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INFORMATION LEAKAGE FROM SHORT SELLERS

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ABSTRACT

Using granular data on the entire Brazilian securities lending market merged with all trades in the centralized stock exchange, we identify information leakage from short sellers. Our identification strategy explores trading execution mismatches between short sellers' selling activity in the centralized exchange and borrowing activity in the over-the-counter securities lending market. We document that brokers learn about informed directional bets by intermediating securities lending agreements and leak that information to their clients. We find evidence that the information leakage is intentional and that brokers benefit from it. We also study leakage effects on stock prices.

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1 Introduction

There is extensive literature documenting that short sellers are informed investors and that they play a critical role in the price discovery process.[1] However, it is still unclear how their valuable information is disseminated to other market participants. When short selling, investors borrow and sell securities, but these steps happen in different markets. Short selling requires investors to operate both in an over-the-counter (OTC) market to borrow securities and in the centralized exchange to sell them. The OTC nature of securities lending means that a short seller needs to directly contact a broker to borrow securities, which reveals to the broker not only the identity of the short seller but also a short-selling position in the making. We document that brokers actively explore this information, leaking the ongoing shorting bet to their other clients depending on how well-informed they believe the short seller is. We use the securities' selling-borrowing trade execution mismatch to control for trading comovement across market participants, ruling out the possibility that the short seller and the other clients of the broker are trading in response to a common information signal.

The richness of our data and the institutional features of the securities lending market allow us to identify information leakage through brokers, establish brokers' intent, study how they benefit from the leakages, and investigate leakage effects on stock prices. We use two unique datasets. The first is contract-level data for the entire Brazilian OTC securities lending market, and the second includes all transactions realized by all investors in the Brazilian stock market at a daily frequency. Both datasets cover the same sample period,

[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 (2018), Rapach, Ringgenberg, and Zhou (2016), and Boehmer et al. (2022). For a detailed review of the short-selling literature, see Reed (2013) and Jiang, Habib, and Hasan (2022), and references therein.

from 2015 to 2018, and by merging these data, we observe every investor's securities lending agreements paired with their trading activity. Our data give us a detailed and complete picture of all short-selling and trading activity in Brazil at a daily frequency.[2]

Our empirical analysis proceeds as follows. First, we characterize informed securities lending events as moments in which directional bets made by short sellers perceived as skilled become salient to brokers. Notably, a broker knows the track record of all its clients in the OTC securities lending market and can screen for skilled short sellers based on their past performance. Hence, we define an informed securities lending event from a broker's perspective when one of its skilled short-seller clients borrows an unusually large number of shares. These events are broker-specific for a particular stock on a given day. This borrowing activity is salient to the broker because such an event is a pivotal moment when a skilled short seller is revealed to be fully committed to a sizeable directional bet. This is valuable information that the broker intermediating the securities lending agreement gets to observe firsthand. In our baseline analysis, we identify 1,404 informed securities lending events over a four-year period across 53 different brokers.

Second, we characterize how institutions trade around informed securities lending events to identify information leakage. Specifically, we analyze the trading behavior of 463 institutions equipped to promptly short sell assets upon receiving information about informed securities lending events. These institutions frequently engage in short selling and do not trade many different stocks per day — these filters are designed to rule out index funds, factor investors, market makers, and algorithmic-based trading. Intuitively, these 463 institutions are stock-pickers who value information about an informed securities lending event

[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). However, merging both datasets to pair all loans and trading deals is unprecedented.

the most and are likely to trade on it to add value to their portfolios.

We analyze how clients of an informed broker trade compared to nonclients of the same broker. For each informed securities lending event, we compute trading imbalance measures, which capture investors' propensity to buy or sell the stock involved in the event. For clients of a broker, the trading imbalance of a particular stock is the net volume bought by all the broker's clients relative to their gross volume bought and sold. We define trading imbalance for nonclients similarly. Trading imbalance measures how likely a group of investors is to buy or sell the stock on a particular day. A positive trading imbalance means that they increased their loadings on that stock, and when negative, it means their loadings decreased.

Through a differences-in-differences approach, we find that clients of the informed broker further reduce their loadings on the stock involved in the informed securities lending event relative to nonclients of that broker. We document that the net volume bought decreases more for clients than for nonclients of the informed broker when an informed securities lending event occurs. In our main specification, our estimates indicate that in the days prior to the event, clients and nonclients keep their positions unchanged in that stock, on average. On the event date, clients of the broker change their behavior and become net sellers, with their net volume sold representing 7.5% of their total gross traded volume. This means clients move towards a bearish-like behavior compared to nonclients on the same day their broker becomes aware of an informed securities lending event. The difference in trading behavior between clients and nonclients is statistically significant and economically large.

Crucial to our identification, we control for the commonality in trading behavior across clients of the same broker. 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 not related to any information leakage. We can directly rule out this possibility. In Brazil, security loans are settled on a same-day basis, but settlement in the stock market occurs three business days after the trade is executed.[3] Different settlement periods between securities lending agreements and trades on centralized exchanges create distinct trading dynamics in these markets. Specifically, 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 of the short seller's bet. In our regression specifications, we can then 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, isolating the effects of the information flow coming exclusively from OTC securities lending market through brokers.

Third, we document that 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 securities lending being an OTC market. The search process of locating securities involves contacting some of its clients and possibly other brokers, which might tip off investors about the existence of a sizable shorting bet. This becomes evident when the broker needs to locate a large volume of securities to borrow 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 securities lending markets.[4]

[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.

[4]Duong, Huszár, Tan, and Zhang (2017) present evidence that some security lenders react to the infor-

Our data allows us to rule out unintended information leakage. Crucially, only the broker knows the short seller identity and track record. Hence, if the leak is unintentional, a securities lending agreement from a skilled or unskilled short seller should lead to the same information leakage. To investigate brokers' intentions, we conduct our empirical exercise focusing on securities lending events generated by short sellers who are perceived as unskilled by the broker. These are investors with a poor track record within the broker, and we call these events uninformed securities lending events. We find that trading behavior between clients and nonclients is indistinguishable when the broker becomes aware of securities lending events he believes to be uninformed. The fact that clients behave differently depending on the type of securities lending event is strong evidence of intentional information leakage.

Fourth, we document 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. We analyze the trading behavior of clients who sold the stock involved in the event but have not traded that security before the event—these clients were tipped off and started trading the security only after the informed securities lending event. We find that, in the subsequent months after the event, these clients bring more business to the broker by engaging in more security borrowing and lending with that broker.

Finally, we investigate how information leakage affects stock prices. To do so, we compare the behavior of stock returns after our benchmark 1,404 informed securities lending events against how stocks behave after another similar group of events. In the second group, an informed short seller also borrows a large volume of shares, but the broker does not know that the short seller is skilled. To construct the second group of events, we classify a short

mation gathered at the securities lending markets.

seller as skilled by considering all its shorting deals in the previous 90 days across *all* brokers. However, by looking only at deals made with the broker of the event, the short seller's track record is not significantly different from zero. There are 562 events in the second group in which the broker does not have evidence that a skilled short seller triggered the event. We first show that, also consistent with the intentional leakage hypothesis, there is no evidence of leakage in these 562 events. Then, by comparing stock prices behavior following both types of events using short-seller fixed effects, we show that the leakage leads to a faster drop in stock prices, lower stock return volatility and lower serial correlation.

We contribute to various strands of literature. The market structure of securities lending implies that brokers are among the first institutions to learn about the short position being made. We are the first to shed light on how brokers play a crucial role in the ways in which information from short sellers gets transmitted to other investors.

Closest to our work is recent literature investigating the role of brokers in information transmission. This area of research has not studied information leaked from short sellers, though. For instance, Di Maggio, Franzoni, Kermani, and Sommavilla (2019) explore the network between 360 managers and 30 brokers, showing that central brokers share information from institutional investors with their best clients. Additionally, Barbon, Di Maggio, Franzoni, and Landier (2019) document that brokers spread information about 385 large portfolio liquidations, and they find brokers sharing information about the upcoming order flows with their best clients.

