Short selling activity and waiting games

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Abstract

The paper studies the reaction of informed investors to the presence of short sellers in the market. We find that other informed investors break down their trades across more brokers when short sellers are active. Consequently, they turn to more unfamiliar brokers and end up bearing higher trading costs. This behavior can lead to a slow-down of information impounding. Consistent with this conjecture, we find that prices are less efficient when short selling occurs in stocks that are intermediated by more brokers. These findings suggest that competition among brokers may in fact reduce price efficiency, if informed traders use it to hide their information.

Keywords: Short selling, Informed trading, Strategic traders, Market efficiency, Competition.
JEL Codes: G30, M41

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NEW YORK, November 15, 2012 - Thomson Reuters, the world's leading source of intelligent information for businesses and professionals, today announced that it has introduced a model to generate alpha by assessing the information contained in the activities of short sellers in the US equity markets. The StarMine Short Interest model profitably ranks stocks based on the observation that stocks with a high number of shares shorted will underperform while those with low short interest will outperform. (Thomson Reuters Launches New Model to Generate Alpha from Short Interest Data. Source: Thomson Reuters Corporation via Thomson Reuters ONE)

Introduction

One of the main tenets in Economics is that competition – i.e., high number of financial intermediaries – increases market efficiency. However, what happens when competition makes it easier to hide information? This paper sheds light on this issue. We study how informed investors react to the presence of short sellers in the market and we show that the presence of many intermediaries with whom to break orders makes it easier to hide information, potentially reducing market efficiency.

There is consensus in the theoretical and empirical literature on the fact that short sales contain information[1] Strengthening this conclusion, market participants exploit the very presence of short sellers to create trading models to "beat the market", as the epigraph of this paper highlights. Consequently, other informed traders in the market may suffer a loss in their informational rents because of the competition from short sellers. Hence, the question arises of how other informed traders in the market adjust their behavior in response to short sellers. To address this question, we investigate empirically whether the presence of short sellers in the market leads other informed investors to modify their trading behavior in a way that can alter the flow of information into prices.

Our empirical analysis draws inspiration from the theoretical literature on speculative trading with asymmetric information. Based on extensions of the Kyle (1985) monopolistic trader model, this literature develops the idea that the trading activity of one group of informed investors (i.e. the short sellers, in our context) affects the behavior of other informed traders by introducing potential competition in trading on private information.

When all traders possess the same information, the competition among them pushes informed investors to trade as fast as possible on their signals, to avoid being front run by other traders (e.g., Holden and Subrahmanyam, 1992, and Foster and Viswanathan, 1993). This intuition suggests that short sellers accelerate the pace of trading of other market participants, who are afraid that their information will become stale if they wait too long. The effort to preempt the short sellers will lead to

[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 (2009)), implying that short sellers are informed.

faster release of information by the other informed traders. This scenario can be described as a "rat race".

However, a more sophisticated informational structure can generate an alternative prediction. If investors' information sets do not perfectly coincide, competition can lead investors to decrease their trading speed (Foster and Viswanathan, 1996). Intuitively, if an informed investor expects other traders to move prices in a direction partly different from her own signal, she will expect further divergence of prices from fundamentals in the future. Hence, it makes sense for this trader to wait in order to profit from the price corrections that will take place later on. Said differently, informed traders have an incentive to slow down their pace of trading because their informational rent will become more valuable in the future. This intuition translates into the conjecture that when short sellers are present in the market, other informed investors will perceive an increase in asymmetric information and trade less aggressively. In this case, other informed investors' strategic behavior will in fact decrease the pace at which information is impounded into prices. We refer to this type of reaction to short selling by other market participants as to the "waiting game".

The assumption that separates the two scenarios is whether other market participants have the same private information as the short sellers. When other informed investors realize that short sellers are active in the market, they fear that they may lose their informational rents. Their reaction will depend on the correlation of their information with the short sellers' information. If the two information sets are perfectly overlapping, they will trade fast to avoid losing their informational rent to the short sellers (rat race). If the correlation is not perfect, they will trade slowly (waiting game). The incentive to wait comes from the fact that each group of informed investors thinks that the other traders are moving the price away from the fundamental value, giving them the opportunity to profit from future price corrections.

We argue that one of the main characteristics of modern financial markets is the fact that information is diffused. Multiple players draw information from sources that are likely to be scarcely related. For example, while some traders rely on fundamental information, others rely on flow-based and sentiment-driven information. Some traders rely on high frequency information and some rely on lower frequency one. This multiple-source, multi-faceted information generates non-nested information sets. Hence, our main conjecture is that the presence of short sellers in the market can lead to a waiting game.[2]

Many channels contribute to make the market aware of the presence of short sellers. For example, brokers that intermediate share loans for short sellers can spread the word with their other clients in order to establish a reputation as valuable sources of information. In addition, data providers make data

[2] An exception to this prediction is the case of corporate insiders. These investors get information from their affiliation with a specific company and exploit such information in the market by trading directly before the short sellers can do it (e.g., Massa, Quian and Zhang, 2015). In this case, the information of the insiders and the short sellers is likely to be highly correlated.

and algorithms available that provide information on short selling activity. (Markit Securities Finance, formerly known as the Data Explorers database, the data source for this study, is one such example.)

What is the impact on price efficiency of a waiting game? The waiting game will reduce the speed at which information is impounded into prices by other investors when they react to short sellers. Consequently, prices become less informative than in the case in which no waiting game occurs. Overall, the waiting game can mitigate the conclusion that short selling unambiguously makes prices more efficient.

In this paper, we investigate these issues by combining short selling information at the stock level from Markit Securities Finance with data on institutional trades from Abel Noser Solutions (ANcerno). Following prior literature, short selling is defined as shares on loan over total shares outstanding (Cohen, Diether, Malloy, 2007), or as shares available to lend over total shares outstanding (Saffi and Sigurdsson, 2011). The institutional trades in ANcerno approximate the trading behavior of other informed investors (henceforth "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, 2015).

We start by studying the relative informational advantage of traders and short sellers. We provide evidence that, in general, traders possess different information than that of short sellers. In particular, we show that traders' order imbalance has predictive ability for returns, which is independent of the predictive power of short selling. Indeed, running a horse race between the traders' order imbalance and short selling activity in predicting next-week abnormal returns, we find that they are both statistically significant. The relevance of this result is twofold. First, it validates the conjecture that traders, as well as short sellers, are informed investors. Hence, we can interpret the interaction between the two groups within the framework of strategic games among differentially informed investors. Second, because traders' order flow has independent predictive power, we infer that the information sets of the two categories of investors do not perfectly overlap. Therefore, our prior leans more towards the waiting game than towards the rat race.

How do traders in the market modify their behavior following short selling? Our main candidate to measure trading speed is the extent to which traders break up their orders across multiple brokers. Brokers operate as aggregators of information from their trading clients. Moreover, they have an incentive to pass this information around to secure business from their more valuable clients. Hence, it makes sense for investors that wish to protect their informational rents to spread their orders across multiple brokers.

The tight identification of a causal effect of short selling on traders' behavior poses empirical challenges. Specifically, endogeneity of short selling is a concern. For example, traders' order flow and short selling activity may be co-determined by events affecting the informational environment of a given stock, such as earnings announcements. To identify exogenous variation in short selling, we exploit the suspension of short-sale price tests for a randomly selected group of stocks (Pilot stocks) during the Reg SHO experiment (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. The literature has shown that short selling increased for Pilot stocks (Diether, Lee, and Werner, 2009a, Alexander and Peterson, 2008, SEC's Office of Economic Analysis, 2007, Grullon, Michenaud, Weston, 2015). We use this exogenously determined variation in short selling to identify the causal effects of short selling activity on traders' behavior. Moreover, the experiment 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, 2015).

Consistent with a waiting game, we find that on average traders increase the number of brokers with whom they transact following an increase in short selling activity in a given stock, as measured by either short interest or the supply of shares available for lending. This result is confirmed in the context of the Reg SHO experiment. Across specifications, the number of brokers increases by up to an economically significant 6.3% of a standard deviation for a one-standard deviation increase in short selling (as proxied by the supply of shares for lending).

Further supporting evidence for a waiting game emerges from the finding that, following an increase in short selling, traders turn to brokers with whom they had less business in the past. In particular, we compute the market share of each broker in the volume generated by a given trader over the prior year. Then, we average this share across all the brokers used by a manager in the week following the short selling and label this variable "broker familiarity". We find that for Pilot stocks broker familiarity decreases by up to 4.4% of a standard deviation. Again, the waiting game implies that traders go out of their way to conceal their information.

If traders are willing to resort to a larger number of brokers, with whom they are less familiar, in order to conceal their information, they are likely to incur higher costs. Each week, we proxy the expensiveness of a broker through the average percentage commission charged by that broker in the prior year. Then, we average this cost across all the brokers that deal in a stock in a given week. We find that, for a one-standard deviation increase in short selling, traders resort to brokers that charge higher fees by up to 4.2% of a standard deviation. Similarly, when using the average price impact of trades with a given broker in the prior year as a measure of trading cost, we find that, for a one-standard deviation increase in short selling, traders use brokers that are more expensive by up to 4.6% of a standard deviation. Consistent with the hypothesis of a waiting game, traders sacrifice trading costs to protect their informational advantage when they perceive the presence of other informed investors in the market.

We corroborate the validity of these results by focusing on the interaction between Pilot stocks and idiosyncratic volatility. Idiosyncratic volatility operates as a constraint on short selling. Hence, the main effect of short selling on traders' waiting game should be less pronounced for stocks where short selling is more limited. Indeed, we find that for Pilot stocks with higher idiosyncratic volatility the effects on the number of brokers, broker familiarity, and broker cost are significantly smaller in absolute value.

Another way to test whether informed investors play a waiting game vis-à-vis short sellers is to study the trading behavior following news. Engelberg, Reed, Ringgenberg (2012) argue that that short sellers are especially skilled in exploiting public information to their advantage. Hence, informational asymmetry between short sellers and the rest of the market is likely more severe when public news is released. We measure stock-level news using the sentiment score computed by RavenPack Analytics for each piece of firm-level news. The sentiment score provides a classification of news into positive and negative. The waiting game suggests that traders should break up their orders more, that is, trade more slowly, when they compete with short sellers in extracting informational rents. Consistent with this conjecture, traders' sell orders are less concentrated for Pilot stocks, following positive news. Intuitively, times of positive public news provide more opportunities to extract informational rents for investors that possess negative private information (i.e. who wish to sell). Exactly at these times, the competition with short sellers is more intense and breaking up the orders to conceal the information makes more sense.

