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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, clients and short sellers 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, 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 equity short-selling and trading activity in Brazil at a daily frequency.[2]

Our empirical analysis proceeds as follows. First, we define informed securities lending events when directional bets made by skilled short sellers become salient to brokers. Notably,

[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), Boehmer et al. (2022), and Cohen, Diether, and Malloy (2007). For a detailed review of the short-selling literature, see Reed (2013) and Jiang, Habib, and Hasan (2022), and references therein.

[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.

a broker knows the track record of all clients of its securities lending desk and can screen for skilled ones based on past performance. An informed securities lending event is specific to each broker for a particular stock on a given day, and it happens when one of its skilled clients borrows an unusually large number of shares. The unusual borrowing activity is salient to the broker because it is a pivotal moment when a skilled short seller fully commits to a sizeable directional bet. In our analysis, we identify 1,404 informed securities lending events over a four-year period across 53 different brokers. These events predict future price declines, and brokers intermediating these securities lending agreements observe this valuable information firsthand.

Second, we characterize how institutions trade around informed securities lending events to identify information leakage. Specifically, we analyze the trading behavior of institutions equipped to promptly short sell assets upon receiving information about informed securities lending events. These are institutions that 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.

Through a differences-in-differences approach, we find that clients of the informed broker further reduce their holdings of the stock involved in an informed securities lending event relative 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. Our estimates indicate that in the days prior to the event, clients and nonclients keep their positions unchanged in that stock. However, on the event date, clients of the broker change their behavior and become net sellers, with their net volume sold representing 8.1% 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 strategy is addressing the possibility that clients of the same broker may share unobserved characteristics—such as similar sources of information—that cause them to trade alike, regardless of any information leakage. In Brazil, short sellers face no formal locate requirement, and securities loans settle on the same day, whereas the stock market settles three business days after a trade is executed.[3] Thus, a short seller can sell

[3]Our dataset is from 2012 to 2018, and throughout our sample, settlement in the Brazilian stock market

shares first and contact the broker up to three days later to borrow them. Because the broker only becomes aware of the short position on the borrowing date, the selling activity of short sellers does not necessarily coincide with the moment brokers learn about a short-selling position. In our empirical specification, we control for the trading activity of the short seller responsible for the informed event, ensuring that any trading comovement between this short seller and other clients at the same broker does not confound our results. This specification allows us to isolate and estimate the effects of broker-mediated information flow in securities lending.

Third, we document that the transmission of information is intentional by analyzing information leakage in two different placebo events. To rule leakage by locating securities on the event day, we considered uninformed securities lending events. These are instances when unskilled short sellers borrow a large number of shares—these are short sellers whose trades do not predict future price declines. Because the broker still needs to locate the shares, information about such a large short position could potentially leak to other clients of the broker. However, we find no evidence of leakage in these uninformed cases.

In another set of placebo events, we consider large borrowing activity by short sellers who appear to be unskilled to a broker (based on poor track records with that broker) but, in fact, have a strong overall track record (with other brokers). We call these under-the-radar informed securities lending events, and they are similar to our baseline events in nearly every dimension. Despite these events accurately predicting price declines, we again see no evidence of broker-driven leakage. This finding reinforces that information leakage is intentional on the part of brokers rather than originating from short sellers themselves or from the process of locating securities.

Fourth, we investigate the effects of information leakage on stock prices. We compare the behavior of stock returns after informed securities events against how stocks behave after under-the-radar events. Although both types of events are similar in nearly every dimension, the key distinction is that brokers leak information in our baseline events but do not in under-the-radar events. We compare stock price behavior following both types of events using short seller fixed effects. We find that the leakage leads to a faster drop in stock prices, lower stock return volatility and lower serial correlation.

Fifth, we look at the incentives of all three parties involved in the information-sharing

was 3 business days. Since May 2019, the settlement in the Brazilian stock market is 2 business days.

arrangement we document: brokers, short sellers, and clients. We find that all three benefit from information sharing. Short sellers secure their positions before any leak, accelerating price discovery and reducing volatility, enabling them to earn a net-of-fee return of 2.05% over their typical 17-day coverage window. Clients receiving this information avoid assets likely to decline (or even take short positions in those assets), improving their portfolios' risk-adjusted performance, and they reward the broker by bringing more business to its lending desk. Interestingly, the incentives play out through quantities rather than prices. When analyzing the lending fees, we find that the short seller generating events and the clients receiving information pay prevailing market rates when borrowing securities, with no detectable premium or discount relative to similar lending agreements.

Finally, we perform several robustness exercises. We consider alternative definitions of informed securities lending events and different groups of investors who might receive broker information. We also show that brokers selectively leak information based on clients' transacted volume and quantify the effects after the event date. In addition, we account for possible lead-lag effects and repeat our analysis excluding securities with public information disclosure.

The remainder of the paper proceeds as follows. Next, we outline our contribution to the related literature. Then, Section 2 introduces the data, and Section 3 describes the informational events used in our empirical analysis. Section 4 provides the main evidence of information leakage, while Section 5 explores placebo events. Section 6 examines the impact of leakage on stock prices, and Section 7 discusses the incentives of the parties involved in information sharing. Section 8 presents various robustness checks, and Section 9 concludes.

Related Literature. 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.

The role of brokers in transmitting information has also been documented by Kumar, Mullally, Ray, and Tang (2020) who showed that brokers share information acquired from their corporate loans with their hedge fund clients. Li, Mukherjee, and Sen (2021) document that brokers also share information acquired from clients who are corporate insiders. These results are consistent with our findings that brokers seem to selectively share with their clients information acquired in their other lines of business.

We make several key contributions to this area of research. 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 and relies on the absence of locate requirements along with 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, 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.[4] Chen, Kaniel, and Opp (2022) document several non-competitive features in securities lending markets and estimate a dynamic model with asymmetric information.[5] Recently, several papers have focused on short-selling costs and their implications

[4]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.

[5]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

for asset prices. Evgeniou, Hugonnier, and Prieto (2022) study the effect of short-selling costs 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 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.[7] 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.

2 Dataset

Transactions in the Brazilian stock market occur in a centralized electronic market, and the transactions in the Brazilian securities lending market occurred over-the-counter (OTC) during our sample period. 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,[8] 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

response to the arrival of overoptimistic investors.

[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 act is reduced.

[7]See Duffie, Malamud, and Manso (2009, 2014); Ahern (2017, 2020); Babus and Kondor (2018); Walden (2019); Allen and Wittwer (2023).

[8]*Comissão de Valores Mobiliários.*

unique identifier of investors (the same one for the centralized market) and brokers, the borrowed volume and the fees charged. Although trading data from centralized exchange do not identify the brokers executing trades, we can observe the brokers involved in securities lending agreements.

To rule out concerns regarding the illiquidity of stocks, we focus on stocks with 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 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.

2.1 Securities lending market in Brazil

The practice of short selling securities is virtually identical in Brazil and in the United States. In both countries, short sellers sell securities on a centralized exchange and borrow them through an over-the-counter (OTC) securities lending market. They need to reach out to a broker, who needs to locate securities to lend. Although the economic incentives and short selling as a trading practice are largely the same in these two economies, there are a few minor institutional differences. This section describes the specific features of the Brazilian market in greater detail.

2.1.1 Locate requirement

In Brazil, there is no formal locate requirement before selling securities. In practice, short sellers inform brokers about their borrowing intentions *after* executing the short sale. The lack of such a requirement is a consequence of the various safeguards in place on the Brazilian exchange, which we describe next.

B3, the Brazilian exchange, acts as both the only exchange and the central counterparty, which allows it to implement multiple risk-management measures. These include managing risks related to clearing and settlement across different markets, setting pre- and post-trading limits, and monitoring trading activities to prevent excessive risk-taking behavior. As a result, the exchange can impose additional controls throughout the settlement process.[9]

For instance, B3's settlement procedure includes strict controls to mitigate the impact of delivery failures. In Appendix A, we outline the key steps involved in settling a closed deal and describe how the exchange addressed delivery failures during our sample period. In short, if the seller fails to deliver the securities on settlement day, the exchange guarantees delivery. At the same time, it lends the securities to the seller and issues a purchase order on the seller's behalf to ensure the borrowed securities are returned to the exchange. This procedure operates at borrowing rates that can be 100 times higher than standard market fees, creating a strong incentive for sellers to meet their delivery obligations.

The lack of a formal locate requirement—which allows short sellers in Brazil to sell short before communicating their borrowing intentions to their brokers—provides a methodological advantage for identifying information leakage. This mismatch between selling and borrowing enables us to isolate the impact of each lending transaction from potential trading comovements among a broker's clients that could arise from shared, unobservable signals.

In the U.S., stricter locate requirements mean short sellers must contact their broker's securities lending desk before selling short so the broker can locate the shares. In this case, the lending desk becomes aware of the short position before or during the selling and borrowing process. As a result, based on borrowing and selling activity alone, it is nearly impossible to pinpoint whether any leakage arises from brokers sharing information or from comovement among clients. In contrast, the absence of a locate requirement, combined with the timing mismatch between borrowing and selling in Brazil, provides an ideal framework for identifying and measuring information leakage, as it allows us to control for trading comovement.

[9]See the exchange clearing and settlement details: https://www.b3.com.br/en_us/products-and-services/clearing-and-settlement/clearing/. Also, see the exchange pre and post monitoring procedures: https://www.b3.com.br/en_us/products-and-services/trading/equities/cash-equities/b3-trading-characteristics-and-rules.htm

2.1.2 Role of securities lending desk and timing of information

In addition to the nonexistent location requirement, another aspect to the Brazilian market is that brokers cannot definitively tell whether a client's selling activity is a short sale. In Brazil, the exchange—not the broker—imposes and manages short-selling controls such as margin requirements. Because of this centralized structure, funds can split their trading activity across multiple brokers, buying securities through one broker and selling them through another, all while the exchange remains the central counterparty and margin setter. The only time a broker can infer that a client is short selling is when the client contacts the broker to borrow a security, often after the sale has already occurred. Consequently, securities lending desks are typically the first to learn about a short position through formal channels.

In the United States, short sellers generally need broker approval before selling a security because of the locate requirement. As a result, the broker becomes aware of the short-selling position before both the sale and the subsequent security borrowing. This means brokers in the U.S. have more immediate, fresher information on short-selling activity than security lending desks in Brazil. Thus, the potential benefits of leaking that information can be greater in the U.S., while in Brazil, the relevant information could be partially dated by the time the lending desk learns of the short position. Given that Brazilian security lending desks receive information later, our empirical findings likely serve as a lower bound on the possible extent of information leakage.

2.1.3 Legal implications

Information leakage may lead to legal consequences, including criminal charges (particularly for insider information) and administrative sanctions for breaches of confidentiality or unfair practices.