We contribute to this area of research for various reasons. First, we provide evidence of information leakage from the securities lending market directly controlling for trading comovement among clients of the same broker. This is only possible because we explore the interplay between two drastically different market structures: OTC securities lending and the centralized stock exchange. Our identification strategy is new as we leverage the mismatch between short sellers' selling and borrowing activity to identify information leakage. Second, we show that the information leakage is intentional. Brokers actively share information about ongoing shorting bets depending on how well-informed they believe the short seller is. Third, we measure the broker's gains from information leakage. Fourth, due to our comprehensive data on the entire Brazilian market, we document that information leakage has implications for asset prices, increasing efficiency and accelerating price discovery.

Our paper also 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. Consistent with our findings, there is specific evidence that short sellers contribute to price discovery.[5] Chen, Kaniel, and Opp (2022) document several non-competitive features in securities lending markets and estimate a dynamic model with asymmetric information. Another recent theoretical framework is the work by Gârleanu, Panageas, and Zheng (2021). They develop a model in which short selling is unstable in equilibrium, and short sellers may exit the market in response to the arrival of overoptimistic investors. Recently, several papers have focused on short-selling costs and their implications for asset prices. Evgeniou, Hugonnier, and Prieto (2022) study the effect of short-selling cost in a general equilibrium model with heterogeneous beliefs, while Drechsler and Drechsler (2018) and Muravyev, Pearson, and Pollet (2022) investigate the relationship between short-selling fees

[5]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.

and asset pricing anomalies.[6] We contribute to this literature on information dissemination from short selling by documenting an important channel through which prices incorporate short sellers' information. Specifically, we explore brokers' role in transmitting short sellers' information.

Finally, our work relates to a literature examining how market structures affect the price discovery process. Allen and Wittwer (2023) use trade-level data on the Canadian government bond market to study the transition of trades from OTC to a centralized platform. They consider that investors may value close relationships with dealers, something that our paper helps to explain. Ahern (2017, 2020) studies information transmission in illegal insider trading networks. Duffie, Malamud, and Manso (2009, 2014) develop a model in which individuals have to search for information that helps understand how information eventually percolates to stock prices. Babus and Kondor (2018) propose a model to examine information diffusion in over-the-counter markets. 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. We contribute to this literature by providing the first direct evidence of information leakage through the securities lending market. Moreover, different from previous studies, our identification explores a mismatch between short sellers' selling and borrowing activity, allowing us to control for trading comovement among investors who are clients of the same broker.

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

[6] Also, 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.

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 securities 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 complete 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,[7] 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 securities lending market, we have granular contract-level data. For each securities lending agreement, 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 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 92% 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

[7] *Comissão de Valores Mobiliários.*

traded volume in the OTC securities lending market is 31% of the daily volume traded in the centralized market, 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 in the OTC securities lending market.

3 Informed securities lending 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 predicts future returns, not all short-sellers are informed.[8] Therefore, we first identify investors who are potentially informed short sellers from the perspective of the broker. Then, we define the informed securities lending events.

We say that a broker perceives an investor as an informed short seller if the investor has a good recent 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 Brazilian Real, which is about US$29,325 U.S. dollars using the average exchange rate at the time,[9] and (ii) in the same previous 90 days, the probability of a stock borrowed by the investor sub-

[8]See, for instance, Boehmer, Jones, and Zhang, 2008, Chague, De-Losso, and Giovannetti, 2019, and Gargano, Sotes-Paladino, and Verwijmeren, 2022b

[9]In our sample, the average exchange rate is R$3.41 Brazilian Real per U.S. dollar.

sequently 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.[10]

Finally, we define an informed securities lending 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 securities lending 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 1,404 informed securities lending events, which is 351 events per year on average. They occur across 96 stocks and 53 brokers from a total of 98 brokers that operate in the Brazilian securities lending market in our sample period. There are 461 different investors responsible for these 1,404 borrows — 143 individuals, responsible for 239 borrows, and 318 institutions, responsible for 1,165 borrows. With respect to the volume borrowed by each investor in each event, the minimum is R$166,144, which is US$48,722 using the average exchange rate at the time. The 25^{th}, 50^{th} and 75^{th} percentiles are R$1,026,160 (US$300,921), R$2,528,475 (US$741,475), and R$8,043,186 (US$2,358,665), respectively. The largest lending agreement among all informed securities lending events is R$720,356,501, which is about US$211.24 million. These events are well-distributed over time, with 358 occurring in 2015, 296 in 2016, 323 in 2017, and 427 in 2018. Figure 1 plots a

[10] Results are robust to changes in these parameters as we show in Section 4.6.1. The 90-window is the same window used in Chague, De-Losso, Genaro, and Giovannetti (2017).

matrix of the events to allow clear visualization of their distribution across stocks and over time.

[Figure 1 about here.]

3.1 Characterizing informed securities lending events

To contextualize the 1,404 informed securities lending events, we analyze the behavior of some market variables around these events. First, we look at what happens to stock prices in a one-month window. To do so, we accumulate the excess returns in the 40 trading days around each event (20 days before, 20 days after). Then, we take the daily average across all 1,404 events. As Figure 2 indicates, the events usually occur after consistent price increases, with increases accelerating in the few days preceding the event day. In contrast, prices revert over the subsequent days after the event. That is, the informed securities lending events contain valuable negative information about the future performance of the stock.[11]

[Figure 2 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 is the difference between the maximum and minimum trading prices divided by the average of the two, and is a proxy for daily volatility. To obtain comparable measures across stocks and over time, we standardize these variables relative to their values observed three months

[11] 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).

before the event day. We report their average around the event dates in Figure 3 and find that, before the events, the stocks experience a higher trading volume, a higher number of investors trading them, and a higher price volatility.

[Figure 3 about here.]

We also examine whether the events coincide with the disclosure of relevant pieces of news. We find a disproportionally large fraction of earnings announcements around the events. In 575 of the 1,404 events, we see an earnings announcement between days t-21 and t+5 of the event. Moreover, in another 198 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 typical event, we see an abnormally higher volume, increased price volatility, a higher number of investors trading and more information being disclosed. This suggests that the firm can be 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: evidence and incentives

In the previous section, we identified informed securities lending events in which brokers see unusually large bets made by informed short sellers. We showed that these events are valuable sources of information. They are a strong signal about the performance of the stock going forward and they are precisely when the broker intermediating a securities lending agreement learns about an informed short position in the midst of its implementation. Moreover, the short seller generating the event is not just testing waters. By design, these are large lending agreements in which the short seller reveals to the broker as fully committed to a sizeable directional bet. The question is what brokers do with this information. In this section, we show that brokers actively share information about securities lending events with their clients, who are equipped to promptly sell assets upon receiving the information.

Section 4.1 describes our empirical specification and provides a first-pass evidence of information leakage. Section 4.2 discusses in detail our identification strategy and contains our main results which control for trading comovement between clients of the same broker. Then, in Section 4.3, we document that the information leakage is intentional. Section 4.4 quantifies broker's gains from leaking information, and Section 4.5 documents the effects of information leakage on stock prices. Finally, Section 4.6 provides several robustness exercises.

4.1 How do institutions trade around informed securities lending events?

To answer this question, we characterize the trading behavior of clients and nonclients of a broker around informed securities lending events before and after the broker becomes aware of the event. Our data contain every single market participant. Next, in Section 4.1.1, we characterize which investors are likely to trade based on information received from their broker. These are going to be institutions that engage in short selling and can act quickly after acquiring information about potential trading opportunities. Then, in Section 4.1.2, we define imbalance measures that characterize trading behavior of investors, and we implement a differences-in-differences approach to compare trading pattern differences between clients and nonclients of the event broker before and after a securities lending event.

4.1.1 Institutions likely to receive information

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 securities lending event. These institutions should trade frequently, engage in short selling, trade non negligible volumes, and likely rely on stock-picking strategies by not trading many 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 (US$29,325) considering the days the institution trades, and iv) trade at most 10 different stocks on the median day the institution trades.[12]

In our sample, 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 4 plots this fraction from 2015 to 2018, which ranges from 8.0% to 23.1% over time.

