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Abstract

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JEL Classification: G30, M41

Keywords: Short selling, Informed trading, Strategic traders, institutional investors, Market Efficiency

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Strategic Trading as a Response to Short Sellers

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We study empirically informed traders' reaction to the presence of short sellers in the market. We find that investors with positive views on a stock strategically slow down their trades when short sellers are present in the same stock. Moreover, they purchase larger amounts to take advantage of the price decline induced by short sellers. Furthermore, they break up their buy trades across multiple brokers, suggesting that they wish to hide from the short sellers. This behavior may impact price discovery, as we find a sizeable reduction of positive information impounding for stocks more exposed to short selling during information sensitive periods. The evidence is confirmed exploiting exogenous variation in short interest provided by the Reg SHO Pilot Program. The findings have relevance for the regulatory debate on the market impact of short selling.

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1. Introduction

At a first approximation, when informed investors trade with uninformed ones, the efficiency of prices improves (e.g. Kyle, 1985). There is consensus in the theoretical and empirical literature on the fact that short sellers are informed traders.[1] Therefore, there are solid theoretical arguments in favor of the conclusion that short sellers increase price informativeness. Some recent empirical literature supports this view (Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Boehmer and Wu, 2013; Porras Prado, Saffi, Sturgess, 2016; Blocher and Ringgenberg, 2018). The favorable regulatory environment for short selling in most developed countries reflects these considerations.

However, a more realistic portrait of the market should include multiple groups of informed investors (e.g., Holden and Subrahmanyam, 1992, and Foster and Viswanathan, 1993 and 1996). In this context, the competition among traders affects the incentives for trading and the revelation of information in prices. In particular, when investors' receive different signals, strategic considerations can lead them to decrease their trading speed (Foster and Viswanathan, 1996). Intuitively, if an informed trader expects other traders to move prices in a direction different from her own signal, she will expect further divergence of prices from fundamentals in the future.

We use this framework to interpret the interaction between short sellers and other investors with positive views on the asset. In particular, if investors with positive information face the competition of short sellers, they may delay their trades to exploit the decrease in price induced by short sellers. Therefore, when information is diverse and dispersed across different groups of traders, the presence of short sellers may lead to a slow-down of the impounding of positive information. We label these conjectures on investor strategic behavior and information impounding the *waiting-game hypothesis*.

[1] Several studies show that the amount of short selling predicts future stock returns: Boehmer, Jones and Zhang (2008), Engelberg, Reed and Ringgenberg (2012), Cohen, Diether and Malloy (2007), Diether, Lee and Werner (2009b). Moreover, Engelberg, Reed and Ringgenberg (2012) explicitly link the information advantage to a superior ability to process public signals.

There is at least one relevant alternative hypothesis to the waiting-game scenario. Positively-informed investors, if they already hold stakes in the stock, may prefer the price to start rising immediately. Consequently, the presence of short sellers may induce long investors to buy the stock aggressively in order to force a rapid closing of the short positions. In this case, short interest can correlate with more aggressive buying and faster impounding of positive information in the price. We call this alternative the *short-squeeze hypothesis*.

The paper brings these conjectures to the data. In more detail, we study whether and how informed investors modify their trading activity when short sellers are present in the market. Then, we investigate the consequences of this behavior for information impounding. Our analysis can inform the theoretical modeling of the impact of short sellers on financial markets, as well as the regulatory stance vis-à-vis short selling.

The theoretical conjectures that motivate our empirical analysis rely on the assumption that the market is populated by investors observing different information signals. This assumption does not seem controversial. One of the main characteristics of modern financial markets is the fact that information is diffuse. Multiple players likely draw information from sources that are scarcely related. For example, while some traders rely on fundamental information, others rely on quantitative signals. Some traders rely on high frequency information and some focus on lower frequency one. This multiple-source, multi-faceted information would suggest that investors' information sets are not fully overlapping.

One may wonder how market participants can actually infer the presence of short sellers. Indeed, several channels contribute to make the market aware of the extent of short selling activity. For example, brokers that intermediate share loans can spread the word to their other clients in order to establish a reputation as valuable sources of information.[2] In addition, data providers publish statistics on short selling activity. Markit Securities Finance, formerly known as the Data Explorers database, one of the data sources for this study, is one such example.

To study informed investors' reaction to short sellers, we combine short selling information at the stock level from Markit Securities Finance with data on institutional trades from Abel Noser

[2] See, e.g., Di Maggio, Kermani, Franzoni, and Sommavilla (2018) and Barbon, Di Maggio, Franzoni, Landier (2018) for evidence of order flow leakage by institutional brokers.

Solutions (ANcerno) from 2002 to 2014. The end date of our sample depends on the availability of the ANcerno database, which we use to capture the trading behavior of informed traders. An abundant literature legitimates us to consider the institutions present in ANcerno as informed investors (Chemmanur, He, and Hu, 2009; Puckett and Yan, 2011; Chemmanur, Hu, and Huang, 2010; Anand, Irvine, Puckett, and Venkataraman 2012; Anand, Irvine, Puckett, and Venkataraman, 2013; Jame, 2017). Additionally, we develop a technique to identify the most active traders in ANcerno. We focus our analysis on this subset of investors, as they are more likely to place informed bets.

For our empirical analysis, we select periods in which there is more likelihood of informed trading. To identify such periods, we follow two strategies. First, the period preceding earnings announcements provides a fitting laboratory, as informed investors trade on their private signals before information becomes publicly available. Consequently, part of our analysis is restricted to the period around earnings releases. Second, we identify informed trading by focusing on large trades, which are defined as cumulative volume in one month in the top quartile of the order-flow distribution for a given manager-stock. In this case, the conjecture is that large trades tend to be informed, which we verify by noticing that on average these trades generate a persistent price impact.

Consistent with the conjecture that short selling activity slows down the trades of other informed investors, we find a significant delay in buy trades in the two weeks before the announcement for stocks with higher short interest. In particular, investors reduce the amount of buying by about 22% relative to the mean in the two weeks before the announcement when short selling in the prior-four weeks is one-standard-deviation higher. Also consistent, the total number of days over which a given amount of buy volume is executed in the two weeks before the announcement increases with the presence of short sellers.

Then, we turn to implications of the waiting-game hypothesis for price informativeness.[3] Arguably, if informed investors with positive views on the stock delay their trading activity

[3] Diether, Lee, and Werner show that some high-frequency measures of market quality (e.g. bid-ask spread and intraday volatility) deteriorated after the release of short sale constraints during the SEC Reg SHO experiment. The authors interpret this evidence as the result of short sellers moving from being forced liquidity providers to more aggressive liquidity demanders. Another possible interpretation is that the release of short sale constraints allowed more differentially informed investors to

before earnings announcements, the price may be less revealing of fundamental information. Specifically, if the reduced trading participation of positively-informed investors causes prices to be less revealing of their private information, price informativeness is reduced in case of good fundamental news. On the other hand, ahead of negative news releases, it is possible that short sellers improve information impounding. This is not, however, a foregone conclusion, given the evidence in Engelberg, Reed and Ringgenberg (2012) that short sellers' informational advantage lies primarily in their ability to interpret *public* news. The net effect of short selling on price informativeness ahead of public information releases is, therefore, an empirical question.

To shed light on this issue, we study the fraction of the cumulative abnormal return in the window between ten days before and one day after the announcement that is realized before the announcement. We find that short selling is related to a decrease in the amount of price discovery before positive earnings announcements. The effect is even stronger for announcements in which institutional investors overall are trading in the right direction relative to the announcement surprise, that is when the potential for information impounding is a priori more pronounced. On the other hand, we do not find that short selling increases information impounding ahead of negative news, consistent with a lack of information advantage of short sellers in the period ahead of earnings releases. Consistent with this evidence, Blau and Wade (2012) find that before earnings announcements short sellers do not seem to have an information advantage.

Overall, the evidence suggests that short selling can hamper price discovery by slowing down the trades of investors with positive information. This result is novel in the literature. It does not, however, contradict previous studies reporting a positive effect of short selling on price efficiency (Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Boehmer and Wu, 2013; Porras Prado, Saffi, Sturgess, 2016). In fact, it is possible that short sellers improve price efficiency over long horizons, especially after the release of public information. At the same time, during concentrated periods when private information is possessed by multiple investors, short selling activity can deter positively-informed investors from impounding their

actively participate in trading, which increased information asymmetry and reduced liquidity. In our paper, we investigate further the implications of differential information for price efficiency.

information. It is also possible that when multiple investors privately possess the negative information that is about to be released, short selling does not add much to price informativeness. On net, the effect of short selling in periods with highly dispersed private information can be detrimental for price efficiency.

To address the issue that short selling is an endogenous variable, we focus on the period of the Reg SHO experiment. In the two years between 2005 and 2007, the SEC suspended short-sale price tests, i.e. the uptick rule, for a randomly selected group of stocks (Pilot stocks) (see Diether, Lee, and Werner, 2009a). This policy was explicitly designed to provide an exogenous release of short selling constraints for one third of the Russell 3000 universe and assess the effect of short selling on different market outcomes. While increasing the potential for short selling activity on the subset of treated stocks, the experiment also provides a valid control group, i.e. the stocks outside the pilot program, effectively setting the stage for a difference-in-difference analysis (Grullon, Michenaud, Weston, 2015, De Angelis, Grullon, Michenaud, 2017).

We use this exogenously determined variation in short interest to identify the causal effects of short selling activity on traders' behavior. Our identification strategy relies on the fact that a priori the distribution of information for Pilot and Control stocks is the same, given that Pilot stocks are randomly selected. Hence, any change in behavior by other investors is the direct reaction to the increase in short selling for Pilot stocks. Prior literature (Diether, Lee, and Werner, 2009a; Alexander and Peterson, 2008; SEC's Office of Economic Analysis, 2007; Grullon, Michenaud, Weston, 2015) shows that short selling activity indeed increases for Pilot stocks during the Reg SHO experiment. We confirm this evidence in our data, establishing a significant first-stage relation between the treatment (i.e. exposure to the Reg SHO experiment) and short selling. Moreover, consistent with a negative impact of short selling on prices, the Pilot stocks experience significantly lower returns during the Reg SHO experiment.

Using this experiment, we re-examine the impact of short selling on trading activity and information impounding around earnings announcements. The evidence is again consistent with the waiting-game hypothesis. We find that the trading speed of active investors decreases for buy trades, but not for sell trades, before earnings announcements for Pilot stocks during the experiment. In particular, we estimate a 13% decrease in trading speed when managers buy Pilot stocks before a release of positive news.

We also study information impounding in the context of the Reg SHO experiment. Corroborating our prior results, the price movement that is realized before positive announcements is smaller by a sizeable 20% relative to the mean for Pilot stocks during the experiment. Instead, we do not find any effect on information impounding before negative earnings surprises, confirming our prior evidence that short sellers do not improve price discovery in this context.

To provide a more precise identification of informed trading, we focus on large trades. As mentioned above, these orders have a permanent price impact on average, consistent with the notion that they are informed. In this context, trade delay is measured using the number of trading days over which a large trade is completed within a month. We find a significant decrease in trading speed for large buy trades, but not for large sell trades, for Pilot stocks during the experiment.

Large trades also allow us to study information impounding in the presence of short sellers. Over five- and ten-day horizons from the start of a large buy trade, cumulative abnormal returns are significantly smaller for Pilot stocks during the experiment. The difference in returns is no longer significant 15 days from the start of the large trade. This effect is not present for sell trades. Again, the evidence suggests that short selling activity slows down positive information impounding. On the other hand, short selling does not appear to improve negative information impounding, when this information is privately owned by a subset of investors.

Inference of bad news from short-selling activity provides an alternative hypothesis to explain the evidence of slow-down in buy trades' speed. According to this alternative, investors make inference from the amount of short selling and, if short selling is large, they conclude that the fundamentals of the stock are bad. This hypothesis can explain a slow-down in buying activity for stocks with large short interest. Importantly, it also predicts that overall buy volume would decrease for stocks with high short selling. On the other hand, in the waiting-game scenario, the buy volume increases because, as short sellers push prices down, the stock becomes more attractive for investors with positive views. The effect of short selling on the amount of buy volume, therefore, provides a way to separate the two hypotheses.

To test the alternative hypothesis that informed investors update their priors downwards after observing short interest, we study buy volume in response to short selling. Ruling out the possibility that investors with positive information turn pessimistic after observing short selling activity, we find a significant increase in buy volume before earnings announcements for Pilot stocks during the Reg SHO experiment. Instead, we observe no significant effect on sell volume. The increase in buy volume, instead, corroborates the view that positively-informed investors take the opportunity of a lower price induced by short selling to increase their exposure to the stock.

Recent evidence suggests that institutional brokers are a source of information leakage (Barbon, Di Maggio, Franzoni, Landier, 2018; Di Maggio, Franzoni, Kermani, Sommavilla, 2018). Thus, we conjecture that informed investors wishing to reduce information leakage should spread their trades across multiple brokers when short sellers are more present in the market.[4] Importantly, evidence of hiding behavior provides an additional way to separate the waiting-game hypothesis from the alternative hypothesis of signal extraction. This alternative hypothesis does not imply that investors hide from short sellers. In particular, concealing the trades does not seem necessary if investors eventually decide to abstain from trading, or to trade in the same direction as the short sellers. Instead, evidence of trade breakup is consistent with the view that investors with positive views wait out the effect of short sellers to profit from a larger price jump (the waiting-game hypothesis).

Accordingly, we study informed investors' hiding behavior in the form of trade breakup across brokers. Consistent with hiding behavior, we find that managers use more brokers in stocks for which there is higher short selling. This result is fully confirmed in the context of the Reg SHO experiment and it is only present for buy trades. We find evidence of trade breakup both before earnings announcements and in the context of large trades. Along with the decrease in trading

[4] Horizontal trade breakup, i.e. across multiple counterparties, in the face of information leakage is modelled by Kondor and Pinter (2018).

speed, the evidence of trade breakup provides a channel for the finding that short selling slows down information impounding.

The paper relates to several strands of the existing literature. First, we contribute to the growing theoretical and empirical literature studying the impact of short selling on price efficiency.[5] While on the one hand, short sellers' trades accelerate the pace at which information is impounded into prices, on the other hand, the presence of informed traders, among which short sellers, increases information asymmetry, reducing the incentives of the other traders to trade. This channel can decrease price efficiency (e.g., Kim and Verrecchia, 1994). We conjecture and test another channel through which short sellers can reduce price efficiency, namely the incentive for investors with positive information to slow down their trade participation in anticipation of future price declines. Like us, Boehmer and Wu (2013) study price efficiency around earnings announcements and use the Reg SHO experiment for identification. These authors find that when short sellers are more active, prices are more accurate and, in particular, the post-earnings announcement drift is reduced for negative earnings news. We differ in that we focus on the time before earnings releases, when the information is still private, and find that prices are less revealing of positive information.