In the United States and Brazil, brokers have fiduciary duties to safeguard sensitive client information.[10] The issue becomes more serious when leaked tips allow brokers' clients to trade ahead of the short sellers who provided the information—a practice known as front-running. In our empirical analysis, front-running is less of a concern because borrowing typically takes place after selling, making it harder for brokers' clients to front-run.

[10]For more on Broker's fiduciary duties, see Brazil's Complementary Law 105: https://www.planalto.gov.br/ccivil_03/leis/lcp/lcp105.htm. Barbon et al. (2019) discuss similar legal implications in the U.S. when brokers disclose information from fire sales.

Even if a short seller benefits from leaked information, brokers' clients who use it could still be held liable for unfair trading.[11] However, proving misconduct in such cases typically requires clear and unequivocal evidence—something notoriously challenging to obtain. This difficulty arises from the subtle nature of information leakage and the complexity of tracing its impact through the intertwined nature of trading and market dynamics.

2.1.4 Securities lenders

Typically, brokerage agreements allow brokers to lend stocks on behalf of their clients. This is often the case for retail investors, who passively receive compensation for lending stocks. However, some large pension funds and passive funds may have dedicated personnel negotiating securities lending agreements through multiple brokers.

2.1.5 Conflict of interests: internal versus external leakage

Brokers often have multiple lines of business, including asset management and proprietary trading, which can lead to conflicts of interest and affect how we interpret our findings. A key concern is whether leakage occurs among the broker's own funds (internal leakage) or among external clients (external leakage).

Because our data is fully anonymized, we cannot directly identify whether a particular investor belongs to the same firm as the broker. Nonetheless, we can observe if an investor consistently benefits from leakage provided by a single broker. Our analysis identifies 292 investors whose trading patterns changed drastically on the event day by selling securities, consistent with receiving information.[12] Interestingly, 72% obtained information from multiple brokers for different informed events. This pattern strongly indicates external leakage because, under internal leakage, funds would repeatedly receive information from the same broker.

Several factors make external leakage more likely. Brokers communicate constantly with their clients—negotiating lending terms, discussing market conditions, and handling

[11] CVM Resolution 62 (Article 2, Clause 4) addresses unfair practices in the stock market: http://antigo.cvm.gov.br/legislacao/resolucoes/resol062.html. This regulation aims to maintain a level playing field by preventing scenarios where investors trading against the broker's clients might gain an unfair advantage.

[12] These institutions were likely to receive information that did not trade the security event before the event but started selling the security on the event day. We discuss these investors later in Section 7.2.

questions—which creates ample opportunities to share information. Although firms are required to monitor external communications, the volume of phone calls, emails and in-person interactions makes real-time oversight challenging.

By contrast, internal leakage would require circumventing more stringent controls. Many firms maintain robust Chinese wall policies, that is, internal information barriers between the lending desk and their own fund management teams. Such barriers include physical separation, restricted data access, and rigorous compliance monitoring. Attempting to share information internally thus carries a higher risk of detection. For instance, internal emails and messages are often more closely monitored, and unauthorized access to sensitive departments can trigger compliance alerts.

Finally, the strong relationships brokers form with clients can encourage external disclosure. These relationships, built on trust and mutual benefit, can stimulate brokers to share confidential tips, potentially for personal gain or to strengthen client loyalty.

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.[13] 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 assume 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,[14] and (ii) in the same previous 90 days, the probability of a stock borrowed by the investor sub-

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

[14] 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.[15]

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.

As mentioned earlier, brokers in Brazil cannot determine whether a client's sale is part of a short position. However, brokers can infer short selling through their securities lending desks as these desks are typically the first to learn about a client's short position. We designed informed securities lending events to capture the moment when a broker's lending desk becomes aware of sizable short positions made by informed short sellers.

3.1 Characterizing informed securities lending events

Based on our definition of informed securities lending events, our sample includes 1,404 such events. These events involve 96 different stocks and 53 of the 98 brokers operating in the Brazilian securities lending market during our sample period. A total of 461 investors initiated these 1,404 events: 143 individuals triggered 239 events, while 318 institutions triggered the remaining 1,165 events.

Regarding the volume borrowed per event, the median lending amount was slightly above US$740,000 (calculated using the average exchange rate in our sample).[16] These events are well-distributed over time, averaging 351 occurrences per year.[17]

Table 1 presents summary statistics of our data at three aggregation levels: deal level,

[15]Results are robust to changes in these parameters as we show in Section 8.1. The 90-window is the same window used in Chague, De-Losso, Genaro, and Giovannetti (2017).

[16]The minimum volume was 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 were 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.

[17]358 events occurred in 2015, 296 in 2016, 323 in 2017, and 427 in 2018. Figure IA.1 in the Internet Appendix depicts a matrix of the events, illustrating their distribution across stocks and over time.

Table 1: Descriptive statistics of lending agreements

This table presents descriptive statistics of securities lending agreements. Section 2 provides a detailed data description. Panel A covers all equity lending deals in Brazil from 2015 to 2018. In contrast, Panel B restricts the sample to agreements involving the 461 short sellers who triggered at least one of the 1,404 informed securities lending events (described in Section 3). In each panel, we report statistics at three aggregation levels: deal level, borrower level, and broker level. At the deal level, we report statistics on the lending agreement volume (in Brazilian Reais, R$) and on the annualized loan fee (percent per year). Specifically, we report the number of observations in Column (1), the mean and standard deviation in Columns (2) and (3), and the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles in Columns (4) through (8). At the borrower level, we calculate each borrower's average borrowed volume and their volume-weighted loan fee. We then report the same set of descriptive statistics as for the deal level. Finally, we apply a similar approach at the broker level, computing each broker's average loan volume and volume-weighted loan fee and presenting the same descriptive statistics.

	obs (1)	mean (2)	std dev (3)	pct 10 (4)	pct 25 (5)	pct 50 (6)	pct 75 (7)	pct 90 (8)
Panel A: Full dataset								
Deal level:								
Volume (R$)	5,152,619	440,854	2,751,254	2,132	8,405	35,581	184,033	774,000
Loan fee (%, p.y.)	5,152,619	2.39	6.66	0.01	0.02	0.35	1.90	7.00
Borrower level:								
Avg. volume per deal (R$)	71,798	46,436	899,342	1,081	3,083	9,008	25,592	70,785
Avg. loan fee (%, p.y.)	71,798	1.88	7.82	0.01	0.02	0.50	1.80	4.54
Broker level:								
Avg. volume per deal (R$)	98	477,442	1,133,533	10,557	58,415	238,642	492,320	963,529
Avg. loan fee (%, p.y.)	98	5.86	41.69	0.02	0.38	1.48	2.72	3.66
Panel B: Deals by investors who triggered informed events								
Deal level:								
Volume (R$)	3,168,572	642,037	3,396,120	3,630	16,382	78,660	354,211	1,233,061
Loan fee (%, p.y.)	3,168,572	2.34	5.80	0.01	0.02	0.32	1.90	7.70
Borrower level:								
Avg. volume per deal (R$)	461	349,803	430,251	77,582	122,587	202,313	408,375	823,109
Avg. loan fee (%, p.y.)	461	1.49	1.49	0.05	0.32	1.03	2.37	3.55
Broker level:								
Avg. volume per deal (R$)	73	550,547	564,818	95,123	208,230	410,163	634,218	1,124,803
Avg. loan fee (%, p.y.)	73	1.69	1.64	0.01	0.25	1.42	2.47	3.55

borrower level, and broker level. These statistics offer insights into the dynamics of securities lending in Brazil. Panel A includes all equity lending deals from 2015 to 2018, totaling around 5.1 million agreements. The average volume of these agreements is about R$440 thousand, and the average loan fee is 2.39% per year. The distribution of both volume and fees is skewed to the right. In fact, the median volume is roughly R$35 thousand, while the median loan fee is 35 basis points.

At the borrower level, we calculate each borrower's average borrowed volume and volume-weighted loan fee, and we report the same set of descriptive statistics. There are 71,798 different borrowers in our sample. On average, they pay 1.88% per year per dollar worth of shares borrowed, and their average volume borrowed is about R$46 thousand. The discrepancy between deal-level and borrower-level averages indicates that few borrowers account for most large-volume agreements.

We apply a similar approach at the broker level, computing each broker's average loan volume and volume-weighted loan fee and presenting the same descriptive statistics. Among the 98 brokers in our data, the average intermediated volume is approximately R$477 thousand, with a volume-weighted average fee of 5.86%. The gap between deal-level and broker-level figures suggests that while typical brokers handle more extensive agreements, a small set of borrowers is responsible for the bulk of lower-fee lending transactions.

In contrast, Panel B restricts the sample to agreements involving the 461 short sellers who triggered at least one of the 1,404 informed securities lending events. These 461 investors are active market participants, being counterparties in about 3.1 million lending agreements. Looking at the borrower-level statistics, their average contract volume is about R$349 thousand, and the average volume-weighted fee paid is 1.49% per year. Hence, the investors who triggered at least one informed securities lending event are active market participants in securities lending, and typically, they borrow larger volumes and pay lower fees than the typical borrower.

Another key characteristic of these events is whether or not they involve liquid securities. Note that to mitigate the influence of illiquid stocks, our working sample includes only stocks with positive trading volume on every trading day of the previous year. To examine the liquidity of the stocks involved in our 1,404 events, we rank all stocks daily by traded volume, and we find that the overwhelming majority of securities lending events (78.1%) involve the most liquid stocks—those in the top quintile of traded volume.[18] Thus, these events occur among the most liquid securities where information leakage might expedite price discovery without significantly impacting the ability to establish short positions.

We also find that events typically involve easy-to-borrow securities. If we rank all securities in the equity lending market daily by their average loan fees and classify them into quintiles based on their average lending fees, we find that the average loan fee per year for each quintile is 0.26%, 0.68%, 1.39%, 2.78%, and 10.11%, respectively. Of all 1,404 informed

[18] Of the 1,404 events in our sample, only 1 event (0.1%) involves a stock in the lowest quintile (least traded), 6 events (0.4%) involve stocks in the second quintile, 56 events (4.0%) involve stocks in the third quintile, 245 events (17.4%) involve stocks in the fourth quintile, and 1,096 events (78.1%) involve stocks in the fifth quintile (most traded).

securities lending events, 674 events (48%) are from stocks in the lowest quintiles (easiest to borrow), 289 events (21%) are from stocks in the second lowest quintile and 147 (10%) from stocks in the third quintile. Only 108 (8%) and 186 events (13%) involve securities in the fourth and fifth quintiles, respectively. This shows that the overwhelming majority of events involve securities that can be easily borrowed.