[Figure 4 about here.]

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

[12]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).

brokers from the securities lending market on average. The minimum number of brokers used is 1, the median is 6, and the maximum is 38.

We also measure their trading performance T days after their stock purchases and sales.[13] 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 1,165 informed securities lending events and 143 individuals were responsible for the remaining 239 events. Out of these 318 institutions, 156 are among the 463 institutions classified as those equipped to promptly short sell assets upon receiving information.

Next, we analyze the trading pattern of these institutions around securities lending events. Specifically, we compare clients versus nonclient of an event broker, before and on the date of the securities lending event.

4.1.2 First-pass evidence

Figure 2 shows that a broker aware of an informed securities lending event has valuable information about the future performance of the event stock as that stock is expected to underperform in the subsequent days after the event. The broker learns about the event

[13] 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 $y \times exret \times (|v| \,/\, |v|_{tot})$.

ahead of other market participants. It knows about it even before that short position is incorporated into the stock-level short interest, which is publicly reported daily.[14] Therefore, on the event day, the broker lending to the informed short seller learns about the informed short-selling bet before others.

We begin by comparing the differences in trading patterns between clients and nonclients of the event broker through a differences-in-differences approach. We measure the difference in trading patterns on the event day relative to the 10 days prior. The first evidence of information leakage by the broker is 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 $\nu = (s, b, l, \tau)$ be an informed securities lending event intermediated by broker b and generated by short seller l 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 securities 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 securities lending event from the imbalance measures. For nonclients, $VImbalance^{n}_{\nu,t}$ follows the same

[14]On the day following an informed securities lending event, the volume shorted gets incorporated into the total short interest of the stock and publicly disclosed to all market participants.

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 nonclients.

[Table 1 about here.]

Figure 5 shows the 95% confidence interval of the average imbalance for clients and nonclients across all informed securities lending 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 already 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 5 about here.]

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

$$y_{\nu,t}^{j} = \beta_0 + \beta_1 Clients_{\nu,t}^{j} + \beta_2 EventDay_{\nu,t}^{j} + \beta_3 Clients_{\nu,t}^{j} \times EventDay_{\nu,t}^{j} + \mu_{\nu} + \epsilon_{\nu,t}^{j}, \qquad (1)$$

where $y_{\nu,t}^{j}$ is either $VImbalance_{\nu,t}^{j}$ or $NImbalance_{\nu,t}^{j}$, the superscript j indicates whether the imbalance measure refers to clients or nonclients, the subscript $\nu = (s, b, l, \tau)$ indicates an informed securities lending event intermediated by broker b and generated by short seller l on security s and day τ. The variable $Clients_{\nu,t}^{j}$ is a dummy equal to one if $y_{\nu,t}^{j}$ refers to clients of the broker and zero if $y_{\nu,t}^{j}$ refers to nonclients of the broker, $EventDay_{\nu,t}^{j}$ is a dummy variable equal to one on the day of the event and zero on the days before the event, and μ_{ν} represents event fixed-effects.

Coefficient β_3 is our parameter of interest as it measures whether the change in $y_{\nu,t}^{j}$ on the day of the event compared to the previous 10 days is different between clients and nonclients of the broker. Importantly, Figure 5 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.

[Table 2 about here.]

Our estimates in Columns 1 and 2 indicate that in the ten days prior to the event, clients and nonclients keep their positions unchanged in that stock, on average, as β_0 and β_1 are both indistinguishable from zero. On the event date, nonclients of the broker become net buyers. They increase their position as their net volume bought represents 3% of their total gross volume traded, on average ($\beta_0 + \beta_2$). However, clients of the broker become net sellers, and their net volume sold represents 6.9% of their total gross traded volume ($\beta_0 + \beta_1 + \beta_2 + \beta_3$). This means clients move towards a bearish-like behavior compared to nonclients after their broker becomes aware of an informed securities lending event. The difference in trading behavior between clients and nonclients, which is 8.7% of their respective gross traded volume, is statistically significant and economically large (β_3).

We document the same trading pattern if we consider the trading imbalance in the number of institutions (columns 3 and 4). We find that $NImbalance$ decreases 5.4% more for clients than for nonclients.

4.2 Main identification: Controlling for trading comovement

The evidence presented in the previous section is consistent with brokers leaking information about informed securities lending events to their clients. However, if clients of a broker share common informational signals or strategies, then we can have comovement in their trading dynamics unrelated to information leakage. In our specific case, this could lead to trading comovement between the short seller generating the event and the other clients of the same broker. The specification in the previous section does not rule out this possible confounding effect, and therefore, it is vital to directly control for this alternative channel.

Our setting allows us to control for this possible trading comovement among clients of the same broker and, thus, correctly identify information leakage. This is only possible because we explore the interplay between two drastically different market structures: OTC securities lending and the centralized stock exchange.

In Brazil, the settlement in the OTC securities 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.[15] 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. Moreover, short-sellers may also be selling around the event stocks that are in their portfolios (before going short) or stocks that were borrowed with other brokers.

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

In our next estimates, we look at the 3 days before the event and the event day itself, consistent with the settlement window described earlier. First, we verify whether the short seller generating the event is indeed selling the bulk of the securities borrowed before actually borrowing them from the broker. For each day in this 4-day window, we compute the fraction between the total volume sold by the short seller in the centralized market and the volume borrowed by the short seller in the equity lending market on the day of the event with the broker of the event. The average of this variable across all events is 16.6%, 38.2%,

[15] 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.

and 46.0% for three, two and one day prior to the event date, respectively. Thus, in the three days before the events day, the short-seller generating an event has already sold a volume slightly larger than the volume being borrowed on the event day with the broker (16.6%+38.2%+46.0%=100.8%). On the event day, the short seller generating the event sells, on average, an additional 18.6% of the borrowed amount.

To control our regressions for the short seller selling dynamics, we compute for each event ν the total volume sold by the short seller in the centralized stock market during the 4-day period. 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 4 days. The dynamics of π varies across events, which we can see in Figure 6 as a heatmap of $\pi_{i,t}$ for each event and day.

[Figure 6 about here.]

As our main specification in the paper, we control for trading comovement among clients of the same broker by estimating the following regression on the 4-day period of each informed securities lending event:

$$
\begin{aligned}
y^j_{\nu,t} =& \beta_0 + \beta_1 Clients^j_{\nu,t} + \beta_2 EventDay^j_{\nu,t} + \beta_3 Clients^j_{\nu,t} \times EventDay^j_{\nu,t} \\
&+ \beta_4 \pi^j_{\nu,t} + \beta_5 Clients^j_{\nu,t} \times \pi^j_{\nu,t} + \mu_\nu + \epsilon^j_{\nu,t},
\end{aligned} \tag{2}
$$

where $\pi^j_{\nu,t}$ is the proportion sold in the centralized stock market by the short seller responsible for event i on each day t, the variable depicted in the heat-map of Figure 6. The other variables are the same as those in Equation (1).

By including $\pi^j_{\nu,t}$ and $Client^j_{\nu,t} \times \pi^j_{\nu,t}$ as controls in our specification, we allow for a direct comovement in the trading activity between the short seller generating the event and other clients of that broker, which is captured by $\beta_4 + \beta_5$. Our specification also allows for a possible direct comovement 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 received by the broker on the event day coming from the informed short seller abnormal borrowing activity in the OTC securities lending market.

Table 3 presents the estimation result of Equation (2). As expected, we document a significant comovement between the selling dynamics of the short seller and of the other clients of the broker ($\beta_4 + \beta_5$), in which the trading imbalance variables decrease when the short seller sells more (higher π). For instance, in column 2, the point estimate of 0.016 and -0.107 for β_4 and β_5, respectively, quantify such comovement. In this case, if the short seller concentrates its selling activity on a given day around the event (i.e., $\pi = 1$), the volume imbalance of the other clients of the same broker, which goes from -1 to 1, will be on average -0.091 ($= 0.016 - 0.107$) that day. The difference in comovement between the short seller and other clients is significantly different from its comovement with nonclients of the short seller's broker; that is, β_5 is significant across all specifications. Furthermore, we find no evidence of comovement between the selling dynamics of the short seller and nonclients of the broker (i.e., β_4 is not significant). These results confirm trading comovement between clients of the same broker and the importance of controlling the regression for π to identify information leakage.