Our results are consistent theories positing that informed traders try to hide their information by choosing specific trading mechanisms. For example, Chakravarty (2001), Anand and Chakravarty (2007), and Alexander and Peterson (2007) document that this is done by reducing the size of the trade. In contrast, Blau and Smith (2014) argue that instead of disguising their trades through the use of smaller sizes, informed traders who face borrowing costs resort to large and potentially revealing trade sizes (see also Froot, Scharfstein, and Stein, 1992). The results in the paper establish breakup of trades across multiple brokers as an alternative way to carry out stealth trading.

Arif, Ben-Rephael, and Lee (2015) focuses on short sellers' reaction to the trades of the institutional investors in ANcerno. Specifically, these authors find that short sellers are able to understand the persistence of mutual fund trades and they use this information to front run

[5] See, for example, Diamond and Verrecchia (1987); Boehmer, Jones, and Zhang (2008, 2013); Boehmer and Wu (2013); Bris, Goetzmann, and Zhu (2007); Bris (2008); Charoenrook and Daouk (2009); Kolasinski, Reed, and Thornock (2009); Saffi and Sigurdsson (2011); Beber and Pagano (2013).

mutual funds. This study, like ours, starts from the premise that the two categories of traders possess different information. However, while they focus on how short sellers react to institutional investors, we focus on the response to short sellers of investors that possess positive information. In this sense, the two papers provide complementary and mutually reinforcing views on the interaction between short sellers and institutional investors.

Possibly closest to our work, Massa, Qian, and Zhang (2015) also focus on the strategic interaction between short sellers and other informed investors. In particular, among the latter, they look at company insiders that wish to trade on negative information. We differ in that we look at informed asset managers, and find results on the subset that has positive information.

Kacperczyk and Pagnotta (2019) find that company insiders slow down and break up their trades if they are exposed to legal risk, leading to lower information impounding. While finding similar evidence, our analysis focuses on a different group of informed agents, institutional investors, and their response to short selling activity.

The paper proceeds as follows. Section 2 describes our sample. Section 3 studies investors' reaction to short selling in terms of trade delay and the relation between short selling and price informativeness before earnings announcements. Section 4 replicates the analysis using exogenous variation in short selling from the Reg SHO experiment. Section 5 provides a narrower definition of informed investors by focusing on large trades. Section 6 sheds more light on the mechanism behind reduce price informativeness by focusing on trade breakup. Section 7 has some robustness analysis. Section 8 concludes.

2. Data

The sample for our empirical analysis results from the combination of different data sets. First, we draw institutional trades from Abel Noser Solutions, formerly known as Ancerno Ltd. (we retain the name of "ANcerno", commonly used in the literature; see Hu, Jo, Wang and Xie, 2018, for a detailed description of this data set). ANcerno provides consulting services for transaction cost analysis to institutional investors and used to make these data available for academic research with a delay of three quarters under the agreement that the names of the client institutions are not made public. While some institutions voluntarily report to ANcerno, the fact that clients submit this information to obtain objective evaluations of their trading costs, and not to advertise their performance, suggests that self-reporting should not bias the data. Indeed, the characteristics of stocks traded and held by ANcerno institutions and the return performance of the trades have been found to be comparable to those in 13F mandatory fillings (Puckett and Yan, 2011; Anand, Irvine, Puckett and Venkataraman, 2012). ANcerno provides information about each single trade execution. Hence, we know: the transaction date; the execution price; the number of shares that are traded; the side (buy or sell); the broker that intermediated the trade and the fees applied; the management company originating the trade (through the variable *managercode*). We are therefore able to identify buyer and seller initiated trades, to keep track of how many brokers are used to trade a certain stock, and the commissions paid for those trades. Management company and broker identifiers, which we use in our analysis, are available to us between 1999 and 2014. Mutual funds, which tend to be long-only investors, are the large majority of the over eight hundred institutions that report to ANcerno. About 100 hedge funds also report their trades in ANcerno (Franzoni and Plazzi, 2015, Jame, 2017). This fact implies that some short sales could be present among the ANcerno trades that we analyze, although there is no flag for short sales in the database.

To make sure that we do consider only fund managers with the ability to react to the presence of short-sellers, we select the subset of Ancerno managers that display the highest level of active trading. In particular, for each manager, we construct a portfolio by cumulating the trading activity over an expanding window of at least two years. Then, we regress the fraction of monthly trading in a given stock on the weight of the stock in the manager's portfolio at the beginning of the month. Intuitively, the more active the manager the less relevant are the existing portfolio weights in explaining the trading activity. Finally, we restrict our analysis to the subset of managers for which the R-squared in these regressions is in the lower half of the distribution across managers.

This identification strategy lends itself to an additional interpretation, which is also consistent with the behavior that we aim to capture. Asset managers whose trades display the largest discrepancies from their existing portfolio weights tend to follow short-term trading strategies (i.e., they are more likely to be momentum than value managers). These investors, therefore, will pay more attention to short interest, or to changes in it, than the rest of the universe.

Second, we draw information on stock level short selling activity from Markit Securities Finance, formerly known as Data Explorers. This firm provides benchmarking information to the securities lending industry and short-side intelligence to the investment management community. Markit Securities Finance collects data from leading industry practitioners, including prime brokers, custodians, asset managers and hedge funds, and is one of the biggest providers of securities lending data. These data are available to us at the monthly frequency from June 2002, at the weekly frequency since August 2004, and at daily frequency since July 2006. We let this sample end in December 2014 to match the ANcerno availability. The short selling variables that we focus on are the total balance of shares on loan or of shares lendable. We divide these variables by total shares outstanding variables to obtain our measures of short interest. In particular, shares on loan measures actual short interest and is obviously endogenous relative to the information environment. Arguably more exogenous, shares lendable measures the potential for short interest (Saffi and Sigurdsson, 2011).

When we measure short selling activity with the balance of shares on loan, our sample ranges between June 2002 and December 2014. The beginning and end of the sample are constrained by the availability of short selling and ANcerno data. Instead, when we focus on the Reg SHO Pilot Program, the sample ranges from May 2002 to July 2007. In this case, we set the end date of the sample to the end of the Reg SHO Pilot Program and we allow for a pre-event period before the start of the Reg SHO experiment (May, 2005).

Finally, we use also data from the Center for Research in Security Prices (CRSP - number shares outstanding, market capitalization, trading volume) and from Compustat (when computing the DGTW adjusted returns). Our final sample includes only ordinary stocks (Share Code 10 or 11 in CRSP) that belong to the Russel 3000 Index and that are present in ANcerno, CRSP, and any other database used to compute the variables of interest. Panel A of Table 1 provides the description of our main variables. Panel B reports descriptive statistics for the key variables used in our analysis distinguishing among the three samples: the sample of stocks included in Markit, the one used for the analysis around Reg SHO and for the tests related to large trades.

Table 2 investigates whether the stocks included in the Pilot and those in the control are indeed comparable. We show that there are no significant differences in terms of market capitalization, and dollar volume. However, we do find that share on loan and shares lendable increase for Pilot stocks during the Reg SHO period, as well as stock returns (raw and adjusted) are lower. This evidence confirms the identifying assumption that hypothesis that Reg SHO increased the presence of short-sellers for the Pilot stocks. Moreover, the release of short sale constraints led to lower returns, consistent with theories suggesting that short sale restrictions prevent prices from reflecting negative views (Miller, 1977).

Unlike us, Diether, Lee, and Werner (2009a) do not find an increase in short interest during the implementation period for Pilot stocks relative to a pre-period. However, these authors find a significant increase in short volume over total volume for Pilot stocks. Because we measure short interest using *weekly* data in Markit and because short positions remain open on average for a limited period[6], our short interest variable is more likely to capture the rise in higher-frequency short selling activity than the short interest variable used by Diether, Lee, and Werner (2009a), which for that period is available at the *monthly* frequency. The difference is in short interest that we identify for Pilot stocks relative non-Pilot in the Reg SHO period is around 6.5% (i.e. [3.409-3.2]/3.2). This magnitude is consistent with the 8.5% increase in short volume for Pilot stocks identified by Diether, Lee, and Werner (2009a).

Finally, Diether, Lee, and Werner (2009a) also look at the effect of Reg SHO on stock returns and, different from us, find no significant evidence. However, they focus on four-day windows around the announcement date (July 28. 2004) and the start date of the Pilot program (May 2, 2005). Instead, our analysis for Table 2 considers monthly returns over the whole period of the experiment. This choice is more likely to identify an effect if the impact of short selling is spread out in time.

[6] For example, Reed (2002) estimates a median loan duration of 3 days, and average of 11 days. Diether, Lee, and Werner (2009b) report a 4-to-5 days to cover ratio for daily short sales to total volume.

3. Response to Short Sellers

This section describes the first set of results of our empirical analysis. In each of these tests, we focus on the period before earnings announcements so that we can identify a clear date when information becomes public. This choice aims to adhere to the theoretical setup in the Foster and Viswanathan (1993) in which privately and differentially informed investors compete before the release of public fundamental information.

3.1 Trade Delay

We start our analysis by testing the conjecture that short selling activity slows down the trades of other informed investors. We do so by estimating the following regression:

$$\boldsymbol{y_{m,i,t} = \alpha_{m,i} + \delta_t + \beta Short\ Selling_{i,t} + X'_{m,i,t}\gamma + \varepsilon_{m,i,t}},$$

where $\boldsymbol{y_{m,i,t}}$ is a variable measuring trade delay for manager *m*, in stock *i*, in the pre-event window preceding an earnings announcement at time *t*.

Table 3 presents the results by using two different measures of trade delay. In Panel A, we proxy delay using a measure of trading speed defined as the ratio between the dollar volume executed by a manager in a stock in the window [-10, -2] relative to the announcement and the total manager-stock volume in the window [-10, 4] around the announcement (the variable is in %). Intuitively, a lower value of this variables implies that investors' trading activity is less intense in the few days pre-announcement, consistent with a slowdown in trading speed. In Panel B, we measure trading delay using execution time, i.e., the (log) number of trading days on which a manager is active in the [-10, -2] window before the announcement, keeping the executed volume constant. Again, the variable aims to measure trading speed, once we control for the total volume that is executed by the manager in that period. Hence, a high number of trading says would capture a lower speed.

In columns (1)-(2), we report estimates for buy trades, while columns (3)-(4) show results for sell trades. In both cases we consider the subsample of trades with a high directionality

($|\boldsymbol{buy} - \boldsymbol{sell}|/(\boldsymbol{buy} + \boldsymbol{sell})$ is at least 0.9) in order to pin down trading behavior that is information motivated. In columns (5)-(8), we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Trading in the right direction means that the sign of the manager's imbalance in the event stock is the same as that of the earnings surprise and that she trades with a pronounced directionality (i.e. the absolute value of the order imbalance is larger than 0.9, as above). Following Della Vigna and Pollet (2009), we define the earnings surprise as the difference between the actual earnings figure and the consensus forecast, scaled by the stock price 5 trading days before the announcement.

We use two proxies for the main explanatory variable, *Short Interest*. The first, *Shares on loan*, is constructed dividing the outstanding amount of shares on loan by the total number of shares outstanding. The measure is then defined as the 4-week average of this quantity, where we consider the 4 weeks starting two months before the news release. The second proxy, *Shares lendable,* is a supply-side measure of short selling constructed as the 4-week average of the total shares available for lending over the total number of shares outstanding. Fixed effects, $\boldsymbol{\alpha_{m,i}}$ and $\boldsymbol{\delta_t}$, are defined at the manager-stock and time level, respectively. The manager-stock fixed effects allow us to make sure that the variation we are exploiting is coming from the same managers trading the same stock when the stock exhibits different short-selling presence. To limit any other time-varying heterogeneity, the vector of control variables, $\boldsymbol{X'_{m,i,t}}$, includes market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the announcement, while the stock turnover from CRSP is averaged across the four weeks before the announcement window. The dataset spans the period between May 22, 2002 and December 31, 2014 and standard errors are double clustered at the manager-stock and time level.

The waiting-game conjecture suggests that only investors with positive information slow down their trading activity as a response to short selling. The evidence in columns (1) and (2) of Panel A, as compared to column (3), is consistent with the conjecture: the delay is present in buy trades, but not in sell trades, we also find that investors trading in the right direction are the ones that slow down their trading behavior the most (columns (5) and (6) compared to (7) and (8)). Panel B mainly confirms these results, although the difference between buy and sell trades, and between trades in the right or the wrong directions is less pronounced possibly indicating that our identification of right direction is subject to error.

The evidence of a slow-down in sell trades in some specifications, which is not contemplated by the waiting-game hypothesis, is possibly the consequence of the endogeneity of short-selling activity. Intuitively, stocks with higher short selling activity might be those for which the eventual public release of news involves more negative information. Because the selling volume *after* the earnings announcement is more pronounced for stocks with more negative news, we may find a negative correlation between short selling sell volume before the announcement as a fraction of total volume (column (3) of Panel A). Similarly, because of the potential correlation between short selling and the amount of negative private information, investors with negative information are more likely to spread their trades over multiple days when short selling is higher, i.e. when their information signal is also stronger. This behavior can explain the negative and significant coefficients in columns (3)-(4) of Panel B. Given this endogeneity issue, Section 4 provides evidence on the waiting game in a setting in which the variation of short selling activity is exogenous.

3.2 Price Informativeness

Next, we test an additional implication of the waiting-game hypothesis. If positively-informed investors delay their trades to take advantage of the price decline induced by short-sellers, we should expect an effect on information impounding. In particular, around *positive* earnings surprises, we expect a smaller fraction of announcement-related price change to take place before the release of public information.

Table 4 presents estimates of a similar specification to the one presented in Table 3 with the dependent variable measuring price informativeness of stock i defined as the ratio two cumulative-abnormal returns (CAR), i.e. the ratio of CAR[-10, -2] to CAR[-10, 1], where day 0 is the day of the earnings release and the abnormal returns are computed with respect to the DGTW benchmark (Daniel, Grinblatt, Titman, Wermers, 1997).

We differentiate between positive (columns (1) and (2)) and negative news (columns (3) and (4)), as well as between trading in the right (columns (5) and (6)) and the wrong direction (columns (7) and (8)).[7] In this case, trading in the right direction means that the sign of the total ANcerno imbalance is the same as that of the earnings surprise and that it is highly directional (i.e. the absolute order imbalance is in the top half of the distribution across stocks).

Our main result is that stock prices impound significantly less information before *positive* information releases when the presence of short-sellers is higher (columns (1)-(2)), consistent with the waiting-game hypothesis. The magnitude is large, as a one-standard deviation increase in short selling The evidence is somewhat stronger when buy trades are in the right direction, that is, in situations in which investors are more likely to possess private information (columns (5) and (6) as compared to columns (7) and (8)).[8]

One could reasonably argue that short sellers improve information impounding ahead of *negative* earnings surprises. If large enough, this effect could justify, from the point of view of overall price efficiency, bearing some information loss ahead of positive news. However, we do not find evidence of a positive impact on price of informativeness ahead of negative announcements (columns (3) and (4)). The lack of an effect on price efficiency at a point when information is still private is consistent with the results in Engelberg, Reed and Ringgenberg (2012). These authors show that the informational advantage of short sellers consists mostly of their ability to interpret public information after its release.