In addition to these statistics, Figure 1 characterizes trading and securities lending activity around securities lending events. Panel A, B and C report trading volume (total volume sold plus the volume bought by all investors), number of investors trading (number of institutions or retail investors who either purchased or sold the stock on a given day) and the intraday price range as 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 before the event day. These three panels indicate stocks associated with securities lending events experience a higher trading volume, a higher number of investors trading them, and a higher price volatility. Panels D and E of Figure 1 report the average securities lending volume for the stock associated with securities lending events—excluding the securities lending agreement that triggered that event itself— and the average securities lending fees. The last two panels suggest that lending volume spikes significantly in the 3 day window around the event days, while fees seem to go up only on the event day.[19]

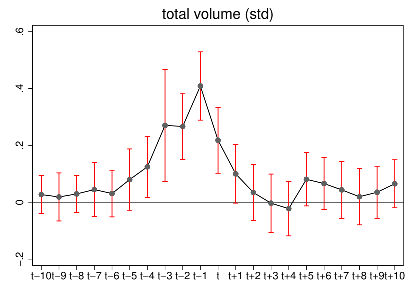
The results from Figure 1 suggest that informed securities lending events are not random, which is somewhat expected given that informed short sellers are unlikely to randomly build large short positions. Short sellers who triggered the events could be responding to temporary price pressure and providing liquidity or could be trading based on some other type of information.

To further investigate what triggers these events, we conduct a stock-day panel regression analysis of a dummy variable indicating whether an event occurred on the following explanatory variables: (i) $Ret^{ex}_{s,t-5,t-1}$ as the cumulative excess returns of stock s over the five trading days preceding the event; (ii) $log(Vol_{s,t-10,t-1})$ as the average logarithm of the trading volume over the last ten trading days; (iii) $Volat_{s,t-10,t-1}$ as the standard deviation of stock returns over the last ten trading days; (iv) $EAs_{s,t-10,t-1}$ as a dummy variable indicating whether there was an earnings announcement in the last ten trading days; (v) $Ret^{ex}_{s,t}$

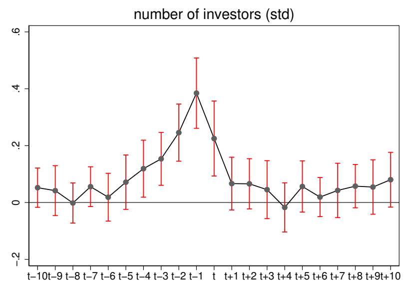
[19]These findings suggest that our 1,404 informed securities lending events coincide with periods resembling market-wide demand shifts out, in line with the definitions in Cohen, Diether, and Malloy (2007).

Figure 1: Trading and borrowing activity around informed securities lending events

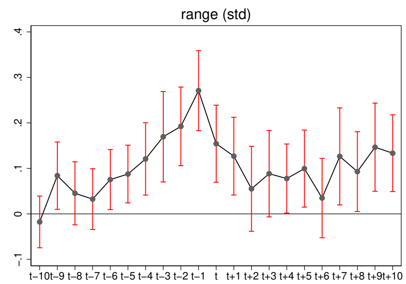
This figure shows various trading and borrowing activity statistics for the 10 days before and 10 days after informed securities lending events (defined in Section 3). Panel A shows the standardized total trading volume (purchases plus sales); Panel B shows the standardized number of different investors trading the stock; and Panel C shows the standardized range—computed as the maximum price minus the minimum price in a day divided by the average of the two. Panel D shows the standardized total lending volume, excluding the lending that generated the event; finally, Panel E shows the standardized, average lending fees. All variables are standardized with respect to the mean and standard deviation computed over the previous 3 months. Black dots indicate the daily average, while red intervals indicate a 95% confidence interval.



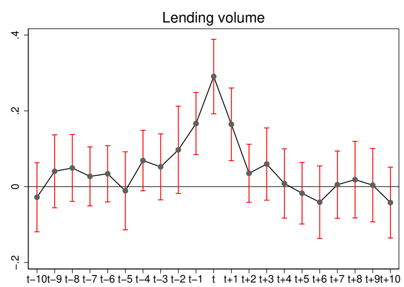
A. Total Volume



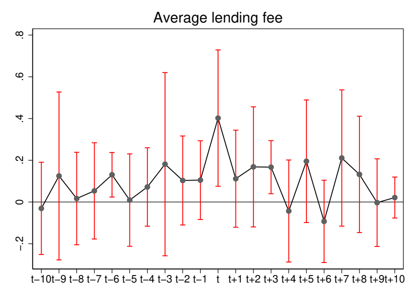
B. Number of Investors



C. Range



D. Lending Volume



E. Lending Fees

as the excess return of stock s on day t relative to the market return; and (vi) $log(Vol_{s,t})$ as the logarithm of the trading volume for stock s on day t. Our regression estimation includes fixed effects at the stock level, and we report these results in Table 2.

Our regression results from Table 2 indicate a significant price decline on the day of the event, given the statistically significant negative coefficient on $Ret^{ex}_{s,t}$. The events also tend to follow recent price increases, as reflected in the positive coefficient on $Ret^{ex}_{s,t-5,t-1}$. Additionally, we observe an increase in total trading volume on the day of the event. The events are more likely to occur during periods of high volatility, as evidenced by the strongly positive coefficient on $Volat_{s,t-10,t-1}$.

Interestingly, earnings announcements play an important role in triggering an event as the

Table 2: Characterizing securities lending events

This table reports the estimation results of a stock-day panel regression of a dummy variable indicating whether an informed securities event involving stock s occurred at day t (defined in Section 3). We use the following explanatory variables: (i) $Ret^{ex}_{s,t-5,t-1}$ as the cumulative excess returns over the five trading days preceding the event; (ii) $log(Vol_{s,t-10,t-1})$ as the average logarithm of the trading volume over the last ten trading days; (iii) $Volat_{s,t-10,t-1}$ as the standard deviation of stock returns over the last ten trading days; (iv) $EA_{s,t-10,t-1}$ as a dummy variable indicating whether there was an earnings announcement in the last ten trading days; (v) $Ret^{ex}_{s,t}$ as the excess return of stock s on day t relative to the market return; and (vi) $log(Vol_{s,t})$ as the logarithm of the trading volume for stock s on day t. Our regression estimation includes fixed effects at the stock level. 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.

		Events	
	(1)	(2)	(3)
Constant	0.011***	-0.020	-0.024*
	(6.53)	(-1.61)	(-1.86)
$Ret_{s,t-5,t-1}$		0.021***	0.019**
		(2.82)	(2.56)
$log(Vol_{s,t-10,t-1})$		0.002**	-0.001
		(2.22)	(-1.34)
$Volat_{s,t-10,t-1}$		0.122**	0.135***
		(2.54)	(2.76)
$EA_{s,t-10,t-1}$		0.002*	0.002*
		(1.87)	(1.91)
$Ret^{ex}_{s,t}$			-0.054***
			(-4.33)
$log(Vol_{s,t})$			0.003***
			(4.62)
Fixed Effect	No	Stock	Stock
Adjusted R-squared	0.00	0.02	0.02
Observations	127,491	127,491	127,491

probability of an event occurring increases by 0.2 percentage points if an earnings announcement was made within the previous 10 trading days. This is an economically meaningful increase since the unconditional probability of an event occurring on any given day with no prior earnings announcements is 1.1%. A total of 274 out of the 1,404 events include an earnings announcement within the 10-day window surrounding the event.[20] If we look at a longer window prior to the event, we see an earnings announcement between days t-21 and t+5 of the event day in 575 of the 1,404 securities lending events. 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 but unrelated to the earnings announcement.

To summarize, in our typical event, we see an abnormally higher volume, increased price

[20]Among the 1,404 events in our sample, there are 30 events with earnings announcements on day t-5, 34 on day t-4, 26 on day t-3, 28 on day t-2, 31 on day t-1, 26 on the event day, 19 on day t+1, 14 on day t+2, 26 on day t+3, 19 on day t+4, and 21 on day t+5.

volatility, a higher number of investors trading, more securities lending, 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, informed short sellers take a large bearish position. In the next section, we show that prices decline significantly after securities lending events, meaning that securities lending desks have access to valuable information about future stock returns when an informed event is triggered.

3.2 Do informed securities lending events forecast returns?

Yes. In this section, we show that informed securities lending events involving a particular security negatively predict future returns of the stock associated with the event—which constitutes a clear opportunity for investors to either reduce exposure to that asset or even sell that particular security short.

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.[21]

As discussed in the previous section, securities lending events are unlikely to be random; to test for their predictive power, it is crucial to control for various return patterns. To do so, we estimate panel regressions at the stock-day level of future excess returns on an event dummy, controlling for several variables known to have predictive power for returns, such as past returns, volume, volatility, earnings announcements, average lending fees and total volume borrowed in securities lending.

Table 3 presents results predicting cumulative returns over different horizons following a securities lending event. Columns (1) and (2) cover a 5-day window, columns (3) and (4) cover 10 days, and columns (5) and (6) cover 20 days. These horizons align with the typical time it takes short sellers to cover their positions. Specifically, we define "days to cover" as

[21]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).

the total number of days needed for an investor to fully close the short position accumulated up to three days prior to the event date. Among the 1,404 events, the median number of days to cover is 17 days.

All cumulative excess returns are expressed in percentage points. Across all columns, the coefficient on $Event_{s,t}$ is negative and statistically significant, indicating that these events are associated with further price declines. In column (1), the event dummy implies an additional return of -37.9 basis points over the subsequent five trading days after controlling for various market conditions. Over longer horizons, the coefficient on $Event_{s,t}$ becomes even more negative, suggesting no price reversion and supporting the interpretation of an informational event. For instance, column (3) implies a 53.6 basis points decline and column (5) a 96.5% decline.

Columns (2), (4), and (6) add controls for securities lending market conditions on the day of the event—namely, the total borrowing volume and the average loan fee. Even after including these controls, $Event_{s,t}$ remains both statistically significant and economically meaningful, reinforcing that the event itself has information about future returns. Specifically, in this most robust specification, we find price declines of approximately 36.6, 51.6, and 93.8 bps over 5, 10, and 20 trading days, respectively, following informed securities lending events.