[Table 3 about here.]

After controlling for π, we still conclude that the propensity of buying the stock on the event date decreases more for clients than for nonclients of the event broker. Our estimates indicate that in the three days prior to the event, clients and nonclients keep their positions unchanged in the stock (β_0 and β_1 are not significant). On the event date, however, only clients of the broker change their behavior, becoming net sellers: β_2 is not significant, and β_3 is significantly negative. The net volume clients sell on the event day represents 7.5% of their total gross traded volume. In terms of $NImbalance$, the difference between clients and nonclients on the event day is statistically significant and equal to -0.046. Thus, using either $VImbalance$ and $NImbalance$ measures, we find that clients become net sellers only when their broker learns about a securities lending event, even after controlling for trading comovement. These results show that brokers leak to their clients information acquired from securities lending.

4.3 Intentional or unintentional information leakage?

In this section, we document that the information leakage is consistent with intentional information sharing. We use two types of placebo securities lending events to establish intent. In the first type, a short seller engages in a sizeable securities lending agreement with a broker, but the short seller has a track record of poor performance with that broker. That is, from the broker's perspective, the short seller is unskilled, and the event itself is not informative. We call these events uninformed securities lending events. In the second type, the short seller has a solid track record of good performance with other brokers but not with the broker intermediating the large lending agreement. In this case, the short seller is skilled, but the broker does not know. We refer to the second type of event as under-the-radar informed securities lending events.

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 whenever 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 the broker's 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.

The first and second placebo securities lending events are subject to this subtle channel but not to intentional information leakage: only the broker knows the identity and track record of the short-seller. In fact, as we show ahead, we do not find evidence of information leakage in both types of events when the broker does not perceive the short seller as skilled, which is evidence of intentional leakage by brokers.

In our second placebo exercise, under-the-radar informed securities lending events rule out another alternative mechanism of information sharing. The informed short seller could directly share information about its position with other clients of the broker after borrowing securities. Investors directly approached by the short seller could be equipped to assess its skill and trade accordingly. If this were to be the case, we should find evidence of information leakage in under-the-radar informed securities lending events because those were generated by skilled short sellers, although the broker is likely unaware of the short seller's positive track record. We do not find evidence of information leakage in these events, which is another indication of intentional information leakage by the broker intermediating securities lending agreements.

4.3.1 Uniformed securities lending events

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

We use the same criteria from Section 3 to define uninformed securities lending events, but we now focus on events generated by unskilled short sellers. These are short sellers with a losing tracking record in the broker of the event. In the 90 days previous to the security loan, the probability that a stock borrowed by the investor with the broker of the event has 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 securities lending events. They occur across 86 stocks and 54 brokers. There are 363 different investors responsible for these events, 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 (US$807,804), a minimum of R$121,112 (US$35,516), and a maximum of R$1,366,205,012 (US$400,639,655). These volume figures are comparable to those observed in informed securities lending 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 as in the previous estimates, we then re-estimate Equation (2) around these 973 uninformed securities lending events. Table 4 presents the results. Differently from the previous section, we now find the estimate of β_3 to be statistically insignificant with close-to-zero point estimates. 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 4 about here.]

4.3.2 Under-the-radar informed securities lending events

In this second type of alternative event, we rule out not only intentional information leakage but also an information-sharing channel in which the skilled short seller could be responsible for the information leakage. This alternative information-sharing channel could generate the same results documented earlier if the skilled short seller directly shares its short position with other clients on the day of the lending agreement. In this case, the selling activity of the clients of the broker could increase more than the selling activity of the nonclients on the event day and afterward.

To rule out this alternative story and to provide additional evidence of intentional information leakage, we explore events when the short seller is skilled but the broker of the event does not have enough evidence of that. If the leakage comes directly from the short seller, we should still find similar results as reported in section 4.2 when we look at these different events. However, if the broker is responsible for the leakage, the results should be null since the broker does not have enough evidence to perceive the skilled short seller as skilled.

As in our definition of our baseline informed securities lending events, we require the investor to have borrowed securities from the broker at least 10 times in the previous 90 days, with an average borrowed volume of at least R$100,000 (US$29,325), and that the borrowed volume is the largest volume relative to all borrowing activity of that short seller in the previous 90 days. The only difference is that the t-statistic of success across the deals intermediated by the broker of the event is below 1, which does not give enough evidence to the broker that the short seller is skilled. However, if we consider all securities lending agreements of that short seller, including agreements intermediated by *other* brokers during that same 90-day period, then the t-statistic is above 1.64. That is, the short-seller is skilled, although the broker of the event does not have enough evidence of that.

There are 562 under-the-radar informed securities lending events. They occur across 73 stocks and 42 brokers. There are 130 different investors responsible for these events, out of which 3 are individuals and 127 are institutions. The volume borrowed by each investor in these events features a median of R$2,908,283 (US$852,868), a minimum of R$223,500 (US$65,542), and a maximum of R$382,620,000 (US$112,205,280). These volume figures are comparable to those observed in the 1,404 informed securities lending events and in the 973 uninformed securities lending events. The 562 under-the-radar informed securities lending events also spread over time, with 216 in 2015, 100 in 2016, 122 in 2017, and 124 in 2018.

Using the same group of clients and nonclients as in the previous estimates, we then re-estimate Equation (2) around these 562 events. Results are reported in Table 5. Consistent with the fact that brokers play a role in the information leakage, we find no significant estimates for the interaction term (β_3). This is additional evidence of intentional information leakage, and it also rules out direct information sharing from the short seller with other clients.

[Table 5 about here.]

4.4 Why do brokers leak information to clients?

An investor receiving information about an informed securities lending event may see this leakage as a valuable service offered by the broker. Indeed, as shown in Figure 2, the event stock is likely to underperform the market after the event. Specifically, short selling the asset after an informed securities lending event leads to roughly 50 basis points risk-adjusted returns in a 10-day window. The benefits from the investor receiving the information are clear.

From the perspective of the short seller generating an informed securities lending event, the information leakage is not necessarily detrimental. As discussed in Section 4.2, when the short seller borrows the stock, it has already sold the securities in the centralized stock market, on average, a volume equal to the volume borrowed. Given that short sellers secure their position before generating informed securities lending events, the information leakage does not necessarily compromise the short seller's performance. As a result, the broker benefits clients by leaking information to them without hurting the short seller who generated the event because, on average, the short seller who generated the event already sold the bulk of its position. Actually, the information leakage could even help the short seller by accelerating the price discovery process and subsequent price declines, as we study later in Section 4.5.

Overall, clients undoubtedly benefit from receiving such information and the 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 expect clients receiving the information to become more loyal to the broker leaking the information. However, we expect short sellers generating the event either to become more loyal or to remain neutral, depending on which of the aforementioned forces dominate.

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.[16] 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 1,404 informed securities lending events; in 549 of those, we observe at least one client who possibly received the event-related information from the event broker.

To evaluate loyalty dynamics, we compute for each event-investor pair, i, the gross volume borrowed and lent by an investor as a fraction of the total amount borrowed and lent by that investor across all brokers. This measure captures how much that investor relies on that particular broker when participating in the securities lending market. Formally, we define the following 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 event broker b in period t and $Vol_{i,t}$ is the total volume borrowed and lent by that investor across all brokers in period t. Because the securities lending market is an over-the-counter market with securities lending agreements sparsely closed over time, we look at a longer time frame. We consider periods of 90 days. 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.

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.

[16] There are clients who would have purchased the stock but received the information from the broker and decided call off the purchases. We cannot identify these investors.

