Information Leakage from Short Sellers*

Fernando Chague[†], Bruno Giovannetti[‡], Bernard Herskovic[§]

April 17, 2023

Abstract

Directional bets by short sellers typically forecast future returns, but direct evidence of how other investors acquire information from these bets is nearly nonexistent. Using granular data on the entire Brazilian OTC security lending market and all trades in the Brazilian stock exchange, we explore institutional features of these markets to identify information leakage in security lending markets. When informed short sellers borrow securities, their broker learns about these informed directional bets by intermediating security lending contracts, and we document that brokers leak that information to their clients.

Keywords: short selling, security lending, brokers, information leakage

JEL Codes: G12, G14, G23, G24

*We thank seminar participants at EESP-FGV, EPGE-FGV, Insper, ITAM Finance Conference, and UCLA Finance Brown Bag for their comments and suggestions. We also thank Marco Bonomo, Pedro Garcia, Antonio Gargano, Vladimir Ponczek, and Fernando Zapatero (discussant) for insightful suggestions and feedback. Chague gratefully acknowledges financial support from CNPq. Giovannetti gratefully acknowledges financial support from FAPESP and CNPq.

[†]Getulio Vargas Foundation - Sao Paulo School of Economics, Brazil. E-mail: fernando.chague@fgv.br.

[‡]Getulio Vargas Foundation - Sao Paulo School of Economics, Brazil. E-mail: bruno.giovannetti@fgv.br.

[§]University of California, Los Angeles (UCLA) - Anderson School of Management; National Bureau of Economic Research (NBER). E-mail: bernard.herskovic@anderson.ucla.edu.

1 Introduction

There is extensive literature documenting short sellers as informed investors,[1] but direct evidence of how their information is transmitted to other investors is scarce. When short selling, investors borrow securities and sell them in the open market; however, these steps happen in different markets. Short selling requires investors to operate simultaneously in an over-the-counter (OTC) market to borrow securities and in the centralized exchange to sell them. The OTC nature of security lending means that a short seller needs to directly contact a broker to borrow securities, which tips off the broker about the short seller's trading bets. Relying on comprehensive data on both these markets in Brazil, we find that brokers play a crucial role in transmitting information from short sellers to other investors. Security lending contracts and trades on the centralized exchange have different settlement periods, which allows us to identify information leakage and control for trading comovement. In this paper, we document that brokers learn about short sellers' directional bets when lending securities and share this information with other clients.

We rely on two unique datasets to identify information leakage from security lending. The first is contract-level data for the entire Brazilian OTC security lending market, and the second database includes all transactions realized in the Brazilian stock market exchange at a daily frequency. By merging these data, we observe every investor's security lending contracts paired with their trading activity. Our data give us a detailed picture of all short-selling and trading activity in Brazil at a daily frequency.[2]

The richness of our data and the institutional features of the security lending market in Brazil allow us to identify information leakage through brokers. When a broker lends securities to an informed short seller, we find that clients of that broker start trading in the same direction as the informed short seller only after the broker becomes aware of the short seller's trading bet. At the same time, we do not observe the same pattern in clients of other brokers. This indicates that brokers learn about short sellers' directional bets through security lending, and their clients benefit by trading accordingly.

[1] See, for instance, Seneca (1967), Figlewski (1981), and, more recently, Aitken, Frino, McCorry, and Swan (1998), Asquith, Pathak, and Ritter (2005), Diether, Lee, and Werner (2009), Drechsler and Drechsler (2014), Rapach, Ringgenberg, and Zhou (2016), and Boehmer et al. (2022).

[2] These data have been used in recent work by Chague, De-Losso, Genaro, and Giovannetti (2017), Chague, De-Losso, and Giovannetti (2019) and Cereda et al. (2022).

One concern is that investors who are clients of the same broker may share some unobserved characteristics, such as access to the same information, and could naturally exhibit similar trading behavior. Our data and the microstructure of these markets allow us to control for this commonality in trading behavior across clients of the same broker. In Brazil, security lending contracts are settled on a same-day basis, but settlement in the stock market occurs three business days after the trade is executed.[3] Hence, a short seller can sell a security in the stock market and contact the broker up to three days later to borrow that security. This market structure implies that the selling activity dynamics of the short seller do not necessarily coincide with the borrowing date, which is when the broker becomes aware short seller's bet. In our regression specifications, we can directly control for the trading activity of the short seller who triggered the information leakage. This effectively controls for trading comovement between the short seller and other clients of the same broker. Therefore, our results control for trading comovement and show robust evidence of information leakage.

As a first step in our analysis, we characterize events in which a directional bet made by an informed short seller becomes salient to a broker. These events occur at the stock-day level when a skilled short seller borrows a substantial volume of shares. The broker knows the track record of all its clients and can screen based on available information to identify which clients are skilled short sellers. Hence, we defined an informed short-selling event from the broker's perspective when one of its skilled short-seller clients borrows an unusually large number of shares. This borrowing activity is, therefore, salient to the broker. We identify 1,408 informed short-selling events in our sample.

To identify information leakage, we characterize how institutions that engage in stock-picking strategies trade around informed short-selling events, and we compare the trading behavior of investors who are clients of the broker aware of the event against the behavior of nonclients of that broker. For each informed short-selling event, we compute trading imbalance measures, which capture investors' propensity to buy the stock involved in the event. We do so for both clients and nonclients of the broker. Specifically, for clients, the trading imbalance of a particular stock is the net volume sold by all the broker's clients relative to their gross volume bought and sold. It measures

[3]Since May 2019, the settlement in the Brazilian stock market is 2 business days, as in the US. Our dataset is from 2012 to 2018, and throughout our sample, settlement in the Brazilian stock market was 3 business days.

how likely those clients were to buy the stock on a particular day. A positive trading imbalance amongst clients means that they increased their loadings on that stock, and when negative, it means that clients decreased their loadings.

Through a differences-in-differences approach, we find that clients of the informed broker further reduced their loadings on the stock involved in the informed short-selling event vis-à-vis nonclients of the broker. We document that the trading imbalance decreases by 8.9 percentage points more for clients than for nonclients on the event date relative to the 10 days prior. We also measure trading imbalance using the number of investors buying and selling instead of their traded volume. In that case, the trading imbalance measure decreases by 5.4 percentage points more for clients than nonclients. As mentioned earlier, our estimates control for comovement in the trading behavior among investors who are clients of the same broker. These statistically significant and economically large trading differences indicate information leakage through brokers.

In addition to documenting information leakage, we investigate whether the transmission of information is intentional. When a short seller contacts a broker to borrow securities, that broker has to find other investors willing to lend them. This is a feature of security lending being an OTC market. The search process of locating securities to lend involves contacting some of its clients and possibly other brokers, which might tip off investors about the existence of a short-selling event. This becomes evident when the broker needs to locate a large volume of securities to be borrowed or has low inventory. Since short sellers are informed investors on average, investors contacted by the broker locating securities could respond by selling them rather than lending. In this case, the broker could unintentionally leak information due to the OTC nature of security lending markets.[4]

Our data allows us to rule out unintended information leakage. If the leak is unintentional, a security lending contract from a skilled or unskilled short seller should lead to the same information leakage. To investigate brokers' intentions, we conduct our empirical exercise for short-selling events generated by unskilled short sellers instead. These are investors with a losing record in short selling, and we call these events uninformed short-selling events. We find that trading behavior between clients and nonclients is indistinguishable when the broker becomes aware of uninformed short-selling events. Since only the broker knows the identity and the record of the short seller generating

[4]Duong, Huszár, Tan, and Zhang (2017) present evidence that some security lenders react to the information gathered at the security lending markets.

short-selling events, the fact that clients behave differently depending type of short-selling event is strong evidence of intentional information leakage.

Finally, we investigate brokers' gains from leaking information. We evaluate the loyalty dynamics of clients after receiving information, and we find that clients who likely received and benefited from the information leakage become more loyal to the broker. These clients sold the stock involved in the event even though they had not traded that security before the event. After an informed short-selling event, these clients bring more business to the broker by engaging in more security borrowing and lending with that broker.

Our paper relates to extensive literature that studies how short sellers contribute to stock price efficiency. Bris, Goetzmann, and Zhu (2007), Saffi and Sigurdsson (2011), and Boehmer and Wu (2013) show that impediments to short-selling result in less informative prices overall. There is also specific evidence that short sellers contribute to price discovery. Christophe, Ferri, and Angel (2004) find that short sellers can correctly anticipate negative earnings announcements. Similarly, Christophe, Ferri, and Hsieh (2010) find that short sellers increase their trading activity before analysts' downgrades. Karpoff and Lou (2010) document abnormal short-selling activity before episodes of financial misconduct are publicly revealed. Examining an even broader news set, Engelberg, Reed, and Ringgenberg (2012) find that short sellers can correctly process publicly available information and act faster than other investors. Chen, Kaniel, and Opp (2022) document several non-competitive features in security lending markets and estimate a dynamic model with asymmetric information. Finally, Gargano, Sotes-Paladino, and Verwijmeren (2022a) show that prices respond faster to new information when short-sellers trade in synchronization, since the uncertainty risks about when other short-sellers will act is reduced. We contribute to this literature of information dissemination from short-selling by showing a specific channel through which prices incorporate short sellers' information. Specifically, we explore brokers' role in transmitting short sellers' information.

Our paper also relates to literature that examines how market structures affect the price discovery process. Duffie, Malamud, and Manso (2009, 2014) develop a model in which individuals have to search for information that help understands how information eventually percolates to stock prices. Babus and Kondor (2018) propose a model to examine information diffusion in over-the-counter markets. Another set of papers examines this question from an empirical perspective.

Walden (2019) develops a rational expectations model to analyze how information flows to different investors in a network, concluding that more connected investors trade alike and that their performance can be explained by a particular network centrality measure. Di Maggio, Franzoni, Kermani, and Sommavilla (2019) explore the network structure in stock markets to show that central brokers leak information from institutional investors to their best clients. Barbon, Di Maggio, Franzoni, and Landier (2019) document that brokers spread information about large portfolio liquidations, and they find brokers sharing information about the upcoming order flows with their best clients. We contribute to this literature by providing the first evidence of information leakage through the security lending market.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the informational events that we consider in our empirical analysis. Section 4 presents our empirical results. Finally, Section 5 concludes.

2 Dataset

Transactions in the Brazilian stock market occur in a centralized electronic market, and the transactions in the Brazilian security lending market occur over-the-counter (OTC). The U.S. and many other countries have the same market structure. In this paper, we rely on a rich dataset that combines the trading activity of all investors in these two distinct markets from 2015 to 2018 in Brazil.

The data is provided by the Securities and Exchange Commission of Brazil,[5] which is equivalent to the U.S. Securities and Exchange Commission (SEC). At the investor-stock-day level, we observe a unique identifier for each investor, the investor type (institution or individual), and any volume—the monetary value and the number of shares—purchased and sold in the centralized stock market. In addition, for the OTC security lending market, we have granular contract-level data. For each security lending contract, we observe the unique identifier of investors (the same one for the centralized market) and brokers, the borrowed volume and the fees charged.