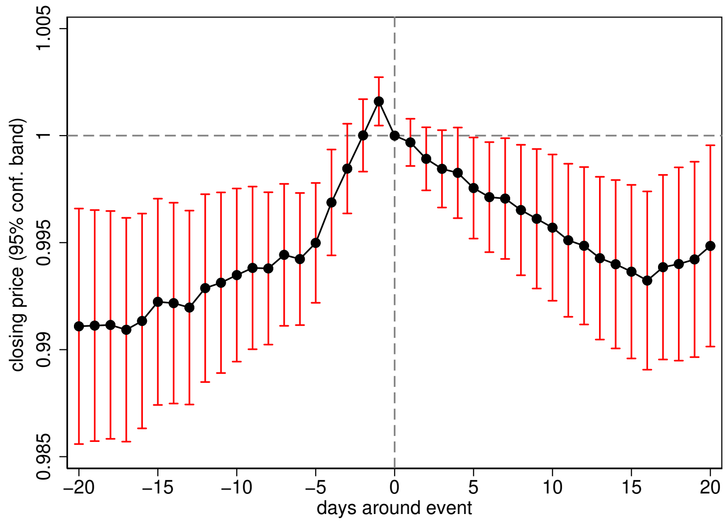
Although the returns used Table 3 do not account for borrowing costs, our results highlight that these events carry information about the future performance of the securities involved in informed securities lending events. A natural question is how the value of this information is split between the broker (who charges a lending fee) and the investor (who benefits from the price decline).[22]

Our dataset is ideal for investigating this question, as we observe actual realized lending agreements for every single transaction in the Brazilian securities lending market. Because securities lending operates over the counter, with considerable heterogeneity across investors and securities, we measure an economically relevant average fee by calculating the volume-weighted average lending fee for each security-day pair. More importantly, for our analysis, we must focus on the average fees investors pay on event days. Across all informed securities lending events, we estimate an unconditional average of 135 bps annually (median 21 bps)

[22] Muravyev, Pearson, and Pollet (2022) show that securities lending fees can have a significant impact on the performance of various anomalies-based long-short strategies.

Figure 2: Price behavior around informed securities lending events

This figure presents the average price behavior of event stocks during the 10 days before and 10 days after informed securities lending events (defined in Section 3). We use returns in excess of the market and normalize the price to 1 on the event day. We report daily averages along with their respective 95% confidence intervals.



for the volume-weighted lending fee. Converting 135 bps annually to 5-, 10- and 20-day windows after the event day yields roughly 2.7, 5.3, and 10.6 bps. Hence, of the total price decline after an informed event, about 7 to 11% is paid back to the broker in fees. For example, based on Column (4) estimates, of the 51.6 bps price decline over ten days, about 5.3 bps is paid back to the broker in fees, leaving the short seller with a net-of-fee return of about 46.3 bps.

4 Evidence of information leakage

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's securities lending desk learns about an informed short position in the midst of its implementation. Moreover, by design, these are large lending agreements in which the short seller reveals to the broker as fully committed to a sizeable directional bet. In this section, we show that brokers actively share information

Table 3: Informed securities lending events and future returns

This table presents stock-day panel regressions of future excess returns on a dummy variable indicating the occurrence of informed securities lending events. The dependent variables $Ret^{ex}_{s,t+1,t+5}$, $Ret^{ex}_{s,t+1,t+10}$, and $Ret^{ex}_{s,t+1,t+20}$ are the cumulative excess returns of stock s from $t+1$ to $t+5$, $t+1$ to $t+10$, and $t+1$ to $t+20$, respectively. The primary explanatory variable, $Event_{s,t}$, equals 1 if there is an informed securities lending event on day t for stock s (defined in Section 3). We also include several controls: $EA_{s,t-10,t-1}$ is a dummy for an earnings announcement in the last ten trading days; $Event_{s,t} \times EA_{s,t-10,t-1}$ is the interaction term of those dummies; $\text{Ret}^{ex}_{s,t}$ represents the daily excess return of stock s on day t; $\text{Ret}^{ex}_{s,t-5,t-1}$ and $\text{Ret}^{ex}_{s,t-20,t-6}$ are the cumulative excess returns over the previous five trading days and from $t-20$ to $t-6$, respectively; $\log(Vol_{s,t})$ and $\log(Vol_{s,t-10,t-1})$ denote the log of trading volume on day t and the average log trading volume over the previous ten days (standardized); $Volat_{s,t-10,t-1}$ is the standard deviation of returns over the past ten days; $\log(Borr_{s,t})$ and $\log(Borr_{s,t-10,t-1})$ indicate the log of total borrowing volume on day t (excluding borrowing by the short seller who triggered the informed event) and its average over the preceding ten days; and $LoanFee_{s,t}$ and $LoanFee_{s,t-10,t-1}$ are the volume-weighted average daily loan fee on day t and over the past ten days, respectively. Standard errors are double-clustered by date and by stock, and the t-statistics are presented in parentheses.*, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	$Ret^{ex}_{s,t+1,t+5}$		$Ret^{ex}_{s,t+1,t+10}$		$Ret^{ex}_{s,t+1,t+20}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Event_{s,t}$	-0.379**	-0.366**	-0.536**	-0.516**	-0.965**	-0.938**
	(-2.40)	(-2.33)	(-2.27)	(-2.20)	(-2.33)	(-2.27)
$Ret^{ex}_{s,t}$	-1.516	-1.565	-1.242	-1.305	-0.307	-0.384
	(-0.88)	(-0.91)	(-0.62)	(-0.65)	(-0.11)	(-0.14)
$Ret^{ex}_{s,t-5,t-1}$	0.071	0.172	0.367	0.531	1.404	1.643
	(0.07)	(0.18)	(0.29)	(0.42)	(0.70)	(0.83)
$Ret^{ex}_{s,t-20,t-6}$	0.819	0.820	1.645	1.649	4.922***	4.930***
	(1.46)	(1.46)	(1.64)	(1.64)	(2.85)	(2.85)
$log(Vol_{s,t})$	0.182***	0.198***	0.255***	0.280***	0.454***	0.489***
	(3.24)	(3.60)	(2.86)	(3.18)	(3.79)	(4.05)
$log(Vol_{s,t-10,t-1})$	-0.081	-0.089	-0.087	-0.102	-0.220	-0.243
	(-1.08)	(-1.20)	(-0.58)	(-0.68)	(-0.67)	(-0.74)
$Volat_{s,t-10,t-1}$	13.416***	13.611***	23.804***	24.236***	34.712***	35.461***
	(2.91)	(2.98)	(3.11)	(3.18)	(2.86)	(2.91)
$EAs_{s,t-10,t-1}$	0.142	0.142	0.302*	0.302*	0.519**	0.518**
	(1.51)	(1.50)	(1.92)	(1.92)	(2.37)	(2.37)
$Event_{s,t} \times EAs_{s,t-10,t-1}$	-0.162	-0.162	-1.209	-1.209	-0.583	-0.581
	(-0.38)	(-0.38)	(-1.61)	(-1.61)	(-0.49)	(-0.49)
$log(Borr_{s,t})$		-0.072***		-0.111***		-0.154***
		(-3.32)		(-3.46)		(-3.29)
$log(Borr_{s,t-10,t-1})$	-0.261***	-0.199***	-0.509***	-0.414***	-0.981***	-0.849***
	(-4.44)	(-3.76)	(-4.66)	(-4.22)	(-4.43)	(-4.01)
$LoanFee_{s,t}$		-0.012		-0.029		-0.052*
		(-1.12)		(-1.53)		(-1.97)
$LoanFee_{s,t-10,t-1}$	0.005	0.016	0.015	0.041	0.041	0.089
	(0.36)	(0.93)	(0.52)	(1.28)	(0.74)	(1.58)
Fixed Effect	Stock	Stock	Stock	Stock	Stock	Stock
Adjusted R-squared	0.006	0.006	0.012	0.012	0.023	0.024
Observations	127,381	127,381	127,381	127,381	127,381	127,381

about securities lending events with some of their clients.

Next, in Section 4.1, we characterize which investors are likely to receive information from the broker and trade based on that information. These are going to be institutions that engage in short selling, granting them access to the broker's securities lending desk, and can act quickly after acquiring information about potential trading opportunities. Then, in Section 4.2, we define imbalance measures that characterize the 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. Section 4.3 discusses in detail our identification strategy and contains our main results, which control trading comovement between clients of the same broker. Finally, Section 4.4 discusses the short seller's choice of which lending desk to borrow from.

4.1 Institutions likely to receive information

Our dataset comprises the trading activity of a wide range of market participants, including retail investors, mutual funds, index funds, hedge funds, pension funds, market makers, algorithmic traders, and even nonfinancial firms. Because this universe of investors is large and diverse, we identify those institutions that are most likely to receive information about information about an informed securities lending event and to act promptly. Specifically, these institutions should trade frequently, engage in short selling, handle non-negligible volumes, and follow stock-picking strategies rather than acting as market makers or funds implementing systematic strategies.

In our baseline analysis, we focus on institutions that meet four criteria: (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.

These requirements help isolate investors who are active in the market and, therefore, are more likely to receive and act on relevant information. Item (i) ensures that they participate regularly, while item (ii) requires them to have access to the securities lending desks, where information sharing occurs (as discussed in Section 2.1.2). Items (iii) and (iv) ensure that these investors trade fewer securities but substantial amounts, making them less likely to be market makers. In Section 8, we conduct various robustness tests by varying these requirements.

Note that criterion (ii) is especially important to our analysis. If we include investors who do not participate in the securities lending market, all these investors would be automatically classified as nonclients of the lending desk in all events. When many investors remain consistently in one group, we cannot accurately compare the behavior of clients versus nonclients. In our main empirical specification, which will be discussed later in Sections 4.2 and 4.3, we define an institution as a broker's client on the event day if it had any open securities lending agreement with that broker during the 90 days preceding the event date.

In our sample, 463 institutions satisfy these criteria,[23] and they account for a significant portion of the overall trading volume in Brazil. On average, they represent 12.9% of the daily volume, although this figure ranges from 8.0% to 23.1% over time.[24]. Their average daily trading volume is around R$4 million, which is about US$1.2 million at the average exchange rate during the sample period. These institutions also tend to use multiple brokers in the securities lending market, using an average of about 9.16 different brokers.[25]

We also measure the trading performance of these investor T days after their stock purchases and sales.[26] 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.

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.

[23]Out of these 463 institutions likely to receive information, 156 triggered at least one informed securities lending event described in Section 3.

[24]Figure IA.2 in the internet appendix plots their volume share over time.

[25]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). The minimum number of brokers used is 1, the median is 6, and the maximum is 38.

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

4.2 First-pass evidence

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. 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.

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 by clients of event broker b. 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 $VImbalance^c_{\nu,t}$ 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 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.[27]

[27] Table IA.3 in the Internet Appendix 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

To test whether client and nonclient trade different on the event day, we estimate the following difference-in-differences regressions:

$$\begin{aligned} y^j_{\nu,t} = \beta_0 + \beta_1 Clients^j_{\nu,t} + \beta_2 EventDay^j_{\nu,t} \\ + \beta_3 Clients^j_{\nu,t} \times EventDay^j_{\nu,t} + \mu_\nu + \epsilon^j_{\nu,t}, \quad t = \tau-10, \tau-9, \ldots, \tau-1, \tau \end{aligned} \tag{1}$$

where $y^j_{\nu,t}$ is either $VImbalance^j_{\nu,t}$ or $NImbalance^j_{\nu,t}$, 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 $Clients^j_{\nu,t}$ is a dummy equal to one if $y^j_{\nu,t}$ refers to clients of the broker and zero if $y^j_{\nu,t}$ refers to nonclients of the broker, $EventDay^j_{\nu,t}$ 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.