Armed with these results, we turn to the implications of the waiting game for price efficiency. As we argue above, the response of informed traders to short selling can reduce the speed of information impounding and this slow-down could attenuate the beneficial effect of short selling on price efficiency. Importantly, this effect should be stronger the higher the number of potential brokers across which traders can spread their orders in order to reduce their market impact.

Indeed, we find support for this view when using standard measures of price efficiency, such as return autocorrelation and the delay in the response of stock returns to market returns. We find strong evidence that price efficiency decreases for stocks with higher short selling and a larger number of active brokers. This effect is strong enough to reverse the beneficial effect of short selling on price efficiency for stocks that have a sufficiently large number of active brokers. For example, when the number of active brokers is one standard deviation above its mean, short selling (as measured by Pilot stocks) increases inefficiency by 5% of a standard deviation.

Overall, our findings mitigate the conclusion that short selling always improves price efficiency. The waiting game played by other informed traders in the market can attenuate, and reverse in some cases, the positive effect of short selling on price discovery. We emphasize a more general implication of this result. Competition among financial intermediaries – in this case, the brokers – provides a screen for informed investors to hide their information and can make prices less efficient.

Our results are consistent with the "stealth trading hypothesis". This theory posits 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).

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

We contribute to the literature linking competition to market efficiency (e.g., Hong and Kacperczyk, 2007, Kelly and Ljungqvist, 2007). While this literature has traditionally focused on the incentives to collect and generate information (for example by analysts), we focus on the incentives to trade on the basis of competition. That is, we contribute by showing that competition may hamper not only information collection but also information dissemination into stock prices.

Our results also contribute to the growing theoretical and empirical literature studying the impact of short selling on price efficiency.[3] 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 investors increases information asymmetry, reducing the incentives of the other investors to trade. This channel can decrease price efficiency (e.g., Kim and Verrecchia, 1994). We find evidence for this second effect.

The paper proceeds as follows. Section II describes our sample and defines the main variables. In Section III, after validating the conjecture that traders possess independent information, we provide the main evidence on the waiting game played by traders in response to short selling activity. Section IV analyzes the implications of the waiting game for price efficiency. Section V concludes.

II. Data Description and Main Variables

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 shorter

[3] See, for example, Diamond and Verrecchia (1987); Boehmer, Jones, and Zhang (2008, 2009, 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).

name of "ANcerno"). ANcerno provides consulting services for transaction cost analysis to institutional investors and makes 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 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 and time; the execution price; the prevailing price when the trade was placed on the market; 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 between 1999 and 2010.

Mutual funds, which tend to be long-only investors, are the large majority of the over eight hundred institutions that report to ANcerno. A few hedge funds also report their trades in ANcerno (eighty-seven according to Franzoni and Plazzi, 2015, and a few less according to Jame, 2015). 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. In our empirical analysis, we do not make a distinction among the different institutions in Ancerno and treat them as a unique pool of informed investors.

Second, we draw information on stock level short selling activity from Markit Securities Finance, formerly known as Data Explorers. This firm provides financial 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 provider of securities lending data. These data are available at the monthly frequency from June 2002, at the weekly frequency from August 2004, and at daily frequency from July 2006, until August 2010. We conduct great part of our analysis at the weekly frequency, using reported information on Wednesday. Because the weekly data are reported on Wednesdays, we continue to focus on Wednesday information also in the later sample, when daily data become available. We label each of these dates a "measurement date" of the shares on loan. The measurement dates coincide with the time when short sellers actually borrow a stock. Because short sellers do not need to borrow a stock until three days after they open a short position, our approach to look at the measurement date is quite conservative as it allows information to spread from the opening of the short selling position through the next three days. The short selling variables that we focus on are the total balance of shares on loan and the total balance of shares available to lend. We divide each of these variables by total shares outstanding to obtain the explanatory variables ONLOAN and LENDABLE, respectively.

The third database that we use in our analysis is the RavenPack's News Analytics dataset. The RavenPack service covers more than 500 corporate events relating to both scheduled and unscheduled news about companies such as layoffs, mergers and acquisitions, product releases, analyst guidance, and earnings announcements. For any detected news event, RavenPack generates an Event Sentiment Score (ESS) signaling its potential stock price impact. We exploit this sentiment score to generate a dummy variable that identifies positive and negative news events (more details below).

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).

We cast our analysis at the weekly frequency, when we assess the effect of short selling on traders' behavior. We resort to a monthly frequency in the regressions that have efficiency measures on the left-hand-side, as we need a full month of daily data to compute the price efficiency variables.

When we measure short selling activity with the balance of shares on loan (ONLOAN) or by the balance of shares available to lend (LENDABLE), our sample ranges between January 2005 and August 2010. The beginning of the sample is constrained by the availability of short selling data at the weekly frequency, the end by the availability of institutional trades. Instead, when we focus on the Reg SHO Pilot Program, the sample ranges from June 2002 to July 2007. The sample starts in June 2002 since this is the earliest date for which we have data in the Markit Securities Finance database. 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 (January 3, 2005). We proxy short selling with a dummy variable (PILOT) that equals one for the stocks included in the Pilot Program during the Reg SHO period and zero otherwise. Hence, PILOT equals one for Pilot stocks between January 3, 2005 and July 7, 2007. Finally, in the analysis on price efficiency, the monthly sample starts in January 2000, when reliable information is available in Ancerno, and ends in July 2007, with the end of the Reg SHO experiment.

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. Only for the analysis focusing on the Reg SHO Pilot Program, we further restrict our sample to the stocks listed on the NYSE that were in the Russell 3000 Index in June 2004 (the period of formation of the Pilot Program stock list). We focus only on NYSE stocks because in this exchange the suspension of the uptick rule (in compliance with the Pilot Program) is likely to have a greater effect than in other markets. Specifically, Diether, Lee and Wermer (2009) argue that in the

NASDAQ the price tests suspension represented a minor discontinuity with respect to the usual trading mechanism.

Next, we provide details on the construction of the main variables. We already introduced ONLOAN and LENDABLE, respectively the outstanding amount of shares on loan, which measure short interest, and the outstanding amount of shares available to lend on the measurement day (i.e., Wednesday of each week), divided by the total number of shares outstanding.

Our broker-related variables are first measured at the management company/stock/week level, then we average them across all management companies that trade in a given stock to obtain the final stock-level measure included in the tests. The management company in ANcerno coincides with what we label “trader”.

BROKER NUMBER is the number of different brokers used by each trader, in a given stock-week. When we use this variable we also control for the total trading volume in the week in terms of number of shares divided by shares outstanding (computed from ANcerno)

BROKER FAMILIARITY is our proxy for the familiarity of the brokers that traders use to place their orders. For each trader, we compute the share of dollar volume traded with each broker in the last year; then we adjust this value by taking into account the average number of brokers used by the trader in the same period. For instance, if the proportion of the trades executed with a broker in the last year is 30% and the average number of brokers used by the trader is five, our adjusted value will be 30% divided by 20%. Thus, we obtain a measure of broker familiarity that we can attach to every broker/trader pair in each week. Finally, we compute the volume weighted average of our broker/trader familiarity proxy in every week. High values of FAMILIARITY mean that traders are executing their trades with brokers that have already been extensively used in the recent past, and therefore are deemed to be more familiar.

BROKER FEES is a proxy for the average expensiveness of the brokers chosen by the traders each week. We assign to each broker-week a measure of trading cost, computed as the average (during the prior year) of the percentage commissions charged. Then, we look at the trades executed during the week by that broker with each trader and compute the volume weighted average of the trading cost measure. Higher values of this measure are associated with a larger use of expensive brokers.

BROKER IMPACT is another proxy for the average expensiveness of the brokers chosen by traders in a week. It is computed in the same way as BROKER FEES, but in this case we keep track of the price impact of the trades executed by a broker in the previous year, instead of the commissions. For buy trades, price impact is computed as the percentage difference between the execution price and the price at the time when the trading desk sends the ticket to the broker (identified in ANcerno by the variable “xpP”, i.e. price at placement). The sign of price impact is the opposite for sell trades. This variable reflects the *Execution Shortfall* measure used by Anand, Irvine, Puckett and Venkataraman (2012).

TRADE CONCENTRATION measures a trader's order splitting during a week. For each trader, in each stock, we compute the (adjusted) Herfindahl index[4] of the number of shares traded in each day of a week (looking separately at buy and sell trades). High values of this measure are associated with a higher concentration of trades within a week.

When we use the TRADE CONCENTRATION variable, we interact it with a dummy variable derived from news releases as reported by RavenPack[5]. We create dummy variables for positive and negative news. The positive (negative) news dummy is equal to one if there is at least a positive (negative) news event concerning the stock in a given week. We discard weeks in which we have both positive and negative news. We consider a news event to be "positive" if its sentiment score is at least 70 (out of 100); we consider it "negative" if its sentiment score is less than or equal to 30 (out of 100). When we include these dummies in the regressions, we also control for the total number of days (within the week) on which news events occur. In this case, we count any news event whose sentiment score is different from zero.

Next, we describe the variables related to market efficiency. All of these variables are computed at the stock/month level and are proxies for price *inefficiency*, therefore a lower value for the variable is associated with an increased efficiency. These variables follow closely the proxies of price efficiency in Saffi and Sigurdsson (2011).

ACTIVE BROKERS proxies for the number of brokers that are active in a given stock in ANcerno over the previous twelve, six or three months. In particular, we use the natural logarithm of the number of active brokers in each stock.

ABS(Autocorrelation) is the absolute value of the autocorrelation of daily raw returns of each stock in a given month.

VARIANCE RATIO is associated to the variance ratio of the raw returns of each stock at daily and weekly frequency. In each month, for each stock, we compute the variance of weekly returns and of daily returns, then we obtain our measure as:

[4] To compute the Herfindahl index we divide the share volume of the trader in each day of the week by the total trading volume in the week, then we compute the sum of squares of these ratios. In the adjusted version of the Herfindahl index we adjust this number by the number of trade-days in the week.