To rule out concerns regarding the illiquidity of stocks, we focus on stocks with positive trading volume every trading day in the year before being included in the sample. As a result, our sample

[5] *Comissão de Valores Mobiliários.*

has 304 different stocks—all 92 stocks included in the Bovespa Index, the leading Brazilian stock market index, and more than 200 other liquid stocks. Our sample represents 93% of the stock market capitalization in Brazil on average. The Brazilian stock market is the largest in Latin America, and in 2022, it had about one trillion dollars in total market capitalization listed. In our sample, the average daily traded volume in the security lending market was 31% of the daily volume, indicating a mature market to lend and borrow securities. Our data contains 741,618 different investors (25,500 institutions and 716,118 individual investors) who traded these 304 stocks in the centralized exchange, out of which 101,057 investors (8,664 institutions and 92,393 individuals) engaged in either borrowing or lending at least one of the 304 stocks.

3 Informed short-selling events

In this section, we characterize events in which brokers become aware of a sizeable directional bet made by an informed short seller. Although aggregate short-selling preditcs future returns, not all short-sellers are informed (see, for instance, Boehmer, Jones, and Zhang, 2008, Chague, De-Losso, and Giovannetti, 2019, and Gargano, Sotes-Paladino, and Verwijmeren, 2022b). Therefore, we first identify investors who are potentially informed short sellers from the perspective of the broker. Then, we define the informed short-selling events that we use to base our evidence of information leakage.

We say that a broker perceives an investor as an informed short seller if the investor has a good track record in borrowing securities that underperform the market after the borrowing date. The broker observes the borrowing activity across all clients and can screen skilled from unskilled short sellers. Formally, we classify an investor as an informed short seller at a given moment in time from the perspective of a broker if she meets two conditions: (i) the investor borrowed securities at least 10 times in the previous 90 days from that broker with an average borrowed volume of at least R$100,000, which is about US$30,000 using the average exchange rate at the time, and (ii) in the same previous 90 days, the probability of a stock borrowed by the investor subsequently underperforming the market in the 20 trading days after the borrowing date (the average duration of the loan deals) is statistically greater than 50% at the 10% confidence. Requirement (i) guarantees that we focus on borrowers who are professional and active short sellers with significant skin in the game, while requirement (ii) selects short sellers who have shown skill in the recent past from the broker's perspective.

Finally, we define an informed short-selling event as a day in which a directional bet made by an informed short seller becomes salient to the broker. Specifically, a stock i on date t constitutes an informed short-selling event for broker j if one of the broker's informed short sellers borrows the largest amount of that stock on that day relative to all borrowing activity of that short seller in the previous 90 days. Hence, an event for a broker is a stock-day pair, in which the broker knows that one of its informed short sellers is taking an unusually large bearish directional bet regarding that stock.

Under this definition, we find 1,408 informed short-selling events, which is 352 events per year on average. They occur across 96 stocks and 53 brokers from a total of 98 brokers that operate in the Brazilian security lending market in our sample period. There are 461 different investors responsible for these 1,408 borrows—143 individuals, responsible for 240 borrows, and 318 institutions, responsible for 1,168 borrows. With respect to the volume borrowed by each investor in each event, the minimum is R$166,144, the 25th percentile is R$1,025,156, the median is R$2,544,975, the 75th percentile is R$7,025,156, and the maximum is R$720,356,501. These events are well-distributed over time, with 359 occurring in 2015, 296 in 2016, 326 in 2017, and 427 in 2018.[6]

3.1 Characterizing events

To contextualize the short-selling events, we describe them by analyzing the behavior of some variables before and after these events occur. First, we look at what happens to stock prices in a one-month window around the short-selling events. To do so, we accumulate the four-factor risk-adjusted returns from 21 days before the event up to 21 days after.[7] Then, we take the daily average of the computed risk-adjusted prices across all 1,408 events. As Figure 1 indicates, the events usually occur after a consistent price increases, with increases accelerating in the few days preceding the event day. In contrast, prices revert and consistently fall over the subsequent weeks

[6] Appendix Figure 7 plots a matrix of the events to allow clear visualization of their distribution across stocks and time.

[7] We first regress the daily stock return in excess of the risk-free rate on the market, SMB, HML and momentum factors for Brazil using trading days $t-252$ and $t-1$ to obtain the corresponding factor loadings. Then, we compute the day t risk-adjusted returns as the day t stock return in excess of the risk-free rate minus the factor loadings computed times the realization of the factor returns. The Brazilian risk factors used are available at www.nefin.com.

after the event. That is, the informed short-selling events contain valuable negative information about the future performance of the stock.[8]

[Figure 1 about here.]

Second, we measure the following: (i) trading volume, which is the volume sold plus the volume bought by all investors; (ii) the number of investors—institutions or retail—who either purchased or sold the stock on the day; and, (iii) the intraday price range, which the difference between the maximum and minimum trading prices divided by the average of the two, and it is a proxy for intraday volatility. To obtain comparable measures across stocks and over time, we standardize these variables relative to their values observed three months before the event day. We report their average around the event dates in Figure 2 and find that, before the event days, the event stocks experience higher trading volume, a higher number of investors trading them, and higher price volatility.

[Figure 2 about here.]

We also examine whether the events coincide with the disclosure of relevant pieces of news. Indeed, we find a disproportionally large fraction of earnings announcements around the events. In 534 of the 1,408 events, we see an earnings announcement between days t-21 and t+5 of the event. Moreover, in another 114 events, we also see the disclosure of a material fact (i.e., an important piece of news formally disclosed by the firm) unrelated to the earnings announcement.

To summarize, in our average event we see an abnormally higher volume, an increased price volatility, a higher number of investors trading and more information being disclosed. This suggests that the firm is experiencing a salience shock, as described by Barber and Odean (2008), and on the event day, short sellers start betting against the overpricing of its securities.

4 Information leakage

In the previous section, we identified 1,408 events in which brokers see unusually large bets made by informed short sellers. These events are valuable sources of information that can be translated

[8] The fact that prices fall after the event is consistent with the fact that short sellers display persistence in their performance. That is, the past performance of short sellers is a good indicator of their future performance. See, for instance, (Chague, De-Losso, and Giovannetti, 2019), and (Gargano, Sotes-Paladino, and Verwijmeren, 2022b).

into alpha-generating trading strategies. Do brokers share this potentially profitable information with its clients that engage in stock-picking strategies?

To answer this question, we characterize the trading behaviors of clients and non-clients of a broker around informed short-selling events before and after the broker becomes aware of the event. Our dataset has every market participant's trading activity, including those by retail investors, mutual funds, index funds, hedge funds, pension funds, market makers, algorithmic trading and even nonfinancial firms trading stocks. Hence, among all these investors, we must first identify a group of institutions most equipped to quickly trade upon receiving information about an informed short-selling event. These institutions should trade frequently, engage in short selling, trade larger volumes, and likely rely on stock-picking strategies by trading fewer stocks on the same day. Specifically, in our baseline analyses, we look at institutions that i) buy or sell securities at least once a week on average, ii) short sell at least once a month on average, iii) trade an average volume of at least R$100,000 considering the days the institution trades, and iv) trade at most 10 different stocks on the median trading day.[9]

[Figure 3 about here.]

A total of 463 institutions satisfy these criteria. They account for a significant fraction of the overall trading volume in Brazil. On average, they represent 12.9% of the daily volume, and Figure 2 plots this fraction from 2015 to 2018, which ranges from 8.0% to 23.1%.

The average daily trading volume these institutions is R$4M, which is about $1.2M U.S. dollars using the average exchange rate during our sample period. The minimum daily volume is R$140,206 ($41,115 USD), the median is R$ 1,690,288 ($495,677 USD), and the maximum is R$86,053,520 ($25.2M USD). Regarding the number of brokers used, they used 9.16 different brokers from the security lending market on average. The minimum number of brokers used is 1, the median is 6, and the maximum is 38.

We also measure the their trading performance T days after their stock purchases and sales.[10]

[9] In a placebo exercise presented ahead, we look at institutions that, on the median trading day, trade more than 10 different stocks per day (possibly factor investors, index funds and market-makers).

[10] For each institution we do as follows. We first compute for each stock-day the variable v, the net traded volume (volume purchased minus volume sold). We then define $y = 1$ if $v > 0$ and $y = -1$ if $v < 0$. We then compute for each stock-day $|v|$, the absolute value of v. We then compute for each stock-day $exret$, the stock return T days ahead of the date minus the value-weighted market return T days ahead of the date. We then compute $|v|_{tot}$, the sum of $|v|$ across all pairs stock-days. Finally, its average performance T days ahead of purchases and sales is given by the sum across all stock-day pairs of $y \times exret \times \left(|v| \,/\, |v|_{tot}\right)$.

These statistics indicate heterogeneity in institutions' performance, but on average, their trade leads to positive outcomes. Across them, the 20-day performance is 0.18% on average, and ranges from -4.85% to 6.33%, with a median of 0.19%. Considering a 60-day window, their average performance is 0.30%, ranging from -7.71% to 8.20%, with a median of 0.24%. For a 120-day window, the minimum, maximum, average and median performance are -14.14%, 13.31%, 0.33% and 0.21%, respectively.

As described in Section 3, 318 institutions were responsible for 1,168 informed short-selling events and 143 individuals were responsible for the remaining 240 events. Out of these 318 institutions, 156 are among the 463 institutions that engage in stock-picking strategies.

We next evaluate how, within each event, the trading behavior of the clients of the broker involved in the event compares with the trading behavior of the nonclients of that broker. Importantly, we control for a possible trading co-movement among clients of the same broker.

4.1 How do institutions trade around informed short-selling events?

Figure 1 shows that a broker aware of an informed short-selling event has valuable information about the future performance of the event stock. This information is private, and the broker learns about it on the day of the event. In the following day, the volume shorted gets incorporated into the total short interest of the event stock and is publicly disclosed to all market participants. The identity of who is taking these short positions remains private, though. Hence, on the event day, the broker lending to the informed short seller learns about the event ahead of other market participants.

We begin by using a differences-in-differences approach, where we compare the differences in trading patterns between clients and nonclients of the event broker. We measure this difference in trading patterns on the event day relative to the 10 days prior. The first evidence of information leakage by the broker would be that the likelihood of selling the event stock significantly increases more for clients of the event brokers on the event day than for nonclients.

We quantify the trading behavior of clients and nonclients around each event by computing two different trading imbalance measures. For notation purposes, let $\nu = (s, b, \tau)$ be an informed short-selling event for broker b on security s and day τ.

Our first measure is a volume-based measure of trading imbalance ($VImbalance$). For clients, let $VImbalance^c_{\nu,t} = \frac{VBuy^c_{\nu,t} - VSell^c_{\nu,t}}{VBuy^c_{\nu,t} + VSell^c_{\nu,t}}$. The variable $VBuy^c_{\nu,t}$ is the total volume of the security s involved in event ν purchased in the centralized stock market on day t (around day τ) by clients of event broker b. We define an institution as a client of a broker in the security lending market if it has borrowed or lent any stock using that broker in the 90 days previous to the date of the event. The term $VSell^c_{\nu,t}$ is the total volume of the stock involved in event ν sold in the centralized stock market on day t by clients of the broker involved in the event ν. The volume-imbalance measure $VImbalance^c_{i,t}$ is a variable that goes from -1 (only sales) to +1 (only purchases). We exclude investors generating the informed short-selling event from the imbalance measures. For nonclients, $VImbalance^n_{\nu,t}$ follows the same procedure but measures volume imbalance for nonclients of the broker involved in the event ν.