Note that for each event, our regression uses time-series data up to and including the event day (τ). The reason is that on the day following the event, the shares borrowed on the event date are incorporated into the total short interest of the stock and publicly disclosed to all market participants. Although the identity of the short sellers remains unknown, any increase in aggregate short interest can be informative about future stock performance and trigger additional selling pressure. Thus, only on the event day can we be certain that information about a large security lending agreement is exclusive to the broker's securities lending desk.

Coefficient β_3 is our parameter of interest as it measures whether the change in $y^j_{\nu,t}$ on the day of the event compared to the previous 10 days is different between clients and nonclients of the broker. Table 4 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.

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

centered at zero, which means that on average the buying activity equals the selling activity, considering clients and nonclients.

Table 4: First-pass evidence

This table presents difference-in-differences regression estimates following Equation 1, as described in Section 4.2. Informed securities lending events are defined in Section 3, while client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 10 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). *Clients* is one for clients of the brokers and *EventDay* is one for the day of the informed 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	-0.010	-0.010	-0.028***	-0.028***
	(-0.80)	(-0.80)	(-2.81)	(-2.81)
EventDay	0.033*	0.033*	0.009	0.009
	(1.84)	(1.84)	(0.86)	(0.86)
Clients × *EventDay*	-0.079***	-0.079***	-0.047***	-0.047***
	(-3.13)	(-3.13)	(-3.13)	(-3.13)
Constant	-0.003	-0.003	0.019**	0.019***
	(-0.27)	(-0.43)	(2.30)	(3.69)
Event F.E.		✓		✓
Obs	30,888	30,888	30,888	30,888
Adj-R2	0.01	0.06	0.01	0.08

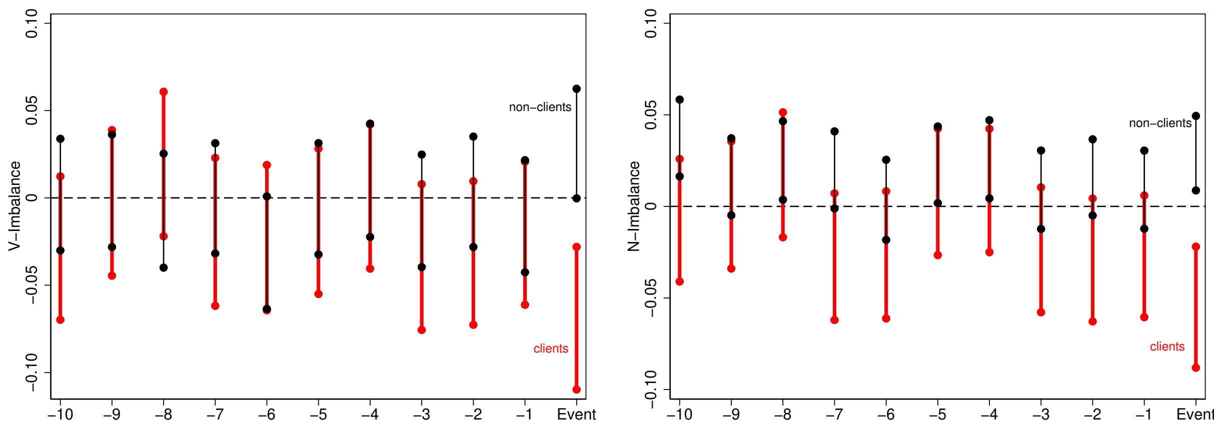
net buyers. They increase their position as their net volume bought represents 3% of their total gross volume traded, on average ($\beta_0 + \beta_2$). However, clients of the broker become net sellers, and their net volume sold represents 5.9% of their total gross traded volume ($\beta_0 + \beta_1 + \beta_2 + \beta_3$). 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 7.9% of their respective gross traded volume, is statistically significant and economically large (β_3).

If we consider the trading imbalance in the number of institutions (columns 3 and 4), we document the same trading pattern. We find that $NImbalance$ decreases 4.7% more for clients than for nonclients.

Figure 3 illustrates the dependent variables' behavior prior to an event day. Panel A shows that, in terms of volume short versus long ($VImbalance$), clients and nonclients do not exhibit different behaviors during the days leading up to an informed securities lending event. Panel B, however, suggests that the fraction of clients who are net sellers ($NImbalance$) differs between the two groups. Specifically, the daily average of $NImbalance$ appears higher

Figure 3: Trading imbalances 10 days before informed events versus event day

This figure shows the trading behavior of the institutions likely to receive information (defined in Section 4.1) before and on the day of the informed securities lending events (defined in Section 3). We split these institutions into clients and nonclients of the broker involved in the event, as discussed in Section 4.2. The variables in Panels A and B are $VImbalance$ and $NImbalance$ respectively. Both imbalance measures are defined in Section 4.2. 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 informed securities lending events.



A. $VImbalance$ B. $NImbalance$

for nonclients from day -10 to day -1.

This pattern is confirmed in Table 4. In columns (1) and (2), the coefficient on the Client dummy is statistically insignificant, while in columns (3) and (4), it is significantly negative. These initial results do not yet account for comovement among clients, so in the next section we introduce controls for clients' trading comovement. Once we do so, the differences between clients and nonclients before the event day become statistically insignificant for both imbalance measures.

4.3 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.[28] 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 short 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%, 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

[28] In 2019, after our sample period, the settlement in the centralized stock market was reduced to $T+2$.

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.[29]

As our main specification, 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 ν on each day t. 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 5 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 0.030 and -0.132 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

[29] The dynamics of π varies across events, which we can see in Figure IA.3 in the Internet Appendix as a heatmap of $\pi_{i,t}$ for each event and day.

Table 5: Information leakage in informed securities lending events

This table presents difference-in-differences regression estimates following Equation 2, as described in Section 4.3. Informed securities lending events are defined in Section 3, while client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). *Clients* is one for clients of the brokers and *EventDay* is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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	0.009	0.009	-0.016	-0.016
	(0.52)	(0.52)	(-1.30)	(-1.30)
EventDay	0.036*	0.036*	0.016	0.016
	(1.89)	(1.90)	(1.45)	(1.47)
Clients × *EventDay*	-0.081***	-0.081***	-0.048***	-0.048***
	(-2.98)	(-2.98)	(-3.08)	(-3.08)
π	0.029	0.030	-0.003	0.001
	(1.29)	(1.37)	(-0.15)	(0.05)
Clients × π	-0.132***	-0.132***	-0.083***	-0.083***
	(-4.60)	(-4.60)	(-3.28)	(-3.28)
Constant	-0.010	-0.012	0.011	0.011
	(-0.77)	(-0.93)	(1.35)	(1.47)
Event F.E.		✓		✓
Obs	11,232	11,232	11,232	11,232
Adj-R2	0.01	0.09	0.01	0.10

-0.102 ($= 0.030 - 0.132$) 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.

Note that the coefficient on *EventDay* on both Tables 4 and 5 are significant for the $VImbalance$ measure but insignificant for $NImbalance$. This suggests that nonclients are acting as liquidity providers to clients on event days. Although a similar fraction of nonclients are net buyers, they represent a significantly larger share of the value bought.

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 8.1% 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 -0.048. 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 indicate that brokers leak to their clients information acquired from securities lending.

Our findings on information leakage also align with those by Di Maggio, Franzoni, Kermani, and Sommavilla (2019). The 1,404 informed events are concentrated among brokers with higher centrality measures, that is, brokers involved in information leakage tend to be centrally located in the securities lending market.[30]

4.4 Short sellers' choice of lending desks

The short seller's choice of which securities lending desk to borrow from is likely endogenous. Although this possible endogeneity does not necessarily affect our estimates, it does change how we interpret our findings. There are two possible scenarios to consider.

First, the short seller might want the broker to leak information. This scenario is in line with Ljungqvist and Qian (2016), where short sellers want to induce selling pressure from other market participants. In this case, the short seller would strategically choose a broker known to be more likely to leak information to other clients. For example, if the short seller has already sold a substantial portion of the position before borrowing the stock and wants the leakage to accelerate the price decline, then this is a likely scenario where the short seller

[30]For each broker, we calculate N_b, the number of distinct investors who engaged in borrowing transactions exceeding R$ 1 million with that broker. This serves as a proxy for the broker's interaction level with prominent short sellers. For interpretability, we normalize N_b by dividing it by its maximum observed value across all brokers, ensuring that the centrality measure ranges from 0 to 1. The distribution of centrality across all 99 brokers in securities lending exhibits an average of 0.07, with a 10th percentile of 0, a median of 0.01, and a 90th percentile of 0.20. In contrast, across the 1,404 informed securities lending events, the distribution of the centrality measure shows an average of 0.39, a 10th percentile of 0.06, a median of 0.305, and a 90th percentile of 1.

would welcome the broker leaking information. Our results in this scenario still measure information leakage—the short seller's choice of which desk to borrow from would not bias our results. Since we control for trading comovement, we actually find that on an event day, clients of the lending desk sell more than nonclients—above and beyond the selling explained by the trading that covaries with the trading of the short seller generating the event. The short seller's choice would simply make the leakage more prominent and easier to observe empirically.

Second, the short seller might want to avoid information leakage. This scenario is consistent with a short seller who still has more securities to sell after borrowing and wants to avoid competitors trading on the leaked information. In this case, the short seller might choose to borrow from a securities lending desk less likely to leak information. Alternatively, the short seller could try to conceal its trade by borrowing across multiple brokers. Both these behaviors would make it more challenging to empirically detect leakage because the short seller's actions are trying to minimize information leakage. In spite of these efforts, our evidence of information leakage would remain valid because, on the borrow day, we are estimating a significantly higher selling activity from desk's clients relative to nonclients, controlling for trading comovement with the short seller generating the event.

Both scenarios are plausible and likely to coexist. We defined informed securities lending events to capture the day when large securities lending agreements are made by a skilled short seller. Hence, these events are more likely to capture short-selling activity when the short seller generating the event is less likely to be trying to conceal its trade. As a result, our events are probably capturing short-selling activity more similar to the first scenario, as we are purposely not focusing on short sellers trying to conceal their trades.

5 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.

5.1 Uninformed 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 6 presents the results in Columns (1) through (4). 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.

5.2 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

Table 6: Information leakage in placebo events

This table presents difference-in-differences regression estimates following Equation 2, applied to uninformed securities lending events and under-the-radar informed securities lending events.. Uninformed securities lending events are defined in Section 5.1, while under-the-radar informed securities lending events are defined in Section 5.2. Client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). $EventDay$ is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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.