Overall, we find evidence consistent with the hypothesis that the interaction between short sellers and investors with positive information deters information impounding. This result, which is novel in the literature, does not contradict previous findings that short selling improves price efficiency. Our analysis focuses on periods before the release of public information. Previous studies (Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Boehmer and Wu, 2013), instead, focus on the unconditional effect of short selling on price efficiency. In fact, it is possible that short sellers improve efficiency over long horizons, especially after the release

[7] We identify a significant larger number of positive earnings surprises than negative surprises. This evidence is consistent with priors findings in the literature. See e.g. Della Vigna and Pollet (2009).

[8] We use the same sample selection as in Weller (2018), i.e. we require the absolute value of the CAR to exceed the standard deviation of returns computed in the pre-event window and scale it by the squared root of the interval length. This choice explains the drop in the number of observations in Table 4 relative to Table 3.

of public information. At the same time, during concentrated periods when private information is dispersed across multiple investors, short selling activity can deter information impounding by positively informed investors, while it does not improve price informativeness in case of negative news. On net, the effect of short selling on price efficiency in periods with highly dispersed private information can be negative.

4. Exogenous variation in Short Selling from Reg SHO

Although our results are robust to the inclusion of several stock-level controls and high-order fixed effects, one main concern is that the results could be partially due to the unobserved differences between stocks that are subject to different short-selling pressure. Moreover, as argued above, there could be correlation between short selling and the amount of negative private information in the market. Hence, by using short selling as explanatory variable we are not comparing across situations with the same private information.

To overcome these concerns, we take advantage of the Reg SHO experiment conducted by the SEC between 2005 and 2007. In this period, for a randomly selected group of about 1000 stocks from the Russell 3000 (Pilot stocks) the short-sale price tests, i.e. the uptick rule for the NYSE and the bid rule for NASDAQ, were removed.[9] This change amounted to a release of short sale constraints. The SEC ranked the firms listed on NYSE, NASDAQ and AMEX by average daily traded volume and selected for the pilot every third firm. In this way, the stratified random sample was representative of the cross-section of stocks and daily volume. The temporary suspension expired in August 6, 2007. However, in our tests, we let the Pilot Program end on July 5, 2007, because this was the compliance date for the new rule that eliminated any short-selling constraints on all stocks.[10]

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[9] NYSE Rule 440B provided that a short sale was only allowed on a plus tick. It was allowed also on a zero tick only if the most recent price change preceding the trade was a plus tick (called a zero-plus tick). According to NASDAQ Rule 3350, short sales were not allowed at or below the (inside) bid when the current inside bid was at or below the previous inside bid.

[10] The objective of the pilot study was to test the impact of Rule 10a-1, NYSE's Uptick rule, and NASDAQ's bid price on the market volatility, price efficiency, and liquidity in order to determine whether these restrictions were necessary going forward. In particular, one of the primary objectives of this regulation was meant to understand how to prevent speculative short sales that could potentially amplify the stock price decline when the stock is already in the midst of a substantial decrease in price during intraday trading.

Boehmer, Jones, and Zhang (2019) argue that after the end of the Reg SHO experiment there was an indirect effect leading to an increase in the aggressiveness of short sellers also on the original Pilot stocks. This issue does not concern our tests, given that our sample ends in July 2007. Still, the same authors also point out an indirect effect of the opposite sign during the experiment, that is, short sellers migrated from non-Pilot stocks to Pilot stocks. This spillover is a concern for the purposes of quantifying the effect of the rule under consideration. However, it does not interfere with our identification, because we are interested on the consequences of the overall increase in short selling, *both the direct and indirect effects*, during the Reg SHO period.

Given the random selection of Pilot stocks, we follow prior literature in running a difference-in-differences analysis in which Pilot firms represent the treatment group, while the Russell 3000 stocks outside the program are the control group (Grullon, Michenaud, and Weston, 2015, De Angelis, Grullon, and Michenaud, 2017). The pre-experiment period starts at the beginning of the overall sample, i.e. May 2002, and ends on May 1, 2005, before the start of the Reg SHO experiment. The post-period ranges between May2, 2005 and July 5, 2007.

Importantly, our identifying assumption is that the Reg SHO experiment increased the *potential* for short selling activity. In other words, Pilot and non-Pilot stocks differ only for the fact that short selling is easier for Pilot stocks during the experiment. The prior literature also established a valid first stage. That is short selling volume increased significantly for Pilot stocks during the experiment (Diether, Lee, and Werner, 2009a). As discussed above, we find consistent evidence in Table 2.

Prior literature suggests that suspension of the uptick rule facilitated arbitrage-based short selling, e.g. index arbitrage, for Pilot stocks (Boehmer, Jones, and Zhang, 2019). On the other hand, this event may not have significantly affected fundamental-based shorting, as these long-term strategies can patiently wait for execution on the limit order book. If this is the case, the Reg SHO experiment did not lead to an increase in information asymmetry for Pilot stocks. This conjecture, however, does not necessarily invalidate our identification strategy. The evidence indicates that short interest, irrespective of its determinants, predicts future price declines (e.g. Boehmer, Jones and Zhang, 2008, Engelberg, Reed and Ringgenberg, 2012, Cohen, Diether and Malloy, 2007, Diether, Lee and Werner, 2009b). To the extent that the rest of the market correctly expected lower returns after observing an increase in short selling activity, playing a waiting game was still a rational strategy to pursue. The evidence in Table 2 of significantly higher short interest and lower returns for Pilot stocks during the Reg SHO period corroborates this argument.

Next, we turn to the empirical evidence. Table 5 reports the results of the following diff-in-diff specification:

$$y_{m,i,t} = \alpha_{m,i} + \delta_t + \beta Pilot_{i,t} \times Program\ Period_{i,t} + X'_{i,t}\gamma + \varepsilon_{m,i,t},$$

where *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program. *Program Period* is an indicator for the time in which the program took place (May 2005 – July 2007). Odd columns focus on the main coefficient of interest, while even columns reports the results controlling for a full set of stock-level characteristics. All specifications include manager-stock and time fixed effects. This choice allows us to compare the behavior of the same manager trading the same stock before and after the implementation of the policy change. In other words, the unobserved heterogeneity that might drive the portfolio strategy of different managers cannot explain our results. The dependent variable and the vector of controls are the same as those in Tables 3 and 4 and standard errors are double clustered at the manager-stock and time level. In all the specification, the levels of *Pilot* and *Pilot Period* are subsumed by manager-stock, and time fixed effects, respectively.

Panel A of Table 5 corroborates the results from Table 3. We find a delay on trading volume before earnings announcements for buy trades on Pilot stocks after the program was in effect, relative to the other stocks and to the same stocks before the experiment. This effect is statistically significant when investors display a strong anticipation of the direction of the announcement (i.e. they trade in the right direction). The economic magnitude is also significant, as we find that managers experience a 50bps decrease in trading speed when they trade Pilot stocks during Reg SHO period compared to a sample mean of about 4%. That is to say, the ratio of volume executed before an earnings announcement over total volume is a sizeable 13% lower when a manager buys a stocks in anticipation of a positive news release.

Panel B measures trade delay with the (log) number of days it takes a manager to execute a given amount of volume. The results are overall consistent with Panel A, with somewhat smaller magnitudes. In particular, execution time increases by about 3% for Pilot stocks during Reg SHO period.

Importantly, Table 5 shows that there is no effect of the Reg SHO experiment on the speed of sell trades. This result supports our prior conjecture that the significance of short selling for the speed of sell trades in some specifications in Table 3 is the result of the endogeneity of short selling. This significance disappears once a source of exogenous variation in potential short selling is used as explanatory variable.

The Reg SHO experiment also allows us to return to the study of price efficiency ahead of earnings announcements. Table 6 follows the layout of Table 4, but replaces short selling with the treatment variable. We confirm that Pilot stocks after the program implementation exhibit a significantly less pronounced stock price reaction in the days before the announcement. Consistent with Table 4, we find that the effects are concentrated in stocks that receive positive news. Additionally, they are present only when investors display abnormal trading volume in the direction of the surprise (i.e. they trade in the right direction, columns (5) and (6)). The magnitude is economically large. Specifically, we find that the ratio of pre-period CAR to total CAR is lower by 8.2% when ANcerno managers trade Pilot stocks in the right direction during Reg SHO period. Given that the average ratio is about 41.5%, this decline represents a sizeable 20% decline relative to the mean.

Figure 1 provides further evidence on these effects. The figure plots the cumulative abnormal return of the Pilot stocks on days [-10, -1] before an earnings announcement during the Reg SHO experiment. The red line with squares represents the cumulative return averaged across Pilot stocks. The green dotted line represents the cumulative return averaged across non-Pilot stocks. The lines are based on estimates from a regression specification similar to the one reported in Table 6, but run on daily observations. Starting one week before a positive earnings announcement, we observe a significant divergence between Pilot and non-Pilot stocks with the former exhibiting significantly lower returns. Hence, it appears that positive information impounding is significantly lower for stocks with a higher potential for short selling. Figure 2 complements this result by showing that this divergence persists until one day before the announcement, after which there is a sudden convergence between Pilot and non-Pilot stocks. As the information becomes public, the retention of private information is no longer relevant for price informativeness.

A legitimate concern about our evidence is that some other channel that was operating as a result of the Pilot program is also driving the effects that we identify. In other words, the evidence we find may not be the direct result of a release of short sale constraints, rather it would be a byproduct of some other behavior triggered by the Reg SHO experiment.

To address this concern, we note that other papers that study this experiment do not point out channels that could create potentially confounding effects. For example, Diether, Lee, and Werner (2009a) find that short-sellers split their orders more as they switch from passive to more active trading strategies. We see no rationale for the order splitting behavior of short sellers to explain our evidence that buyers slow down their trading activity in the same stock. Moreover, Grullon, Michenaud, and Weston (2015) and De Angelis, Grullon, and Michenaud (2017) identify effects of the Reg SHO experiment on capital expenditures and compensation policies, respectively. Neither dimension seems to have direct relevance for traders' behavior and price informativeness. Closer to our variables of interest, Fang, Huang, and Karpoff (2016) find that Pilot firms reduced several measures of earnings management. This effect, if anything, is likely to make prices more revealing of information, the opposite of what we find. Also relevant, Li and Zhang (2015) find that Pilot firms reduced the precision and readability of bad news releases. This behavior matters for price discovery around bad news, while our results emerge before the release of good news. Finally, Massa, Qian, Xu, and Zhang (2015) find that the presence of short sellers induces company insiders to trade more aggressively on negative information. While this behavior may impact price informativeness around negative news, it does not seem to matter for positive news, which is our focus.

5. Large Trades

To provide further evidence that we are really describing the response of informed investors to short selling, we focus on a subset of trades that we believe are more likely to be informed.

Specifically, we follow Di Maggio, Franzoni and Sommavilla (2018) and consider the subsample of large trades executed by ANcerno managers. According to our definition, a trade is large if the absolute value of a manager's imbalance in a stock during a given month is greater than the 75th percentiles of the distributions of the prior 6-month imbalances computed across managers for a given stock and across stocks for a given manager (i.e. a large trade is in the top quartiles for both distributions). Intuitively, these trades are large bets on the stock and so are more likely to be motivated by information than by liquidity or portfolio rebalancing needs. In fact, Di Maggio et al. (2018) also show that these trades have a persistent price impact, which is consistent with our assumption that they are driven by private information.

Figure 3 replicates the evidence on the impact of large trades in the context of the Reg SHO sample that we use for the analysis (May 2002- July 2007). We find that the price impact of large buy trades is substantial at 60bps over one trading month. We also notice that before the start of the trade cumulative returns did not diverge significantly from zero. In the case of large sell trades, we also find a non-reverting price impact, although somewhat smaller at 20bps over twenty trading days. This lower magnitude, along with the evidence of a small run-up in prices before the start of the large sell trade suggests that some of these sell trades have a contrarian motive, which is not necessarily information based.

By focusing on large trades, we face a tradeoff. On the one hand, we improve the identification of informed trading by ANcerno managers. On the other hand, there is no identifiable time period when the information becomes public, which forces us to depart somewhat from the theoretical setup in Foster and Viswanathan (1996).

Tables 7 and 8 study trading speed and price informativeness and the analysis is cast in the context of the Reg SHO experiment. Because we focus on the subset of large trades and no end-date with public information release is identified, we are forced to re-define the dependent variables. Specifically, in Table 7, we measure execution time as the number of days in which the manager is active over the month in which the large trades takes place. More days correspond to a lower trading speed. In Table 8, price informativeness is the ratio of CAR[0,h] over CAR[0,20]. That is, we measure the fraction of the total price change that occurs over the first h days in the month of the large trade. Faster information impounding corresponds to a higher ratio.

In Table 7, we find that managers executing large trades take longer for Pilot stocks during the Reg SHO experiment relatively to control stocks. The evidence of slow-down is consistent with Tables 3 and 5. This effect is only present for buy trades, consistent with the behavior of a strategic trader that tries to take advantage of the price declines induced by short sellers.

Table 8 tests the effect on price informativeness. For the horizon over which we study information impounding, we choose values of h equal to 5, 10, and 15 days after the beginning of the trade. The comparison across trading horizons suggests that the price path of Pilot stocks is significantly different from that of control stocks. In particular, at shorter horizons, i.e. 5 and 10 days, Pilot stocks display significantly lower information impounding. The effect wears out as the large trade progresses towards completion. Eventually, the market becomes aware of the private information in the large trade and the difference between Pilot- and non-Pilot stocks has no reason to persist.

Overall, this evidence further confirms the baseline results that short-sellers deter information impounding from investors with positive information. This behavior, in turn, negatively impacts price informativeness.

6. Mechanism

There is at least one legitimate alternative explanation to the waiting-game hypothesis for the evidence that we have presented so far. In the waiting-game scenario, investors take advantage of the presence of short-sellers and they strategically delay their trades, because they expect that they will be able to buy more cheaply due to the downward price pressure. Alternatively, one can conjecture that investors with positive priors might infer from the presence of short-sellers that their signal might not be as precise as they thought or that they should update their posterior beliefs. Also, in this case, investors would end up placing less aggressive by trades. We call this conjecture the *learning hypothesis*. Although in principle both of these channels may be at play, this section provides evidence that is more consistent with the waiting-game hypothesis.

The first test we propose to shed some lights on the mechanism behind our results is based on the following argument. If long-only investors aim to take advantage of the temporary reduction in price due to the presence of short-sellers, we might expect them to trade a higher volume as their buy trades become more profitable. Instead, we would not expect an increase in buy volume if investors are less convinced of their positive information after observing short selling, i.e. under the learning hypothesis.

We tease out these hypotheses in Table 9, using the Reg SHO experiment as a source of exogenous variation for potential short selling activity. In particular, we examine whether the total dollar volume traded by manager m in the window [-10,-2] before an earnings release is higher for Pilot stocks during the experiment. Columns (1)-(4) focus on buy trades, while Columns (5)-(8) focus on sell trades. We find that overall buy volume increase by about 7% for Pilot stocks, while the coefficients for sell trades are negative but not significant. We can further refine this test by focusing on positive news and trades with large amounts either in the direction of the surprise (the right direction) or in the wrong direction. This refinement allows us to single out the subsample of managers that are more likely to be informed ex ante. Columns (1)-(4) of Panel A show that managers who purchase in anticipation of positive news do so more forcefully when short-sellers are in the market. Columns (5)-(8) show that this is not the case for those trading in the opposite direction. Overall, the trading behavior we uncover corroborates the hypothesis that our results are indeed driven by a strategic response by informed traders to the presence of short-sellers, consistent with the waiting-game hypothesis.