Our second measure is based on the number of institutions trading in a particular direction ($NImbalance$). For clients of the broker b involved in the event ν, let $NImbalance^c_{\nu,t} = \frac{NBuy^c_{\nu,t} - NSell^c_{\nu,t}}{NBuy^c_{\nu,t} + NSell^c_{\nu,t}}$. The variable $NBuy^c_{\nu,t}$ is the number of different clients of broker b who purchased the stock in the centralized stock market on day t, while $NSell^c_{\nu,t}$ is the number of different clients who sold the stock in the centralized stock market on day t. The number-imbalance measure $NImbalance^c_{i,t}$ is a variable that goes from -1 (only sales) to +1 (only purchases). As in the previous measure, we exclude the informed short seller generating the event as well, and for nonclients, $NImbalance^n_{\nu,t}$ follows the same procedure but measures number imbalance for nonclients of the broker involved in the event ν.

Table 1 presents the distributions of these variables over the 10 days before the event and the day of the event, that is, $t = \tau - 10, \tau - 9, ..., \tau$, where τ is the event day. They are roughly centered at zero, which means that on average the buying activity equals the selling activity, considering clients and non-clients.

[Table 1 about here.]

As a first pass evidence, Figure 4 shows the 95% confidence interval on the average imbalance between clients and nonclients across all informed short-selling events from 10 days before the events to the event day. Panel A and B report confidence intervals for volume- and number-imbalance measures, respectively. The figure shows that the trading behavior of clients and nonclients is only different on the day of the event, when the propensity of buying the stock is lower for clients of the broker aware of the event.

[Figure 4 about here.]

To confirm this difference, we estimate the following difference-in-differences regressions:

$$y^j_{\nu,t} = \beta_0 + \beta_1 Clients^j_{\nu,t} + \beta_2 EventDay^j_{\nu,t} + \beta_3 Clients^j_{\nu,t} \times EventDay^j_{\nu,t} + \mu_\nu + \epsilon^j_{\nu,t} \tag{1}$$

where y is either $VImbalance$ or $NImbalance$, $Clients$ is a dummy variable equal to one if y refers to clients of the broker and zero if y refers to nonclients of the broker, $EventDay$ is a dummy variable equal to one on the day of the event and zero on the days before the event, j indicates whether the imbalance measure refers to clients or nonclients, and μ represents event fixed-effects.

Parameter β_3 measures whether the change in y on the day of the event compared to the previous 10 days is different between clients and nonclients of the broker. Importantly, Figure 4 shows that the dependent variables present no pre-trends, which is crucial for standard difference-in-differences analyses.

Table 2 presents the estimates for Equation (1) considering both variables $VImbalance$ and $NImbalance$. We obtain a negative and significant estimate for β_3 in all columns, confirming that the propensity of buying the stock on the event date decreases more for clients of the broker than for nonclients. Including event fixed-effects do not change the point estimates. Considering the trading imbalance in volume (columns 1 and 2), we find that $VImbalance$ decreases 0.089 more for clients than for nonclients on the event date compared to the 10 previous days. Considering the trading imbalance in the number of institutions (columns 3 and 4), we find that $NImbalance$ decreases 0.054 more for clients than for nonclients.

[Table 2 about here.]

The day of the event is special because on this day only the broker knows about the large loan of the informed short seller. On the next day, however, the fact that a large loan occurred on the day before could possibly be inferred by all investors from public data: the Brazilian exchange discloses on a daily basis, before the stock market opens, the short-interest of each stock updated until the previous day. Nevertheless, it is reasonable to imagine that the information inside the broker will continue to be richer than the public information on the days following the event date: only the broker knows that a large short came from a skilled short seller.

Accordingly, we also compute the estimate the 95% confidence interval for $VImbalance$ and $NImbalance$, across all informed short-selling events for 10 days after the event. Figure 5 plots the imbalance measure 10 days before and 10 days after the events. Even though clients of the broker had already sold the stock on the day of the event, as shown in Figure 4, their selling activity continues to be more pronounced on the days following the event, compared to the activity of nonclients. This pattern is clearer for $NImbalance$ in Panel B of Figure 5. Interestingly, the plots indicate that nonclients of the event broker trade in the opposite direction, possibly providing liquidity to clients. As depicted in Figure 1, they should on average lose on those trades because prices are falling on average.

[Figure 5 about here.]

Finally, we re-estimate Equation (1), but excluding the event date and including the 10 days after the event date. The dummy variable $EventDay$ is replaced by the dummy variable $After$, which is one for the 10 days after the event and zero for the 10 days before the event. Table 3 presents the results. Again, we obtain a negative and significant estimate for β_3 in all columns, at 10% significance in Columns 1 and 2 and at 5% in Columns 3 and 4.

[Table 3 about here.]

4.2 Main regression: Controlling for the selling activity of the short seller

The evidence presented in the previous section is consistent with brokers leaking information about informed short-selling events to their clients. However, if clients of a broker share common informational signals or strategies, then we could observe co-movement in the trading dynamics across clients of the same broker. In our case, this is the co-movement between the short seller generating the event and the other clients. This mechanism holds even without any information leakage by the broker, and the previous specification does not rule it out. Thus, it is vital to directly control for this alternative channel. Our setting allows us to control for trading co-movement and correctly identify information leakage.

In Brazil, the settlement in the OTC security lending market occurs on the same day that the loan deal is closed. However, the settlement in the centralized stock market occurs 3 business days after the trade is executed.[11] Accordingly, short sellers can wait a few days to borrow the stock after selling, which could reduce the cost of taking short positions. As a result, the selling dynamics of short sellers no longer necessarily coincides with the borrowing date, which is when the broker becomes aware of directional bets made by short sellers, clients of the broker.

In terms of the empirical strategy, the non-coincidental dynamics of selling and borrowing allows us to control for trading co-movement. We can directly control for the actual selling dynamics of the short seller generating the informed short-selling event in regression (1). By doing so, the estimate of β_3 is not polluted by the possible co-movement in the trading dynamics between the shot seller generating the event and the other clients of the same broker. The estimated coefficient, therefore, captures the information leakage from brokers to clients after brokers acquired valuable information lending securities.

We first show that the short seller's actual selling activity is not concentrated on the event date. For each event ν, we compute the total volume sold by the short seller in the centralized stock market during the 7-day period around the event date (3 days before the event, the event day, and 3 days after). Then, for each day t within this period, we compute $\pi_{\nu,t}$ as the fraction between the volume sold by the short seller on day t and the total volume sold during the 7 days. For each day t, we compute the average of $\pi_{\nu,t}$ across all 1,408 events and plot it in Panel A of Figure 6. On average, 11% of the sales made by short sellers during the 7 days around the borrowing event occur 3 days before the event, 21% 2 days before, and 31% 1 day before. On the day of the event, we observe 11% of the sales and, after that, lower fractions. The dynamics of π also varies across events, which we can see in Panel B as a heatmap of $\pi_{i,t}$ for each event and day.

[Figure 6 about here.]

As our main specification, we control for trading co-movement by estimating the following

[11] In 2019, after our sample period, the settlement in the centralized stock market was reduced to $T + 2$, which is the same as in the US.

regression on the 7-day period around each informed short-selling event:

$$y^j_{\nu,t} = \beta_0 + \beta_1 Clients^j_{\nu,t} + \beta_2 After^j_{\nu,t} + \beta_3 Clients^j_{\nu,t} \times After^j_{\nu,t} \\ + \beta_4 \pi^j_{\nu,t} + \beta_5 Clients^j_{\nu,t} \times \pi^j_{\nu,t} + \mu_\nu + \epsilon^j_{\nu,t} \quad (2)$$

where $After$ is a dummy variable equal to one on the day of the event and the following 3 days, $\pi^j_{\nu,t}$ is the proportion sold in the centralized stock market by the short seller responsible for event i on each day t (the variable shown in the heat-map of Figure 6), and the other variables were already defined in the previous section.

By including in the regression $\pi^j_{\nu,t}$ and $Client^j_{\nu,t} \times \pi^j_{\nu,t}$, we allow for a direct co-movement in the trading activity between the broker's clients and the short seller generating the event (who is also a client), which is captured by $\beta_4 + \beta_5$. Our specification also allows for a possible direct co-movement in the trading activity between the broker's nonclients and the short seller, captured by β_4. As a result, β_3 measures only the effect of the informational shock inside the broker on the event day coming from the informed short sellers generating the event.

Table 4 presents the estimation result of Equation (2). As expected, we see a significant co-movement between the selling dynamics of the short seller and of the other clients of the broker ($\beta_4 + \beta_5$). The trading imbalance variables also decrease when the short seller sells more (higher π). In turn, there is no evidence of co-movement between the selling dynamics of the short seller and the nonclients of the broker (i.e., β_4 is not significant). These results confirm the importance of controlling the regression for π. However, even after controlling for π, the estimate of β_3 continues to indicate that the propensity of buying the stock on the event date and afterward decreases more for clients of the event broker relative to nonclients.

[Table 4 about here.]

4.3 Intentional or unintentional information leakage?

Next, we determine whether the leakage is intentional or not. There is a subtle channel through which information from short sellers could be transmitted to other investors without the broker actively sharing it. When a short seller contacts a broker to borrow a large volume of securities, the broker has to locate them to meet its contractual obligations. In practice, the broker searches for a lender to fulfill the short seller's demand in case the broker does not have enough securities in its inventory. Hence, even if the broker does not intentionally leak information about short-selling bets, searching for a lender could make his clients aware of significant borrowing needs. Since short sellers are well-informed investors on average, this search process would tip off clients of the broker, and they would reduce their demand for the event stock. In this case, the information leakage is unintentional, and we would also observe a negative and significant β_3.

To rule out unintentional information leakage, we can evaluate what happens to trade patterns when the broker intermediates a large security lending contract in which the counterpart borrowing the securities is an unskilled short seller. We call these uninformed short-selling events. If information leakage is unintentional, we should find similar trade patterns regardless of whether the short-selling event is informed or uninformed.

We use the same criteria from Section 3 to define uninformed short-selling events, but we now focus on events generated by unskilled short sellers. These are short sellers with losing tracking records. In the 90 days previous to the security loan, the probability that a stock borrowed by the investor had subsequently underperformed the market in the 20 trading days after the borrowing date is statistically lower than 50% at the 10% confidence.

There are 973 uninformed short-selling events. They occur across 86 stocks and 54 brokers. There are 363 different investors responsible for these events is 363, out of which 120 are individuals, and 243 are institutions. The volume borrowed by each investor in these events features a median of R$2,754,658, a minimum of R$121,112, and a maximum is R$1,366,205,012. These volume figures are comparable to those observed in informed short-selling events. The uninformed events also spread over time, with 137 in 2015, 346 in 2016, 240 in 2017, and 250 in 2018.