	Uninformed events				Under-the-radar events			
	$VImbalance$		$NImbalance$		$VImbalance$		$NImbalance$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Clients$	-0.022	-0.022	-0.029*	-0.029*	-0.015	-0.015	-0.050***	-0.050***
	(-0.97)	(-0.97)	(-1.78)	(-1.78)	(-0.70)	(-0.70)	(-3.25)	(-3.25)
$EventDay$	0.012	0.011	0.034**	0.034**	-0.001	-0.001	0.018	0.018
	(0.47)	(0.46)	(2.29)	(2.42)	(-0.01)	(-0.02)	(1.07)	(1.06)
$Clients \times EventDay$	-0.001	-0.001	-0.029	-0.029	0.005	0.005	-0.009	-0.009
	(-0.01)	(-0.01)	(-1.51)	(-1.51)	(0.10)	(0.10)	(-0.26)	(-0.26)
π	0.017	-0.021	-0.065***	-0.060***	-0.068	-0.081*	-0.079**	-0.090**
	(-0.54)	(-0.68)	(-2.83)	(-2.65)	(-1.63)	(-1.90)	(-2.26)	(-2.41)
$Clients \times \pi$	-0.083**	-0.083**	-0.011	-0.011	0.053	0.053	0.056	-0.056
	(-2.08)	(-2.08)	(-0.30)	(-0.30)	(0.84)	(0.84)	(1.24)	(1.24)
$Constant$	0.016	0.017	0.026	0.025	-0.004	-0.001	0.020	0.022
	(0.84)	(1.43)	(2.04)	(2.75)	(-0.20)	(-0.08)	(1.62)	(2.30)
Event F.E.		✓		✓		✓		✓
Obs	7,784	7,784	7,784	7,784	4,496	4,496	4,496	4,496
Adj-R2	0.01	0.11	0.01	0.11	0.01	0.09	0.01	0.10

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 4.3 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 6 in Columns (5) through (8). 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.

5.3 Comparing events

We provided evidence of information leakage when brokers' securities lending desk became aware of an informed securities lending event taking place. The two placebo events studied in Sections 5.1 and 5.2—uninformed and under-the-radar informed securities lending events—indicate that the leakage is intentional. The placebo exercises show that when a broker is intermediating a large securities lending agreement, but the short seller generating the event is either unskilled, and the broker knows that, or skilled but does not know that, then we observe no leakage. This suggests that brokers actively share information about ongoing shorting bets depending on the skill level of the short seller building a large short position. Next, we assess the similarities and differences between our baseline informed securities lending events and the two placebo events considered.

We expect uninformed securities lending events to be inherently different in some dimensions—given that the short sellers who generated those events are unskilled, at least in their recent trading record—but it is vital to focus on one specific dimension: volume of the securities lending agreement that triggered the event. The uninformed securities lending events are designed to rule out unintentional information leakage that takes place in the process of locating securities for lending.

Table 7 reports various statistics for our baseline events as well as for the placebo events. Column (1) shows statistics for the baseline informed securities lending events, while Column (2) shows the same statistics for the uninformed securities lending events. Column (3) reports the differences. We report the average volume borrowed by the short seller who generated the event in the event, stock total return on the event day and on the 10 days prior to the event, stock return in excess of the market on the event day and on the 10 days prior to the event, stock volume on the event day and on the 10 days prior to the event, stock volatility and auto-correlation on the 10 days prior to the event, and probability of earnings or material fact announcements on the event day and on the 10 days prior to the event. We measure stock volatility as the standard deviation of daily stock returns, and we measure auto-correlation of stock returns as the R^2 from a regression of stock returns on its three lags.

Uninformed securities lending agreements are typically triggered by larger securities lending agreements, which ensure that the information transmission through the process of locating securities for lending is as strong as in the baseline events, if not stronger. As expected, uninformed events differ in various other dimensions regarding the past performance and volume of the security involved in the event, as well as its traded volume and volatility. Specifically, returns in the previous 10 ten are larger for securities in informed events, indicating perhaps a bet on short-term reversals; past traded volume is also larger, which could suggest more salient securities.

Columns (4) and (5) of Table 7 present the same statistics for under-the-radar informed events and their differences relative to baseline events. We designed under-the-radar events to be nearly identical to the baseline, except that the broker does not realize the short seller is skilled. In line with this design, the two sets of events should show no significant differences in observable security characteristics, as confirmed by the statistically insignificant results in Column (5). This reaffirms that the determining factor for leakage is the broker's awareness of short sellers' past performance.

Additionally, we can compute the time it takes for the short sellers generating events to cover their short position. Specifically, our data allows us to calculate the number of days it takes for the short seller to fully cover all the selling activity reported up to three days before the event day. The informed securities lending events have a median number of days to cover of 17 days, with 25th and 75th percentiles being 5 and 44 days, respectively. Under-the-radar informed securities lending events feature a similar distribution of days to cover. The median is 21, while the 25th and 75th percentiles are 5 and 55 days, respectively. Finally, for the uninformed securities lending events, the median is 14, the 25th percentile is 4, and the 75th percentile is 47. Overall, the frequency of covering days for our baseline events is similar to that of the under-the-radar events, while uninformed events have slightly shorter covering periods.

5.4 Testing leakage differences

The analyses presented in Sections 5.1 and 5.2 are useful as they indicate the leakage observed in informed securities lending events to be intentional. Although the estimated leakage effect under each placebo event is indistinguishable from zero, we still need to determine whether these estimates differ statistically from the leakage observed in the baseline informed securities lending events.

A natural way to do this is to create a dataset with all events together and test for differences in slopes by adding dummies accordingly. Specifically, in a dataset that includes all informed securities lending events as well as both placebos events, we augment the specification from Equation 2 by including one dummy for each placebo event and the appropriate interaction terms. We report these estimations in Table 8.

Note that including the set of variable interactions as controls imply that the slope on $Client \times EventDay$ reported in Table 8 exactly matches the corresponding coefficients on

Table 7: Comparing informed securities lending events with placebos

This table reports various statistics for the informed securities lending events in Column (1), for uninformed securities lending events in Column (2), and for under-the-radar informed securities lending events in Column (4). Columns (3) reports the difference between Columns (1) and (2), while Column (5) reports the difference between Columns (1) and (4). We defined 1,404 informed securities lending events in Section 3, 973 uninformed securities lending events in Section 5.1 and 562 under-the-radar informed securities lending events in Section 5.2. We report the following statistics: volume borrowed by the short seller who generated the event in the event, stock total return on the event day and on the 10 days prior to the event, stock return in excess of the market on the event day and on the 10 days prior to the event, stock volume on the event day and on the 10 days prior to the event, stock volatility and auto-correlation on the 10 days prior to the event, probability of earnings or material fact announcements on the event day and on the 10 days prior to the event. We measure stock volatility as the standard deviation of daily stock returns, and we measure auto-correlation of stock returns as the R^2 from a regression of stock returns on its three lags. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Informed events	Uninformed events		Under-the-radar events	
		Avg.	Diff.	Avg.	Diff.
	(1)	(2)	(3)	(4)	(5)
Volume borrowed in event (R$ mm)	11.47***	15.85***	-4.38**	8.99***	2.48
	(12.18)	(8.42)	(-2.26)	(9.55)	(1.55)
Stock total return (day 0)	-0.135%**	0.195%***	-0.330%***	-0.034%	-0.101%
	(-2.07)	(2.24)	(-3.09)	(-0.29)	(-0.80)
Stock excess return (day 0)	-0.136%**	0.102%	-0.238%***	-0.055%	-0.081%
	(-2.48)	(1.43)	(-2.68)	(-0.56)	(-0.76)
Stock volume (day 0, R$ mm)	253.8***	312.5***	-58.7***	246.9***	6.9
	(29.12)	(23.5)	(-3.85)	(18.56)	(0.43)
Stock volume (-10 -1, R$ mm)	244.0***	296.8***	-52.8***	228.3***	15.7
	(32.05)	(25.31)	(-3.95)	(20.03)	(1.12)
Stock total return (-10 -1)	1.482%***	3.942%***	-2.459%***	2.094%***	-0.612%
	(6.43)	(14.42)	(-6.86)	(5.36)	(-1.39)
Stock excess return (-10 -1)	0.852%***	2.534%***	-1.683%***	1.439%***	-0.587%
	(4.25)	(11.21)	(-5.51)	(5.51)	(-1.55)
Stock volatility (-10 -1)	2.343%***	2.542%***	-0.199%***	2.376%***	-0.033%
	(67.35)	(52.69)	(3.44)	(40.62)	(0.49)
Auto-correlation (-10 -1)	28.7%***	28.7%***	0.001%	29.9%***	1.19%
	(58.32)	(47.97)	(0.07)	(39.42)	(1.30)
Prob. Earnings Announc. (day 0)	1.9%***	2.2%***	-0.3%	2.5%***	-0.6%
	(5.15)	(4.63)	(0.53)	(3.79)	(0.90)
Prob. Material Fact (day 0)	2.1%***	1.7%***	0.4%	2.1%***	0.001%
	(5.53)	(4.16)	(0.67)	(3.50)	(0.01)
Prob. Earnings Announc. (-10 -1)	17.5%***	17.2%***	0.3%	16.2%***	1.3%
	(17.22)	(14.19)	(0.19)	(10.41)	(0.68)
Prob. Material Fact (-10 -1)	13.2%***	13.8%***	-0.6%	15.1%***	-1.9%
	(14.59)	(12.46)	(0.41)	(10.00)	(1.13)

$Client \times EventDay$ from Table 5.

The coefficient on $Client \times EventDay \times P1$ ($Client \times EventDay \times P2$) in Table 8 indicates whether the leakage effect of uninformed (under-the-radar informed) securities lending events differ significantly from those of the baseline informed events, where the dummy $P1$ equals 1 on the day of any of the 973 uninformed securities lending events and the dummy $P2$ equals

1 on the day of any of the 562 under-the-radar informed securities lending events.

Although Table 6 shows no evidence of leakage when either of the placebo events takes place, a closer look at these results shows the point estimates are different depending on the imbalance measure used, with $VImbalance$ featuring a point estimates close to zero or slightly positive and $NImbalance$ a slightly negative ones.

When we combine all events in Table 8, the results for $VImbalance$ remain largely unchanged when we test whether the leakage under the placebo events is different from leakage under our baseline informed securities lending events. Specifically, the coefficients on both $Client \times EventDay \times P1$ and $Client \times EventDay \times P2$ are positive and significant when using $VImbalance$ as a dependent variable, suggesting that leakage in our baseline events is different from that under either placebo events. However, for $NImbalance$ as a dependent variable, the point estimates are positive but not statistically significant.