Next, we bring to the data the conjecture that informed investors' reaction to short selling also involves hiding behavior. In particular, informed investors with positive information may decide to make their trades less visible fearing that short sellers will update their priors, if they observe concentrated buying activity. This inference would reduce the negative price pressure from short sellers and traders with positive information would experience a reduction in expected profits. On the other hand, hiding behavior does not seem to be a core prediction of the learning hypothesis. Short sellers already have a negative view on the stock. Observing that other investors in the market follow their lead would not cause them to close their short sales. Hence, analyzing hiding behavior through trade breakup further allows us to tease out different explanations.

We measure trade breakup as the (log) number of brokers that are used to execute a given amount of volume. Table 10 shows results of a difference-in-difference specification around Reg SHO experiment. In Panel A, we measure the dependent variable in the window [-10, -2] before the earnings release. In Panel B, instead, we use the sample of large trades that we also used in Table 7.

We find a significant increase in the number of brokers that managers use to execute trades on Pilot stocks during the experiment. This result is valid both before earnings announcements and for large trades. Moreover, this effect is present only for buy trades and for those in the right direction. The coefficient in column (1) of Panel A suggests that managers buying Pilot stocks during the Reg SHO Pilot Program period use 3.1% more brokers in the two weeks preceding an earnings announcement.

The evidence of trade breakup is more likely to support the waiting-game hypothesis, as it is consistent with the view that investors with a positive prior hide from short sellers to prevent that they reverse their trades. On the other, it seems less likely that investors that updating their beliefs downward decide to hide, especially because we do not observe that investors with more definite negative views breakup their trades. That is, there is no evidence of trade breakup on the sell side.

Finally, trade breakup sheds additional evidence on the channel for the decrease of price informativeness. Hiding behavior on the buy side of trades is likely to conduce to less impounding of positive information.

7. Robustness Checks

One potential concern with our identification strategy based on the Reg SHO experiment is that the behavior that we uncover is not really specific to the policy intervention that we exploit as source of exogenous variation, but due to some correlated market movements. In particular, although unlikely given the random selection of the treated stocks, there could pre-trends in the variables of interest. To rule out this possibility, we run placebo difference-in-differences analysis focusing on periods that either precede or follow the experiment, but do not overlap with it. Specifically, in one case, we use a period ranging from January 1999 (date on which ANcerno starts) to July 2004 (date on which the Reg SHO experiment was announced). In this case, the placebo-treated group contains the same stocks that are treated during the actual Reg SHO program, but in the period July 2002 – July 2004. In another set of specifications, the sample ranges from November 2010 (after the financial crisis and after the re-introduction of the uptick rule) to December 2014 (the end of the ANcerno sample). The placebo-treatment occurs in the period November 2012 – December 2014.

A separate concern is the extent to which the managers that we flag as Active in ANcerno really represent informed investors. In particular, one may wonder whether the behavior that we identify characterizes all investors, irrespectively of their information set. To address this concern, we replicate the previous analysis on the complementary ANcerno sample, i.e. on the managers that are not flagged as Active. We remind that a manager is active if the adjusted-R^2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers R^2 distribution. Thus, non-Active managers are closer to adjusting their portfolios on the basis of the existing portfolio weights. Hence, these managers are likely to be indexers or quasi-indexers who do not trade based on private information.

Table 11 replicates the manager-stock level tests in prior tables for the set of non-Active managers in the actual Reg SHO sample and, for Active managers, in the placebo samples (Panels A, B, D, E). In Panel C, we replicate the stock-level price informativeness analysis in the placebo samples. In particular, Panel A uses trading speed as the dependent variable, while execution time is displayed in Panel B. Panel C performs a price informativeness analysis using the price jump ratio. Panel D reports results when the dependent variable is the log-dollar volume executed before the earnings announcement. Finally, the log-number of brokers used by a manager before an earnings announcement is displayed in Panel E.

For each set of tests, the first column reports estimates for buy trades, while the second focuses on sell trades. In both cases we consider the subsample of trades with a high directionality ($|buy - sell|/(buy + sell)$ is at least 0.9). In the third and fourth columns, we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Consistently across panels, we find the coefficients of interests on the interaction between Pilot and Program Period is statistically insignificant, and sometimes even the sign is not in accordance with our baseline results. This evidence reassures us that we are indeed capturing a behavior specific to the active managers in our sample and to the policy that relaxed short-selling constrains.

8. Conclusion

According to a commonly held view in the literature, short selling improves the informational content of asset prices. However, the presence of short sellers in the market can modify the behavior of other informed investors. Theory predicts that differentially informed traders strategically reduce their speed of trading to avoid dissipating their information rents too soon, as in a waiting game (Foster and Viswanathan, 1996).

We argue that short sellers and other informed investors fit the description of traders with heterogeneous information. It is, therefore, possible that short selling activity induces other investors with positive priors to trade less aggressively on their own information. Because of this waiting game, one can expect that prices incorporate positive information more slowly when there is large dispersion in priors.

In this paper, we study the trading behavior of other market participants in response to short selling activity. The behavior of other investors is inferred from institutional trading data (ANcerno). Among these institutions we select those that behave more like active investors. Moreover, in part of our analysis, we focus on large trades with a permanent price impact, which are likely to capture information-driven trades.

We find that informed traders react to short selling activity by delaying their trades. Additionally, investors spread their trades across multiple brokers when short interest is higher, arguably in order to prevent short sellers from inferring their information. These results are confirmed in a setting with exogenous variation in short selling activity (the Reg SHO experiment). Furthermore, they hold for the buy side and not for the sell side, consistent with the view that only investors with positive information play the waiting game.

Importantly, we also study the impact of the waiting game on the information content of prices before earnings announcements and during informed large trades. We show that prices are less informative when short selling is higher. In particular, the price path reaches the new fundamental level more slowly for stocks with greater short interest. These results are confirmed using exogenous variation in potential short selling induced by the Reg SHO experiment.

Our results have implications for the debate around the role of short selling on financial markets and the consequent regulatory stance. While the commonly-held belief in the finance literature is that short selling improves price efficiency, our results suggest that this may not always be the case. In particular, when there is a wide dispersion of information in the market, short selling can deter traders with positive views from timely impounding their information into prices. The scenarios that we focus on, i.e. the period before earnings announcements and large institutional orders, are likely to capture instances when other investors in the market have an informational edge. In fact, prior literature shows that short sellers' information advantage is mostly present *after* the release of public information. In sum, while short selling can improve price efficiency unconditionally, in some circumstances it can have negative implications for price informativeness. Accordingly, the regulation of short selling could be made contingent on the extent of information dispersion across investors and on the timing of specific information releases. The practical implementation of this recommendation obviously presents many difficulties, not least the measurement of information dispersion, and is therefore left for future research.

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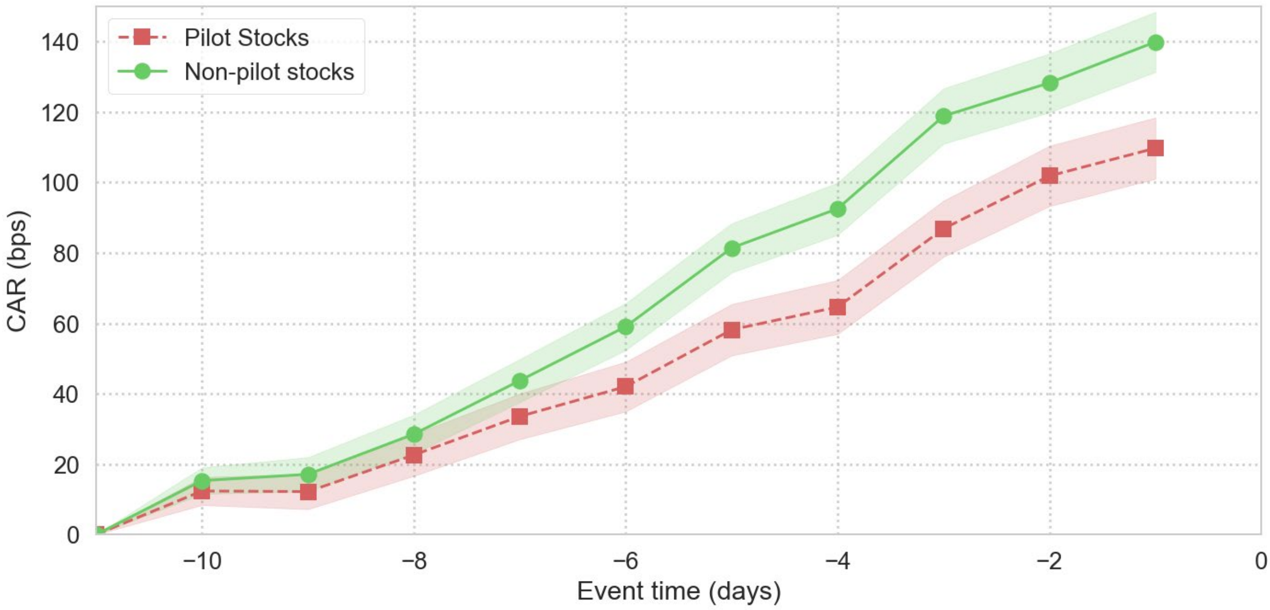


Figure 1: Price Paths Pilot vs Non-Pilot Stocks. The figure plots the cumulative abnormal return of the Pilot stocks on days [-10; -1] before an earnings announcement during the Reg SHO Pilot Program. The red squared line represents the cumulative return averaged across Pilot stocks. The green dotted line represents the cumulative return averaged across Non-Pilot stocks. The lines are based on estimates from a regression specification similar to the one reported in Table 6, but run on daily observations.

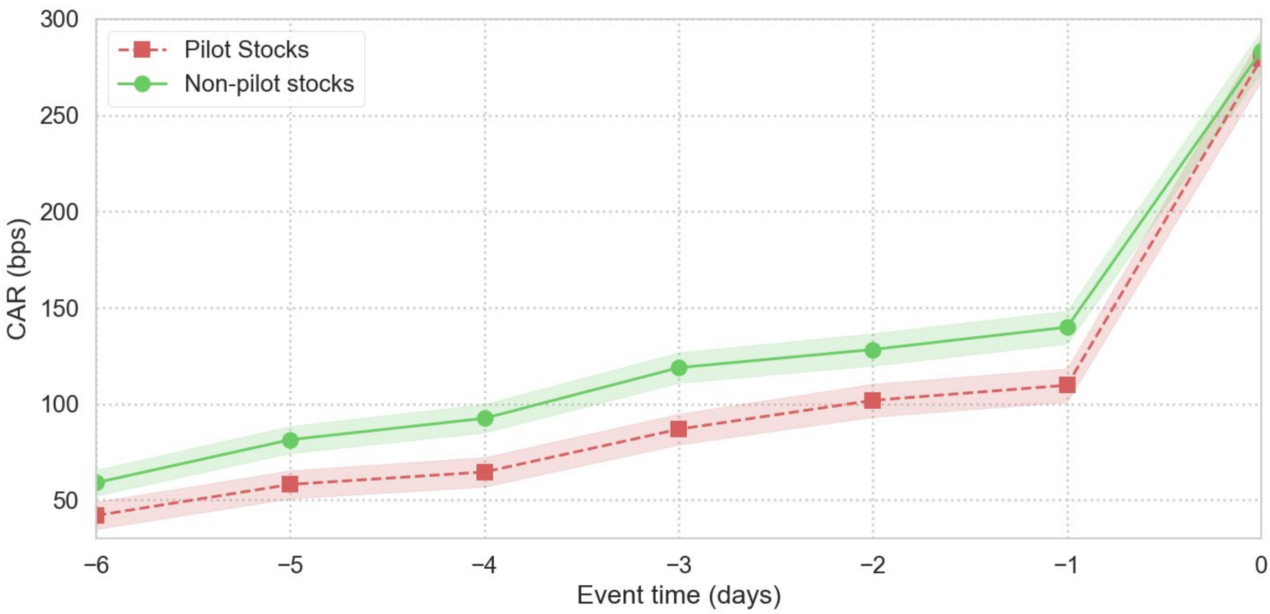
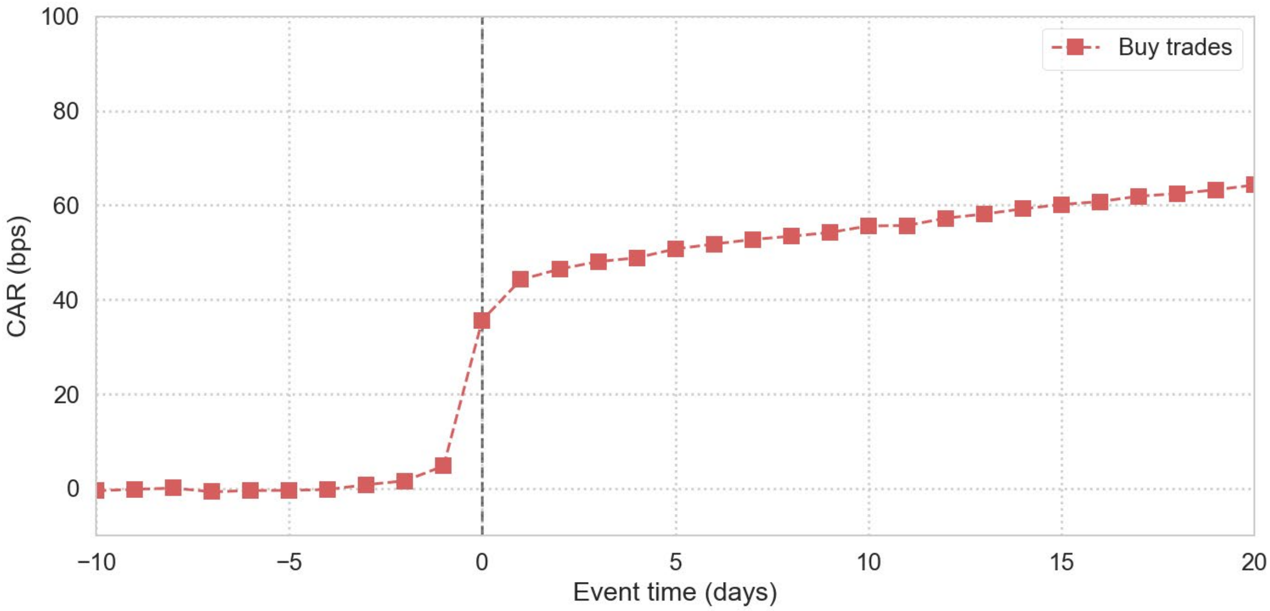


Figure 2: Price Convergence Pilot vs Non-Pilot Stocks. The figure plots the cumulative abnormal return of the Pilot stocks on days [-6; 0] before an earnings announcement during the Reg SHO Pilot Program. The red squared line represents the cumulative return averaged across Pilot stocks. The green dotted line represents the cumulative return averaged across Non-Pilot stocks. The lines are based on estimates from a regression specification similar to the one reported in Table 6, but run on daily observations.