Using the same group of clients and nonclients used so far, we then re-estimate Equation (2) around these 973 uninformed short-selling events. Table 5 presents the results. Differently from the previous section, we now find the estimate of β_3 to be not significant. That is, when the borrow comes from an investor the broker sees as an unskilled short seller, there seems to be no information leakage. This is evidence of intentional information leakage.

[Table 5 about here.]

4.4 Looking at institutions that trade more than 10 stocks per day

In Section 4, we focus on institutions that i) trade on average more than once a week, ii) sell short on average more than once a month, iii) trade an average volume above R$ 100,000 per day with iv) a median number of different stocks traded per day of 10 or less. We now study the trading behavior around the informed short-selling events of institutions who also satisfy (i)-(iii) but display a median number of different stocks traded per day above 10. These are 158 institutions out of the 621 who satisfied conditions (i)-(iii).

These 158 institutions are less likely to follow stock-picking strategies because they usually trade a larger number of stocks on the days they trade. For instance, institutions that run factor-investing strategies, index funds, and market makers are more likely to be in this group. Hence, estimating equation (2) around informed short-selling events for this group of 158 institutions is a placebo exercise. Given that they are less likely to run stock-picking strategies, we should find weaker or no evidence of information leakage.

Table 6 presents the results. As expected, we find the point estimate of β_3 to be close to zero and statistically insignificant. That is, when we evaluate the trading behavior of institutions that are less likely to pursue stock-picking strategies, we find no evidence of information leakage.

[Table 6 about here.]

4.5 Why do brokers leak information to his clients

An investors who receives information about an informed short-selling event may see this leakage as a valuable service offered by the broker. Indeed, as shown in Figure 1, the event stock is likely to underperform the market after the event. From the perspective of the short seller, the information leakage is not necessarily detrimental. As discussed in Section 4.2, when the short seller borrows the stock, a significant volume of the have already been sold in the centralized stock market on the days before—on average, 63% of the entire selling activity of the short seller over the 7 days around the event happened before the event date. Thus, most of the short seller's position is locked in by the event day. As a result, the broker benefits clients by leaking information to them without hurting the short seller who generated the event. This incentive structure favors information leakage. To confirm our intuition, we now evaluate loyalty dynamics among clients of the broker leaking information. Specifically, we focus on clients possibly receiving information and on the short seller who generated the event.

We identify clients who possibly received the information as the broker's clients who (i) are not the short seller responsible for the event, (ii) sold the stock on the day of an event, and (iii) were not selling that stock in the 15 days before the event.[12] According to this definition, 292 institutions (out of the 463) are likely to have received event-related information from their brokers. The number of event-investor pairs with a possible leakage is 1,348. There is a total of 1,408 informed short-selling events; in 549 of those, we observe at least one client who possibly received the event-related information from his broker.

To evaluate loyalty dynamics, we compute for each event-investor pair i the variable $Loyalty_{i,t} = \frac{Vol^b_{i,t}}{Vol_{i,t}}$, where $Vol^b_{i,t}$ is the total volume borrowed and lent by the investor using the broker under the event in period t and $Vol_{i,t}$ is the total volume borrowed and lent by the investor using any broker in period t. Because the security lending market is OTC and contracts are sparsely closed over time, we look at a longer time frame. We consider 90-day windows as periods. Let us define $t = \{-2, -1, 0, +1\}$ where $t = -2$ refers to the 90 days from 180 to 91 days before the event date, $t = -1$ refers to 90 days before the event, $t = 0$ refers to the 90 days from the event day onward, and $t = +1$ refers to the subsequent 90-day period. That is, $Loyalty_{i,t}$ captures the loyalty of the investor with the broker involved in the event with respect to the trades in the security lending market.

We estimate loyalty dynamics before and after the event through the following specification:

$$Loyalty_{i,t} = \beta_0 + \beta_1 \times t_{i,t} + \beta_2 \times After_{i,t} + \mu_i + \epsilon_{i,t} \tag{3}$$

where $After$ is a dummy variable equal to one for $t = 0, 1$ and μ are event-investor fixed-effects.

Parameter β_2 captures a possible change in the dynamics of $Loyalty_{i,t}$ that may have been caused by the information leakage episode. We run the same regression with and without investor-event fixed effects. We estimate this relation across all 1,348 event-investor pairs where the investor is an investor who possibly received the information. In addition, we run this regression across all 1,342 event-short-seller pairs as well. In this case, we look at the loyalty of the short seller who

[12] Naturally, there may also be clients who would have purchased the stock but received the information from the broker. In this case, they might have called off the purchases. We cannot identify these investors.

generated the informed short-selling event.

Table 7 presents the results. Considering the investors who received the information, we find that β_2 is positive and significant—see Column 2 with the event-investor fixed effect. This indicates that there is a discontinuous increase in their loyalty after the event. In turn, considering the short sellers, we find that β_2 is positive but not significant, indicating that their loyalty after the event with the respective broker does not change in a discontinuous way.

[Table 7 about here.]

These results suggest that institutions who receive the information value the leakage and become more loyal to the broker. They engage in more securities lending contracts with that brokers. On the other hand, we do not find evidence of short sellers becoming more or less loyal to brokers leaking information.

4.6 The effects of the information leakage on stock prices

How does the information leakage affect stock prices? In this section we assess this important and challenging question. We do that by comparing the behavior of stock returns after the 1,408 events studied so far with their behavior in 487 other events. In both groups of events there is a skilled short seller borrowing an abnormal volume with a broker. However, there are lower chances of leakage among the 487 events: the brokers involved in those events do not perceive the short sellers as skilled, although they are.

As already discussed, in the 1,408 events, the broker involved in the event perceives the short-seller as skilled. This is because the investor borrowed securities at least 10 times in the previous 90 days from that broker and, by observing those deals, the broker infers that the probability that the stock borrowed by the investor subsequently underperforms the market in the 20 trading days after the borrowing date to be more than 50% at the 10% confidence level (t-statistic above 1.64).

In the 487 events we now add to the sample, the broker involved in the event does not perceive the short-seller as skilled, although she is. Specifically, the investor borrowed securities at least 10 times in the previous 90 days from that broker but the t-statistic of success across those deals is below 1. However, when we look at all borrowing deals the investor made in *all brokers* during that same 90-day period, the t-statistic is above 1.64 (the broker involved in the event does not know that).

Do future returns behave differently among those 487 events, where the chances of leakage are lower, compared to the 1,408 events? To evaluate this, we estimate the following cross-sectional regression across the 1,895 events:

$$y_{\nu} = \beta_0 + \beta_1 Leakage_{\nu} + \mu_{\nu} + \epsilon_{\nu} \tag{4}$$

where y can be the cumulative stock return h trading days ahead (h = 5, 10, 20), the volatility (standard deviation) of the daily return in those periods, or a measure of the serial-correlation of the stock return (the R2 of the regression of the daily stock return on its 3 lags) in those periods, *Leakage* is a dummy variable equal to one for the 1,408 events and μ represents short seller fixed-effects.

By estimating equation 4 with short-seller fixed-effects, we are comparing what happens with future returns after a given skilled short-seller borrows an abnormal volume with a broker in two situations: when he is perceived by the broker as skilled, what increases the chances of a leakage, and when he is not.

Table 8 reports the results when y refers to cumulative returns. When we look at the 5-day window after the event, stock prices drop more when the chances of leakage are higher. However, when we look at the 10- and 20-day windows, we see no significant difference. Taken together, these results indicate that the leakage simply makes stock prices to drop faster.

[Table 8 about here.]

Table 9 reports the results for the daily return volatility. According to the results, when information is leaked, stocks become about 10 percent less volatile in the near future: considering the 20-day ahead window, the volatility is about 0.024 for events with no leakage and 0.022 for events with leakage.

[Table 9 about here.]

Finally, Table 10 reports the results for the daily return serial-correlation. As occurs with volatility, our measure of serial correlation (the R2 of the regression of the daily stock return on its 3 lags) is about 10 percent lower for events with possible leakage.

[Table 10 about here.]

These results indicate that the leakage does not affect the new price level 20 days ahead of the event, but affects how the stock price reaches its new level. When information is leaked, price efficiency seems to be higher.

4.7 Robustness

In Section 3 we had to make assumptions to define informed short-selling events. Our assumption choices were guided to identify bets made by informed short sellers that would likely be salient to brokers. We made reasonable and well-intended assumptions. However, we know there are other ways to define these events, and this section shows that our main results are robust to alternative definitions.

As discussed in Section 3, salient and informed short-selling events occur when an informed short seller builds an unusually large short position. Two crucial assumptions are behind the definition of informed short sellers. First, we require these investors to be skilled short sellers, and second, we require them to be active market participants.

To identify skilled short sellers from a broker's perspective, we considered investors with a record of outperforming the market when short selling. Specifically, we looked at all security loans made by a short seller with a particular broker. On a 90-day rolling window, we estimated the probability of beating the market in the 20 trading days after shorting, which is the average duration of security loans. If this probability was statistically greater than 50% with 10% confidence (i.e., t-statistic > 1.64), we classified that short seller as skilled from the perspective of that broker. However, the broker could be less selective when defining the skill of a short seller. Our results still hold if we consider a lower critical value. For example, if we use a critical value of 1, the total number of informed short-selling events increases to 1,981. Columns 1 and 4 of Table 11 estimate Equation (2) for these less selective events. We again find a negative and significant β_3. Compared to Table 4, the point estimates and the t-statistics decrease, which is consistent with relying on slightly less skilled short sellers to construct informed short-selling events.

[Table 11 about here.]

When focusing on active short sellers, we also imposed that the average volume of securities borrowed is above R$100,000 (US$ 29,325). Intuitively, this volume is large enough for the short-seller to be noticed by the broker. However, in our sample, there are 1,155,939 security loans above this cutoff, an average of 11,795 borrows per broker or about 245 per broker each month. Arguably, it is tricky to keep track of all of them. As robustness, we apply more conservative cutoffs to redefine informed short-selling events. Specifically, we use R$250,000 and R$1,000,000 as alternative cutoff values and report the results for our main specification, Equation (2), in Columns 2, 3, 5, and 6 of Table 11. For R$250,000 cutoff (columns 2 and 5), the number of events decreases from 1,408 to 980, and in both columns, β_3 is significant at the 10% level. However, when we use R$1,000,000 in Columns 3 and 6, the number of events reduces to 407, and β_3 is significant only in column 6 (at 5%). The lower significance is due to a higher standard error of the estimates, not because of lower point estimates. This is consistent with lower statistical power as the cutoff increases, reducing the number of events.[13]

4.7.1 Evidence of leakage not using events

We have focused on short-selling events to document information leakage by brokers to their clients. However, all trading activity by short sellers is potentially informative and likely to provide insightful trading signals. For example, Rapach, Ringgenberg, and Zhou (2016) find that short interest is a strong predictor of aggregate stock returns, and even the absence of short selling can be used as a bullish signal as shown by Boehmer, Huszar, and Jordan (2010).

This subsection documents broader evidence consistent with security lending desks sharing information with investors. We show that investors connected to more lending desks make better trading decisions when compared to investors connected to fewer lending desks, controlling for a number of variables. Our results hold for both sales and buying decisions.

