419	4,631	5,830	1,220
R-squared	0.24	0.12	0.17	0.18
Controls	Yes	Yes	Yes	Yes

Panel B: Bad News	Non-Busy Day	Busy Day	Non-Friday EA	Friday EA
	(1)	(2)	(3)	(4)
$Event$	0.054	0.047 **	0.030	0.056
	(1.47)	(2.33)	(1.31)	(0.32)
$HighTA_{\text{Sell}}$	0.015	-0.027	-0.025	0.037
	(0.46)	(-1.23)	(-1.35)	(0.61)
$Event \cdot HighTA_{\text{Sell}}$	-0.009	0.064 **	0.054 *	-0.013
	(-0.17)	(1.98)	(1.81)	(-0.21)
N	2,291	4,541	5,736	1,096
R-squared	0.24	0.15	0.17	0.35
Controls	Yes	Yes	Yes	Yes