[5] In RavenPack, every news event comes with a date/time stamp attached and an Event Sentiment Score that signals its potential stock price impact (we consider only events with a non-missing sentiment score that are associated with a relevance score of 100 out of 100, i.e. roughly the 92.5% of all the events with a non-missing sentiment score). We aggregate all the observations at daily level, taking the simple average of the sentiment score in case we have multiple new events during the same date. If a news event falls on the weekend, after 4PM or on a holiday, we replace its date with the following business date.

$$\text{VARIANCE RATIO} = \left| \frac{\sigma^2_{WEEK}}{5 \cdot \sigma^2_{DAY}} - 1 \right|$$

LAGGED MARKET CORRELATION (1) is a variable linked to the correlation between the raw returns of a stock and the lagged market return (we use CRSP value weighted benchmark as the market return). Each month, we regress the daily raw returns of a stock on the contemporaneous return of the market and its (one day) lag: this is the unconstrained regression. Then, we run the same regression, but this time omitting the lagged market return: this is the constrained regression. Finally, we compute our measure as one minus the ratio of the R-squared of the two regressions:

$$\text{LAGGED MARKET CORRELATION (1)} = 1 - \frac{R^2_{CONSTR.}}{R^2_{UNCONSTR.}}$$

LAGGED MARKET CORRELATION (2) is an alternative measure of correlation between the raw returns of a stock and the lagged return of the market. Each month, we regress the daily raw returns of a stock on the contemporaneous returns of the market and its (one day) lag. We compute our measure as:

$$\text{LAGGED MARKET CORRELATION (2)} = \frac{|\beta^{MKT}_{t-1}|}{|\beta^{MKT}_{t-1}| + |\beta^{MKT}_{t}|}$$

where β^{MKT}_{t-1} is the coefficient on the lagged market return and β^{MKT}_{t} is the coefficient on the contemporaneous market return.

The control variables in our regressions are: market capitalization (measured at the end of the previous week or month, depending on the frequency of the regression); turnover (the trading volume in CRSP in the previous month, divided by the total number of shares outstanding); the raw return of the stock in the previous period (week or month, depending on the frequency of the regression); the ANcerno-based order imbalances in the previous period (week or month, depending on the specification), computed as the difference between shares traded in buyer-initiated trades and shares traded in seller-initiated trades, divided by shares outstanding.

Table 1 provides descriptive statistics for these variables. In Panel A, we report the average, standard deviation, median, 25th and 75th percentiles. In Panel B, we report their correlations. In Panel B, we compute the correlation between our variables both at the weekly level (Panel B1) and at the monthly level (Panel B2), depending on the frequency at which variables are used in the analysis.

The average percentage of shares on loan on shares outstanding (ONLOAN) is 4.4%, (median of 2.7%). These numbers are comparable, although somewhat lower, to the values reported by Saffi and

Sigurdsson (2011) for US stocks (average of 8.9%), but their sample is different both in terms of time and stocks included. They are definitely higher than the one reported by Cohen, Diether, and Malloy (2007), for whom the average is 0.6%, and the median is 0.16%, but these authors use a different database and report statistics for a randomly chosen date. The average percentage of shares to lend on shares outstanding (LENDABLE) is 20.4%, very similar to the 23.6% reported by Saffi and Sigurdsson (2011), for US stocks only. We see that the average and median values for IMBALANCES are very close to zero, as expected. The abnormal return with respect to the DGTW benchmark is very close to zero on average, while the raw return is slightly positive (average of 19 bps per week). The average value for the broker impact measure is roughly 10bps. With some caveat, we can compare it to the 25bps average execution shortfall in Anand, Irvine, Puckett and Venkataraman (2012). In particular, we should note that the execution shortfall is just the starting point of our broker impact measure. Our variable, in fact, takes also into account the choice operated by the traders, both in terms of which broker to use and how much to trade with the chosen broker. Therefore, since we expect them to avoid trading too much with the most expensive brokers, it makes sense for our broker impact variable to be lower, on average, than the simple execution shortfall computed in Anand, Irvine, Puckett and Venkataraman (2012). Moreover, we are not including the first three years of ANcerno, in which the average execution shortfall is roughly double than its average value in the following years.

The average number of brokers used is not too high at 1.66, but we emphasize that this is the number of different brokers used by a single trader on a single stock during a week, averaged out across all traders in ANcerno. One should not confound this variable with the average number of active brokers in the previous 3, 6, or 12 months, which is computed for each stock across all the different traders, counting every broker that executes at least one trade. The median value for this last measure, before taking the natural logarithm, ranges from 35 (when we look at the active brokers in the last 3 months) to 61 (when we look at the last 12 months).

III. Evidence of the Waiting Game

We start by establishing a preliminary result. We show that traders have independent information with respect to short sellers. Then, we provide the main evidence on the waiting game played by traders vis à vis short sellers.

A. Do Traders Possess Independent Information?

For the interaction between traders and short sellers to be described as a game between differentially informed investors, the necessary condition is that these categories of investors possess non-overlapping information about fundamentals (Foster and Viswanathan, 1996). While it is an established fact that short sellers' activity can predict future price drops (e.g. Cohen, Diether, Malloy, 2007; Diether, Lee, and Werner, 2009b; Boehmer, Huszar, Jordan, 2010; Engelberg, Reed, Ringgenberg, 2012) and that the institutional investors in ANcerno have private information (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, 2015), still it is not clear whether the sources of information for these two sets of players are the same. We therefore test whether each investor category has independent predictive power for returns in our data.

To this purpose, we run a horse race between the predictive ability of short selling activity and traders' order flow for future stocks returns. We measure short selling with shares on loan (ONLOAN) over total shares outstanding in a given stock-week. Traders' order flow is captured by the percentage order imbalance (IMBALANCE_PCT), which is the difference between shares in buyer-initiated trades and shares in seller-initiated trades from ANcerno in the same stock-week when short selling is measured, divided by their sum. We measure returns in the following week. Returns are adjusted for the performance of known risk factors using the Daniel, Grinblatt, Titman, and Wermers (1997) methodology. We provide specifications with different combinations of week- and stock-fixed effects, as well as Fama and MacBeth (1973) regressions (labeled FMB in the tables). The standard errors are clustered at the week level to avoid the bias resulting from potential cross-sectional correlation in the dependent variable, except in the Fama and MacBeth (1973) specifications. The regressions also include the lagged dependent variable (when stock effects are not included) to absorb any potential autocorrelation in returns triggered by the trades of either short sellers or traders. We include controls for firm size (market capitalization) and liquidity (average turnover over the prior month).

We report the results in Table 2. Consistent with the prior literature, an increase in short selling predicts significantly lower future abnormal returns. This result is economically significant. In Column (5), a one-standard deviation increase in short selling predicts a 1.5% of a standard deviation decrease in returns in the following week.

In addition, we find that traders' order imbalance has a strong predictive power for future returns over and above that of short selling. In Column (5), a one-standard deviation increase in traders' order flow predicts an increase in returns of 75 basis points in the following week. This suggests that, consistent with the set up in Foster and Viswanathan (1996), the information sets of short sellers and traders may be related, but they are not perfectly overlapping, as they have independent predictive power.

The relevance of the evidence in Table 2 is twofold. First, it validates the conjecture that traders, as well as short sellers, are informed investors. Hence, we can rule out the fact that traders are uninformed investors that merely try to prevent adverse selection in trading. Rather, we can cast the rest of the analysis in the context of the theories that model the game played by differentially informed investors (e.g. Foster and Viswanathan, 1996). Second, because traders' order flow has independent predictive power, we infer that the information sets of the two categories of investors do not perfectly overlap. Therefore, we expect the waiting game hypothesis – i.e., traders slow down their trades when short sellers are around – to find more support in the data than the rat race hypothesis, which predicts a rush to trading.

B. Traders' Behavior in Response to Short Sellers

As we mention above, the waiting game hypothesis predicts that the informed traders will reduce their speed of trading as well as engage in actions meant to reduce the pace of information revelation, while the rat race hypothesis predicts the opposite. The next empirical analysis aims to separate these hypotheses.

Our main candidate to measure trading speed is the extent to which traders break up their orders across multiple brokers. Brokers operate as aggregators of information from their trading clients. Moreover, they have an incentive to pass this information around to secure business from their more valuable clients or from new ones. Hence, it makes sense for traders that wish to protect their informational rents to spread their orders across multiple brokers. We test this conjecture by regressing the average number of brokers used by the traders onto short selling. To this purpose, we construct a stock-level variable by computing the number of brokers used by each manager in ANcerno when trading a given stock in a given week and then we average this number across managers (BROKER NUMBER). This construction is repeated for all traders in a given stock-week, for buy trades only, and for sell trades only.

The waiting game can take place on both buy and sell trades. This prediction arises because it makes sense for a trader to wait in case of both more positive and more negative information than that possessed by short sellers. Intuitively, in case traders are more positive about fundamentals than short sellers, they have an incentive to hold off buying the stock in the expectation that short sellers push prices too low. Perhaps less intuitively, traders have an incentive to wait *even* when they are more pessimistic than short sellers. This incentive originates from the expectation that short sellers will be the first to withdraw from the market. At that point, there will be more space for traders to profit from price corrections.[6]

[6] In more details, adjusting the Foster and Vishwanathan's (1996) logic to our context, after a few rounds of trade, the price level will reflect the average information possessed by short sellers and traders. That is, the price will be below the short sellers' more positive belief and above the traders' more pessimistic expectation of fundamentals. At that point, short sellers will withdraw from the market. Following this withdrawal, the price will increase and move further above traders' expectation. The expectation of this price move, gives traders an incentive to wait, because it magnifies their expected profits from price corrections. The evidence in Boehmer, Huszar, and Jordan (2010) that a lower level of short selling implies higher future returns provides empirical support for the claim that it makes sense for traders with a pessimistic view to wait the exit of short sellers from the market.

The identification of a causal effect of short selling on traders' behavior poses empirical challenges. Specifically, endogeneity of short selling is a concern. For example, traders' order flow and short selling activity may be co-determined by events affecting the informational environment of a given stock, such as earnings announcements.