Our evidence is based on investor-stock-day panel regressions considering all trades in the centralized stock market by the 463 institutions that engage in stock-picking (1,170,985 purchases

[13]Another aspect of an active short seller is to have borrowed securities at least 10 times with a given broker in the previous 90 days. In untabulated results, we find that our results are robust to using short sellers with longer or shorter track records.

and 1,084,054 sales). We regress risk-adjusted returns τ days after a buying day, $ret_{i,s,t}(\tau)$, on $NumberDesks_{i,t}$, a variable that indicates the number of different lending desks that institution i is connected on day t. We say an institution is connected to a broker if it either borrowed or lent any stock using that broker over the past six months. In our sample, the average value of $NumberDesks_{i,t}$ is 3.59, the standard deviation of 5.38, the median is 1, the 25th percentile is 0, and the 75th percentile is 5.

[Table 12 about here.]

We measure performance over the following horizons: $\tau = 5$, $\tau = 10$, $\tau = 21$, and $\tau = 63$ trading days. A buying day is a day when the institution purchases any amount of the stock, not selling any shares. We define a selling day similarly, but the performance measure after a selling day is multiplied by minus one to capture the gains from selling. To compare institutions that are similar to each other, we include several controls: (i) the log of the volume traded by institution i on stock s on day t, (ii) the log of the average number of stocks traded by institution i during our sample period, (iii) the log the average volume traded by institution i during our sample period; additionally, we include as controls the log of the total volume shorted on stock s on day t, the log the total volume traded on stock s on day t, stocks fixed effects, μ_s, and day fixed effects, μ_t. More specifically, we run

$$ret_{i,s,t}(\tau) = \beta \times NumberDesks_{i,t} + Controls_{i,s,t} + \mu_t + \mu_s + \epsilon_{i,s,t} \tag{5}$$

Table 12 shows the results. Returns are in percentage points, and standard errors double clustered by day and by stock. The estimates of β are positive and statistically significant at all horizons and for both sales and purchases. Considering purchases and the five-day horizon regression, $\tau = 5$, we find that one additional connection with a security lending desk increases the performance by 0.91% (0.91% = 0.018% $\times$ 252/5) in annualized risk-adjusted returns. At longer horizons, the magnitudes are 0.73% at $\tau = 10$, 0.40% at $\tau = 21$, and 0.18% at $\tau = 63$. Considering selling decisions, the magnitudes are 0.86% at $\tau = 5$, 0.53% at $\tau = 10$, and 0.31% at $\tau = 21$. At $\tau = 63$, the coefficient is not statistically different from zero. The fact that the information superiority is stronger at shorter horizons is consistent with the evidence that most short sellers are informed about short-term price changes.[14]

5 Conclusion

In this paper, we examine how the information from short sellers is transmitted to other investors. Specifically, we document a channel largely unexplored by the literature: information leakage through the security lending market. This is an over-the-counter market in which transactions are not anonymous to the broker intermediating contracts. We find that a broker, who intermediates a large security lending contract to a skilled short seller, leaks information to its clients. We find evidence that this relation is not due to trading comovement among clients of the same broker. We also show evidence that the information leakage is intentional and makes the clients receiving the information more loyal to the broker providing the information.

[14]See, for instance, Diether, Lee, and Werner (2009), and Chague, De-Losso, and Giovannetti (2019) for further evidence based on the same dataset used in this paper.

References

Aitken, M. J., Frino, A., McCorry, M. S., Swan, P. L., 1998. Short Sales Are Almost Instantaneously Bad News: Evidence from the Australian Stock Exchange. Journal of Finance 53, 2205–2223.

Asquith, P., Pathak, P. A., Ritter, J. R., 2005. Short interest, institutional ownership, and stock returns. Journal of Financial Economics 78, 243–276.

Babus, A., Kondor, P., 2018. Trading and Information Diffusion in Over-the-Counter Markets. Econometrica 86, 1727–1769.

Barber, B. M., Odean, T., 2008. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. Review of Financial Studies 21, 785–818.

Barbon, A., Di Maggio, M., Franzoni, F., Landier, A., 2019. Brokers and Order Flow Leakage: Evidence from Fire Sales. The Journal of Finance 74, 2707–2749.

Boehmer, E., Huszar, Z. R., Jordan, B. D., 2010. The good news in short interest. Journal of Financial Economics 96, 80–97, bibtex: BoehmerHuszarJordan2010.

Boehmer, E., Huszár, Z. R., Wang, Y., Zhang, X., Zhang, X., 2022. Can Shorts Predict Returns? A Global Perspective. The Review of Financial Studies 35, 2428–2463.

Boehmer, E., Jones, C. M., Zhang, X., 2008. Which Shorts Are Informed? The Journal of Finance 63, 491–527, bibtex: BoehmerJonesZhang2008.

Boehmer, E., Wu, J. J., 2013. Short Selling and the Price Discovery Process. Review of Financial Studies 26, 287–322.

Bris, A., Goetzmann, W. N., Zhu, N., 2007. Efficiency and the Bear: Short Sales and Markets Around the World. The Journal of Finance 62, 1029–1079, bibtex: Bris.Goetzmann.Zhu2007.

Cereda, F., Chague, F., De-Losso, R., Genaro, A., Giovannetti, B., 2022. Price transparency in OTC equity lending markets: Evidence from a loan fee benchmark. Journal of Financial Economics 143, 569–592.

Chague, F., De-Losso, R., Genaro, A., Giovannetti, B., 2017. Well-connected short-sellers pay lower loan fees: A market-wide analysis. Journal of Financial Economics 123, 646–670.

Chague, F., De-Losso, R., Giovannetti, B., 2019. The short-selling skill of institutions and individuals. Journal of Banking & Finance 101, 77–91.

Chen, S., Kaniel, R., Opp, C. C., 2022. Market power in the securities lending market. Available at SSRN 4100699 .

Christophe, S. E., Ferri, M. G., Angel, J. J., 2004. Short-Selling Prior to Earnings Announcements. The Journal of Finance 59, 1845–1876.

Christophe, S. E., Ferri, M. G., Hsieh, J., 2010. Informed trading before analyst downgrades: Evidence from short sellers. Journal of Financial Economics 95, 85–106, bibtex: ChristopheFerriHsieh2010.

Di Maggio, M., Franzoni, F., Kermani, A., Sommavilla, C., 2019. The relevance of broker networks for information diffusion in the stock market. Journal of Financial Economics 134, 419–446.

Diether, K. B., Lee, K.-H., Werner, I. M., 2009. Short-Sale Strategies and Return Predictability. Review of Financial Studies 22, 575–607, bibtex: DietherLeeWerner2009.

Drechsler, I., Drechsler, Q. F., 2014. The shorting premium and asset pricing anomalies. Tech. rep., National Bureau of Economic Research.

Duffie, D., Malamud, S., Manso, G., 2009. Information Percolation With Equilibrium Search Dynamics. Econometrica 77, 1513–1574.

Duffie, D., Malamud, S., Manso, G., 2014. Information percolation in segmented markets. Journal of Economic Theory 153, 1–32.

Duong, T. X., Huszár, Z. R., Tan, R. S. K., Zhang, W., 2017. The Information Value of Stock Lending Fees: Are Lenders Price Takers?*. Review of Finance 21, 2353–2377.

Engelberg, J. E., Reed, A. V., Ringgenberg, M. C., 2012. How are shorts informed?: Short sellers, news, and information processing. Journal of Financial Economics 105, 260–278, bibtex: EngelbergReedRinggenberg2012.

Figlewski, S., 1981. The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence. Journal of Financial and Quantitative Analysis 16, 463–476.

Gargano, A., Sotes-Paladino, J., Verwijmeren, P., 2022a. Out of Sync: Dispersed Short Selling and the Correction of Mispricing. Journal of Financial and Quantitative Analysis pp. 1–73.

Gargano, A., Sotes-Paladino, J., Verwijmeren, P., 2022b. Short of capital: Stock market implications of short sellers' losses. Working Paper .

Karpoff, J. M., Lou, X., 2010. Short Sellers and Financial Misconduct. The Journal of Finance 65, 1879–1913, bibtex: KarpoffLou2010.

Rapach, D. E., Ringgenberg, M. C., Zhou, G., 2016. Short interest and aggregate stock returns. Journal of Financial Economics 121, 46–65.

Saffi, P. A. C., Sigurdsson, K., 2011. Price Efficiency and Short Selling. Review of Financial Studies 24, 821–852, bibtex: SaffiSigurdsson2011.

Seneca, J. J., 1967. Short Interest: Bearish or Bullish?*. Journal of Finance 22, 67–70.

Walden, J., 2019. Trading, Profits, and Volatility in a Dynamic Information Network Model. Review of Economic Studies 86, 2248–2283.

Appendix

A Additional Figures

[Figure 7 about here.]

Figures

Figure 1: Stock price around the event

This figure shows average the cumulative risk-adjusted stock returns 21 trading days before and after the day of the event.

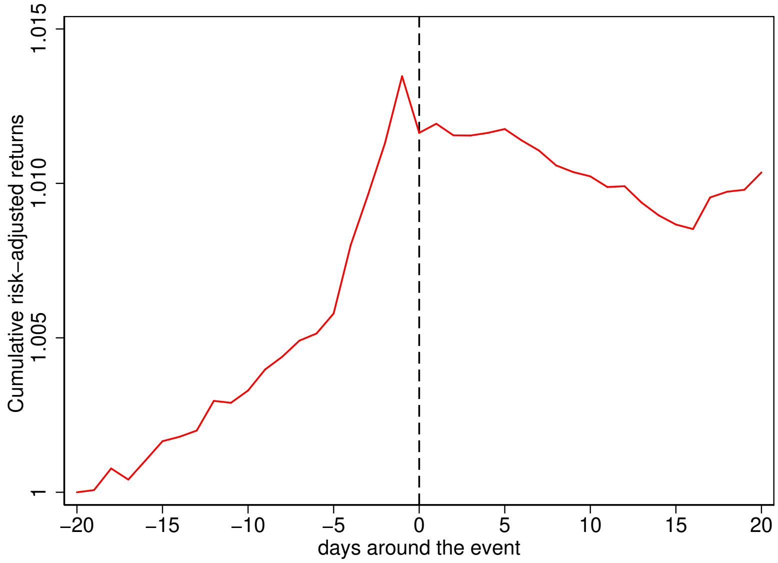
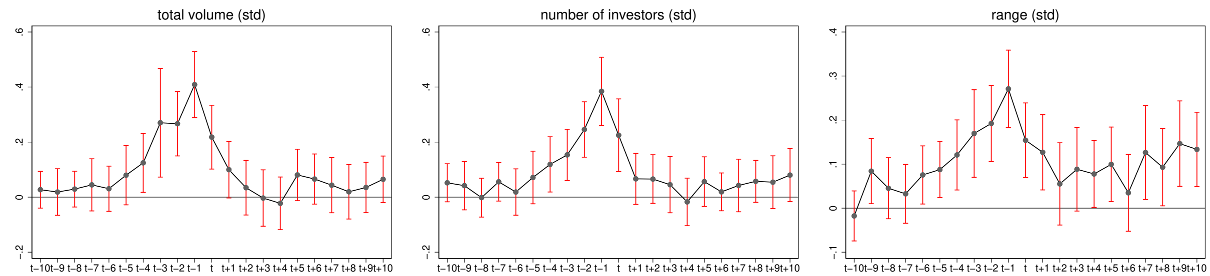


Figure 2: Stock trading around the event

Panel A shows the standardized total trading volume (purchases plus sales) 10 days before and 10 days after the events. The points indicate the daily average standardized total volume, and the red intervals indicate a 95% confidence interval. Panel B shows the standardized number of different investors trading the stock, and Panel C the standardized range, where the range is computed as the maximum price minus the minimum price in a day divided by the average of the two. All variables are standardized with respect to the mean and standard deviation computed over the previous 3 months. We exclude from the analysis all day-trades (i.e., investors who purchased and sold the same stock, in the same quantities, on a day).