Panel A



Panel B

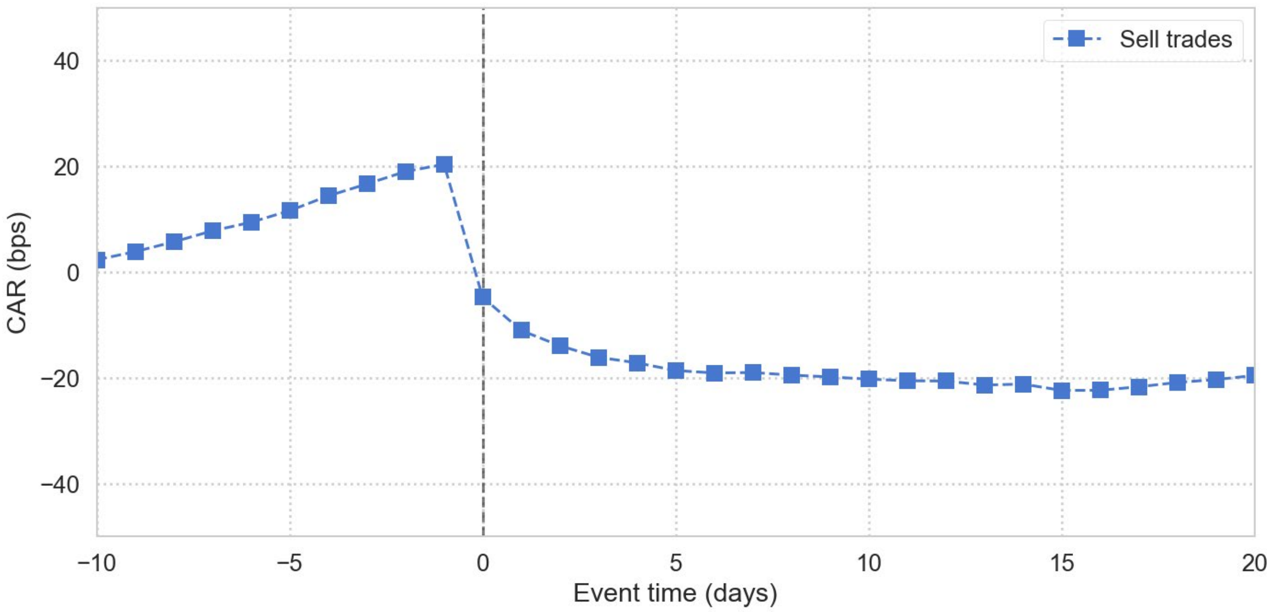


Figure 3: Price impact of large trades. The figure plots the cumulative abnormal returns (in bps) for large trades executed by active managers. We define a trade as large if the absolute value of a manager's imbalance in a stock during a given month is greater than the 75th percentile of the distributions of past 6-month imbalances computed at the manager, and stock level. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. Event time equal to zero refers to the first day of the large trade month in which a manager trades. Panel A reports the CAR for buy trades, while sell trades are reported in Panel B. The sample used for this figure is that of the Reg SHO Pilot Program analysis (May 2002 – July 2007).

Table 1
Summary statistics

This table reports statistics for the main variables used in the analysis. Panel A describes the main variables used in the analysis. Panel B reports mean, standard deviation, and number of observations, together with the 25th, 50th, and 75th percentiles for the main dependent and explanatory variables. We report statistics for the three samples used in the analysis separately. The three distinct datasets are: *(i)* The sample of earnings announcements when we use the short selling variables from Markit Securities Finance (May 2002-December 2014), *(ii)* the sample of earnings announcements for the diff-in-diff analysis around Reg-SHO (May 2002-July 2007), and *(iii)* the sample of large trades for the diff-in-diff analysis around Reg-SHO (May 2002-July 2007). We define a trade as large if the absolute value of a manager's imbalance in a stock during a given month is greater than the 75th percentile of the distributions of past 6-month imbalances computed at the manager, and stock level. The samples are at the manager-stock level and observations are recorded before an earnings announcement for the Markit and Reg-SHO sample, or in the month in which the trade is executed for the large trades sample. For price jump ratios (Jump) the sample is at the stock level. We consider the universe of active managers only. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution.

Panel A	Description of main variables
Variable name	Description
Execution time	Log-number of days needed to complete a trade. In the earnings announcements sample we look at trades executed in the window [-10, -2] before the announcement, while large trades are identified on a monthly basis.
Trading speed	Fraction of total dollar volume executed in the window [-10, -2] before the release of earnings information. The total dollar volume is computed in the window [-10, 4]. We express this variable in %.
(log) Number of brokers	Log-number of brokers used by a manager to execute a trade. In the earnings announcements sample we look at trades executed in the window [-10, -2] before the announcement, while large trades are identified on a monthly basis.
(log) Dollar volume (before event)	Log-dollar volume executed by a manager in the window [-10, -2] before an earnings announcement.
Jump[t-j, t]	Defined ad CAR[t-j, t]/CAR[t-j, t+h], where CAR is the cumulative (DGTW) abnormal return. In the earnings announcement sample, we choose *t-j* equal to day -10, *t* equal to day -2, and *t+1* equal to day +1. In the large trade sample, we pick *t-j = 0 (first day of trade)*, *t = [5, 10, 15]*, and *t+h = 20*.
Onloan	Previous month average of weekly number of shares on loan divided by total shares outstanding.
Lendable	Previous month average of weekly number of shares available for lending divided by total shares outstanding.
(log) Dollar volume (event)	Log-dollar volume executed by a manager in the window [-10, 4] around an earnings announcement or in the entire large trade window [0, 20].
(log) Market capitalization	Log-market capitalization lagged one period.
Stock turnover (%)	Average (weekly) stock turnover in month *t-1,* defined as the ratio of CRSP share volume over total shares outstanding.
Amihud illiquidity	Previous year average of $10^6 \times$ |ret|/$ Volume.
(log) Stock price	Previous year average of log-stock price.
(log) Return volatility	Previous year daily return volatility.
(log) Number of analysts	Number of analysts recorded in I/B/E/S that issue an earnings forecast within 90 days before the report date.

Panel B	Summary statistics					
Markit sample (earnings release)						
	Mean	SD	p25	p50	p75	N
Execution time	0.540	0.677	0.000	0.000	1.099	685,051
Trading speed	4.171	12.827	0.011	0.112	1.239	685,410
(log) Number of brokers	0.408	0.596	0.000	0.000	0.693	685,295
(log) Dollar volume (before event)	12.030	2.688	10.180	11.891	13.637	685,325
Jump [-10, -2]	0.422	0.474	0.122	0.404	0.716	35,982
(log) Dollar volume (event)	18.829	2.504	17.239	19.039	20.630	685,711
(log) Market capitalization	22.112	1.697	20.863	21.950	23.283	685,620
Stock turnover (%)	0.002	0.002	0.001	0.002	0.003	685,711
Amihud illiquidity	0.008	0.197	0.000	0.001	0.002	676,378
(log) Stock price	3.274	0.813	2.810	3.297	3.741	675,966
(log) Return volatility	-3.780	0.487	-4.121	-3.797	-3.469	675,966
(log) Number of analysts	1.915	0.891	1.386	2.079	2.565	685,711
Reg-SHO sample (earnings release)						
	Mean	SD	p25	p50	p75	N
Execution time	0.744	0.753	0.000	0.693	1.386	357,195
Trading speed	3.873	11.737	0.020	0.169	1.408	357,554
(log) Number of brokers	0.487	0.639	0.000	0.000	0.693	357,056
(log) Dollar volume (before event)	12.162	2.578	10.388	12.059	13.753	357,086
Jump [-10, -2]	0.415	0.472	0.109	0.396	0.717	14,292
(log) Dollar volume (event)	18.778	2.351	17.289	18.956	20.482	357,855
(log) Market capitalization	21.999	1.666	20.760	21.827	23.137	357,844
Stock turnover (%)	0.002	0.002	0.001	0.001	0.002	357,855
Amihud illiquidity	0.007	0.048	0.000	0.001	0.003	357,495
(log) Stock price	3.186	0.803	2.748	3.210	3.622	357,421
(log) Return volatility	-3.889	0.446	-4.207	-3.898	-3.599	357,421
(log) Number of analysts	1.841	0.898	1.099	1.946	2.565	357,855
Large trades sample						
	Mean	SD	p25	p50	p75	N
Execution time	1.518	0.916	0.693	1.609	2.197	874,157
(log) Number of brokers	0.900	0.793	0.000	0.693	1.609	874,157
Jump [0, 5]	0.312	0.361	0.064	0.279	0.537	161,512
Jump [0, 10]	0.536	0.416	0.267	0.542	0.808	161,512
Jump [0, 15]	0.763	0.367	0.570	0.797	0.987	161,512
(log) Dollar volume (event)	14.559	2.023	13.145	14.334	15.822	874,157
(log) Market capitalization	21.216	1.705	20.039	21.067	22.268	872,741
Stock turnover (%)	0.002	0.002	0.001	0.001	0.002	874,157
Amihud illiquidity	0.082	1.321	0.000	0.002	0.008	860,706
(log) Stock price	3.030	0.852	2.562	3.064	3.510	860,847
(log) Return volatility	-3.802	0.461	-4.122	-3.818	-3.506	860,847

Table 2
Descriptive statistics Pilot v. Control stocks

This table reports descriptive statistics of Pilot and Control stocks. We report the mean before and after the start of the Reg SHO Pilot Program (May 2005), together with the diff-in-diff estimation (lower right of each panel). We report statistics for the market capitalization (in million) at the beginning of the month, the Amihud illiquidity measure computed from daily returns in the previous year, the stock volatility in the previous year, the monthly dollar volume (in million), the monthly stock returns (in bps), the monthly DGTW-adjusted returns (in bps), the number of shares on loan as a percent of shares outstanding (monthly average). Standard errors are double-clustered at the stock and month level and reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Before	After	Diff	Before	After	Diff
	Market cap (mil)			*Dollar volume (mil)*		
Pilot	3513.286	4035.526	522.240***	512.063	640.208	128.146***
			(4.440)			(5.406)
Control	2935.309	3545.779	610.470***	424.116	532.008	107.892***
			(7.267)			(6.200)
Diff	577.977*	489.748	-88.230	87.947**	108.200**	20.254
	(1.730)	(1.464)	(-0.787)	(2.198)	(2.425)	(1.068)
	Shares Onloan (%)			*Shares Lendable (%)*		
Pilot	1.002	3.409	2.407***	1.803	12.663	10.860***
			(15.648)			(16.043)
Control	1.017	3.200	2.182***	1.627	11.737	10.110***
			(16.796)			(15.937)
Diff	-0.015	0.209	0.224**	0.176***	0.926***	0.750***
	(-0.269)	(1.585)	(2.108)	(3.183)	(4.248)	(3.824)
	Stock return (bps)			*DGTW-adjusted return (bps)*		
Pilot	164.563	138.500	-26.063	20.626	-9.782	-30.408***
			(-0.221)			(-2.986)
Control	154.876	152.234	-2.642	7.009	2.226	-4.782
			(-0.022)			(-0.517)
Diff	9.687	-13.734	-23.421**	13.618**	-12.008	-25.626**
	(1.437)	(-1.570)	(-2.232)	(2.250)	(-1.175)	(-2.204)

Table 3
Short selling and trading delay around earnings announcements

This table reports estimates for the following regression:

$$y_{m,i,t} = \alpha_{m,i} + \delta_t + \beta Short\ Selling_{i,t} + X'_{m,i,t}\gamma + \varepsilon_{m,i,t},$$

where, $y_{m,i,t}$ is a variable measuring trading delay for manager m, in stock i, in the pre-event window preceding an earnings announcement at time t. In Panel A, we proxy delay using a measure of trading speed defined as the ratio between the dollar volume executed by a manager in a stock in the window [-10, -2] and the total manager-stock dollar volume in the window [-10, 4] before an earnings announcement (the variable is in %). In Panel B, we measure trading delay using execution time, i.e., the (log) number of trading days needed to put in place the manager's strategy before the earnings announcement. Following Della Vigna and Pollet (2009), we define the earnings surprise as the difference between the actual earnings figure and the consensus forecast, scaled by the stock price 5 trading days before the announcement. In columns (1)-(2), we report estimates for buy trades, while columns (3)-(4) show results for sell trades. In both cases we consider the subsample of trades with a high directionality ($|buy - sell|/(buy + sell)$ is at least 0.9). In columns (5)-(8), we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Trading in the right direction means that the sign of the manager's imbalance in the event stock is the same as that of the earnings surprise and that she trades with a pronounced directionality. We use two proxies for the main explanatory variable, $Short\ Selling_{i,t}$. The first, *Shares on loan*, is constructed by dividing the outstanding amount of shares on loan by the total number of shares outstanding. The measure is then defined as the 4-week average of this quantity, where we consider the 4 weeks starting two months before the news release. The second proxy, *Shares lendable,* is an supply-side measure of short selling constructed as the 4-week average of the total shares available for lending over the total number of shares outstanding. $\alpha_{m,i}$ and δ_t represent manager-stock and time fixed effects, respectively. The vector of control variables, $X'_{m,i,t}$, includes the total volume traded by the manager, market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the announcement, while the stock turnover is averaged across the four weeks before the announcement window. The dataset spans the period between May 22, 2002 and December 31, 2014. We consider the subsample of ANcerno traders that we define active. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. Standard errors are double clustered at the manager-stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The explanatory variables are standardized.