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 also run the same regression with and without investor-event fixed effects. We estimate this relation across all event-investor pairs where the investor possibly received the information from the broker about an informed securities lending event. Table 6 presents these results in Columns (1) and (2). Considering the investors who received the information, we find that β_2 is positive and significant. Column (1) reports the estimates without fixed-effects while Column (2) estimates include investor-event fixed-effects. The estimated coefficient β_2 with fixed-effects is 0.026 (Column 2), and it is statistically significant. This indicates a discontinuous increase in their loyalty after the event. Specifically, investors who likely received information from a broker engaged in more future securities lending agreements with that broker, borrowing and lending an additional 2.6 percentage points of their gross volume after the event.

[Table 6 about here.]

In addition, we run this regression across all event-short-seller pairs as well. In this case, we look at the loyalty of the short seller who generated the informed securities lending event. We report those estimates in Columns (3) and (4) of Table 6. When considering the loyalty of the short sellers who generate an informed securities lending event, we find that β_2 is positive but not significant. This indicates that their loyalty after the event with the respective broker remains unchanged.

Our results indicate that institutions receiving information value the leakage and become more loyal to the broker. They engage in more securities lending agreements with those brokers. At the same time, short sellers generating informed securities lending events do not become more or less loyal to brokers leaking information.

4.5 The effects of the information leakage on stock prices

In this section, we investigate how information leakage affects stock prices. This is a critical question to improve our understanding of the price discovery process and its implications for market efficiency and asset pricing.

To measure the implications of information leakage for asset prices, we analyze the behavior of stock returns after informed securities lending events. Specifically, we compare two types of events generated by skilled short sellers. One is our baseline 1,404 informed securities lending events defined earlier in Section 3, in which the broker has evidence that the short seller generating the event is skilled. The second type is the 562 under-the-radar informed securities lending events discussed in Section 4.3.2. These 562 events are also generated by skilled short sellers, but the broker intermediating the lending agreements is unaware of the skill of the short seller triggering the event. As we showed in Section 4.3.2, there is no evidence of leakage when the event broker does not perceive the short seller generating the event as skilled. Hence, both types of events are informative about the future performance of the asset, but there is evidence of information leakage in only one of them. Comparing the differences in the behavior of stock returns in these two types of events allows us to measure the effects of information leakage.

Crucially, we employ short-seller fixed-effects in our analysis. Hence, in practice, we compare what happens with future returns after a given skilled short seller borrows an abnormal volume with a broker in two situations: when there is information leakage (because the broker perceives the short seller as skilled) versus when there is no leakage (because the broker does not perceive the short seller as skilled).[17]

[17] There are 461 different short-sellers among the 1,404 informed securities lending events and 130 among the 562 under-the-radar informed securities lending events. A total of 115 short sellers appear in both types of events.

We estimate the following cross-sectional regression across both types of events:

$$y_{\nu,h} = \beta_0 + \beta_1 Leakage_{\nu} + \mu_l + \epsilon_{\nu}, \tag{4}$$

where $y_{\nu,h}$ 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 measured by the R^2 of the regression of the daily stock return on its 3 lags. The subscript $\nu = (s, b, l, \tau)$ indicates an informed securities lending event intermediated by broker b and generated by short seller l on security s and day τ. The variable *Leakage* is a dummy variable equal to one when the event is one of our baseline 1,404 informed securities lending events and zero when the event is one of the 562 under-the-radar informed securities lending events, and μ_l represents short seller fixed-effects.

Overall, we find evidence that information leakage accelerates the price discovery process and improves efficiency. 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 there is leakage. However, we see no significant difference when we look at the 10- and 20-day windows. These results indicate that the leakage leads to a steeper decline in stock prices. Table 9 reports the results for the daily return volatility. According to these results, when information is leaked, stocks become about 10 percent less volatile in the near future. For instance, considering the 20-day ahead window, the volatility is about 0.024 for events with no leakage and 0.022 for events with leakage. Finally, Table 10 reports the results for the daily return serial correlation. As occurs with volatility, our measure of serial correlation, which is the R^2 of a regression of the daily stock return on its 3 lags, is about 10 percent lower for events with leakage.

[Table 7 about here.]

[Table 8 about here.]

[Table 9 about here.]

These results combined 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, prices adjust more quickly, volatility is lower, and the stock returns become less serially correlated. This is evidence that information leakage ends up making the price discovery process more efficient.

4.6 Robustness and placebo exercises

In this section, we conduct robustness and placebo exercises. First, in Section 4.6.1, we show that our benchmark results are robust to alternative definitions of informed securities lending events. Then, in Section 4.6.2, we show additional evidence of information leakage by documenting that investors connected to more trading desks make better trading decisions when buying or selling securities. Finally, in Section 4.6.3, we look at the trading behavior of investors who trade many stocks on a typical day (possibly index funds and market makers) and, as such, are less likely to trade based on leaked information from short sellers. Indeed, we find no evidence of leakage amongst this group of investors.

4.6.1 Different definition of informed securities lending events

In Section 3, we had to make assumptions to define our informed securities lending 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. Next, we show that our results are robust to these choices.

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 securities lending events increases to 1,982. Columns 1 and 4 of Table 10 estimate Equation (2) for these less selective events. We again find a negative and significant β_3. Compared to Table 3, the point estimates and the t-statistics decrease, which is consistent with relying on slightly less skilled short sellers to construct informed securities lending events.

[Table 10 about here.]

To focus on active short sellers, we imposed the average volume of securities borrowed to be above R$ 100,000 (US$ 29,325). Intuitively, this volume is large enough for a short-seller to be noticed by the broker. Results are also robust to lower cutoffs. For instance, if we set the cutoff to be R$ 50,000, we end up with 1,774 events and, as presented in columns 2 and 5 of Table 10, we also find a negative and significant β_3.

To focus on borrowing deals that are salient to the broker, our baseline 1,404 events were defined when one of the broker's skilled short sellers borrows a volume that is larger than the maximum volume borrowed by that investor with that broker in the previous 90 days. Results are also robust to lower cutoffs. For instance, if we require the volume to be larger than 50% of the maximum value, we end up with 4,728 events and, as presented in columns 3 and 6 of Table 10, we also find a negative and significant β_3.[18]

4.6.2 A non event-based analysis

Throughout our analysis, we have focused on informed securities lending 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 securities 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 as defined in Section 4.1.1. Their trades combined add to 1,170,985 purchases and 1,084,054 sales in our sample. 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

[18] 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.

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 11 about here.]

We measure risk-adjusted performance after buying and selling days 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 estimate the following regression:

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

Table 11 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 securities 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.[19]

4.6.3 Looking at institutions that trade many stocks per day

As discussed in Section 4.1.1, we have been studying the trading activity of 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 (US$ 29,325) per day with iv) a median number of different stocks traded per day of 10 or less. In this section, we look at the trading behavior around our baseline informed securities lending events of institutions that satisfy (i)-(iii) but display a median number of different stocks traded per day above 10. These are 158 institutions out of the 621 that 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 the baseline 1,404 informed securities lending 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 12 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

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

information leakage.

[Table 12 about here.]

5 Conclusion

In this paper, we examine how information from short sellers is transmitted to other investors. Specifically, we document a channel largely unexplored by the literature, which is information leakage through the securities lending market. This is an over-the-counter market in which transactions are not anonymous to the broker intermediating lending agreements. We find that a broker, intermediating a large securities lending agreement 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. Finally, we find the information leakage accelerates the price discovery process and makes it more efficient.

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Figures

Figure 1: The distribution of the 1,404 events across stocks and time

This figure presents the distribution of the 1,404 events across the 96 stocks and 923 days. A red mark represents the occurrence of an event for that stock on that day inside some brokerage house.