(a) Total Volume (b) Number of Investors (c) Range

Figure 3: Importance of the 463 stock-pickers in the stock market volume

This figure shows the daily proportion of the trading volume by the 463 stock-pickers from 2015 to 2018. To compute this time-series, we do as follows. For each investor-stock-day, we compute q, which is the number of shares purchased minus the number of shares sold (since we have a market-wide data set, the sum of q across all investors in the dataset within a pair stock-day is always 0). We then compute $|q|$, the absolute value of q. Within each stock-day, we then aggregate $|q|$ across all investors ($|q|_{all}$) and aggregate $|q|$ across the 463 stock-pickers ($|q|_{sp}$). For each stock-day we then compute $\pi = |q|_{sp} \, / \, |q|_{all}$. This figure plots for each day the average of π across all stocks.

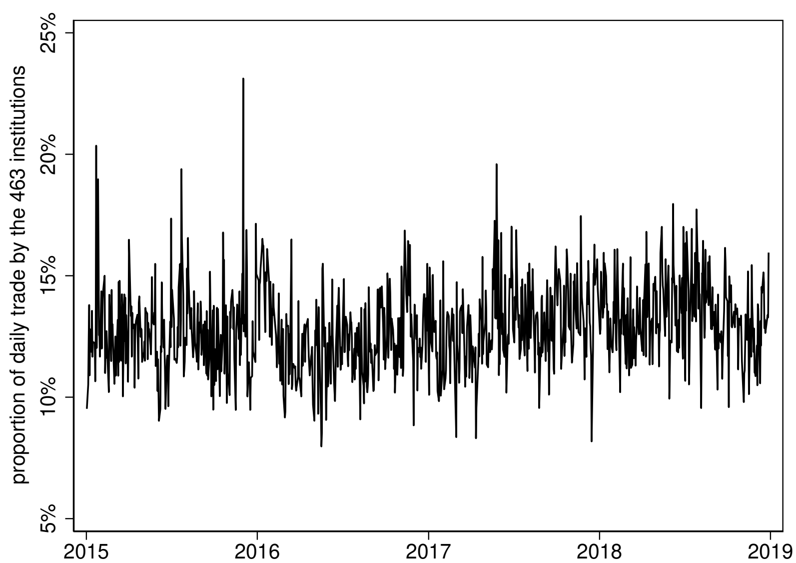
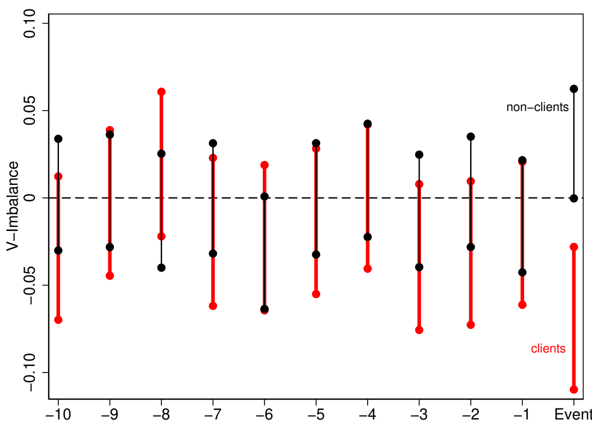
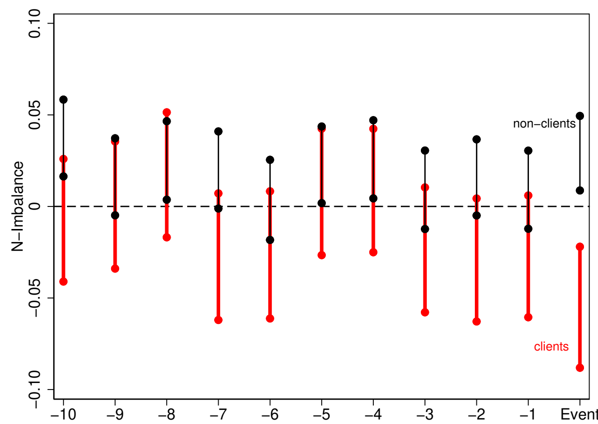


Figure 4: Trading imbalances 10 days before event vs. event day

This figure shows the trading behavior of stock-pickers before and on the day of the event, separating stock-pickers into clients and not clients of the broker involved in the event.The variable in Panel A is $VImbalance = \frac{VBuy-VSell}{VBuy+VSell}$, where $VBuy$ ($VSell$) is the total volume of the stock involved in the event purchased (sold) in the centralized stock market each day. The variable in Panel B is $NImbalance = \frac{NBuy-NSell}{NBuy+NSell}$, where $NBuy$ ($NSell$) is the number of different stock-pickers who purchased (sold) the stock involved in the event in the centralized stock market each day. We compute $VImbalance$ and $NImbalance$, which range from -1 (only sales) to +1 (only purchases), for each event and each day (10 days before the event and the event day) and then compute the 95% confidence interval for each day across all 1,408 events.



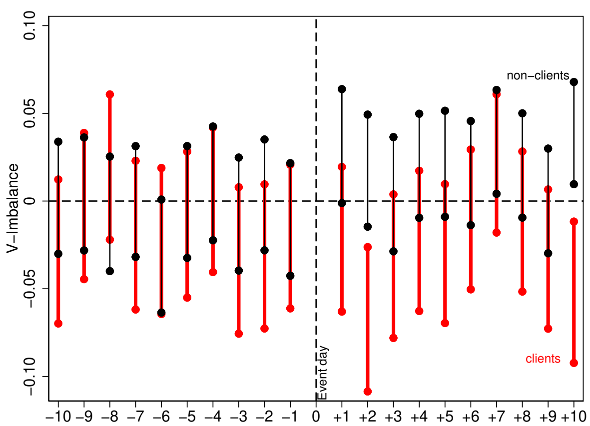
(a) $VImbalance$



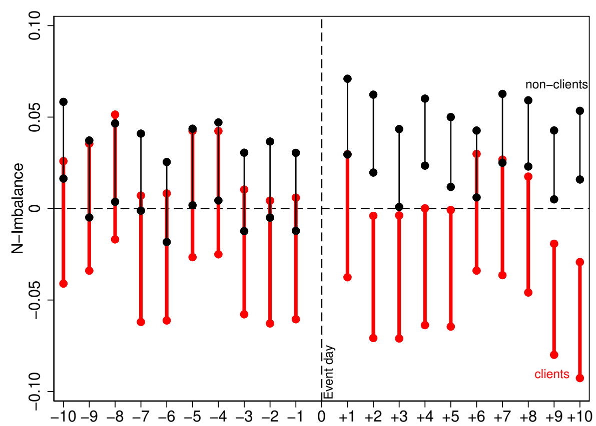
(b) $NImbalance$

Figure 5: Trading imbalances 10 days before event vs. 10 days after event

This figure shows the trading behavior of stock-pickers 10 days before the event and 10 days after the event, separating stock-pickers into clients and not clients of the broker involved in the event.The variable in Panel A is $VImbalance = \frac{VBuy-VSell}{VBuy+VSell}$, where $VBuy$ ($VSell$) is the total volume of the stock involved in the event purchased (sold) in the centralized stock market each day. The variable in Panel B is $NImbalance = \frac{NBuy-NSell}{NBuy+NSell}$, where $NBuy$ ($NSell$) is the number of different stock-pickers who purchased (sold) the stock involved in the event in the centralized stock market each day. We compute $VImbalance$ and $NImbalance$, which range from -1 (only sales) to +1 (only purchases), for each event and each day (10 days before the event and 10 days after the event) and then compute the 95% confidence interval for each day across all 1,408 events.



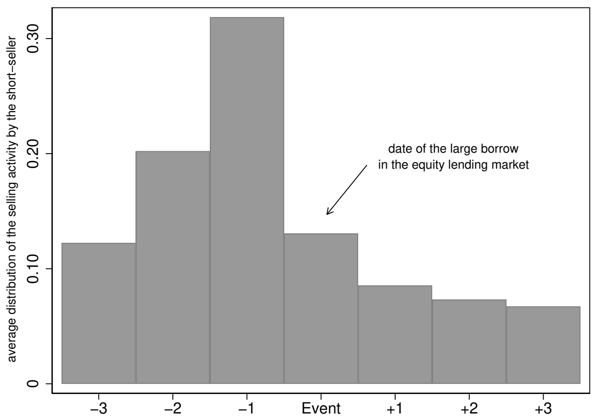
(a) $VImbalance$



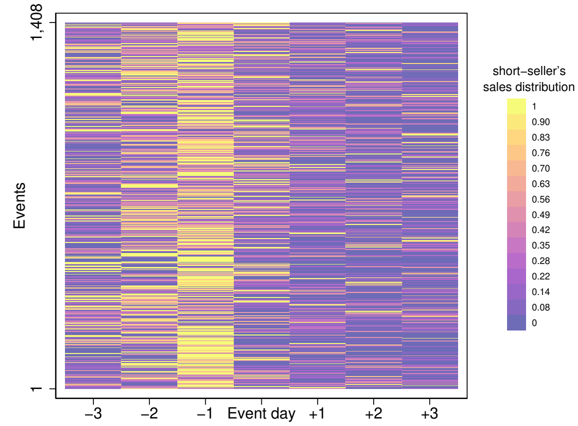
(b) $NImbalance$

Figure 6: Average distribution of the selling activity by short sellers around the event date

This figure shows distribution of the selling activity in the centralized stock market by the short sellers responsible for the events. We compute for each event the total volume sold by the short seller in the centralized stock market on the 7 days around the event (3 days before, the event day, and 3 days after). In Panel A, we plot for each day the average of this proportion across all informed short-selling events, and in Panel B, we plot the distribution as a heatmap.