Panel A	Dependent variable: Trading speed							
	Buy trades		Sell trades		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shares on loan	-0.304***		-0.023		-0.230***		-0.079*	
	(-6.435)		(-0.412)		(-4.046)		(-1.689)	
Shares lendable		-0.937***		-0.343***		-0.879***		-0.427***
		(-8.459)		(-3.375)		(-6.882)		(-4.781)
Manager volume	0.015	0.015	0.030*	0.029	0.031	0.028	-0.016	-0.018
	(0.739)	(0.777)	(1.685)	(1.610)	(1.099)	(0.973)	(-0.983)	(-1.085)
Market Cap	-4.213***	-4.162***	-3.287***	-3.301***	-3.871***	-3.847***	-3.354***	-3.343***
	(-13.880)	(-13.839)	(-10.210)	(-10.292)	(-9.847)	(-9.878)	(-13.145)	(-13.193)
Turnover	-0.529***	-0.609***	-0.402***	-0.403***	-0.500***	-0.559***	-0.343***	-0.362***
	(-8.985)	(-10.427)	(-5.713)	(-5.831)	(-7.192)	(-8.046)	(-6.090)	(-6.514)
Amihud Illiquidity	0.309***	0.306***	0.049	0.048	0.379***	0.376***	0.338	0.338
	(3.277)	(3.264)	(0.419)	(0.412)	(2.892)	(2.890)	(1.468)	(1.479)
Return Volatility	0.063	0.055	-0.017	-0.023	0.048	0.043	0.080	0.079
	(0.739)	(0.652)	(-0.196)	(-0.263)	(0.465)	(0.410)	(1.083)	(1.067)
Stock Price	-0.200	-0.129	-0.197	-0.183	-0.006	0.061	0.044	0.061
	(-1.137)	(-0.746)	(-1.194)	(-1.113)	(-0.024)	(0.272)	(0.338)	(0.463)
Number of Analysts	-0.189***	-0.199***	-0.053	-0.053	-0.126**	-0.135**	-0.039	-0.041
	(-3.985)	(-4.188)	(-1.011)	(-1.001)	(-2.106)	(-2.246)	(-0.906)	(-0.944)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	215,723	215,723	203,020	203,020	129,763	129,763	224,422	224,422
R-squared	0.449	0.449	0.428	0.428	0.482	0.482	0.382	0.382

Panel B	Dependent variable: Execution time (log-days)							
	Buy trades		Sell trades		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shares on loan	0.012***		0.008***		0.013***		0.016***	
	(4.531)		(2.789)		(3.637)		(5.542)	
Shares lendable		0.018***		0.021***		0.026***		0.039***
		(3.220)		(3.518)		(3.731)		(6.584)
Manager volume	0.001	0.001	0.010***	0.010***	0.000	0.000	0.002	0.002
	(0.444)	(0.340)	(5.595)	(5.601)	(0.174)	(0.158)	(1.384)	(1.384)
Market Cap	0.144***	0.140***	0.125***	0.122***	0.163***	0.160***	0.219***	0.214***
	(9.513)	(9.318)	(8.059)	(7.910)	(8.638)	(8.552)	(14.867)	(14.493)
Turnover	-0.014***	-0.010***	-0.011***	-0.009**	-0.010**	-0.006	-0.003	0.001
	(-3.984)	(-3.033)	(-3.074)	(-2.520)	(-2.310)	(-1.519)	(-0.937)	(0.226)
Amihud Illiquidity	-0.002	-0.002	0.005*	0.005*	-0.000	0.000	0.002	0.002
	(-1.316)	(-1.307)	(1.655)	(1.659)	(-0.003)	(0.033)	(0.570)	(0.526)
Return Volatility	0.024***	0.023***	0.012**	0.012**	0.019***	0.019***	0.016***	0.016***
	(4.535)	(4.468)	(2.541)	(2.492)	(3.094)	(3.035)	(3.269)	(3.130)
Stock Price	0.002	0.001	-0.013	-0.014	-0.012	-0.014	-0.008	-0.009
	(0.275)	(0.140)	(-1.527)	(-1.611)	(-1.222)	(-1.408)	(-1.021)	(-1.173)
Number of Analysts	0.004*	0.005**	-0.000	-0.000	0.005	0.006*	0.002	0.003
	(1.765)	(1.981)	(-0.172)	(-0.080)	(1.626)	(1.797)	(0.846)	(1.056)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	215,173	215,173	203,020	203,020	129,246	129,246	224,422	224,422
R-squared	0.581	0.581	0.445	0.445	0.609	0.609	0.645	0.645

Table 4
Short selling and price informativeness before earnings announcements

This table reports estimates for the following regression:

$$y_{i,t} = \alpha_i + \delta_t + \beta Short\ Selling_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t},$$

where $y_{i,t}$ is a variable measuring price informativeness of stock *i* and earnings announcement of time *t*, defined as the ratio of CAR[-10, -2] to CAR[-10, 1], where day 0 is the day of the earnings release and the abnormal returns are computed with respect to the DGTW benchmark. Following Della Vigna and Pollet (2009), we define the earnings surprise as the difference between the actual earnings figure and the consensus forecast, scaled by the stock price 5 trading days before the announcement. In columns (1)-(2), we report estimates for positive news, while columns (3)-(4) show results for negative news. In columns (5)-(8), we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Trading in the right direction means that the sign of the total ANcerno imbalance is the same as that of the earnings surprise and it has a pronounced directionality (i.e. stock-level $|buy - sell|/(buy + sell)$ is above median). A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. We use two proxies for the main explanatory variable, $Short\ Selling_{i,t}$. The first, *Shares on loan*, is constructed by dividing the outstanding amount of shares on loan by the total number of shares outstanding. The measure is, then, defined as the 4-week average of this quantity, where we consider the 4 weeks starting two months before the news release. The second proxy, *Shares lendable,* is a supply-side measure of short selling constructed as the 4-week average of the total shares available for lending over the total number of shares outstanding. α_i and δ_t represent stock and time fixed effects, respectively. The vector of control variables, $X'_{i,t}$, includes market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the announcement, while the stock turnover is averaged across the four weeks before the announcement window. The dataset is at the stock level and spans the period between May 22, 2002 and December 31, 2014. Standard errors are double clustered at the manager-stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The explanatory variables are standardized.

Dependent variable	Jump [-10, -2]							
	Positive news		Negative news		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shares on loan	-0.014**		0.002		-0.022**		-0.001	
	(-2.411)		(0.149)		(-2.278)		(-0.058)	
Shares lendable		-0.035***		-0.055***		-0.036**		-0.003
		(-3.315)		(-2.878)		(-2.182)		(-0.161)
Market Cap	-0.001	0.002	-0.127***	-0.136***	0.006	0.012	-0.017	-0.017
	(-0.054)	(0.106)	(-3.407)	(-3.642)	(0.163)	(0.326)	(-0.420)	(-0.426)
Turnover	-0.004	-0.008	0.014	0.017	-0.019*	-0.027***	0.012	0.012
	(-0.492)	(-1.074)	(1.044)	(1.301)	(-1.713)	(-2.584)	(0.820)	(0.849)
Amihud Illiquidity	-0.008***	-0.008***	-0.009	-0.010	-0.011***	-0.011***	0.016	0.016
	(-2.678)	(-2.688)	(-1.316)	(-1.511)	(-2.848)	(-2.946)	(1.030)	(1.021)
Return Volatility	0.012	0.012	-0.007	-0.011	0.014	0.014	-0.007	-0.007
	(1.092)	(1.057)	(-0.354)	(-0.555)	(0.840)	(0.863)	(-0.384)	(-0.391)
Stock Price	0.010	0.013	0.016	0.025	0.020	0.024	0.021	0.021
	(0.695)	(0.882)	(0.655)	(1.002)	(0.826)	(0.947)	(0.834)	(0.845)
Number of Analysts	0.015**	0.014**	0.009	0.011	0.007	0.006	0.026**	0.026**
	(2.276)	(2.192)	(0.766)	(0.904)	(0.721)	(0.619)	(2.218)	(2.228)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,392	15,392	6,495	6,495	7,472	7,472	6,550	6,550
R-squared	0.313	0.313	0.453	0.454	0.422	0.422	0.458	0.458

Table 5
Earnings announcements and trading delay around Reg-SHO

This table reports results for the following diff-in-diff regression around Reg-SHO:

$$y_{m,i,t} = \alpha_{m,i} + \delta_t + \beta Pilot_{i,t} \times Program\ Period_{i,t} + X'_{i,t}\gamma + \varepsilon_{m,i,t},$$

where, the dependent is a variable measuring trading delay for manager m, in stock i, in the pre-event window preceding an earnings announcement at time *t*. In Panel A, we proxy delay using a measure of trading speed defined as the ratio between the dollar volume executed by a manager in a stock in the window [-10, -2] and the total manager-stock dollar volume in the window [-10, 4] before an earnings announcement (the variable is in %). In Panel B, we measure trading delay using execution time, i.e., the (log) number of trading days needed to put in place the manager's strategy before the earnings announcement. Following Della Vigna and Pollet (2009), we define the earnings surprise as the difference between the actual earnings figure and the consensus forecast, scaled by the stock price 5 trading days before the announcement. In columns (1)-(2), we report estimates for buy trades, while columns (3)-(4) show results for sell trades. In both cases we consider the subsample of trades with a high directionality ($|buy - sell|/(buy + sell)$ is at least 0.9). In columns (5)-(8), we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Trading in the right direction means that the sign of the manager's imbalance in the event stock is the same as that of the earnings surprise and that she trade with a pronounced directionality. We consider the subsample of ANcerno managers defined as being active. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program. *Program Period* is an indicator for the time in which the program took place (May 2005 – July 2007). The vector of control variables, $X'_{m,i,t}$, includes market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the announcement, while the stock turnover is averaged across the four weeks before the announcement window. The sample is at the manager-stock-event level and spans the period between May 2002 and July 2007. Standard errors are clustered at the manager-stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The explanatory variables are standardized.

Panel A	Dependent variable: Trading speed							
	Buy trades		Sell trades		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	-0.134	-0.146	-0.112	-0.175	-0.486**	-0.496**	-0.013	-0.075
	(-0.739)	(-0.827)	(-0.498)	(-0.788)	(-2.297)	(-2.404)	(-0.071)	(-0.404)
Manager volume		-3.479***		-1.407***		-3.113***		-1.912***
		(-26.673)		(-10.965)		(-20.467)		(-16.767)
Market Cap		-0.886**		-2.051***		-0.881*		-1.189**
		(-2.218)		(-3.681)		(-1.715)		(-2.486)
Turnover		0.080		-0.285**		0.130		-0.098
		(1.005)		(-2.393)		(1.274)		(-1.025)
Amihud Illiquidity		0.493***		0.262		0.623***		0.288*
		(4.168)		(1.556)		(4.308)		(1.868)
Return Volatility		0.115		0.409***		0.415**		0.493***
		(0.899)		(2.617)		(2.564)		(3.863)
Stock Price		-0.064		-0.640*		0.023		-0.380
		(-0.268)		(-1.930)		(0.072)		(-1.315)
Number of Analysts		-0.148**		0.041		-0.121		0.103
		(-2.542)		(0.548)		(-1.568)		(1.549)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,968	116,779	94,938	94,817	66,777	66,637	100,474	100,340
R-squared	0.485	0.502	0.506	0.510	0.519	0.534	0.459	0.465

Panel B	Dependent variable: Execution time (log-days)							
	Buy trades		Sell trades		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.029**	0.028**	-0.008	-0.005	0.026*	0.023	0.001	0.001
	(2.487)	(2.418)	(-0.688)	(-0.424)	(1.794)	(1.610)	(0.048)	(0.096)
Manager volume		0.091***		0.119***		0.082***		0.102***
		(20.171)		(24.067)		(13.841)		(20.901)
Market Cap		0.137***		-0.013		0.148***		0.152***
		(5.942)		(-0.526)		(4.936)		(6.378)
Turnover		0.008		-0.013**		0.012*		0.008
		(1.584)		(-2.159)		(1.928)		(1.451)
Amihud Illiquidity		-0.002		-0.002		-0.000		0.008*
		(-0.449)		(-0.661)		(-0.015)		(1.953)
Return Volatility		0.047***		0.019**		0.051***		0.013*
		(6.513)		(2.541)		(5.451)		(1.797)
Stock Price		-0.031**		0.013		-0.031*		0.027*
		(-2.275)		(0.869)		(-1.713)		(1.950)
Number of Analysts		0.007**		-0.004		0.010**		-0.001
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,405	116,215	94,938	94,817	66,239	66,096	100,474	100,340
R-squared	0.597	0.602	0.493	0.499	0.629	0.633	0.632	0.637

Table 6
Earnings announcements and price informativeness around Reg-SHO

This table reports results for the following diff-in-diff regression around Reg-SHO:

$$y_{i,t} = \alpha_i + \delta_t + \beta Pilot_{i,t} \times Program\ Period_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t},$$

where $y_{i,t}$ is a variable measuring price informativeness of stock *i* and earnings announcement of time *t*, defined as the ratio of CAR[-10, -2] to CAR[-10, 1], where day 0 is the day of the earnings release and the abnormal returns are computed with respect to the DGTW benchmark. Following Della Vigna and Pollet (2009), we define the earnings surprise as the difference between the actual earnings figure and the consensus forecast, scaled by the stock price 5 trading days before the announcement. In Panel A, we show estimates for buy and sell trades without any regards on the sign of the news release, while in Panel B, we focus on positive news and distinguish between managers trading in the right and wrong direction. Trading in the right direction means that the sign of the total ANcerno imbalance (for the active managers) is the same as that of the earnings surprise and that they trade with a pronounced directionality ($|buy - sell|/(buy + sell)$ is above median). A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program. *Program Period* is an indicator for the time in which the program took place (May 2005 – July 2007). α_i and δ_t represent stock and time fixed-effects, respectively. We control for the market capitalization, the stock turnover, the number of analysts from which we compute the consensus forecast, the Amihud illiquidity measure, the stock price, and the return volatility. The last three control variables are computed in the year before the announcement, while the stock turnover is averaged across the four weeks before the announcement window. The sample is at the stock-event level and spans the period between May 2002 and July 2007. Standard errors are clustered at the stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The explanatory variables are standardized.

Dependent variable	Jump [-10, -2]							
	Positive news		Negative news		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	-0.067***	-0.067***	-0.021	-0.020	-0.082**	-0.081**	-0.079	-0.077
	(-2.655)	(-2.619)	(-0.399)	(-0.377)	(-2.011)	(-1.971)	(-1.598)	(-1.573)
Market Cap		0.030		-0.099		0.057		-0.019
		(0.743)		(-1.227)		(0.748)		(-0.242)
Turnover		-0.015		0.025		-0.011		-0.029*
		(-1.275)		(0.922)		(-0.515)		(-1.719)
Amihud Illiquidity		0.080		0.302**		-0.061		0.124
		(1.256)		(2.161)		(-0.522)		(1.268)
Return Volatility		-0.003		-0.060		0.030		-0.002
		(-0.143)		(-1.490)		(0.946)		(-0.049)
Stock Price		-0.008		-0.037		-0.034		0.036
		(-0.232)		(-0.600)		(-0.588)		(0.668)
Number of Analysts		0.024**		0.032		0.004		0.040**
		(2.385)		(1.546)		(0.237)		(2.119)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,145	8,145	2,724	2,724	3,525	3,525	3,173	3,173
R-squared	0.379	0.380	0.564	0.569	0.531	0.531	0.548	0.550

Table 7
Large trades and delay around Reg-SHO

This table reports results for the following diff-in-diff regression around Reg-SHO:

$$y_{m,i,t} = \alpha_{m,i} + \delta_t + \beta Pilot_{i,t} \times Program\ Period_{i,t} + X'_{m,i,t}\gamma + \varepsilon_{m,i,t},$$

where, the dependent is a variable measuring trading delay for manager m, in stock i in month t. We proxy delay with a measure of execution time defined as the log-number of trading days needed to complete a large trade during month t. *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program, while *Program Period* is an indicator for the period in which the program took place (May 2005 – July 2007). The sample is at the manager-stock level and spans the period between May 2002 and July 2007. $\alpha_{m,i}$ and δ_t represent manager-stock and time fixed effects, respectively. The vector of control variables, $X'_{m,i,t}$, includes total manager's volume, market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the dependent variable is measured, while the stock turnover is averaged across the four weeks before the start of the trade. We consider the subsample of large trades executed by active managers. We define a trade as large if the absolute value of a manager's imbalance in a stock during a given month is greater than the 75th percentile of the distributions of past 6-month imbalances computed at the manager, and stock level. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. Columns (1)-(4) report estimates for buy trades, while columns (5)-(8) focuses on sell trades. Standard errors are clustered at the manager-stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The control variables are standardized.