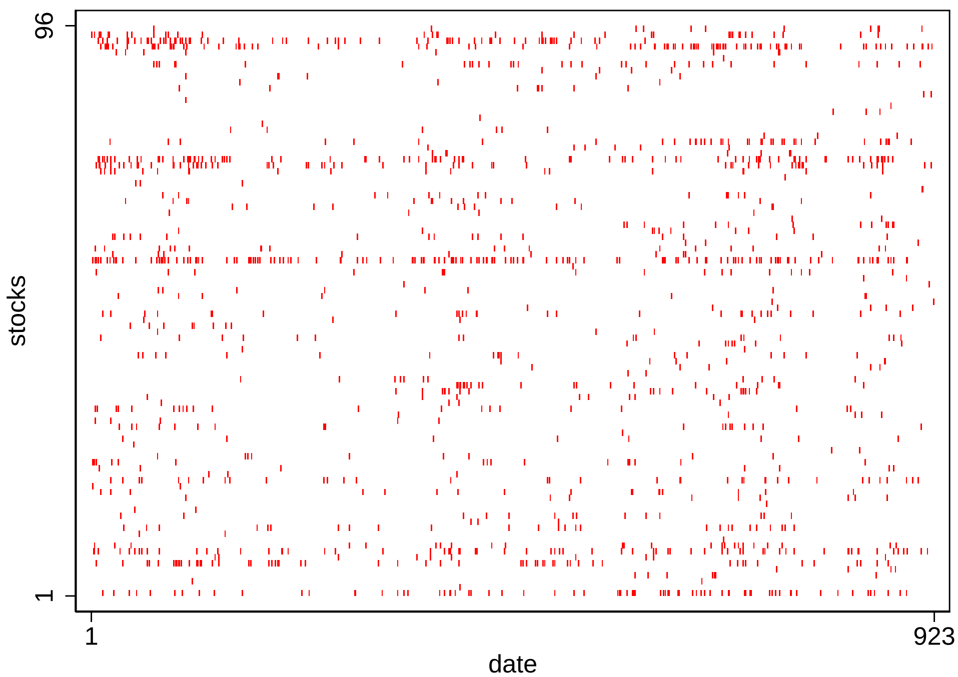


Figure 2: Stock price behavior around the events

This figure shows the 95% confidence band for the average behavior of the stock prices (normalized to 1) during the 40-day window around the 1,404 events. We use returns in excess to the market.

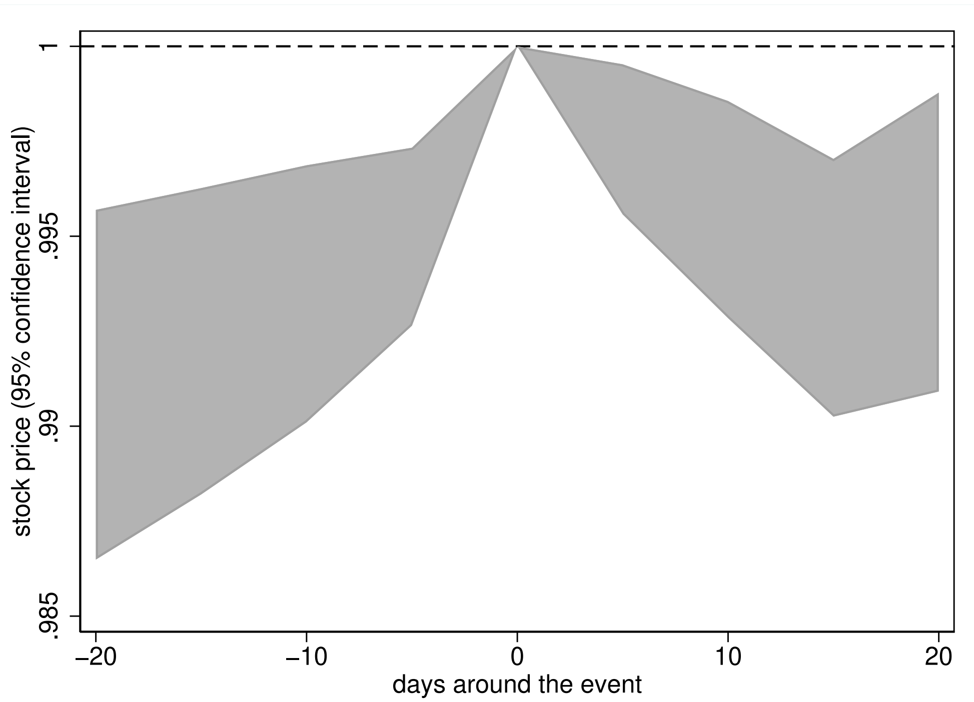
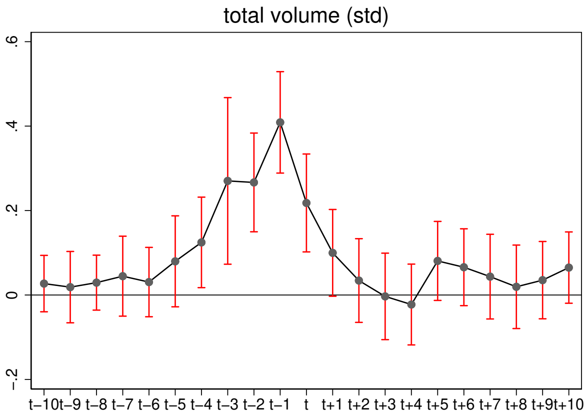
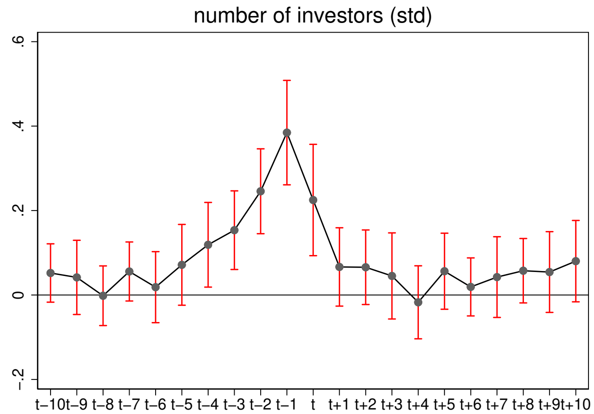


Figure 3: Stock trading around the events

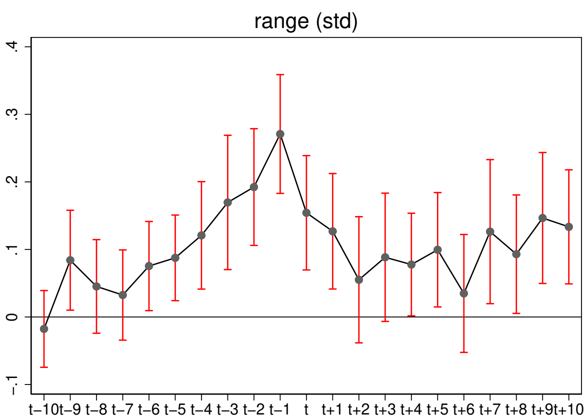
Panel A shows the standardized total trading volume (purchases plus sales) 10 days before and 10 days after the 1,404 events. The points indicate the daily average standardized total volume, and the red intervals indicate a 95% confidence interval. Panel B shows the standardized number of different investors 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.



(a) Total Volume



(b) Number of Investors



(c) Range

Figure 4: 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.