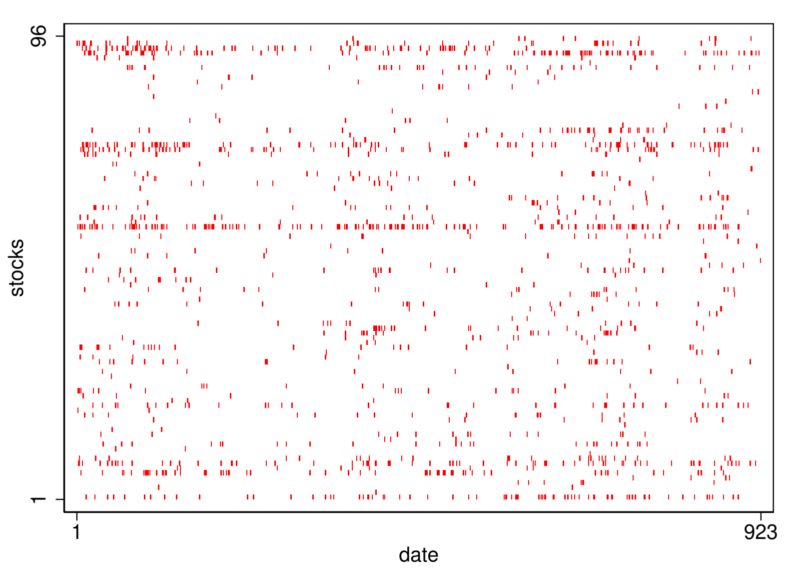
(a) Histogram



(b) Heatmap

Figure 7: The distribution of the 1,408 events across stocks and time

This figure presents the matrix of the distribution of the 1,408 events across stocks and time.



Tables

Table 1: Distributions of $VImbalance$ and $NImbalance$

This table shows the distributions of the trading imbalances variables ($VImbalance^c$, $VImbalance^n$, $NImbalance^c$, and $NImbalance^n$) across the event-day (non-missing) observations. There are 1,408 events and 11 days (10 days before the event and the day of the event).

	obs. (1)	mean (2)	std. (3)	min. (4)	pct 25 (5)	pct 50 (6)	pct 75 (7)	max (8)
$VImbalance^c$	13,226	-0.02	0.79	-1	-0.88	-0.05	0.85	1
$VImbalance^n$	15,370	-0.01	0.61	-1	-0.53	-0.01	0.53	1
$NImbalance^c$	13,226	-0.01	0.65	-1	-0.50	0	0.50	1
$NImbalance^n$	15,370	0.02	0.40	-1	-0.23	0	0.29	1

Table 2: Difference-in-differences regressions: 10 days before the event vs. the day of the event

This table shows the estimates of difference-in-differences regressions. For each event-day, we have variables for the stock-pickers who are clients of the broker involved in the event and for the stock-pickers that are not clients of the broker. Days include the 10 days before the event and the day of the event. $VImbalance$ goes from -1 (all volume traded by stock-pickers was on the selling side) to +1 (all volume traded by stock-pickers was on the buying side) and $NImbalance$ also goes from -1 (all stock-pickers who traded on the day sold the stock) to +1 (all stock-pickers who traded on the day purchased the stock). *Clients* is one for clients of the brokers. *EventDay* is one for the day of the event. Standard-errors are double-clustered by event and by stock and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$VImbalance$		$NImbalance$	
	(1)	(2)	(3)	(4)
Clients	-0.012	-0.010	-0.029**	-0.028**
	(-0.81)	(-0.74)	(-2.57)	(-2.44)
EventDay	0.035**	0.035**	0.010	0.011
	(2.00)	(2.03)	(1.06)	(1.07)
Clients × *EventDay*	-0.089***	-0.089***	-0.054***	-0.054***
	(-3.16)	(-3.12)	(-3.28)	(-3.27)
Constant	-0.004	-0.004	0.018**	0.018***
	(-0.36)	(-0.63)	(2.21)	(3.32)
Event F.E.		✓		✓
Obs	28,596	28,596	28,596	28,596
Adj-R2	0.01	0.07	0.01	0.09

Table 3: Difference-in-differences regressions: 10 days before the event vs. 10 days after the event

This table shows the estimates of difference-in-differences regressions. For each event-day, we have variables for the stock-pickers who are clients of the broker involved in the event and for the stock-pickers that are not clients of the broker. Days include the 10 days before the event and the 10 days following the event. We exclude the day of the event. $VImbalance$ goes from -1 (all volume traded by stock-pickers was on the selling side) to +1 (all volume traded by stock-pickers was on the buying side) and $NImbalance$ also goes from -1 (all stock-pickers who traded on the day sold the stock) to +1 (all stock-pickers who traded on the day purchased the stock). $Clients$ is one for clients of the brokers. $After$ is one for the 10 days after the event. Standard-errors are double-clustered by event and by stock and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$VImbalance$		$NImbalance$	
	(1)	(2)	(3)	(4)
$Clients$	-0.012	-0.011	-0.029**	-0.030**
	(-0.81)	(-0.78)	(-2.57)	(-2.53)
$After$	0.023***	0.022**	0.017***	0.017***
	(2.76)	(2.47)	(3.00)	(2.81)
$Clients \times After$	-0.037*	-0.037*	-0.034**	-0.033**
	(-1.85)	(-1.84)	(-2.21)	(-2.16)
$Constant$	-0.004	-0.004	0.018**	0.019***
	(-0.36)	(-0.63)	(2.21)	(3.41)
Event F.E.		✓		✓
Obs	43,326	43,326	43,326	43,326
Adj-R2	0.01	0.06	0.02	0.07

Table 4: Controlling the dif-in-dif regression for the selling dynamics of the short seller

This table shows the estimates of difference-in-differences regressions. For each event-day, we have variables for the stock-pickers who are clients of the broker involved in the event and for the stock-pickers that are not clients of the broker. Days include the 3 days before the event, the day of the event, and the 3 days following the event. $VImbalance$ goes from -1 (all volume traded by stock-pickers was on the selling side) to +1 (all volume traded by stock-pickers was on the buying side) and $NImbalance$ also goes from -1 (all stock-pickers who traded on the day sold the stock) to +1 (all stock-pickers who traded on the day purchased the stock). $Clients$ is one for clients of the brokers. $After$ is one for the day of the event and the following 3 days. π is the proportion on each day of the total volume sold by the short seller responsible for the event in the centralized stock market during the 7-day period. Standard-errors are double-clustered by event and by stock and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$VImbalance$		$NImbalance$	
	(1)	(2)	(3)	(4)
$Clients$	0.010	0.009	-0.016	-0.019
	(0.58)	(0.51)	(-1.20)	(-1.32)
$After$	0.029***	0.028***	0.022***	0.022***
	(2.69)	(2.70)	(2.66)	(2.67)
$Clients \times After$	-0.066***	-0.066***	-0.043***	-0.043***
	(-3.03)	(-3.13)	(-2.65)	(-2.72)
π	0.023	0.024	-0.018	-0.017
	(0.94)	(0.97)	(-1.01)	(-0.96)
$Clients \times \pi$	-0.156***	-0.158***	-0.099***	-0.099***
	(-5.26)	(-5.49)	(-4.43)	(-4.55)
$Constant$	-0.009	-0.009	0.015	0.016**
	(-0.70)	(-0.76)	(1.69)	(2.04)
Event F.E.		✓		✓
Obs	18,211	18,211	18,211	18,211
Adj-R2	0.01	0.09	0.01	0.10

Table 5: Events by unskilled short sellers

This table shows the estimates of difference-in-differences regressions. Events are now produced by unskilled short sellers. For each event-day, we have variables for the stock-pickers who are clients of the broker involved in the event and for the stock-pickers that are not clients of the broker. Days include the 3 days before the event, the day of the event, and the 3 days following the event. $VImbalance$ goes from -1 (all volume traded by stock-pickers was on the selling side) to +1 (all volume traded by stock-pickers was on the buying side) and $NImbalance$ also goes from -1 (all stock-pickers who traded on the day sold the stock) to +1 (all stock-pickers who traded on the day purchased the stock). $Clients$ is one for clients of the brokers. $After$ is one for the day of the event and the following 3 days. π is the proportion on each day of the total volume sold by the short seller responsible for the event in the centralized stock market during the 7-day period. Standard-errors are double-clustered by event and by stock and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$VImbalance$		$NImbalance$	
	(1)	(2)	(3)	(4)
$Clients$	-0.026	-0.025	-0.029	-0.030
	(-1.01)	(-0.94)	(-1.47)	(-1.51)
$After$	-0.012	-0.012	0.009	0.008
	(-0.73)	(-0.73)	(0.86)	(0.83)
$Clients \times After$	0.005	0.003	-0.012	-0.012
	(0.26)	(0.13)	(-0.72)	(-0.80)
π	-0.032	-0.033	-0.057***	-0.057***
	(-1.08)	(-1.08)	(-2.90)	(-2.92)
$Clients \times \pi$	-0.084*	-0.085*	-0.027	-0.027
	(-1.72)	(-1.73)	(-0.72)	(-0.72)
$Constant$	0.019	0.019	0.024*	0.025**
	(1.03)	(1.30)	(1.93)	(2.58)
Event F.E.		✓		✓
Obs	12,537	12,537	12,537	12,537
Adj-R2	0.01	0.09	0.01	0.09

Table 6: Trading behavior of investors who trade more stocks per day

This table shows the estimates of difference-in-differences regressions. Events are again the 1,408 produced by skilled short sellers. However, now we study the trading behavior around the events of investors who trade more than 10 stock per day (median) considering the days they trade. For each event-day, we have variables for these investors who are clients of the broker involved in the event and for the ones that are not clients of the broker. Days include the 3 days before the event, the day of the event, and the 3 days following the event. $VImbalance$ goes from -1 (all volume traded by these investors was on the selling side) to +1 (all volume traded by these investors was on the buying side) and $NImbalance$ also goes from -1 (all these investors who traded on the day sold the stock) to +1 (all these investors who traded on the day purchased the stock). $Clients$ is one for clients of the brokers. $After$ is one for the day of the event and the following 3 days. π is the proportion on each day of the total volume sold by the short seller responsible for the event in the centralized stock market during the 7-day period. Standard-errors are double-clustered by event and by stock and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$VImbalance$		$NImbalance$	
	(1)	(2)	(3)	(4)
$Clients$	0.009	0.008	-0.017*	-0.017*
	(0.51)	(0.46)	(-1.72)	(-1.71)
$After$	0.007	0.007	0.012**	0.012**
	(0.89)	(0.89)	(2.26)	(2.26)
$Clients \times After$	-0.007	-0.008	-0.008	-0.008
	(-0.45)	(-0.49)	(-0.77)	(-0.82)
π	0.028	0.028	-0.006	-0.006
	(1.61)	(1.61)	(-0.70)	(-0.70)
$Clients \times \pi$	-0.102***	-0.099***	-0.087***	-0.085***
	(-3.34)	(-3.27)	(-5.01)	(-4.89)
$Constant$	-0.023**	-0.023***	0.002	0.002
	(-2.97)	(-2.73)	(0.38)	(0.41)
Event F.E.		✓		✓
Obs	19,108	19,108	19,108	19,108
Adj-R2	0.01	0.07	0.01	0.08

Table 7: Why do brokers leak information?