With this caveat in mind, the first three specifications in Table 3 regress the number of brokers on short interest (ONLOAN). Given the availability of the Markit data on short selling, our sample ranges between January 2005 and August 2010 and the regressions are run at the weekly frequency. In this table, as in the rest of the analysis, standard errors are clustered at the week level. Moreover, we always include time and stock fixed effects. In Table 3, the controls also include the stock-level trading volume from ANcerno in the same week as the dependent variable. This specification allows us to directly focus on the strategic choice to modify the number of brokers, separately controlling for the effect of an increase in trading volume, which would mechanically affect the number of brokers.

When all trades are jointly considered in the computation of the dependent variable (first column in Table 3), we find statistically significant evidence of an increase in the number of brokers following short selling. This result is consistent with the waiting game hypothesis. Some marginally significant evidence of this effect is present also in the third column, which focuses on buy trades. These results are only suggestive, given the potential endogeneity of short selling.

In the next three specifications in Table 3, following Saffi and Sigurdsson (2011), we proxy for short selling with an arguably less endogenous variable, that is, the supply of shares in the lending market (LENDABLE). The rationale for this measure as a proxy for short selling is that it drives the cost of shorting, and therefore the amount of short interest, while it is less dependent on the potentially endogenous incentives for short selling. The evidence in favor of the waiting game is strong across the three specifications. In all cases, an increase in short selling predicts a statistically significant increase in the number of brokers across which traders spread their orders. Focusing on all trades (fourth column), a one-standard deviation increase in LENDABLE predicts a 6% of a standard deviation increase in the number of brokers, which appears as economically important.

Finally, to identify truly exogenous variation in short selling, we exploit the suspension of short-sale price tests for a randomly selected group of stocks (Pilot stocks) during the Reg SHO experiment (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.[7] The literature has shown that short selling increased for Pilot stocks (Diether, Lee, and Werner, 2009a, Alexander and Peterson, 2008, SEC's Office of Economic Analysis, 2007, Grullon, Michenaud, Weston, 2015). We use this

[7] Stocks were bunched into three groups – Amex, Nasdaq, and NYSE – and "ranked in each group by average daily dollar volume over the one year prior to the issuance of this order from highest to lowest for the period. In each group, we then selected every third stock from the remaining stocks" (SEC Release No. 50104).

exogenously determined variation in short selling to identify the causal effects of short selling activity on traders' behavior.

In the last three columns in Table 3, we regress the number of brokers on a dummy for the inclusion among Pilot stocks during the Reg SHO experiment period (PILOT). In particular, given the horizon of the experiment, our sample ranges from June 2002 to July 2007 and the regressions are run at the weekly frequency. The PILOT dummy is equal to one for Pilot stocks during the Reg SHO period (January 2005 to July 2007). Before this period, PILOT is equal to zero for all stocks. Again, we find strong support for the view that traders try to protect their informational rents when short selling is higher. For stocks with higher short selling on average (Pilot stocks), the number of brokers that traders use is significantly higher. The result holds for all trades together, as well as for buy and sell trades separately.

Overall, using tighter and tighter identification strategies, Table 3 suggests that short selling activity leads traders to play a waiting game. In particular, traders appear to break their orders across a higher number of brokers when short selling increases.

If traders spread their orders across multiple brokers, they necessarily have to resort to brokers with whom they had less interaction in the past. This behavior may serve well the purpose of preserving their informational rents. Arguably, less familiar brokers are not as good in interpreting the informational content of traders' activity.

To test this conjecture, we exploit the proxy of broker familiarity defined in Section II and we estimate its link to short selling. Table 4 reports the results of regressions of broker familiarity onto our different measures of short selling activity. The evidence is mixed when using short interest (ONLOAN). In two specifications, broker familiarity decreases with short selling (All trades and Buy trades) and, in one specification, it increases (Sell trades). We do not wish to put excessive emphasis on these results, given the known issues with the endogeneity of short interest. In the next three specifications, we use the supply of shares in the lending market (LENDABLE) as a proxy for short selling activity. The two specifications in which LENDABLE is significant point to a decrease in broker familiarity. For example, in the fourth column (All trades), a one-standard deviation increase in LENDABLE leads to a 5% of a standard deviation decrease in broker familiarity. Finally, we use the Reg SHO experiment to identify exogenous variation in short selling. In the last three columns of Table 4, the PILOT dummy is always negative and significant. Overall, we conclude that the evidence provides robust support for the view that market trades go out of their way, by choosing less familiar brokers, in order to protect their informational rents.

In turning to less familiar brokers, traders trade off the benefit of preserving their private information against the cost of doing business with suboptimal brokers. If the benefit of protecting their information is higher at times of higher short selling activity, also the cost of trading must increase. We test this conjecture by measuring changes in the expensiveness of the brokers to which traders resort in the presence of short selling. Broker expensiveness is *pre-determined* relative to the measure of short selling. In particular, we impute to each broker its cost in the prior year, measured as either percentage commissions or price impact. Then, we average this cost across the brokers that are chosen by a given trader in a given week following short selling activity. Finally, we average across traders at the stock week-level to obtain our measures of broker cost.

In Table 5, we use broker percentage fees as a measure of broker cost. Across specifications, using different measures for short selling activity, the sign of the coefficients is predominantly positive. The significant estimates are located in the All trades and Buy trades samples. For example, a one-standard deviation increase in LENDABLE is associated with an increase of about 4% of a standard deviation in the fees paid by traders to their brokers. Overall, Table 5 suggests that short selling activity leads traders to use brokers that charge higher fees. This choice appears consistent with the goal of protecting the informational rents.

In Table 6, the average price impact of a given broker's trades in the prior year is the measure of broker expensiveness. As explained in Section 2, price impact is defined as the percentage difference between the execution price and the price at the time of order placement. The layout of the specifications reflects the previous tables. The evidence provides additional support to the view that short selling pushes traders to bear higher trading costs. The significant coefficients are on All trades, Buy trades, and Sell trades. The magnitudes are comparable to the previous tables, suggesting that the underlying driver of this effect is the same across dependent variables.

In order to corroborate the validity of our identifying assumption, we study whether the main effects that we measure vary as a function of the cost of short selling. In particular, we use idiosyncratic volatility as a proxy for short selling costs (Stambaugh, Yu, and Yuan, 2015) and interact it with the Pilot dummy. If the effect that we measure is really due to short selling, it should be attenuated for stocks with higher idiosyncratic volatility (IVOL). IVOL is estimated from daily returns in the prior month.

Table 7 presents the estimates from these regressions. The dependent variables are the same as in the previous analysis: the number of brokers, broker familiarity, broker fees, and broker impact. In most specifications, the sign of the interaction variable is opposite to the sign on the PILOT dummy. Statistical significance is especially strong for the number of brokers and broker familiarity. Overall, these results further confirm the fact that the presence of short selling affects traders' behavior.

To conclude, we provide evidence of the waiting game using an alternative strategy. For this analysis, the chosen measure of trading speed is the concentration of traders' orders in a given stock-week, measured using the Herfindahl index of traders' orders, as described in Section II. We expect that the stocks in which traders display a higher concentration of trading within the week -i.e. the trade is not spread over time - are the ones in which they try to trade faster. We cast this analysis in the framework of the Reg SHO experiment, which provides the most exogenous approach to identification. We select stocks for which there are news releases in a given week. This information comes from the RavenPack database. As detailed in Section II, using the sentiment indicator provided by RavenPack, we classify news into positive and negative and create dummy variables accordingly. Then, we measure the impact of short selling activity, as proxied by the PILOT dummy, on trade concentration in the following week, for stocks with positive and negative news. We also control for the total number of news in the week. The added benefit of introducing news in this analysis is to single out situations in which the information asymmetry between traders and short sellers is likely to be more impactful for trading performance.

The waiting game hypothesis leads to the conjecture that traders reduce their selling speed on Pilot stocks, in case of positive news. Indeed, times of positive (negative) public news provide more opportunities to extract informational rent for investors that possess negative (positive) private information. In other words, given that private information going against the direction of public information is more valuable, it increases the incentives of the informed traders to hide. The presence of short sellers – i.e., investors that can compete on the same side of the informed traders – will therefore exacerbate the incentives of informed traders to hide in the case of positive news. Hence, the waiting game hypothesis predicts a slowdown of sell trades when the competition with short sellers is more intense, that is, for Pilot stocks.

The results reported in Table 8 support this conjecture. We find that traders reduce their selling speed on Pilot stocks, in case of positive news.

Overall, we conclude that the evidence in this section corroborates the hypothesis that the presence of short sellers leads other informed traders to play a waiting game. It appears that other informed market participants take actions to conceal their trading activity, when short selling is more pronounced. The next question that we tackle is the effect of this behavior on price efficiency.

IV. The Effect of the Waiting Game on Price Efficiency and the Role of Competition among Brokers

The models with privately informed traders, such as Foster and Vishwanathan (1996), link the waiting game to price informativeness. In particular, when informed investors slow down the pace of their trades, prices are less informative. Intuitively, if informed traders abstain from trading, prices do not reflect their private information.

On the other hand, prior theoretical and empirical literature points out that a release of short selling constraints improves price efficiency (see references in footnote 1). The standard interpretation of these results considers short sellers as informed traders. When short sales are limited, short sellers cannot impound their information into prices.

Motivated by our prior finding that short selling activity leads informed investors to slow down their trades, we now ask whether this waiting game can attenuate the beneficial impact of short selling on price efficiency. We expect this effect to be more pronounced in the presence of a higher number of brokers, that is, when informed traders have the possibility to spread their trades and hide their information.

In particular, we identify stocks for which the waiting game is likely to be more severe and test whether short selling activity leads to lower price efficiency for these stocks. According to the results in Section III, the waiting game takes place through the increase in the number of brokers that traders use to execute their orders. Then, the number of active brokers in a given stock constrains the possibility of a waiting game. In other words, if a stock is intermediated by fewer brokers, the possibility of breaking up the trade across multiple brokers is lower. Following this intuition, we use ANcerno data to measure the number of brokers that actively intermediate a given stock over a period that *precedes* the measurement of short selling activity.

For robustness, we consider three different periods for the measurement of active brokers: three, six, and twelve months before the time when short selling activity takes place. To measure short selling activity, we use our preferred empirical strategy and focus on the exogenous variation in short selling for Pilot stocks in the Reg SHO experiment. Our working hypothesis is that the waiting game attenuates the beneficial impact of short sales on price informativeness especially in the presence of more active brokers.