Dependent variable	Exectution time (log-days)							
	Buy trades				Sell trades			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.024***	0.023**	0.024***	0.024***	0.018	0.020	0.018	0.018
	(3.158)	(2.492)	(2.749)	(2.867)	(1.402)	(1.553)	(1.462)	(1.503)
Manager Volume		0.392***	0.391***	0.391***		0.408***	0.408***	0.409***
		(7.936)	(7.916)	(7.843)		(11.360)	(11.330)	(11.272)
Market Cap		-0.042	-0.042	-0.039		-0.106***	-0.104**	-0.120**
		(-0.642)	(-0.645)	(-0.513)		(-2.694)	(-2.578)	(-2.412)
Amihud Illiquidity			0.008***	0.008***			0.015***	0.015***
			(6.903)	(4.959)			(3.190)	(3.092)
Turnover				-0.015**				-0.033**
				(-2.138)				(-2.544)
Return Volatility				0.037***				0.025***
				(6.128)				(2.886)
Stock Price				0.008				0.029
				(0.319)				(0.931)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	430,746	430,274	423,235	423,235	350,505	349,712	345,192	345,192
R-squared	0.623	0.672	0.674	0.674	0.519	0.583	0.584	0.584

Table 8
Large trades and price informativeness around Reg-SHO

This table reports results for the following diff-in-diff regression around Reg-SHO:

$$y_{i,t} = \alpha_i + \delta_t + \beta Pilot_{i,t} \times Program\ Period_{i,t} + X'_{i,t}\gamma + \varepsilon_{i,t},$$

where, the dependent variable (Jump [0, h]) is the ratio of CAR[0, h] to CAR[0, 20], where day 0 is the day in which the large trade starts and the abnormal returns are computed with respect to the DGTW benchmark. We choose h to be equal to 5, 10, and 15 days after the beginning of the trade. *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program, while *Program Period* is an indicator for the period in which the program took place (May 2005 – July 2007). The sample is at the stock level and spans the period between May 2002 and July 2007. α_i and δ_t represent stock and time fixed effects, respectively. The vector of control variables, $X'_{m,i,t}$, includes total manager's volume, market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the dependent variable is measured, while the stock turnover is averaged across the four weeks before the start of the trade. We consider the subsample of large trades executed by active managers. We define a trade as large if the absolute value of a manager's imbalance in a stock during a given month is greater than the 75th percentile of the distributions of past 6-month imbalances computed at the manager, and stock level. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. Columns (1)-(4) report estimates for buy trades, while columns (5)-(8) focuses on sell trades. Standard errors are clustered at the stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The control variables are standardized.

Dependent variable	Jump [0, h]											
	Buy trades						Sell trades					
Horizon (h)	5 days		10 days		15 days		5 days		10 days		15 days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pilot × Program Period	-0.020***	-0.019***	-0.021**	-0.021**	-0.012	-0.011	0.007	0.007	-0.003	-0.003	0.007	0.007
	(-2.958)	(-2.929)	(-2.616)	(-2.593)	(-1.516)	(-1.470)	(1.059)	(1.092)	(-0.335)	(-0.329)	(0.933)	(0.982)
Manager Volume		0.027***		0.028***		0.023***		0.025***		0.025***		0.020***
		(11.546)		(9.369)		(9.279)		(9.456)		(7.406)		(6.523)
Market Cap		-0.002		0.000		-0.002		0.009		0.008		0.002
		(-0.851)		(0.095)		(-0.636)		(1.315)		(1.493)		(0.549)
Amihud Illiquidity		-0.023**		-0.042***		-0.050***		-0.004		-0.009		-0.022
		(-2.060)		(-2.864)		(-5.018)		(-0.281)		(-0.554)		(-1.532)
Turnover		-0.002		0.001		0.002		0.006**		0.006**		-0.001
		(-0.790)		(0.170)		(0.655)		(2.015)		(2.048)		(-0.370)
Return Volatility		-0.008		-0.005		-0.003		-0.006		-0.005		-0.002
		(-1.630)		(-0.870)		(-0.756)		(-1.272)		(-0.918)		(-0.356)
Stock Price		-0.016**		-0.001		0.015**		-0.001		-0.004		0.009
		(-2.270)		(-0.096)		(2.621)		(-0.161)		(-0.398)		(1.026)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	84,863	84,798	84,863	84,798	84,863	84,798	75,787	75,737	75,787	75,737	75,787	75,737
R-squared	0.067	0.070	0.068	0.071	0.065	0.068	0.074	0.077	0.076	0.078	0.070	0.072

Table 9
Earnings announcements and trading volume around Reg-SHO

This table reports results for the following diff-in-diff regression around Reg-SHO:

$$y_{m,i,t} = \alpha_{m,i} + \delta_t + \beta Pilot_{i,t} \times Program\ Period_{i,t} + X'_{i,t}\gamma + \varepsilon_{m,i,t},$$

where, the dependent variable is the dollar volume traded by manager *m* in the event stock *i* in the window [-10, -2] before an earnings release occurring at time *t*. Following Della Vigna and Pollet (2009), we define the earnings surprise as the difference between the actual earnings figure and the consensus forecast, scaled by the stock price 5 trading days before the announcement. In Panel A, we report estimates for buy trades, while columns (3)-(4) show results for sell trades. In both cases we consider the subsample of trades with a high directionality ($|buy - sell|/(buy + sell)$ is at least 0.9). In Panel B, we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Trading in the right direction means that the sign of the manager's imbalance in the event stock is the same as that of the earnings surprise and that she trade with a pronounced directionality. We consider the subsample of ANcerno managers defined as being active. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program. *Program Period* is an indicator for the time in which the program took place (May 2005 – July 2007). $\alpha_{m,i}$ and δ_t represent manager-stock and time fixed effects, respectively. The vector of control variables, $X'_{i,t}$, includes market capitalization, stock turnover, number of analysts following the company, Amihud illiquidity, stock volatility, and average stock price. The last three control variables are computed in the year before the dependent variable is measured, while the stock turnover is averaged across the four weeks before the start of the trade. The sample is at the manager-stock-event level and spans the period between May 2002 and July 2007. Standard errors are clustered at the manager-stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The explanatory variables are standardized.

Panel A	Buy and sell trades (all news)							
Dependent variable	Log-dollar volume [-10, -2]							
	Buy trades				Sell trades			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.076**	0.078**	0.073**	0.071**	-0.025	-0.025	-0.026	-0.031
	(2.172)	(2.245)	(2.093)	(2.049)	(-0.538)	(-0.540)	(-0.558)	(-0.660)
Market Cap		1.207***	1.168***	1.323***		1.195***	1.139***	1.352***
		(26.674)	(25.403)	(18.725)		(18.238)	(17.243)	(13.764)
Turnover			0.122***	0.130***			0.094***	0.070***
			(7.854)	(7.864)			(4.098)	(2.932)
Amihud Illiquidity			0.006	0.004			-0.044***	-0.047***
			(0.719)	(0.417)			(-3.010)	(-3.192)
Return Volatility				-0.003				0.139***
				(-0.126)				(4.675)
Stock Price				-0.126***				-0.166***
				(-3.032)				(-2.898)
Number of Analysts				0.008				0.038**
				(0.711)				(2.448)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,886	116,884	116,724	116,696	94,938	94,932	94,834	94,817
R-squared	0.615	0.619	0.620	0.620	0.576	0.579	0.579	0.579

Panel B	Positive news							
Dependent variable	Log-dollar volume [-10, -2]							
	Right direction				Wrong direction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.107**	0.116**	0.107**	0.105**	-0.029	-0.026	-0.029	-0.034
	(2.282)	(2.516)	(2.323)	(2.275)	(-0.657)	(-0.593)	(-0.673)	(-0.786)
Market Cap		1.181***	1.139***	1.307***		1.230***	1.189***	1.420***
		(19.552)	(18.511)	(13.652)		(20.539)	(19.610)	(14.038)
Turnover			0.127***	0.129***			0.098***	0.090***
			(6.023)	(5.748)			(4.419)	(3.844)
Amihud Illiquidity			0.020	0.016			-0.005	-0.009
			(1.602)	(1.348)			(-0.325)	(-0.551)
Return Volatility				0.025				0.082***
				(0.864)				(3.014)
Stock Price				-0.138**				-0.184***
				(-2.446)				(-3.022)
Number of Analysts				0.019				0.041***
				(1.229)				(2.768)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,701	66,701	66,583	66,558	100,267	100,263	100,152	100,134
R-squared	0.642	0.646	0.646	0.646	0.540	0.543	0.543	0.543

Table 10
Broker splitting

This table reports results for regressions in which the dependent variable is the log-number of brokers used by a manager to trade the event stock in the window [-10, -2] before the earnings release (Panels A) or to execute a large trade (Panel B). We run a diff-in-diff specification around Reg-SHO Pilot Program. *Pilot* is a dummy equal to one if the stock is included in the Reg-SHO Pilot Program, while *Program Period* is an indicator for the time in which the program took place (May 2005 – July 2007). Columns (1)-(2) of Panel A report estimates for buy trades, while columns (3)-(4) show results for sell trades. In both cases we consider the subsample of trades with a high directionality ($|buy - sell|/(buy + sell)$ is at least 0.9). In columns (5)-(8), we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or wrong direction. Trading in the right direction means that the sign of the manager's imbalance in the event stock is the same as that of the earnings surprise and that she trades with a pronounced directionality. Columns (1)-(4) and (5)-(8) of Panel B report estimates for buy and sell trades, respectively. We consider the subsample of ANcerno managers defined as being active. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. We control for the manager's total volume around the announcement window [-10 ,4] (Panel A), or executed in the large trade (Panel B), the market capitalization, the stock turnover, the number of analysts following the stock (in Panel A only), the Amihud illiquidity measure, the stock price, and the return volatility. The last three control variables are computed in the year before the window in which the dependent variable is measured, while the stock turnover is averaged across the four weeks before. The sample is at the manager-stock-event level and spans the period between May 2002 and July 2007. Standard errors are clustered at the manager-stock and time level, and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The explanatory variables are standardized.

Panel A	Difference-in-differences around Reg-SHO (behavior measured before earnings announcements)							
Dependent variable	Log-number of brokers							
	Buy trades		Sell trades		Right direction (positive news)		Wrong direction (positive news)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.031***	0.030***	-0.003	-0.001	0.026**	0.025**	0.002	0.003
	(3.093)	(3.097)	(-0.313)	(-0.122)	(2.146)	(2.118)	(0.150)	(0.265)
Manager volume		0.070***		0.088***		0.066***		0.072***
		(19.762)		(20.905)		(14.120)		(17.677)
Market Cap		0.156***		0.040*		0.163***		0.148***
		(8.199)		(1.938)		(6.377)		(6.989)
Turnover		0.004		-0.011**		0.005		-0.003
		(1.013)		(-2.098)		(0.857)		(-0.524)
Amihud Illiquidity		0.001		-0.001		0.002		0.007***
		(0.619)		(-0.580)		(0.512)		(3.340)
Return Volatility		0.032***		0.020***		0.033***		0.008
		(5.407)		(3.082)		(4.184)		(1.245)
Stock Price		0.000		0.007		0.003		0.029**
		(0.028)		(0.584)		(0.226)		(2.424)
Number of Analysts		0.010***		0.001		0.009**		0.004
		(3.675)		(0.326)		(2.203)		(1.193)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,853	116,663	94,938	94,817	66,668	66,525	100,267	100,134
R-squared	0.572	0.577	0.505	0.509	0.598	0.603	0.640	0.644

Panel B	Difference-in-differences around Reg-SHO (behavior measured during large trades)							
Dependent variable	Log-number of brokers							
	Buy trades				Sell trades			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.020**	0.020*	0.024**	0.023**	0.009	0.011	0.010	0.010
	(2.012)	(1.838)	(2.217)	(2.242)	(1.060)	(1.426)	(1.380)	(1.401)
Manager Volume		0.260***	0.261***	0.261***		0.261***	0.263***	0.263***
		(4.880)	(4.917)	(4.948)		(5.008)	(5.076)	(5.135)
Market Cap		0.107	0.106	0.075		0.033	0.034	-0.004
		(1.211)	(1.223)	(0.876)		(0.898)	(0.944)	(-0.092)
Amihud Illiquidity			0.005***	0.005**			0.012**	0.013**
			(2.848)	(2.627)			(2.495)	(2.318)
Turnover				-0.006				-0.018***
				(-0.726)				(-4.767)
Return Volatility				0.020***				0.019*
				(2.797)				(1.686)
Stock Price				0.031**				0.043*
				(2.425)				(1.748)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	430,424	429,954	422,920	422,920	350,481	349,688	345,167	345,167
R-squared	0.685	0.717	0.718	0.718	0.617	0.652	0.652	0.652

Table 11
Placebo tests

This table reports results for a placebo difference-in-differences analysis with dependent variables measured before an earnings announcement as in Tables 3-4-9-10. Panel A uses trading speed as the dependent variable, while execution time is displayed in Panel B. Panel C performs a price informativeness analysis using the price jump ratio. Panel D reports results when the dependent variable is the log-dollar volume executed before the earnings announcement. Finally, the log-number of brokers used by a manager before an earnings announcement is displayed in Panel E. Columns 1-4 of each panel show results when we run a placebo difference-in-differences analysis around Reg-SHO Pilot Program for the sample of non-active managers. A manager is active if the adjusted-r2 of the regression of next month trading in a stock (as a % of total volume traded next month) onto current stock holdings (as a percentage of portfolio holdings) ranks below the median of the across-managers r-squared distribution. In columns 5-12 we focus on active manager, but move the actual start of the Reg-SHO Pilot Program to a placebo period. In columns 5-8, *Pilot Period* is set to one in the period July 2002-July 2004, i.e., just before the Reg SHO Pilot Period was announced (July 28, 2004), and the sample is from July 1999 to July 2004. In columns 9-12, *Pilot Period* is set to one in the period November 2012-December 2014, and the sample is from November 2010, i.e. right after the reintroduction of the uptick rule on November 10, 2010 to December 2014, when the ANcerno sample ends. We control for the manager's trading volume, the stock market capitalization, the stock turnover, the number of analysts from which we compute the consensus forecast, the Amihud illiquidity measure, the stock price, and the return volatility. The last three control variables are computed in the year before the announcement, while the stock turnover is averaged across the four weeks before the announcement window. For each placebo sample, the first column reports estimates for buy trades, while the second focuses on sell trades. In both cases we consider the subsample of trades with a high directionality ($|buy - sell|/(buy + sell)$ is at least 0.9). In the third and fourth columns, we focus on positive news only and distinguish the case in which active ANcerno managers trade in the right or the wrong direction. Trading in the right direction means that the sign of the manager's imbalance in the event stock is the same as that of the earnings surprise and that she trade with a pronounced directionality. Standard errors are clustered at the manager-stock and time level (Panel A-B-D-E) or at the stock and time level (Panel C), and t-statistics reported in parenthesis. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The control variables are standardized.