This table shows the estimates of equation 3. The dependent variable is $Loyalty_t = \frac{Vol_t^b}{Vol_t}$, where Vol_t^b is the total volume borrowed and lent by the investor using the broker under the event in period t and Vol_t is the total volume borrowed and lent by the investor using any broker in period t. This variable is computed for all stock-pickers who potentially received the information leakage from a broker about an event and also for all short sellers whose borrowing activity was potentially leaked. t is defined as $t = \{-2, -1, 0, +1\}$ where $t = -2$ refers to the 90-day period from days -180 to -91 prior to the event date, $t = -1$ refers to the 90-day period from days -90 to -1, $t = 0$ refers to the 90-day period from days 0 to +89 after the event date, and $t = +1$ refers to the 90-day period from days +90 to +179. $After$ is one for $t = 0, 1$. Standard-errors are clustered by event-investor and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Loyalty of Stock Pickers		Loyalty of Short Sellers	
	(1)	(2)	(3)	(4)
t	0.018***	0.011*	0.024***	0.019***
	(2.63)	(1.80)	(3.00	(2.66)
$After$	0.019	0.026**	0.015	0.012
	(1.31)	(2.06)	(0.89)	(0.83)
$Constant$	0.245***	0.238***	0.447***	0.446***
	(16.74)	(27.96)	(24.25)	(44.97)
Event-investor F.E.		✓		✓
Obs	2,724	2,724	2,399	2,399
Adj-R2	0.01	0.78	0.01	0.80

Table 8: Effect of the leakage on future returns

This table shows the effect of a potential leakage on the cumulative return using a cross-section regression across events. The observations are the 1,408 events used throughout the paper plus other 487 events. In these 487 events the short-seller is skilled considering all his shorting deals in the last 90 days (in all brokers) but, looking only at his deals inside the broker of the event, his shorting skill is not significantly different from zero. That is, in these 487 events, the broker does not perceive the short-seller who is shorting an abnormal volume to be skilled. The dummy *Leakage* is equal to one for the 1,408 events and equal to zero for the 487 events. Standard errors are clustered by event-investor and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Cumulative return					
	5 days ahead		10 days ahead		20 days ahead	
$Leakage = 1$	-0.005*	-0.008**	0.001	-0.001	0.001	-0.001
	(-1.71)	(-2.04)	(0.17)	(-0.28)	(0.21)	(-0.09)
Constant	0.003	0.005	-0.002	-0.004	0.001	0.001
	(1.17)	(1.63)	(-0.60)	(-0.11)	(0.01)	(0.24)
Short-seller F.E.		✓		✓		✓
Obs	1,895	1,895	1,895	1,895	1,895	1,895
Adj-R2	0.01	0.26	0.00	0.27	0.00	0.32

Table 9: Effect of the leakage on volatility

This table shows the effect of a potential leakage on the return volatility (standard deviation of daily returns) using a cross-section regression across events. The observations are the 1,408 events used throughout the paper plus other 487 events. In these 487 events the short-seller is skilled considering all his shorting deals in the last 90 days (in all brokers) but, looking only at his deals inside the broker of the event, his shorting skill is not significantly different from zero. That is, in these 487 events, the broker does not perceive the short-seller who is shorting an abnormal volume to be skilled. The dummy *Leakage* is equal to one for the 1,408 events and equal to zero for the 487 events. Standard errors are clustered by event-investor and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Volatility					
	5 days ahead		10 days ahead		20 days ahead	
$Leakage = 1$	-0.002***	-0.002***	-0.002***	-0.002***	-0.001**	-0.002***
	(-2.64)	(-2.57)	(-2.60)	(-2.66)	(-2.53)	(-2.86)
Constant	0.023***	0.023***	0.024***	0.024***	0.024***	0.024***
	(36.72)	(31.62)	(45.32)	(39.33)	(52.14)	(44.62)
Short-seller F.E.		✓		✓		✓
Obs	1,895	1,895	1,895	1,895	1,895	1,895
Adj-R2	0.01	0.32	0.01	0.33	0.01	0.37

Table 10: Effect of the leakage on return serial-correlation

This table shows the effect of a potential leakage on the return serial-correlation (the R2 of the regression of the daily return on its 3 lags) using a cross-section regression across events. The observations are the 1,408 events used throughout the paper plus other 487 events. In these 487 events the short-seller is skilled considering all his shorting deals in the last 90 days (in all brokers) but, looking only at his deals inside the broker of the event, his shorting skill is not significantly different from zero. That is, in these 487 events, the broker does not perceive the short-seller who is shorting an abnormal volume to be skilled. The dummy *Leakage* is equal to one for the 1,408 events and equal to zero for the 487 events. Standard errors are clustered by event-investor and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Return serial-correlation					
	5 days ahead		10 days ahead		20 days ahead	
$Leakage = 1$	-0.026**	-0.002	-0.032***	-0.023*	-0.016***	-0.012*
	(-1.97)	(-0.09)	(-3.21)	(-1.76)	(-2.86)	(-1.69)
Constant	0.704***	0.686***	0.328	0.323	0.169	0.167
	(64.07)	(50.49)	(38.34)	(30.30)	(34.66)	(28.04)
Short-seller F.E.		✓		✓		✓
Obs	1,895	1,895	1,895	1,895	1,895	1,895
Adj-R2	0.05	0.27	0.01	0.26	0.01	0.24

Table 11: Alternative informed short-selling events

This table shows the estimates of difference-in-differences regressions. Events are now produced by unskilled short sellers. For each event-day, we have variables for the stock-pickers who are clients of the broker involved in the event and for the stock-pickers that are not clients of the broker. Days include the 3 days before the event, the day of the event, and the 3 days following the event. $VImbalance$ goes from -1 (all volume traded by stock-pickers was on the selling side) to +1 (all volume traded by stock-pickers was on the buying side) and $NImbalance$ also goes from -1 (all stock-pickers who traded on the day sold the stock) to +1 (all stock-pickers who traded on the day purchased the stock). $Clients$ is one for clients of the brokers. $After$ is one for the day of the event and the following 3 days. π is the proportion on each day of the total volume sold by the short seller responsible for the event in the centralized stock market during the 7-day period. Standard-errors are double-clustered by event and by stock and the t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$VImbalance$			$NImbalance$		
	(1)	(2)	(3)	(4)	(5)	(6)
Alternative events:	t-stat > 1 1,981 events	$AV >$ R\$250k 980 events	$AV >$ R\$1M 407 events	t-stat > 1 1,981 events	$AV >$ R\$250k 980 events	$AV >$ R\$1M 407 events
$Clients$	-0.009	-0.025	-0.015	-0.033**	-0.039**	-0.034
	(-0.60)	(-1.20)	(-0.45)	(-2.38)	(-2.37)	(-1.35)
$After$	0.008	0.019	-0.008	0.014*	0.014	-0.006
	(0.77)	(1.42)	(-0.37)	(1.94)	(1.55)	(-0.46)
$Clients \times After$	-0.031**	-0.045*	-0.041	-0.036***	-0.027*	-0.047**
	(-2.00)	(-1.94)	(-1.44)	(-2.98)	(-1.80)	(-2.47)
π	-0.005	-0.005	0.021	-0.031*	-0.004	-0.019
	(-0.22)	(-0.19)	(0.55)	(-1.92)	(-0.20)	(-0.82)
$Clients \times \pi$	-0.117***	-0.061	-0.137**	-0.068***	-0.071**	-0.086*
	(-3.78)	(-1.54)	(-2.23)	(-3.18)	(-2.45)	(-1.92)
$Constant$	-0.001	0.008	0.015	0.024***	0.022**	0.041***
	(-0.13)	(0.65)	(0.69)	(3.17)	(2.52)	(2.71)
Event F.E.	✓	✓	✓	✓	✓	✓
Obs	25,550	12,757	5,410	25,550	12,757	5,410
Adj-R2	0.08	0.09	0.09	0.10	0.10	0.09

Table 12: Investor performance with multiple lending desks

This table show investor-stock-day (i-s-t) panel regressions of risk-adjusted returns τ days after a buying day, $ret_{i,s,t}(\tau)$, on $NumberDesks_{i,t}$, a variable that indicates the number of different lending desks that investor i is connected on day t. We say an investor is connected to a broker if she either borrowed or lent any stock using the broker over the past six months. We measure performance over the following horizons: $\tau = 5$, $\tau = 10$, $\tau = 21$, and $\tau = 63$ trading days. We include the controls: (i) the log of the volume traded by the investor i on stock s on day t, (ii) the log of the average number of stocks traded by the investor i during our sample periods, (iii) the log the average volume traded by the investor i during our sample period, (iv) the log of the total volume shorted on stock s on day t, (v) the log the total volume traded on stock s on day t. Additionally, we include stocks fixed effects, and day fixed effects. Only stock pickers are included, i.e., investors who (i) are institutional investors, who (ii) frequently trade by buying or selling securities at least once a week on average, (iii) frequently borrow securities by engaging in security lending contacts at least once a month on average, (iv) make relatively large trading bets, i.e., a traded volume of at least R$100,000 daily when trading, and finally, (v) trade at most 10 different stocks traded on the median trading day. Returns are in percentage points and standard errors double clustered by day and by stock. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Purchases				Sales			
	$\tau = 5$	$\tau = 10$	$\tau = 21$	$\tau = 63$	$\tau = 5$	$\tau = 10$	$\tau = 21$	$\tau = 63$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NumberDesks_{i,t}$	0.018***	0.029***	0.033***	0.045**	0.017***	0.021***	0.026***	0.021
	(0.004)	(0.006)	(0.009)	(0.019)	(0.003)	(0.004)	(0.006)	(0.013)
$Volume_{i,s,t}$	-0.021***	-0.020*	-0.011	-0.063*	-0.026***	-0.017*	-0.001	0.031
	(0.007)	(0.011)	(0.018)	(0.037)	(0.007)	(0.010)	(0.014)	(0.030)
$Trades_i$	-0.013	-0.017	0.001	-0.016	-0.013	-0.020	-0.017	-0.020
	(0.012)	(0.018)	(0.026)	(0.059)	(0.012)	(0.019)	(0.030)	(0.067)
$AvgVolume_i$	0.029***	0.029***	0.013	0.032	0.032***	0.017	0.001	0.001
	(0.009)	(0.014)	(0.024)	(0.051)	(0.009)	(0.013)	(0.021)	(0.045)
$NumberStocks_i$	-0.030	-0.060	-0.064	-0.234	-0.097***	-0.108**	-0.106	-0.096
	(0.034)	(0.056)	(0.096)	(0.208)	(0.031)	(0.042)	(0.070)	(0.153)
$Volume_{s,t}$	-0.037	-0.198**	-0.400**	-1.706***	0.120*	0.271***	0.657***	1.884***
	(0.059)	(0.095)	(0.160)	(0.430)	(0.067)	(0.101)	(0.168)	(0.473)
$ShortVolume_{s,t}$	-0.219***	-0.383***	-0.740***	-1.983***	0.193***	0.344***	0.657***	1.850***
	(0.065)	(0.110)	(0.209)	(0.608)	(0.066)	(0.117)	(0.218)	(0.588)
Adj-R2	3.12%	4.11%	6.03%	13.79%	3.09%	3.97%	5.82%	5.82%
Obs	1,170,985	1,170,985	1,170,985	1,170,985	1,084,054	1,084,054	1,084,054	1,084,054