To measure price efficiency, we rely on prior literature. In particular, we draw inspiration from Saffi and Sigurdsson (2011), who develop four measures to capture the impact of short selling activity on stock prices.[8] First, we look at the autocorrelation of daily returns within a month. We take the absolute value of this measure because both positive and negative return autocorrelations capture deviations of stocks prices from a random walk. Second, we compute the ratio of the variance of five-day returns to five times the variance of daily returns, both estimated within a month. We subtract one from this ratio and take the absolute value. This measure reflects the notion that, if prices follow a random walk, the variance should scale linearly with the horizon (see Lo and MacKinlay, 1988). Any deviation from a random walk inflates this measure. The third and fourth measures capture the timeliness of the reaction of stock returns to market returns. In particular, the third measure compares the R-squared from market-model regressions that either include or exclude the lagged market return. In case of no delay in the reaction to public news, the two R-squared should be the same. Building, on the same intuition, the fourth measure contrasts the magnitude of the slope on the lagged market return

[8] These variables are described in more detail in Section II.

to the slope of the contemporaneous market return. Importantly, all these variables are defined to measure price *inefficiency*.

Table 9 reports the results from these tests. The main variable of interest is the interaction between the PILOT dummy and the number of active brokers, measured over different horizons in the past. Using the absolute autocorrelation as dependent variable (first three specifications), we find marginally significant evidence that for Pilot stocks with more active brokers there is a deterioration in price efficiency (i.e. the coefficient on the interaction is positive). Also important, the main effect of short selling, as captured by the PILOT dummy, is to reduce inefficiency, consistent with the prior literature (e.g. Saffi and Sigurdsson, 2011). This pattern of coefficients, for both the interaction and the main effect of PILOT, persists across the remaining specifications.

When the dependent variable is the variance ratio, the statistical significance improves slightly. The most statistically robust results come from the specifications focusing on the delay in the reaction to market news (columns (7)-(12)). Irrespective of the horizon over which the number of active brokers is computed, we find strong evidence that price inefficiency increases for stocks with higher short selling (Pilot stocks) and a larger number of active brokers. This effect is strong enough to reverse the main effect of short selling for stocks that have a sufficiently large number of active brokers. For example, in column (7), when the number of active brokers is one standard deviation above its mean, short selling (as measured by Pilot stocks) increases inefficiency by 5% of a standard deviation.[9]

The fact that the results are stronger when we use the efficiency measures that capture the reaction to market-wide shocks (columns (7)-(12) in Table 9) suggests that short sellers play a more important role in impounding information after the release of public news. This finding resonates with the evidence in Engelberg, Reed, Ringgenberg (2012), who show that a substantial portion of short sellers' trading advantage comes from their ability to analyze publicly available information.

A legitimate concern related to this analysis is that the number of active brokers is endogenous with respect to price efficiency. In particular, smaller stocks, whose prices are less efficient, are intermediated by fewer brokers. In fact, this effect would make finding our results more difficult. We show that short selling activity in stocks with more brokers leads to less efficient prices, which goes in the opposite direction of the spurious effect due to the correlation between stock size and the number of active brokers.

Overall, the analysis in this section confirms the claims in prior literature that short selling improves price efficiency for the average stock in the market. However, we also find significant evidence that in

[9] The number of active brokers enters these regressions in logarithms. The mean and standard deviation of the logarithm of active brokers in the prior 12 months are 4.028 and 0.717, respectively (see Table 1). Hence, using the coefficients from column (7) in Table 9, the effect for Pilot stocks when the number of brokers is at its mean is: $-0.459 + 0.107 * 4.028 = -0.028$. This negative coefficient implies that short selling improves efficiency for the average stock in the market. However, for stocks whose number of active brokers is one standard deviation above its mean the effect becomes: $-0.459 + 0.107 * (4.028 + 0.717) = 0.049$, which reverses the main effect of short selling.

the presence of a high number of brokers for informed investors to trade, price efficiency can deteriorate because of short selling activity. We interpret this result as suggesting that higher competition among brokers does indeed lead to lower price efficiency because waiting games can be more easily played and information is not immediately impounded into prices.

V. 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 also increases information asymmetry and can modify the behavior of other informed investors. Some theories predict that differentially informed investors strategically reduce their speed of trading to avoid losing their information rents too soon, as in a waiting game (Foster and Viswanathan, 1996). We argue that short sellers and other traders fit the description of investors with heterogeneous information. It is, therefore, possible that short selling activity induces other investors to trade less aggressively on their own information. Because of this waiting game, one can expect that prices incorporate fundamental information more slowly.

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 trading data of institutions (ANcerno), which in previous literature are shown to have some private information. As a preliminary result, we confirm that the trades of these institutions have independent predictive power for future returns that goes beyond that of short selling activity.

In the main part of our analysis, we find that other investors react to short selling by spreading their trades across multiple brokers, consistent with the conjecture of a waiting game. Consequently, they resort to less familiar brokers and pay higher trading costs. In addition, after the release of public news, informed investors spread out their trades more when short selling activity is higher. The latter result can be interpreted in light of the literature suggesting that short sellers excel in exploiting public information to their advantage (Engelberg, Reed, Ringgenberg, 2012). Arguably, it makes sense for other investors to be more cautious when public news is released, because these are times when asymmetric information is more acute.

Finally, we focus on the impact of the waiting game on price efficiency. We show that prices are less efficient when short selling takes place in stocks in which investors have more possibilities of playing the waiting game. Overall, we confirm prior literature arguing that price efficiency for the average stock in the market improves because of short selling efficiency (e.g. Saffi and Sigurdsson, 2011; Beber and Pagano, 2013). However, we also suggest that in situations in which the waiting game is more intense, short selling can actually reduce the speed of information revelation and make prices less efficient. A more general implication of our results is that competition among financial intermediaries, in our case brokers, can provide a screen for informed investors to act strategically.

References

Arif, Salman, Azi Ben-Rephael, and Charles Lee, 2015, Do Short-Sellers Profit from Mutual Funds? Evidence from Daily Trades, Rock Center for Corporate Governance at Stanford University Working Paper 195.

Alexander, G.J., and M. A. Peterson, 1999, Short Selling on the New York Stock Exchange and the Effects of the Uptick Rule, Journal of Financial Intermediation 8, 90–116.

Anand, A., and S. Chakravarty, 2007, Stealth trading in Options Markets Journal of Financial and Quantitative Analysis 42, 167-188.

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2012, Performance of institutional trading desks: An analysis of persistence in trading costs, Review of Financial Studies 25, 557-598.

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2013, Institutional trading and stock resiliency: Evidence from 2007-2009 financial crisis, Journal of Financial Economics 108, 773-793.

Arnold, T., A.W. Butler, T.F. Crack, and Y. Zhang, 2005, The Information Content of Short Interest: A Natural Experiment. Journal of Business 78, 1307-1335.

Beber, Alessandro, and Marco Pagano, 2013, Short-selling bans around the world: Evidence from the 2007–09 crisis, Journal of Finance 68(1), 343-381.

Boehmer E., Jones C. M., Zhang X., 2008. Which shorts are informed?. Journal of Finance 63, 491-527.

Boehmer E., Jones C. M., Zhang X., 2012. What Do Short Sellers Know?. Working Paper.

Boehmer, E., Jones, C. M. and Zhang, X., 2013, Shackling Short Sellers: The 2008 Shorting Ban. Review of Financial Studies, 26 (6):1363-1400.

Boehmer E., Huszar Z., Jordan B., 2010. The good news in short interest. Journal of Financial Economics 96, 80-97.

Boehmer E., Wu J., 2013. Short selling and the price discovery process. Review of Financial Studies 26, 287-322.

Chakravarty, S., 2001, Stealth Trading: Which Trader's Trades Move Prices? Journal of Financial Economics 61, 289-307.

Chemmanur, Thomas J., Shan He, and Gang Hu, 2009, The role of institutional investors in seasoned equity offerings, Journal of Financial Economics 94, 384-411.

Chemmanur, Thomas J., Gang Hu, and Jiekun Huang, 2010, The role of institutional investors in initial public offerings, Review of Financial Studies 23, 4496-4540.

Cohen L., Diether K., Malloy C., 2007. Supply and demand shifts in the shorting market. Journal of Finance 62, 2061-2096.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks, Journal of Finance 52, 1035–1058.

De Angelis, David, Gustavo Grullon, and Sebastien Michenaud, 2015, The effects of short-selling threats on incentive contracts: Evidence from a natural experiment. Working Paper, Rice University

Diamond, D. and R. Verrecchia, 1987, Constraints on Short Selling and Asset Price Adjustment to Private Information. Journal of Financial Economics 18, 277-312.

Diether K., Lee K-H., Werner I., 2009a. It's SHO time! Short-sale price-tests and market quality. Journal of Finance 64, 37-73.

Diether K., Lee K-H., Werner I., 2009b. Short-Sale strategies and return predictability. Review of Financial Studies 22, 575-607.

Engelberg J., Reed A., Ringgenberg M., 2012. How are shorts informed? Short sellers, news, and information processing. Journal of Financial Economics 105, 260-278.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy, 607-636.

Foster F., and S. Viswanathan, 1993, The effect of public information and competition on trading volume and price volatility. Review of Financial Studies 6, 23–56.

Foster, F.D., and S. Viswanathan, 1996, Strategic Trading When Agents Forecast the Forecast of Others, Journal of Finance, 51, 1437-1478.

Froot, K.A., Scharfstein, D.S., and Stein, J.C., 1992, Herd on the street: Informational inefficiences in a market with short-term speculation. Journal of Finance 47, 1461 –1484.

Grullon, G., Michenaud, S. and Weston, J.P., 2015. The real effects of short-selling constraints. Review of Financial Studies, 28(6), pp.1737-1767.

Holden C., and Subrahmanyam A., 1992. Long-lived private information and imperfect competition. Journal of Finance 47, 247–270.

Hong, H., and M. Kacperczyk, 2010, Competition and Bias, Quarterly Journal of Economics 125(4), 1683-1725.

Jame, Russell, 2015, Liquidity Provision and the Cross-Section of Hedge Fund Skill, Working Paper, University of Kentucky. Kelly, B. and A. Ljungqvist, 2007, The value of research, Stern NYU, Working Paper.

Kyle A. S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315-1335.