Panel A	Dependent variable: Trading speed											
Sample	Non-active managers				Before announcement of Reg-SHO Pilot Program				After reintroduction of uptick rule			
	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pilot × Program Period	-0.041	-0.071	0.138	-0.094	-0.287	-0.505	-0.423	-0.172	-0.390	-0.054	-0.296	0.090
	(-0.178)	(-0.374)	(0.442)	(-0.499)	(-1.109)	(-1.589)	(-1.313)	(-0.600)	(-1.194)	(-0.183)	(-0.753)	(0.400)
Manager volume	-1.703***	-1.215***	-1.495***	-1.258***	-4.804***	-3.086***	-4.580***	-3.753***	-2.962***	0.447***	-2.694***	-2.063***
	(-13.226)	(-11.585)	(-8.674)	(-12.636)	(-27.132)	(-15.658)	(-21.163)	(-21.411)	(-14.074)	(2.709)	(-10.907)	(-14.115)
Market Cap	-1.073**	-1.774***	-1.352*	-1.152***	-2.108***	-2.050***	-1.213**	-0.491	-4.677***	-2.463**	-5.547***	0.193
	(-2.077)	(-3.934)	(-1.880)	(-2.633)	(-4.944)	(-3.292)	(-2.253)	(-0.862)	(-2.973)	(-2.182)	(-3.219)	(0.238)
Turnover	-0.144*	-0.165	-0.035	-0.187*	0.342***	-0.056	0.287*	-0.007	-0.494**	-0.012	-0.450*	0.219
	(-1.659)	(-1.623)	(-0.312)	(-1.906)	(2.819)	(-0.332)	(1.817)	(-0.047)	(-2.491)	(-0.068)	(-1.806)	(1.344)
Amihud Illiquidity	0.488**	0.121	0.879***	0.006	1.181***	1.030***	1.103***	0.880***	0.141	-0.339*	0.327	2.905***
	(2.302)	(0.501)	(4.306)	(0.032)	(3.777)	(3.447)	(3.499)	(5.051)	(0.845)	(-1.907)	(1.434)	(7.754)
Return Volatility	-0.060	0.129	0.041	0.023	-0.350*	-0.201	-0.201	0.115	0.378	0.037	0.108	-0.053
	(-0.371)	(1.092)	(0.196)	(0.197)	(-1.883)	(-0.872)	(-0.864)	(0.529)	(1.616)	(0.171)	(0.381)	(-0.313)
Stock Price	-0.256	0.385	0.048	0.520**	0.305	-0.419	0.275	-0.209	1.505*	-0.882	1.996**	-1.203***
	(-0.846)	(1.430)	(0.115)	(2.003)	(1.331)	(-1.242)	(0.899)	(-0.708)	(1.667)	(-1.493)	(2.123)	(-2.683)
Number of Analysts	-0.011	0.043	0.049	0.022	-0.139*	-0.066	-0.159	-0.027	-0.021	-0.232*	-0.111	-0.065
	(-0.146)	(0.654)	(0.480)	(0.373)	(-1.665)	(-0.630)	(-1.483)	(-0.289)	(-0.159)	(-1.889)	(-0.665)	(-0.709)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,503	89,232	45,472	80,550	90,531	63,646	50,540	66,906	42,253	48,460	24,274	60,560
R-squared	0.481	0.441	0.508	0.400	0.524	0.559	0.561	0.514	0.572	0.488	0.604	0.441

Panel B	Dependent variable: Execution time (log-days)											
Sample	Non-active managers				Before announcement of Reg-SHO Pilot Program				After reintroduction of uptick rule			
	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pilot × Program Period	0.010	-0.004	0.016	-0.010	-0.023	0.003	-0.036*	-0.012	-0.006	-0.018	-0.001	-0.019
	(0.758)	(-0.275)	(0.853)	(-0.757)	(-1.644)	(0.224)	(-1.928)	(-0.821)	(-0.369)	(-1.174)	(-0.050)	(-1.562)
Manager volume	0.094***	0.084***	0.087***	0.063***	0.125***	0.145***	0.119***	0.135***	0.071***	0.092***	0.065***	0.048***
	(18.378)	(17.570)	(12.128)	(12.809)	(22.524)	(21.313)	(15.465)	(20.780)	(10.814)	(14.593)	(6.727)	(9.777)
Market Cap	0.040	-0.012	0.060	0.119***	0.120***	-0.037	0.114***	0.113***	0.086*	0.116**	0.101*	0.173***
	(1.376)	(-0.420)	(1.402)	(3.897)	(5.620)	(-1.567)	(4.231)	(5.011)	(1.937)	(2.490)	(1.717)	(4.977)
Turnover	-0.005	-0.009	0.002	-0.005	-0.005	-0.023***	-0.003	0.002	-0.015*	0.004	-0.021*	0.012
	(-0.874)	(-1.473)	(0.305)	(-0.803)	(-0.686)	(-3.432)	(-0.403)	(0.292)	(-1.708)	(0.385)	(-1.768)	(1.497)
Amihud Illiquidity	0.010	0.006	0.014*	0.000	0.008***	0.002	0.007**	0.008*	-0.002	0.001	-0.003	-0.008
	(1.586)	(1.369)	(1.661)	(0.072)	(2.944)	(0.448)	(2.574)	(1.747)	(-1.034)	(0.285)	(-1.082)	(-0.978)
Return Volatility	-0.010	-0.011	0.010	-0.008	0.019**	0.008	0.015	0.004	-0.011	-0.021**	-0.016	-0.025***
	(-1.244)	(-1.345)	(0.870)	(-0.971)	(2.196)	(0.871)	(1.274)	(0.447)	(-1.007)	(-1.987)	(-1.010)	(-3.035)
Stock Price	-0.028	0.040**	-0.031	0.033*	-0.001	0.016	0.006	0.006	0.039*	-0.006	0.021	0.006
	(-1.642)	(2.456)	(-1.275)	(1.854)	(-0.103)	(1.248)	(0.352)	(0.445)	(1.674)	(-0.239)	(0.631)	(0.311)
Number of Analysts	0.003	0.001	-0.004	-0.001	-0.002	-0.002	0.001	0.007	-0.010	-0.001	-0.003	-0.003
	(0.768)	(0.211)	(-0.690)	(-0.131)	(-0.403)	(-0.420)	(0.216)	(1.453)	(-1.614)	(-0.253)	(-0.427)	(-0.628)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,503	89,232	45,472	80,550	90,274	63,646	50,278	66,906	42,253	48,460	24,274	60,560
R-squared	0.556	0.546	0.592	0.612	0.524	0.511	0.564	0.622	0.717	0.583	0.726	0.751

Panel C	Dependent variable: Jump (-10, -2)							
Sample	Before announcement of Reg-SHO Pilot Program				After reintroduction of uptick rule			
	Positive news	Negative news	Right (positive)	Wrong (positive)	Positive news	Negative news	Right (positive)	Wrong (positive)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pilot × Program Period	0.026	-0.023	0.033	-0.082	0.019	-0.050	0.024	0.080
	(0.835)	(-0.308)	(0.497)	(-1.541)	(0.582)	(-0.798)	(0.407)	(1.130)
Market Cap	0.072*	-0.053	0.156*	0.045	0.124	-0.247*	0.328**	0.087
	(1.842)	(-0.591)	(1.828)	(0.792)	(1.590)	(-1.894)	(2.456)	(0.534)
Turnover	-0.024	0.013	-0.022	-0.037	0.043**	0.020	0.055	0.017
	(-1.426)	(0.289)	(-0.688)	(-1.495)	(2.038)	(0.549)	(1.622)	(0.452)
Amihud Illiquidity	0.009	0.041	-0.014	-0.102**	-0.035***	-0.167	-0.058***	0.532***
	(0.559)	(0.978)	(-0.558)	(-1.979)	(-3.143)	(-0.517)	(-2.957)	(3.521)
Return Volatility	-0.003	-0.020	-0.003	0.019	0.027	-0.020	0.066	-0.056
	(-0.141)	(-0.382)	(-0.072)	(0.435)	(0.914)	(-0.398)	(1.377)	(-1.006)
Stock Price	0.020	-0.088	-0.028	0.059	-0.057	-0.095	-0.121	0.009
	(0.723)	(-1.325)	(-0.469)	(1.442)	(-1.029)	(-1.161)	(-1.225)	(0.088)
Number of Analysts	0.018	0.048	0.004	0.021	0.017	0.064**	-0.025	0.070**
	(1.429)	(1.508)	(0.153)	(0.912)	(1.191)	(2.559)	(-0.968)	(2.549)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,742	1,373	1,983	2,245	4,382	1,694	1,854	1,470
R-squared	0.440	0.639	0.560	0.587	0.432	0.572	0.594	0.582

Panel D	Dependent variable: Log-dollar volume [-10, -2]											
Sample	Non-active managers				Before announcement of Reg-SHO Pilot Program				After reintroduction of uptick rule			
	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pilot × Program Period	-0.046	-0.024	0.029	-0.082	-0.051	0.032	-0.091*	0.040	-0.072	0.006	-0.028	-0.056
	(-0.783)	(-0.445)	(0.356)	(-1.521)	(-1.378)	(0.645)	(-1.780)	(0.839)	(-1.037)	(0.087)	(-0.314)	(-1.011)
Market Cap	1.120***	1.023***	1.059***	1.189***	1.239***	1.286***	1.253***	1.447***	1.104***	1.610***	0.849***	1.874***
	(9.604)	(8.981)	(6.266)	(9.728)	(20.798)	(16.186)	(16.129)	(17.100)	(6.504)	(7.616)	(3.402)	(12.133)
Turnover	0.089***	0.091***	0.098***	0.087***	0.135***	0.067**	0.140***	0.083***	0.028	0.103***	0.020	0.104***
	(3.537)	(3.495)	(2.962)	(3.156)	(7.095)	(2.575)	(5.843)	(3.321)	(0.676)	(2.584)	(0.324)	(3.448)
Amihud Illiquidity	0.031	-0.039**	0.063***	-0.013	0.025***	-0.017	0.034***	0.013	0.004	0.009	0.002	0.104***
	(1.543)	(-2.220)	(2.877)	(-0.656)	(3.344)	(-0.921)	(4.161)	(0.932)	(0.697)	(0.987)	(0.202)	(3.083)
Return Volatility	-0.001	-0.014	0.054	-0.011	-0.005	0.031	-0.012	0.055	0.029	-0.015	0.003	-0.005
	(-0.044)	(-0.466)	(1.217)	(-0.331)	(-0.207)	(0.895)	(-0.367)	(1.568)	(0.650)	(-0.314)	(0.041)	(-0.146)
Stock Price	-0.095	0.198***	-0.094	0.178**	-0.128***	-0.146***	-0.121***	-0.143***	-0.034	-0.085	-0.116	-0.148*
	(-1.321)	(2.861)	(-0.923)	(2.487)	(-3.621)	(-3.218)	(-2.657)	(-2.958)	(-0.369)	(-0.689)	(-0.862)	(-1.687)
Number of Analysts	0.028	0.027*	-0.011	0.017	-0.016	0.008	-0.016	0.031*	-0.009	-0.043*	-0.008	-0.015
	(1.608)	(1.674)	(-0.442)	(0.944)	(-1.369)	(0.490)	(-1.007)	(1.915)	(-0.372)	(-1.712)	(-0.241)	(-0.754)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,503	89,232	45,472	80,427	90,496	63,646	50,505	66,756	42,253	48,460	24,274	60,479
R-squared	0.621	0.570	0.648	0.547	0.608	0.607	0.637	0.569	0.692	0.604	0.718	0.582

Panel E	Dependent variable: Log-number of brokers											
Sample	Non-active managers				Before announcement of Reg-SHO Pilot Program				After reintroduction of uptick rule			
	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)	Buy trades	Sell trades	Right (positive)	Wrong (positive)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pilot × Program Period	0.002	0.011	0.010	0.007	-0.015	0.005	-0.023	-0.009	0.006	-0.013	0.009	-0.014
	(0.181)	(0.923)	(0.596)	(0.468)	(-1.423)	(0.365)	(-1.569)	(-0.750)	(0.379)	(-0.870)	(0.422)	(-1.073)
Manager volume	0.090***	0.094***	0.087***	0.081***	0.085***	0.104***	0.085***	0.098***	0.082***	0.103***	0.083***	0.073***
	(20.174)	(21.652)	(14.128)	(16.144)	(20.110)	(18.666)	(14.522)	(18.904)	(11.993)	(17.939)	(8.697)	(14.376)
Market Cap	0.076***	0.023	0.088**	0.187***	0.106***	0.014	0.124***	0.113***	0.071*	0.114***	0.049	0.278***
	(3.050)	(0.889)	(2.459)	(5.984)	(6.403)	(0.680)	(5.836)	(6.086)	(1.806)	(2.648)	(0.953)	(7.609)
Turnover	-0.004	-0.002	0.006	-0.006	0.014***	-0.003	0.012	0.003	-0.004	0.010	-0.010	0.011
	(-0.721)	(-0.337)	(0.890)	(-0.853)	(2.756)	(-0.543)	(1.619)	(0.542)	(-0.507)	(1.105)	(-0.909)	(1.458)
Amihud Illiquidity	0.001	0.002	0.002	0.001	0.010***	0.008***	0.009***	0.011***	-0.002	0.004***	-0.003	0.010
	(0.214)	(0.653)	(0.231)	(0.186)	(5.716)	(2.845)	(5.080)	(5.458)	(-0.962)	(4.758)	(-0.881)	(1.473)
Return Volatility	0.001	-0.006	0.016	-0.003	-0.007	0.001	-0.011	-0.005	-0.003	-0.012	-0.010	-0.023***
	(0.197)	(-0.863)	(1.596)	(-0.411)	(-1.007)	(0.088)	(-1.186)	(-0.644)	(-0.269)	(-1.228)	(-0.704)	(-2.782)
Stock Price	-0.015	0.027*	-0.020	0.013	0.005	-0.005	0.002	-0.019**	0.052**	-0.006	0.047	0.008
	(-1.036)	(1.740)	(-1.014)	(0.766)	(0.598)	(-0.478)	(0.171)	(-1.997)	(2.364)	(-0.250)	(1.485)	(0.427)
Number of Analysts	0.004	0.006*	-0.003	0.007*	0.007**	0.001	0.009*	0.004	-0.005	-0.000	0.003	-0.001
	(1.192)	(1.803)	(-0.652)	(1.746)	(2.260)	(0.359)	(1.897)	(0.993)	(-0.876)	(-0.043)	(0.428)	(-0.262)
Manager-Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,503	89,232	45,472	80,427	90,489	63,646	50,498	66,756	42,253	48,460	24,274	60,479
R-squared	0.572	0.528	0.606	0.604	0.546	0.546	0.578	0.664	0.699	0.574	0.714	0.743