These contrasting results offer an interesting insight into how brokers leak information. Recall that $VImbalance$ measures trading imbalance weighted by transaction volume, whereas $NImbalance$ measures the fraction of clients net buying the security. Thus, Table 8 suggests that brokers leak information about informed securities lending events, prompting clients to significantly reduce their exposure in terms of traded volume without drastically changing the fraction of clients net selling that security. In other words, the leak is more evident when looking at trading volumes—which is arguably the most economically relevant metric—rather than at the fraction of clients reducing their positions.

Table 8: Testing leakage differences between informed securities lending events and placebos

This table presents difference-in-differences regression estimates described in Section 5.4. The sample includes all informed securities lending events defined in Section 3 as well as the two placebo events described in Section 5.1 and 5.2. Client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). $EventDay$ is one for the day of an informed securities lending event. π is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the event. The variable $P1$ is a dummy equal to one on the day of an uninformed securities lending event $P2$ is a dummy equal to one on the day of an under-the-radar informed securities lending 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)
$Clients$	0.00855	0.00855	-0.0165	-0.0165
	(0.52)	(0.52)	(-1.30)	(-1.30)
$EventDay$	0.0361*	0.0361*	0.0159	0.0162
	(1.89)	(1.90)	(1.45)	(1.47)
$Clients \times EventDay$	-0.0806***	-0.0806***	-0.0484***	-0.0484***
	(-2.98)	(-2.98)	(-3.08)	(-3.08)
π	0.0292	0.0301	-0.00269	0.000945
	(1.29)	(1.37)	(-0.15)	(0.05)
$Clients \times \pi$	-0.132***	-0.132***	-0.0834***	-0.0834***
	(-4.60)	(-4.60)	(-3.28)	(-3.28)
$Clients \times P1$	-0.0308	-0.0308	-0.0129	-0.0129
	(-1.16)	(-1.16)	(-0.63)	(-0.63)
$Clients \times P2$	-0.0239	-0.0239	-0.0337	-0.0337
	(-0.89)	(-0.89)	(-1.63)	(-1.63)
$EventDay \times P1$	-0.0245	-0.0248	0.0185	0.0185
	(-0.91)	(-0.93)	(1.22)	(1.22)
$EventDay \times P2$	-0.0364	-0.0366	0.00215	0.00170
	(-1.35)	(-1.37)	(0.11)	(0.09)
$Clients \times EventDay \times P1$	0.0803*	0.0803*	0.0188	0.0188
	(1.96)	(1.96)	(0.73)	(0.73)
$Clients \times EventDay \times P2$	0.0852*	0.0852*	0.0396	0.0396
	(1.76)	(1.76)	(1.06)	(1.06)
$\pi \times P1$	-0.0466	-0.0515	-0.0628**	-0.0612**
	(-1.26)	(-1.47)	(-2.40)	(-2.24)
$\pi \times P2$	-0.0972**	-0.112***	-0.0759**	-0.0907***
	(-2.35)	(-2.65)	(-2.46)	(-2.72)
$Clients \times \pi \times P1$	0.0491	0.0491	0.0726	0.0726
	(1.01)	(1.01)	(1.53)	(1.53)
$Clients \times \pi \times P2$	0.186***	0.186***	0.139***	0.139***
	(2.75)	(2.75)	(2.74)	(2.74)
$P1$	0.0259		0.0138	
	(1.29)		(1.11)	
$P2$	0.00655		0.00766	
	(0.33)		(0.59)	
$Constant$	-0.0101	0.000380	0.0123	0.0180***
	(-0.77)	(0.05)	(1.35)	(3.38)
Event F.E.		✓		✓
Obs	23,512	23,512	23,512	23,512
Adj-R2	0.01	0.09	0.01	0.10

6 Effects on stock prices

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 5.2. 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 5.2, 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.

As discussed in Section 5.3, we find that under-the-radar informed securities lending events to be statistically indistinguishable from informed securities lending events—see Column (5) of Table 7. Under-the-radar events are nearly identical to our baseline events, except that the broker does not realize the short seller generating the event is skilled. Hence, we can attribute any observed differences in post-event price behavior to the leakage effect itself rather than to intrinsic differences in event characteristics.

Crucially, we employ short seller fixed-effects in our analysis. As a result, 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).[31]

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

$$y_{\nu,h} = \beta_0 + \beta_1 Leakage_\nu + \mu_l + \epsilon_\nu, \tag{3}$$

[31] 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.

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. We report the regression estimates in Table 9.

Overall, we find evidence that information leakage accelerates the price discovery process and improves efficiency. Panel A of Table 9 shows that prices decline for both informed securities lending events and under-the-radar informed securities lending events at a longer horizon of 20 days—the constant coefficient is negative and significant as reported in Columns (5) and (6). However, at a shorter horizon of 5 days, stock prices drop more when there is leakage, as shown in Columns (1) and (2).

Panel B of Table 9 reports the effects on return volatility. We find that when information is leaked, stocks become almost 10 percent less volatile in the near future relative to when there is an informed event without leakage. For instance, considering the 20-day ahead window, the volatility is about 0.024 (38.1% annualized) for events with no leakage and 0.022 (34.9% annualized) for events with leakage. Finally, Panel C reports the results for the daily return serial correlation. Similar to the effect of return 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 informed events with leakage.

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 evidence is consistent with information leakage making price discovery more efficient. In terms of the incentives of the short seller who generated an informed securities lending event, the fact that prices adjust more quickly and volatility declines when information is leaked suggests that the short seller generating informed securities lending events benefits from the leakage.

Table 9: Effect of the leakage on future returns

This table reports estimates from Equation (3), as described in Section 6, using event-level data from the 1,404 informed securities lending events (Section 3) and the 562 under-the-radar events (Section 5.2). The indicator *Leakage* equals 1 for an informed securities lending event and 0 otherwise. Panel A focuses on cumulative future returns and shows three sets of regressions. Columns (1) and (2) use a 5-day ahead return horizon, with and without short seller fixed effects, respectively; Columns (3) and (4) extend the horizon to 10 days; and Columns (5) and (6) use 20 days. Panels B and C use the same horizons as in Panel A but examine future return volatility (standard deviation of daily returns) and future return serial correlation (the R^2 from regressing daily returns on their three lags), respectively. 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.

	5 days ahead		10 days ahead		20 days ahead	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cumulative return						
Leakage = 1	-0.004*	-0.006***	0.001	-0.002	0.002	0.001
	(-1.83)	(-2.79)	(0.46)	(-0.58)	(0.50)	(0.06)
Constant	0.001	0.003	-0.006*	-0.003	-0.008**	-0.006**
	(0.48)	(1.75)	(-1.78)	(-1.33)	(-1.80)	(-2.06)
Short seller F.E.		✓		✓		✓
Obs	1,895	1,895	1,895	1,895	1,895	1,895
Adj-R2	0.01	0.01	0.01	0.01	0.01	0.01
Panel B: Return volatility						
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
Panel C: Return serial-correlation						
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

7 Incentives

An investor receiving information about an informed securities lending event may regard this leakage as a valuable service the broker provides. Indeed, as shown in Figure 2—and corroborated by the regressions in Table 3—the event stock tends to underperform the market after the event. For instance, as we report in reported in Columns 2, 4, and 6 of Table 3, if an investor sells the security following an informed securities lending event, our estimates indicate that its risk-adjusted returns are -36.6, -51.6, and -93.8 basis points over the subsequent 5, 10, and 20 trading days, respectively. Thus, the benefit for the investor receiving the information is clear: reducing exposure to the asset yields a clear improvement in risk-adjusted returns.

However, the implications for the broker leaking this information and for the short seller generating the event are less straightforward. In this section, we document these incentives in more detail. Section 7.1 analyzes the implications for the short seller generating an informed securities lending event, and Section 7.2 investigates the broker's incentives to leak information.

7.1 Short sellers generating informed securities lending events

In this section, we examine the costs and benefits of information leakage for the short seller who generates an informed event. Our findings indicate that the short seller benefits substantially: front-running concerns are minimal, the net-of-fee performance on the short position is large, and the leakage induces a faster price decline. Notably, these advantages have little downside, as the short seller only pays the prevailing market rates to borrow securities.

Front-running. From the perspective of the short seller generating an informed securities lending event, information leakage could be detrimental if it leads to front-running—that is, if other market participants start selling that security before the short seller who triggered the event finishes building its position. In Section 4.3, we show that when the short seller borrows securities, it has already sold a volume in the exchange that, on average, slightly exceeds the volume borrowed. Since short sellers secure their positions before generating informed securities lending events, information leakage does not necessarily compromise their performance.

However, if the short seller continues selling after the event day, future sales performance could be affected—particularly if the short position is built gradually and leakage occurs during this process. To assess whether this is the case, we examine how often short sellers who generate informed securities lending events continue selling after the event day.

We find that in 609 out of 1,404 events, the short seller did not continue selling in the three days following the event. Moreover, in 929 of these events, either (i) the short seller exhibits no selling activity in the three days post-event, or (ii) post-event sales account for less than 25% of the total volume sold in the 7-day window surrounding the event. Thus, in the majority of cases, short sellers either stop selling after the event day or significantly reduce their selling activity. This suggests that for the short sellers who triggers an informed events front-running concerns are minimal.

Price discovery. Focusing on pre-event sales, the information leakage helps the short seller by accelerating the price discovery process. As discussed in Section 6, we document that information leakage leads to faster price decline, lower volatility and lower serial autocorrelation.

Net-of-fee performance. To verify whether the short sellers who generate informed events actually profited from their short positions, we account for borrowing costs and execution prices for selling and buying. We begin by tracking the net flow for each shorting event, starting from the first sale date (up to three days before the borrowing occurs) until the accumulated net flow returns to zero (i.e., the short is fully covered). We exclude deals that remain open beyond our sample period (222 shorting events), leaving us with a median number of days to cover of 17 days.

Next, to assess profitability, we sum all sales and purchases until the position is fully covered. We define the rate of return as the total profit of the deal (revenue from selling minus the cost of purchasing the securities back) divided by the value of all sales. Since short positions vary in duration, we normalize the returns to a fixed 17-day period, the median number of days to cover. The raw average return is 2.14%, which is relatively high for a 17-day window.

We then incorporate the actual borrowing fees paid by the short sellers. The average loan fee is 1.45% per year, as expected for predominantly easy-to-borrow stocks. Consequently, lending costs only slightly affect net-of-fee returns. After accounting for borrowing fees, the average net-of-fee return across events is 2.05%.

Lending Fees. Another dimension to consider is the fee paid by short sellers who trigger an informed securities lending event. Brokers could charge higher fees in exchange for withholding the short seller's private information, or lower fees in return for receiving it. Both channels are plausible. However, as detailed in the Internet Appendix B, our analysis shows that informed short sellers do not pay significantly different fees for these events. One explanation is that the opposing incentives cancel each other out. Another is that brokers must charge uniform fees for comparable agreements to avoid legal exposure of any perceived quid pro quo.