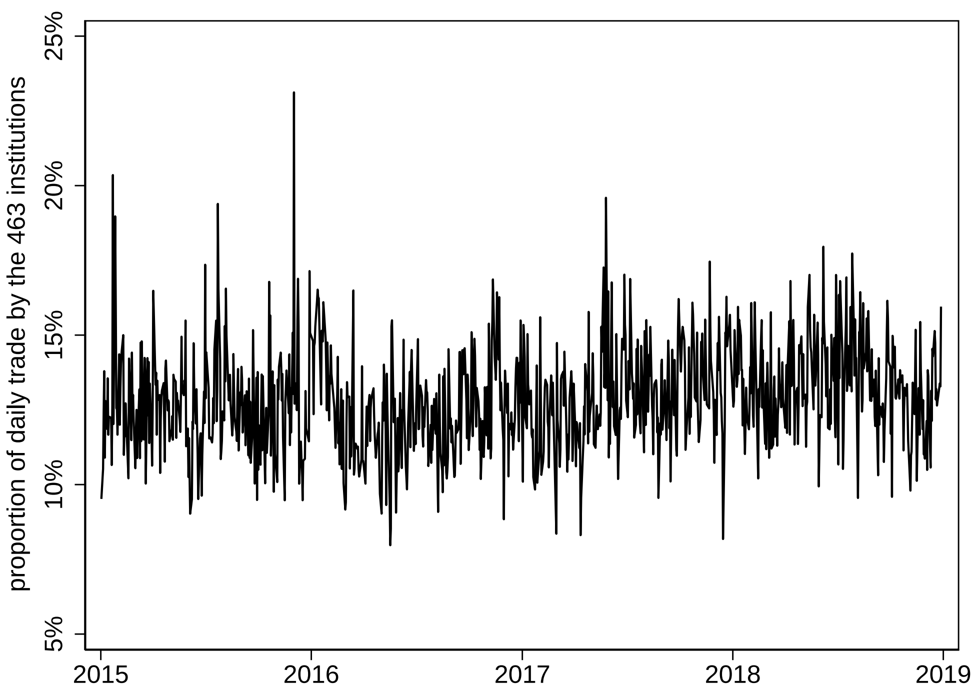
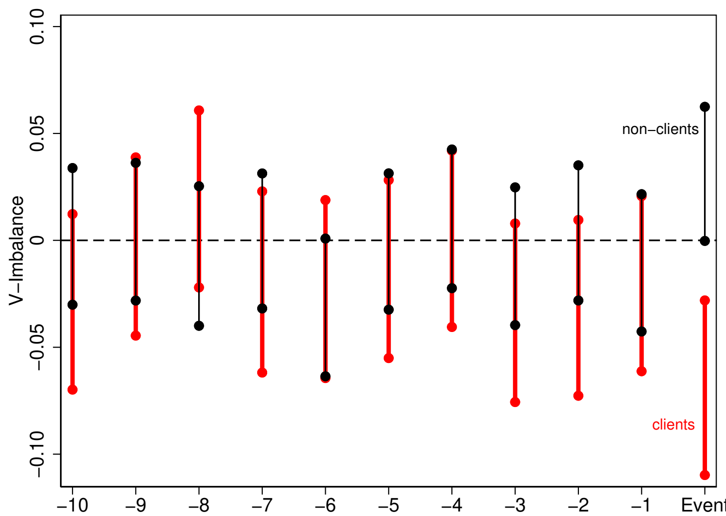
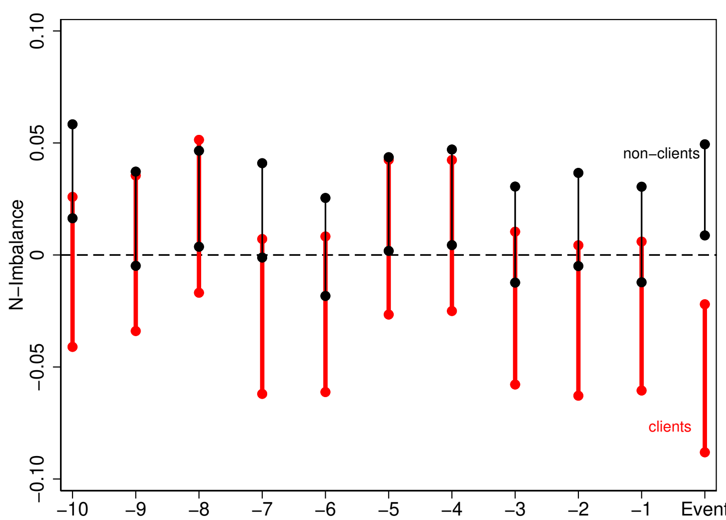


Figure 5: Trading imbalances 10 days before event vs. event day

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 1,404 events.



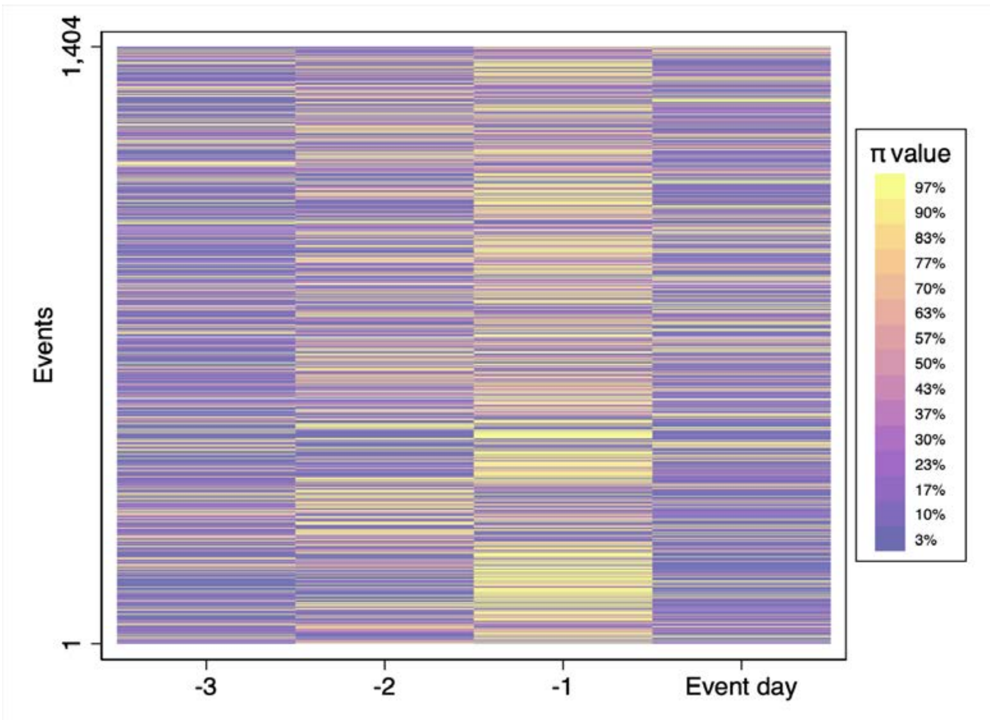
(a) $VImbalance$



(b) $NImbalance$

Figure 6: Distribution of the selling activity by short sellers (π)

This figure shows for each one of the 1,404 events the distribution of the selling activity by the short seller in the centralized stock market during the 4-day period that contains the 3 days before the event and the day of the event. The variable presented in the heat-map (π) is the volume sold by the short-seller on the day divided by the total volume sold by him in the 4-day period.



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 1,404 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

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	-0.012	-0.030***	-0.030**
	(-0.88)	(-0.83)	(-2.66)	(-2.52)
$EventDay$	0.033*	0.033**	0.009	0.009
	(1.84)	(1.87)	(0.86)	(0.87)
$Clients \times EventDay$	-0.087***	-0.087***	-0.054***	-0.053***
	(-3.09)	(-3.04)	(-3.16)	(-3.15)
$Constant$	-0.003	-0.003	0.019**	0.018***
	(-0.27)	(-0.48)	(2.30)	(3.45)
Event F.E.		✓		✓
Obs	28,519	28,519	28,519	28,519
Adj-R2	0.01	0.07	0.01	0.09

Table 3: 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 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. 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 4-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)
$Clients$	-0.002	-0.001	-0.023	-0.023
	(-0.11)	(-0.02)	(-1.46)	(-1.40)
$EventDay$	0.031	0.029	0.016	0.015
	(1.63)	(1.58)	(1.43)	(1.36)
$Clients \times EventDay$	-0.079**	-0.075**	-0.048**	-0.046**
	(-2.58)	(-2.42)	(-2.49)	(-2.38)
π	0.016	0.016	-0.003	-0.003
	(0.71)	(0.70)	(-0.19)	(-0.21)
$Clients \times \pi$	-0.112***	-0.107***	-0.084***	-0.081***
	(-3.61)	(-3.54)	(-3.05)	(-3.00)
$Constant$	-0.008	-0.009	0.011	0.010
	(-0.52)	(-0.73)	(1.10)	(1.23)
Event F.E.		✓		✓
Obs	9,832	9,832	9,832	9,832
Adj-R2	0.01	0.10	0.01	0.11