Lo, Andrew W., and Archie Craig MacKinlay, 1988, Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test, Review of Financial Studies 1(1), 41–66.

Massa, M., W. Quian, W. Zu and H.Zhang, 2014, Copmetition of the Informed: Does the Presence of Short Sellers Affect Insider Selling, forthcoming Journal of Financial Economics. Puckett, Andy, and Xuemin (Sterling) Yan, 2011, The interim trading skills of institutional investors, Journal of Finance 66, 601-633.

Saffi P., Sigurdsson K., 2011. Price efficiency and short selling. Review of Financial Studies 24, 821-852.

Securities and Exchange Commission (SEC), 2007, Economic Analysis of the Short Sale Price Restrictions under the Regulation SHO Pilot, Office of Economic Analysis, Washington, DC.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle, Journal of Finance 70, 1903-1948.

Table 1. Summary Statistics. The table reports average, standard deviation, median, 25th and 75th percentiles (Panel A) and correlations (Panel B) of our main variables. In Panel B, we compute the correlation between our variables at both the weekly level (Panel B1) and the monthly level (Panel B2). ONLOAN is the outstanding amount of shares on loan divided by the total number of shares outstanding in a given week. LENDABLE is the outstanding amount of shares available to be lend out, divided by the total number of shares outstanding in a given week. IMBALANCES is the difference between shares traded in buyer-initiated trades and shares traded in seller-initiated trades from ANcerno, divided by the total number of shares outstanding. MKTCAP is the natural logarithm of market capitalization. TURNOVER is the average trading volume in CRSP in the last month, divided by the total number of shares outstanding. ABNORMAL RETURN is the abnormal return (with respect to the DGTW benchmark) of the stock. RAW RETURN is the cumulative raw return of the stock in the week. BROKER NUMBER is the average number of brokers used by traders in the stock-week. BROKER FAMILIARITY is our proxy for the familiarity between the traders and the brokers in a stock-week. BROKER FEES is the average expensiveness of the brokers chosen by traders in terms of percentage commissions. BROKER IMPACT is the average expensiveness in terms of average price impact of the broker. TRADE CONCENTRATION measures order splitting during a week for a given stock, measured as the adjusted Herfindahl index of the daily trading volume from the trader over the week. IDIOSYNCRATIC VOLATILITY is the average daily idiosyncratic volatility for a stock over four weeks. ABS(Autocorrelation) is the absolute value of the autocorrelation of daily raw returns of each stock in any given month. LAGGED MARKET CORRELATION 1 and 2 are proxies for the correlation between the raw returns of a stock and the lagged market return. VARIANCE RATIO is the absolute deviation from one of the ratio between weekly variance and daily variance (multiplied by five). ACTIVE BROKERS measures the natural logarithm of the number of brokers that are active (in a given stock) in ANcerno over the past twelve, six, or three months.

Panel A: Summary statistics

	Average	StdDev	Median	p25	p75
ONLOAN	0.04404	0.04630	0.02736	0.01034	0.06242
LENDABLE	0.20441	0.11017	0.20543	0.11522	0.28686
MARKET CAP	20.88950	1.39109	20.67756	19.81812	21.76267
TURNOVER	0.04947	0.03924	0.03837	0.02241	0.06393
ABNORMAL RETURN	-0.00006	0.04477	-0.00131	-0.02424	0.02263
RAW RETURN	0.00186	0.05547	0.00146	-0.27482	0.03051
IMBALANCES	0.00012	0.00425	0.00006	-0.00124	0.00151
BROKER NUMBER	1.65833	0.54355	1.58333	1.25000	2.00000
BROKER FAMILIARITY	3.37171	1.78552	3.04293	2.28926	4.05533
BROKER FEES	0.00127	0.00045	0.00118	0.00093	0.00155
BROKER IMPACT	0.00095	0.00050	0.00090	0.00067	0.00123
TRADE CONCENTRATION (BUY)	0.28920	0.19536	0.26339	0.13826	0.39853
TRADE CONCENTRATION (SELL)	0.31384	0.21523	0.29460	0.14297	0.43966
IDIOSYNCRATIC VOLATILITY	0.02223	0.01402	0.01880	0.01326	0.02696
ABS(AUTOCORRELATION)	0.18577	0.13692	0.15956	0.07515	0.26988
VARIANCE RATIO (DEVIATION)	0.56642	0.44943	0.50119	0.24957	0.76961
LAGGED MARKET CORRELATION	0.21298	0.27111	0.08931	0.01825	0.30338
LAGGED MARKET CORRELATION	0.28701	0.21492	0.24072	0.12132	0.40117
ACTIVE BROKERS 12M	4.02750	0.71720	4.11087	3.58352	4.55388
ACTIVE BROKERS 6M	3.73963	0.73789	3.82864	3.29584	4.26268
ACTIVE BROKERS 3M	3.42670	0.78501	3.55535	2.99573	3.97029

Panel B1: Correlation of broker-related variables

	BROKER NUMBER	BROKER FAMILIARITY	BROKER FEES	BROKER IMPACT	TRADE CONC. (BUY)	TRADE CONC.(SELL)	MARKET CAP	TURNOVER	RAW RETURN	IMBALANCES	IDIOS. VOLATILITY	ONLOAN
BROKER NUMBER	1											
BROKER FAMILIARITY	-0.059	1										
BROKER FEES	-0.1321	-0.3189	1									
BROKER IMPACT	0.1307	-0.0019	0.1354	1								
TRADE CONCENTRATION (BUY)	0.1012	0.0214	-0.0178	0.0205	1							
TRADE CONCENTRATION (SELL)	0.1397	-0.013	-0.0336	0.0299	0.0434	1						
MARKET CAP	0.5343	-0.1906	0.064	0.0014	0.099	0.1802	1					
TURNOVER	0.1564	-0.0752	-0.07	0.0946	0.0544	0.0645	0.0842	1				
RAW RETURN	-0.006	0.0023	0.0285	0.034	-0.0282	0.0133	-0.0008	-0.0063	1			
IMBALANCES	-0.0048	0.0013	0.0089	0.0052	-0.0081	0.0151	-0.0187	0.0071	0.1078	1		
IDIOSYNCRATIC VOLATILITY	-0.1301	0.0876	0.0063	0.1639	0.0021	-0.0517	-0.4191	0.3084	-0.0024	0.0114	1	
ONLOAN	0.029	0.0354	-0.3018	0.0001	0.0027	-0.005	-0.1558	0.3484	-0.0216	0.0082	0.1665	1
LENDABLE	0.265	-0.0243	-0.3943	0.1696	0.0243	0.0372	0.046	0.2188	-0.017	-0.0104	0.0336	0.4727

Panel B2: Correlation of efficiency-related variables

	ABS(AUTOCORREL.)	VAR. RATIO (DEVIATION)	LAG MKT CORR. (1)	LAG MKT CORR. (2)	ACTIVE BROKERS 12M	ACTIVE BROKERS 6M	ACTIVE BROKERS 3M	MARKET CAP	TURNOVER	RAW RETURN
ABS(AUTOCORRELATION)	1									
VARIANCE RATIO (DEVIATION)	0.1526	1								
LAGGED MARKET CORRELATION (1)	0.0498	0.0186	1							
LAGGED MARKET CORRELATION (2)	0.0763	0.0238	0.9603	1						
ACTIVE BROKERS 12M	-0.0805	-0.0314	-0.0863	-0.0906	1					
ACTIVE BROKERS 6M	-0.0806	-0.0304	-0.0904	-0.0949	0.9765	1				
ACTIVE BROKERS 3M	-0.0801	-0.0306	-0.0946	-0.0991	0.9470	0.9755	1			
MARKET CAP	-0.0700	-0.0228	-0.0703	-0.0753	0.7897	0.7878	0.7818	1		
TURNOVER	-0.0631	-0.0200	-0.0327	-0.0341	0.3111	0.3172	0.3205	0.0599	1	
RAW RETURN	0.0107	-0.0057	0.0172	0.0212	-0.0068	-0.0066	0.0017	0.0145	-0.0177	1
IMBALANCES	-0.0052	0.0009	-0.0064	-0.0086	-0.0354	-0.0277	-0.0204	-0.0375	0.0096	0.0946

Table 2. Returns on Short Selling and Traders' Activity. The table reports regressions at the weekly frequency of the abnormal return (with respect to the DGTW benchmark) of the stock in the five trading days after the measurement of short selling on: short selling (ONLOAN), the contemporaneous trade imbalances, and control variables. IMBALANCES_PCT is the difference between shares traded in buyer-initiated trades and shares traded in seller-initiated trades from ANcerno contemporaneous to the measurement of shares on loan, divided by their sum; ONLOAN is the outstanding amount of shares on loan divided by the total number of shares outstanding in a given stock-week. The control variables are: the market capitalization of the stock, the average trading volume in the last month, and the lagged dependent variable (but only when we do not include firm fixed effects). ONLOAN is standardized; the dependent variable is not standardized. Standard errors are clustered at the time level (week). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-week level and ranges between the first week of January 2005 and the last week of August 2010.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	ABNORMAL RETURN				
ONLOAN	-0.00784*	-0.00204	-0.00986**	-0.0148***	-0.0156***
	(-1.692)	(-0.358)	(-2.137)	(-2.724)	(-3.587)
IMBALANCES_PCT	0.00697***	0.00439**	0.00727***	0.00427**	0.00747***
	(3.424)	(2.241)	(3.972)	(2.424)	(4.317)
Mktcap	4.27e-06	-0.146***	-0.000285	-0.190***	-0.00223
	(0.00192)	(-8.336)	(-0.128)	(-9.140)	(-0.894)
Turnover	0.116	-0.383***	0.103	-0.225*	0.129
	(0.754)	(-3.381)	(0.655)	(-1.842)	(0.820)
Dependent Variable (t-1)	-0.497***		-0.493***		-0.383***
	(-3.204)		(-3.186)		(-3.375)
R-squared	0.001	0.011	0.004	0.015	0.021
Firm FE	No	Yes	No	Yes	
Time FE	No	No	Yes	Yes	FMB

Table 3. The Effect of Short Selling on the Number of Brokers Used by Traders. The table reports regressions of the average number of brokers used by the traders (BROKER NUMBER) on short selling and the control variables. ONLOAN is the outstanding amount of shares on loan divided by the total number of shares outstanding in a given stock-week. LENDABLE is the outstanding amount of shares available to be lent out, divided by the total number of shares outstanding in a given stock-week. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The control variables are: the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one week. We also control for the total trading volume (respectively in all trades, buy trades, and sell trades) during the week in which we measure the broker number. The dependent variables, as well as ONLOAN and LENDABLE, are standardized. Standard errors are clustered at the time level (week). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-week level and, when we use ONLOAN or LENDABLE, it ranges between the first week of January 2005 and the last week of August 2010; when we use the PILOT dummy the sample ranges between the first week of May 2002 and the first week of July 2007.