Table 4: Events by unskilled short sellers

This table shows the estimates of our main specification defined in Equation (2). However, events (973) 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 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. 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 4-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)
$Clients$	-0.017	-0.015	-0.029	-0.032*
	(-0.68)	(-0.59)	(-1.51)	(-1.67)
$EventDay$	0.017	0.018	0.038***	0.039***
	(0.70)	(0.76)	(2.76)	(2.79)
$Clients \times EventDay$	0.001	-0.005	-0.029	-0.035
	(0.01)	(-0.15)	(-1.32)	(-1.56)
π	-0.010	-0.011	-0.056**	-0.047**
	(-0.36)	(-0.39)	(-2.45)	(-2.52)
$Clients \times \pi$	-0.092**	-0.099**	-0.026	-0.026
	(-2.39)	(-2.58)	(-0.81)	(-0.81)
$Constant$	0.009	0.010	0.021	0.023**
	(0.48)	(0.80)	(1.62)	(2.47)
Event F.E.		✓		✓
Obs	6,867	6,867	6,867	6,867
Adj-R2	0.01	0.11	0.01	0.12

Table 5: Events by skilled short sellers that the broker does not perceive as skilled

This table shows the estimates of our main specification defined in Equation (2). However, we now we use 562 events produced by skilled short sellers but in which the broker involved does not have enough evidence that the short seller is skilled. 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 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. 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 4-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	-0.021	-0.042**	-0.049**
	(-0.37)	(-0.81)	(-2.22)	(-2.63)
$EventDay$	-0.002	-0.001	0.015	0.017
	(-0.07)	(-0.04)	(0.89)	(0.96)
$Clients \times EventDay$	-0.004	-0.006	-0.013	-0.016
	(-0.09)	(-0.12)	(-0.35)	(-0.42)
π	-0.068**	-0.069**	-0.076***	-0.078***
	(-2.10)	(-2.17)	(-2.90)	(-2.99)
$Clients \times \pi$	0.017	0.025	0.002	0.009
	(0.27)	(0.40)	(0.05)	(0.23)
$Constant$	0.001	0.006	0.025**	0.028***
	(0.05)	(0.41)	(2.02)	(2.73)
Event F.E.		✓		✓
Obs	4,075	4,075	4,075	4,075
Adj-R2	0.01	0.10	0.01	0.11

Table 6: 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 investors 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 Investors		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 7: 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. We compare two types of events generated by skilled short sellers. One is our baseline 1,404 informed securities lending events. The second type is the 562 under-the-radar informed securities lending events. In the 562 under-the-radar informed securities lending 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 562 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 1,404 events and equal to zero for the 562 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 8: 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. We compare two types of events generated by skilled short sellers. One is our baseline 1,404 informed securities lending events. The second type is the 562 under-the-radar informed securities lending events. In the 562 under-the-radar informed securities lending 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 562 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 1,404 events and equal to zero for the 562 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 9: 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. We compare two types of events generated by skilled short sellers. One is our baseline 1,404 informed securities lending events. The second type is the 562 under-the-radar informed securities lending events. In the 562 under-the-radar informed securities lending 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 562 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 1,404 events and equal to zero for the 562 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 10: Alternative informed lending events

This table shows the estimates of our main specification, Equation (2), using informed lending events defined under alternative parameters. In columns 1 and 4 we use a lower critical level (t-statistic of 1) to define skilled short-sellers (the number of events increase to 1,982). In columns 2 and 5 we require the average shorting volume by the short-seller to be greater than 50 thousand reais instead of 100 thousand reais (the number of events increases to 1,774). In columns 3 and 6 we require the volume borrowed by the short-seller to be greater than 50% of the maximum value borrowed by that short-seller with that broker in the previous 90 days (instead of greater than the maximum value; the number of events increase to 4,728). 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 1,982 events	$AV >$ R\$50k 1,774 events	$V > 0.5Max$ 4,728 events	t-stat > 1 1,982 events	$AV >$ R\$50k 1,774 events	$V > 0.5Max$ 4,728 events
$Clients$	-0.020	-0.013	-0.031**	-0.038**	-0.026*	-0.044***
	(-1.07)	(-0.74)	(-2.36)	(-2.45)	(-1.69)	(-3.89)
$EventDay$	0.007	0.018	0.013	0.008	0.013	0.005
	(0.50)	(1.18)	(1.24)	(0.89)	(1.28)	(0.75)
$Clients \times EventDay$	-0.038*	-0.068***	-0.040**	-0.032**	-0.050***	-0.023*
	(-1.75)	(-2.62)	(-2.19)	(-2.05)	(-2.93)	(-1.69)
π	-0.004	0.001	0.001	-0.021	-0.025	-0.008
	(-0.20)	(0.09)	(0.02)	(-1.46)	(-1.82)	(-0.91)
$Clients \times \pi$	-0.075**	-0.088***	-0.062***	-0.052*	-0.067***	-0.050***
	(-2.29)	(-3.71)	(-3.12)	(-1.96)	(-3.23)	(-2.77)
$Constant$	-0.001	0.006	0.010	0.022***	0.020***	0.024***
	(-0.11)	(0.59)	(1.35)	(2.73)	(2.62)	(4.26)
Event F.E.	✓	✓	✓	✓	✓	✓
Obs	13,823	12,377	32,166	13,823	12,377	32,166
Adj-R2	0.08	0.10	0.10	0.10	0.12	0.11

Table 11: Investor performance as a function of number of brokers

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. t-statistics are presented in parentheses. *, **, 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
	(5.01)	(4.98)	(3.55)	(2.31)	(6.28)	(5.46)	(4.28)	(1.58)
$Volume_{i,s,t}$	-0.021***	-0.020*	-0.011	-0.063*	-0.026***	-0.017*	-0.001	0.031
	(-2.78)	(-1.91)	(-0.62)	(-1.70)	(-3.82)	(-1.75)	(-0.02)	(1.03)
$Trades_i$	-0.013	-0.017	0.001	-0.016	-0.013	-0.020	-0.017	-0.020
	(-1.08)	(-0.98)	(0.06)	(-0.27)	(-1.04)	(-1.10)	(-0.56)	(-0.29)
$AvgVolume_i$	0.029***	0.029***	0.013	0.032	0.032***	0.017	0.001	0.001
	(3.02)	(2.01)	(0.53)	(0.63)	(3.40)	(1.27)	(0.04)	(0.01)
$NumberStocks_i$	-0.030	-0.060	-0.064	-0.234	-0.097***	-0.108**	-0.106	-0.096
	(-0.88)	(-1.07)	(-0.66)	(-1.12)	(-3.11)	(-2.56)	(-1.54)	(-0.63)
$Volume_{s,t}$	-0.037	-0.198**	-0.400**	-1.706***	0.120*	0.271***	0.657***	1.884***
	(-0.63)	(-2.09)	(-2.51)	(3.97)	(1.79)	(2.68)	(2.93)	(3.98)
$ShortVolume_{s,t}$	-0.219***	-0.383***	-0.740***	-1.983***	0.193***	0.344***	0.657***	1.850***
	(-3.39)	(-3.47)	(-3.53)	(-3.26)	(2.94)	(2.95)	(3.02)	(3.15)
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

Table 12: Trading behavior of investors who trade many stocks per day

This table shows the estimates of our main specification defined in Equation (2) using our baseline 1,404 events. However, now we study the trading behavior around these 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 and the day of 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. *EventDay* is one for the day of the event. 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 4-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	0.003	0.001	-0.021*	-0.021*
	(0.15)	(0.21)	(-1.88)	(-1.95)
EventDay	0.002	0.002	0.010	0.010
	(0.21)	(0.21)	(1.28)	(1.28)
Clients × *EventDay*	-0.001	-0.001	-0.009	-0.010
	(-0.01)	(-0.03)	(-0.60)	(-0.67)
π	0.043***	0.043***	0.004	0.004
	(2.69)	(2.69)	(0.38)	(0.38)
Clients × π	-0.072***	-0.069**	-0.067***	-0.065***
	(-2.68)	(-2.57)	(-3.69)	(-3.57)
Constant	-0.032***	-0.031***	-0.002	-0.002
	(-3.50)	(-3.27)	(-0.40)	(-0.33)
Event F.E.		✓		✓
Obs	10,345	10,345	10,345	10,345
Adj-R2	0.01	0.07	0.01	0.08