	BROKER NUMBER								
	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades
ONLOAN	0.00910***	-0.00417	0.00545*						
	(3.699)	(-1.273)	(1.736)						
LENDABLE				0.0635***	0.0295***	0.0472***			
				(14.76)	(6.510)	(8.370)			
PILOT							0.0142***	0.0154**	0.0213***
							(2.598)	(2.391)	(3.299)
Mktcap	0.374***	0.398***	0.260***	0.365***	0.395***	0.255***	0.285***	0.238***	0.202***
	(56.29)	(58.22)	(37.27)	(55.23)	(57.46)	(36.70)	(40.03)	(28.76)	(24.10)
Turnover	-0.241***	-0.0506	-0.0939*	-0.225***	-0.0798	-0.0876	-1.279***	-0.665***	-1.642***
	(-4.931)	(-0.889)	(-1.697)	(-4.632)	(-1.411)	(-1.606)	(-11.95)	(-5.723)	(-13.70)
Return (t-1)	0.271***	0.310***	0.213***	0.280***	0.317***	0.219***	0.138***	0.0969*	0.218***
	(8.960)	(9.311)	(6.230)	(9.235)	(9.460)	(6.347)	(2.624)	(1.709)	(3.615)
Imbalances (t-1)	0.867***	1.669***	-1.836***	0.860***	1.685***	-1.887***	0.922***	4.637***	-5.293***
	(3.634)	(5.925)	(-6.312)	(3.579)	(5.975)	(-6.389)	(2.608)	(9.730)	(-13.33)
Trading Volume	48.71***	70.96***	94.77***	48.41***	70.79***	94.63***	55.90***	80.87***	104.9***
	(77.99)	(58.11)	(92.17)	(76.92)	(57.42)	(92.62)	(84.38)	(62.36)	(83.26)
Observations	592,452	570,082	559,463	586,377	564,007	553,474	265,693	260,870	253,994
R-squared	0.487	0.430	0.417	0.489	0.431	0.418	0.515	0.398	0.370
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. The Effect of Short Selling on the Familiarity of the Brokers used by Traders. The table reports regressions of the familiarity of the brokers chosen for trading (FAMILIARITY) on short selling and control variables. BROKER FAMILIARITY is our proxy for familiarity of the brokers chosen for trading in a stock-week; the measure is normalized to account for the average number of brokers used by each trader. A high value of BROKER FAMILIARITY means that the traders are executing their trades with brokers that have already been extensively used in the recent past, therefore are deemed to be more familiar. ONLOAN is the outstanding amount of shares on loan divided by the total number of shares outstanding in a given stock-week. LENDABLE is the outstanding amount of shares available to be lent out, divided by the total number of shares outstanding in a given stock-week. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The control variables are: the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one week. The dependent variables, as well as ONLOAN and LENDABLE, are standardized. Standard errors are clustered at the time level (week). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-week level and, when we use ONLOAN or LENDABLE, it ranges between the first week of January 2005 and the last week of August 2010; when we use the PILOT dummy the sample ranges between the first week of May 2002 and the first week of July 2007.

	BROKER FAMILIARITY								
	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades
ONLOAN	-0.00651*	-0.00794**	0.0109***						
	(-1.869)	(-2.187)	(2.621)						
LENDABLE				-0.0512***	-0.0468***	0.00599			
				(-7.333)	(-8.123)	(0.753)			
PILOT							-0.0335***	-0.0184**	-0.0437***
							(-4.546)	(-2.527)	(-5.189)
Mktcap	-0.299***	-0.317***	-0.232***	-0.292***	-0.311***	-0.233***	-0.163***	-0.101***	-0.0511***
	(-35.28)	(-30.38)	(-19.43)	(-35.13)	(-30.40)	(-20.06)	(-13.67)	(-8.134)	(-4.088)
Turnover	-1.563***	-1.629***	-1.403***	-1.571***	-1.648***	-1.354***	-0.704***	-0.816***	-0.131
	(-21.73)	(-20.38)	(-17.10)	(-21.85)	(-20.58)	(-16.20)	(-4.859)	(-6.108)	(-0.847)
Return (t-1)	0.0778**	0.130***	-0.0696	0.0667*	0.117***	-0.0705	0.0390	0.107	-0.0765
	(2.033)	(3.026)	(-1.456)	(1.744)	(2.723)	(-1.472)	(0.466)	(1.334)	(-0.879)
Imbalances (t-1)	-0.299	-4.867***	3.664***	-0.296	-4.866***	3.680***	0.869**	-0.152	2.209***
	(-1.158)	(-15.52)	(10.60)	(-1.130)	(-15.36)	(10.61)	(2.006)	(-0.315)	(4.464)
Observations	647,083	625,890	597,828	640,601	619,427	591,436	268,644	263,383	254,564
R-squared	0.249	0.281	0.191	0.250	0.282	0.192	0.165	0.162	0.123
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. The Effect of Short Selling on the Expensiveness of Brokers used by Traders: Percentage Fees. The table reports regressions of the average expensiveness of the chosen brokers, in terms of percentage commissions (BROKER FEES), on short selling and control variables. ONLOAN is the outstanding amount of shares on loan divided by the total number of shares outstanding in a given stock-week. LENDABLE is the outstanding amount of shares available to be lent out, divided by the total number of shares outstanding in a given stock-week. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The control variables are: the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one week. The dependent variable, as well as ONLOAN and LENDABLE, are standardized. Standard errors are clustered at the time level (week). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-week level and, when we use ONLOAN or LENDABLE, it ranges between the first week of January 2005 and the last week of August 2010; when we use the PILOT dummy the sample ranges between the first week of May 2002 and the first week of July 2007.

	BROKER FEES								
	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades
ONLOAN	0.00852***	0.00989***	0.00504						
	(3.481)	(3.584)	(1.632)						
LENDABLE				0.00735	0.0425***	0.00710			
				(1.410)	(10.25)	(1.216)			
PILOT							0.0110***	0.0173***	-0.00470
							(3.623)	(4.300)	(-1.052)
Mktcap	0.189***	0.274***	0.173***	0.187***	0.267***	0.171***	0.109***	0.122***	0.0762***
	(30.59)	(29.08)	(22.31)	(30.99)	(28.92)	(22.80)	(22.31)	(20.31)	(12.47)
Turnover	0.709***	0.912***	0.775***	0.737***	0.933***	0.794***	1.123***	1.051***	0.673***
	(13.11)	(15.30)	(11.31)	(13.83)	(15.70)	(11.45)	(18.18)	(13.58)	(9.331)
Return (t-1)	0.0658**	0.000777	0.144***	0.0670**	0.0119	0.146***	-0.0670**	-0.175***	-0.00658
	(2.019)	(0.0199)	(3.967)	(2.054)	(0.305)	(3.994)	(-2.098)	(-4.668)	(-0.169)
Imbalances (t-1)	0.494**	7.440***	-4.695***	0.520**	7.430***	-4.668***	0.930***	5.104***	-1.669***
	(2.355)	(26.42)	(-17.10)	(2.456)	(26.39)	(-16.83)	(4.750)	(20.25)	(-6.749)
Observations	643,229	626,236	595,172	636,751	619,769	588,791	262,614	257,192	249,961
R-squared	0.533	0.445	0.462	0.532	0.445	0.461	0.832	0.761	0.761
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. The Effect of Short Selling on the Expensiveness of Brokers used by Traders: Price Impact. The table reports regressions of the average expensiveness of the chosen brokers, in terms of average price impact of the broker (BROKER IMPACT), on short selling and control variables. ONLOAN is the outstanding amount of shares on loan divided by the total number of shares outstanding in a given stock-week. LENDABLE is the outstanding amount of shares available to be lent out, divided by the total number of shares outstanding in a given stock-week. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The control variables are: the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one week. The dependent variable, as well as ONLOAN and LENDABLE, are standardized. Standard errors are clustered at the time level (week). t-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-week level and, when we use ONLOAN or LENDABLE, it ranges between the first week of January 2005 and the last week of August 2010; when we use the PILOT dummy the sample ranges between the first week of May 2002 and the first week of July 2007.

	BROKER IMPACT								
	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades
ONLOAN	0.00962***	0.00173	0.0139***						
	(3.803)	(0.559)	(4.282)						
LENDABLE				0.0305***	0.0271***	0.0466***			
				(6.958)	(5.432)	(9.183)			
PILOT							0.0381***	0.0453***	0.0118
							(5.394)	(5.858)	(1.607)
Mktcap	0.109***	0.131***	0.105***	0.104***	0.127***	0.0983***	0.205***	0.169***	0.150***
	(14.48)	(12.76)	(11.07)	(13.99)	(12.49)	(10.59)	(18.96)	(13.95)	(13.48)
Turnover	0.374***	0.482***	0.460***	0.396***	0.476***	0.499***	0.448***	0.370***	0.107
	(5.845)	(6.083)	(5.654)	(6.080)	(6.016)	(5.890)	(3.722)	(3.189)	(0.870)
Return (t-1)	0.0474	0.175***	-0.00279	0.0540	0.180***	0.00939	0.248***	0.527***	-0.158**
	(1.401)	(4.501)	(-0.0763)	(1.586)	(4.577)	(0.257)	(4.149)	(8.863)	(-2.365)
Imbalances (t-1)	1.005***	2.025***	-0.243	0.996***	2.048***	-0.312	0.736*	1.346***	-0.424
	(4.722)	(7.694)	(-0.953)	(4.641)	(7.713)	(-1.216)	(1.882)	(3.110)	(-0.911)
Observations	637,297	617,303	589,692	630,947	610,965	583,440	266,590	260,515	253,915
R-squared	0.564	0.501	0.505	0.564	0.501	0.506	0.314	0.282	0.244
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. The Effect of Short Selling on Traders' Behavior, interacted with Idiosyncratic Volatility. The table reports regressions of the average number of brokers used by traders (BROKER NUMBER), familiarity of the brokers chosen for trading (BROKER FAMILIARITY), average expensiveness of the chosen brokers in term of percentage commissions (BROKER_FEES) and in terms of average price impact of the broker (BROKER IMPACT), on: short selling (PILOT), average daily idiosyncratic volatility in the last month (IVOL), the interaction between the two, and control variables. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The control variables are: the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one week. All the dependent variables are standardized. Standard errors are clustered at the time level (week). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-week level and ranges between the first week of May 2002 and the first week of July 2007.

	BROKER NUMBER			BROKER FAMILIARITY			BROKER FEES			BROKER IMPACT		
	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades	All trades	Buy trades	Sell trades
PILOTxIVOL	-6.403***	-4.827***	-6.255***	6.518***	7.571***	4.731***	-0.0111	-3.190***	0.786	-0.602	-0.968	-0.501
	(-6.475)	(-3.961)	(-5.479)	(5.126)	(5.436)	(3.707)	(-0.0221)	(-4.928)	(1.333)	(-0.604)	(-0.854)	(-0.508)
PILOT	0.102***	0.0816***	0.107***	-0.123***	-0.122***	-0.108***	0.0114	0.0610***	-0.0155*	0.0453***	0.0578***	0.0186
	(6.901)	(4.619)	(6.117)	(-6.774)	(-6.215)	(-5.560)	(1.540)	(6.580)	(-1.723)	(2.936)	(3.201)	(1.260)
IVOL	2.561***	2.121***	2.914***	-2.016***	-2.222***	-1.735***	0.231	-0.0764	0.472*	0.227	0.192	0.274
	(7.179)	-4.837	(7.298)	(-4.178)	(-4.405)	(-3.245)	(1.041)	(-0.271)	(1.681)	(0.494)	(0.351)	(0.543)
Mktcap	0.297***	0.248***	0.215***	-0.172***	-0.111***	-0.0591***	0.109***	0.122***	0.0776***	0.207***	0.171***	0.153***
	(42.05)	(29.81)	(25.69)	(-14.32)	(-8.757)	(-4.615)	(22.65)	(20.48)	(12.51)	(19.10)	(14.28)	(13.79)
Turnover	-1.378***	-0.749***	-1.770***	-0.650***	-0.754***	-0.0812	1.103***	1.107***	0.622***	0.445***	0.371***	0.0923
	(-12.38)	(-6.163)	(-14.38)	(-4.438)	(-5.352)	(-0.517)	(16.86)	(13.51)	(8.736)	(3.558)	(3.023)	(0.717)
Return (t-1)	0.134**	0.0953*	0.213***	0.0402	0.110	-0.0781	-0.0685**	-0.175***	-0.00849	0.245***	0.523***	-0.158**
	(2.541)	(1.675)	(3.551)	(0.481)	(1.384)	(-0.896)	(-2.144)	(-4.689)	(-0.217)	(4.096)	(8.791)	(-2.367)
Imbalances (t-1)	0.931***	4.632***	-5.271***	0.875**	-0.147	2.220***	0.940***	5.093***	-1.655***	0.722*	1.325***	-0.395
	(2.646)	(9.750)	(-13.27)	(2.025)	(-0.305)	(4.502)	(4.811)	(20.22)	(-6.713)	(1.866)	(3.046)	(-0.851)
Trading Volume	55.83***	80.78***	104.8***									
	(84.20)	(62.22)	(83.33)									
Observations	265,467	260,674	253,811	268,413	263,185	254,381	262,403	257,009	249,791	266,376	260,326	253,744
R-squared	0.515	0.398	0.371	0.166	0.162	0.123	0.832	0.761	0.761	0.315	0.282	0.244
Firm 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

Table 8. The Effect of Short Selling on Trade Concentration. The table reports regressions of the concentration in traders' orders (TRADE CONCENTRATION) on short selling and control variables. We use the PILOT dummy as a proxy of short selling. TRADE CONCENTRATION is a proxy of how much each trader is splitting her trades during a week, measured as the adjusted Herfindahl index of the daily trading volume from the trader. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The dependent variable is interacted with a dummy variable (NEWS) that is equal to one if there is a positive (or negative) news event concerning the stock in the week. We consider a news event to be positive if its sentiment value is at least 70 (out of 100), negative if it is less than or equal to 30 (out of 100). The control variables are the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one week. We also control for the total number of days (within the week) in which news concerning the stock is released; we count any news event whose sentiment value is different from zero. The dependent variable is standardized. Standard errors are clustered at the time level (week). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between the first week of May 2002 and the first week of July 2007.

	TRADE CONCENTRATION			
	Buy Trades		Sell trades	
PILOT x Positive NEWS	-0.0149		-0.190**	
	(-0.184)		(-2.279)	
Positive NEWS	-0.0645*		0.0329	
	(-1.858)		(0.791)	
PILOT x Negative NEWS		0.0918		0.0595
		(0.376)		(0.260)
Negative NEWS		0.0136		0.0457
		(0.142)		(0.417)
News in the week	0.0197***	0.0195***	0.0114***	0.0114***
	(7.046)	(6.996)	(4.501)	(4.508)
PILOT	-0.0101	-0.0102	0.0179*	0.0172*
	(-1.189)	(-1.196)	(1.932)	(1.864)
Mktcap	0.0725***	0.0724***	0.148***	0.148***
	(5.667)	(5.661)	(14.00)	(13.99)
Turnover	1.031***	1.030***	1.040***	1.040***
	(7.675)	(7.668)	(7.758)	(7.750)
Return (t-1)	-0.528***	-0.529***	0.222***	0.222***
	(-6.930)	(-6.936)	(3.019)	(3.016)
Imbalances (t-1)	0.587	0.586	3.307***	3.307***
	(1.089)	(1.088)	(6.117)	(6.116)
Observations	235,254	235,254	195,695	195,695
R-squared	0.106	0.106	0.084	0.084
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table 9. The Effect of Short Selling and Brokers' Availability on Market Efficiency. The table reports regressions of our proxies for market efficiency on short selling (PILOT), interacted with the availability of brokers in a given stock (ACTIVE BROKERS). ABS(Autocorrelation) is the absolute value of the autocorrelation of daily raw returns of each stock in any given month. VARIANCE RATIO is the absolute deviation from one of the ratio between weekly variance and daily variance (multiplied by five). LAGGED MARKET CORRELATION 1 and 2 are proxies for the correlation between the raw returns of a stock and the lagged market return. ACTIVE BROKERS measures the natural logarithm of the number of brokers that are active (in a given stock) in ANcerno over the past 12, 6, or 3 months. PILOT is a dummy equal to one for the Pilot stocks during the Reg SHO period and zero otherwise. The control variables are the lagged raw return, the market capitalization of the stock, the average trading volume in the last month, the trade imbalances lagged by one month. All the dependent variables are standardized. Standard errors are clustered at the time level (month). *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample is at the stock-month level and ranges between January 2000 and July 2007.

	Abs(Autocorrelation)			Variance Ratio			Lagged Market Correlation (1)			Lagged Market Correlation (2)		
	12m	6m	3m	12m	6m	3m	12m	6m	3m	12m	6m	3m
PILOTxACTIVE BROKERS	0.0636*	0.0647*	0.0655*	0.0452*	0.0448**	0.0419**	0.107***	0.0872**	0.0742**	0.115***	0.0950***	0.0744**
	(1.740)	(1.829)	(1.927)	(1.876)	(2.032)	(2.058)	(3.015)	(2.550)	(2.301)	(3.172)	(2.725)	(2.278)
ACTIVE BROKERS	-0.0864***	-0.0810***	-0.0596***	-0.0359	-0.0267	-0.0327*	0.00828	0.00855	0.0149	-0.00718	-0.00788	-0.00128
	(-3.824)	(-3.999)	(-3.281)	(-1.492)	(-1.263)	(-1.852)	(0.307)	(0.364)	(0.724)	(-0.270)	(-0.336)	(-0.0632)
PILOT	-0.296*	-0.282*	-0.266*	-0.176	-0.161*	-0.137*	-0.459***	-0.344**	-0.267**	-0.495***	-0.378**	-0.269**
	(-1.796)	(-1.888)	(-1.986)	(-1.642)	(-1.764)	(-1.722)	(-2.893)	(-2.403)	(-2.141)	(-3.049)	(-2.583)	(-2.127)
Mktcap	-0.0286**	-0.0268**	-0.0317**	-0.0397***	-0.0413***	-0.0382**	-0.131***	-0.132***	-0.134***	-0.129***	-0.128***	-0.130***
	(-2.071)	(-1.996)	(-2.335)	(-2.638)	(-2.727)	(-2.502)	(-8.091)	(-8.172)	(-8.208)	(-8.017)	(-7.983)	(-8.021)
Turnover	-0.112**	-0.105**	-0.109**	0.0242	0.0228	0.0309	0.0317	0.0292	0.0223	0.0332	0.0332	0.0285
	(-2.163)	(-1.988)	(-2.062)	(0.540)	(0.502)	(0.679)	(0.449)	(0.412)	(0.312)	(0.490)	(0.487)	(0.416)
Return (t-1)	0.0995*	0.0998*	0.103*	-0.00362	-0.00280	-0.00306	-0.0866	-0.0866	-0.0862	-0.0937	-0.0939	-0.0932
	(1.838)	(1.842)	(1.900)	(-0.0672)	(-0.0523)	(-0.0574)	(-1.304)	(-1.306)	(-1.298)	(-1.572)	(-1.578)	(-1.566)
Imbalances (t-1)	-0.582*	-0.558*	-0.540*	-0.0587	-0.0489	-0.0397	-0.599**	-0.605**	-0.612**	-0.812***	-0.813***	-0.816***
	(-1.984)	(-1.902)	(-1.839)	(-0.200)	(-0.166)	(-0.134)	(-1.999)	(-2.011)	(-2.029)	(-2.740)	(-2.734)	(-2.734)
Observations	95,262	95,262	95,262	95,262	95,262	95,262	88,431	88,431	88,431	88,552	88,552	88,552
R-squared	0.047	0.047	0.047	0.039	0.039	0.039	0.148	0.148	0.148	0.147	0.147	0.147
Firm 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