7.2 Broker leaking information

Overall, clients benefit from receiving information about informed events because it enables them to reduce exposure to assets likely to decline in value. The short seller generating the informed event also gains from the leakage, as discussed in Section 7.1. The remaining party in this information chain is the broker, and in this section, we explore the broker's incentives to leak information.

We find that by leaking information, the short sellers who generate informed events do not reduce their borrowing activity with the lending desks after a leakage. Hence, the leakage of information does not seem detrimental to the relationship between the broker leaking information and the short seller generating informed events.

More importantly, our findings indicate that clients who receive such information bring more future business to the lending desk; however, these clients continue to pay standard market rates when borrowing securities. In other words, the leak affects the *quantity* of business rather than the *price* at which they borrow, making it beneficial to brokers to leak information.

Loyalty. To evaluate loyalty dynamics among clients of the broker leaking information, we focus on clients possibly receiving information and on the short seller who generated the event.

We identify clients who possibly received the information as the broker's clients who (i) are not the short seller responsible for the event, (ii) sold the stock on the day of an event, and (iii) were not selling that stock in the 15 days before the event.[32] According to this definition, 292 institutions (out of the 463) are likely to have received event-related information from their brokers. 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

[32]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.

event broker. Although clients trade in all 1,404 events, in 549 of these events, some investors exhibit a clear trading pattern consistent with receiving information on the event day.[33]

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:

$$Loyalty_{i,t} = \beta_0 + \beta_1 \times t_{i,t} + \beta_2 \times After_{i,t} + \mu_i + \epsilon_{i,t} \tag{4}$$

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

Parameter β_2 captures a possible change in the dynamics of $Loyalty_{i,t}$ that may have been caused by the information leakage episode. We 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 10 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

[33]Re-estimating the main analysis for this subset of 549 events is a valuable exercise. Since these events suggest more active information sharing, we expect to observe stronger leakage effects. As anticipated, the difference-in-differences coefficient increases, as we now focus on events where at least one client only decided to sell on the event day. Table IA.4 in the appendix reports these results.

Table 10: Loyalty of clients receiving information and short sellers triggering informed securities lending events and

This table reports estimates from Equation (4), as described in Section 7.2. The dependent variable is $Loyalty_{i,t}$, for event-investor pair, 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 variable is computed for all investors who potentially received information leakage from a broker about an event and also for all short sellers whose borrowing activity was potentially leaked. A period 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

future securities lending agreements with that broker, borrowing and lending an additional 2.6 percentage points of their gross volume after the event.

In addition, we run this regression across all event-short seller pairs. 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 10. 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.

To summarize, our results indicate that institutions receiving information value the leakage and become more loyal to the broker by engaging in more securities lending agreements with that broker going forward. At the same time, the broker's lending desk does not lose business from the short sellers generating informed securities lending events.

Lending fees. Another aspect of broker incentives involves the fees paid by clients receiving information. In Internet Appendix C, we compare the borrowing fees for investors likely to receive information who borrow securities on event days. We find that clients receiving information from the brokers do not pay significantly higher or lower fees when borrowing the event stock on or immediately after an informed event. This outcome is consistent with brokers charging uniform fees for comparable agreements.

8 Robustness

In this section, we conduct robustness and placebo exercises. In Sections 8.1 and 8.2, we show that our benchmark results are robust to alternative definitions of informed securities lending events and to alternative definitions of institutions likely to receiver information, respectively. Then, in Section 8.3, we show that leakage is selective to higher volume clients. Section 8.4 presents additional robustness tests, including analysis with actual short positions, investigation of leakage several days after the event day, estimation that controls for lead-lag effects, and exclusion of events with public information disclosures.

8.1 Alternative informed securities lending events

In Section 3, we made assumptions to define our informed securities lending events. These choices were designed to identify bets made by informed short sellers that would likely be salient to brokers. While we believe these assumptions are reasonable and well-founded, we now demonstrate that our results remain robust to alternative specifications. Table 11 reports these robustness estimates.

Skill of the short sellers generating events. 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 examined all security loans made by a short seller with a particular broker. Using a 90-day rolling window, we estimated the probability that the short seller outperformed the market in the 20 trading days following the short sale—the average duration of security loans. If this probability was statistically greater than 50% at a 10% confidence level (i.e., t-statistic > 1.64), we classified the short seller as skilled from the broker's perspective. However, brokers may be more or less selective when assessing short sellers' skills.

Our results remain robust under different thresholds. Loosening the criteria such as using a critical value of 1 increases the total number of informed securities lending events to

1,982. Columns 1 and 7 of Table 11 estimate Equation (2) under this relaxed threshold. We still find a negative and significant β_3. Compared to Table 5, both the point estimates and t-statistics decrease, as expected, when including slightly less skilled short sellers.

Alternatively, tightening the criteria by using a critical value of 1.96 for a 5% confidence level reduces the total number of informed securities lending events to 1,180. Columns 2 and 8 of Table 11 report these estimates, and we again find a negative and significant β_3. Compared to Table 5, the point estimates and t-statistics increase, consistent with identifying more skilled short sellers.

Average traded volume. To focus on active short sellers, we set a minimum average borrowing volume of R$ 100,000 (US$ 29,325), ensuring that the short seller is salient to the broker. Our results remain robust under lower cutoffs. For example, reducing the threshold to R$ 50,000 results in 1,774 events, and as shown in columns 3 and 9 of Table 11, we still find a negative and significant β_3.

Volume threshold for defining an event. Our baseline 1,404 events were defined as instances where a broker's skilled short seller borrowed more than their previous 90-day maximum with that broker. The rationale behind this threshold is to focus on lending agreements that are salient to brokers. However, our results remain robust under a lower volume threshold. If we require the borrowed volume to be only 50% of previous 90-day maximum with that broker, the number of events increases to 4,728. As shown in columns 4 and 10 of Table 11, we still find a negative and significant β_3.

Time window for assessing short seller skill. In our baseline definition, we assessed short seller skill using a 90-day rolling window and estimated their probability of beating the market 20 days after taking a short position. Our results remain robust when using a longer 180-day rolling window, which results in 1,170 events. As shown in columns 5 and 11 of Table 11, we continue to find a negative and significant β_3.

Finally, we shift the period to assess short seller skill by 20 days. In this case, we identify only 1,295 informed lending events compared to the original 1,404, and Columns 6 and 12 of Table 11 report our leakage estimates using those events. We find that our results remain nearly identical when we shift the window back by 20 trading days.

Table 11: Alternative definitions of informed lending events

This table shows the estimates of our main specification, Equation (2), using informed lending events defined under alternative parameters, as described in Section 8.1. In columns 1 and 7, we use a lower critical level (t-statistic of 1) to define skilled short sellers (the number of events increases to 1,982). In columns 2 and 8, we use a higher critical level (t-statistic of 1.96) to define skilled short sellers (the number of events decreases to 1,180). In columns 3 and 9, we require the average shorting volume by the short seller to be greater than 50 thousand Brazilian Reais instead of 100 thousand Brazilian Reais (the number of events increases to 1,774). In columns 4 and 10, we require the volume borrowed by the short seller generating the event 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 increases to 4,728). In columns 5 and 11, we require the volume borrowed by the short seller generating the event to be greater than the maximum value borrowed by that short seller with that broker in the previous 180 days (instead of in the previous 90 days; the number of events decreases to 1,170). In columns 6 and 12, we shift the 90-day period to assess short seller skill by 20 days the number of events decreases to 1,295). Client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these alternative definitions of informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). $Clients$ is one for clients of the brokers and $EventDay$ is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for 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)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alternative events:	t-stat > 1 1,982 events	t-stat > 1.96 1,180 events	$AV >$ R$50k 1,774 events	$V >$ $0.5Max$ 4,728 events	180 days 1,170 events	shifting window 1,295 events	t-stat > 1 1,982 events	t-stat > 1.96 1,180 events	$AV >$ R$50k 1,774 events	$V >$ $0.5Max$ 4,728 events	180 days 1,170 events	shifting window 1,295 events
$Clients$	-0.020	0.010	-0.013	-0.031**	0.037*	-0.010	-0.038**	-0.017	-0.026*	-0.044***	-0.008	-0.035**
	(-1.07)	(0.58)	(-0.74)	(-2.36)	(1.90)	(-0.62)	(-2.45)	(-1.25)	(-1.69)	(-3.89)	(-0.51)	(-2.37)
$EventDay$	0.007	0.054***	0.018	0.013	0.011	0.013	0.008	0.022**	0.013	0.005	-0.002	0.005
	(0.50)	(2.69)	(1.18)	(1.24)	(0.57)	-0.77	(0.89)	(1.97)	(1.28)	(0.75)	(0.16)	(0.42)
$Clients$ $\times EventDay$	-0.038*	-0.095***	-0.068***	-0.040**	-0.070***	-0.073***	-0.032**	-0.055***	-0.050***	-0.023*	-0.046**	-0.047**
	(-1.75)	(-3.66)	(-2.62)	(-2.19)	(-2.67)	(-2.83)	(-2.05)	(-3.63)	(-2.93)	(-1.69)	(-2.26)	(-2.56)
π	-0.004	0.025	0.001	0.001	0.035	0.009	-0.021	-0.005	-0.025	-0.008	0.002	-0.008
	(-0.20)	(1.14)	(0.09)	(0.02)	(1.42)	-0.35	(-1.46)	(-0.23)	(-1.82)	(-0.91)	(0.10)	(-0.41)
$Clients \times \pi$	-0.075**	-0.136***	-0.088***	-0.062***	-0.129***	-0.123***	-0.052*	-0.085***	-0.067***	-0.050***	-0.097***	-0.065**
	(-2.29)	(-3.91)	(-3.71)	(-3.12)	(-3.21)	(-3.13)	(-1.96)	(-2.87)	(-3.23)	(-2.77)	(-3.47)	(-2.18)
$Constant$	-0.001	-0.020*	0.006	0.010	-0.035***	-0.009	0.022***	0.006	0.020***	0.024***	0.005	0.01
	(-0.11)	(-1.71)	(0.59)	(1.35)	(3.08)	(-0.96)	(2.73)	(0.77)	(2.62)	(4.26)	(0.54)	(1.45)
Event F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	13,823	9,440	12,377	32,166	9,360	10,360	13,823	9,440	12,377	32,166	9,360	10,360
Adj-R2	0.08	0.09	0.10	0.10	0.09	0.11	0.10	0.11	0.12	0.11	0.11	0.10

Table 12: Alternative definitions of institutions likely to receive information

This table shows the estimates of our main specification, Equation (2), using alternative definitions of institutions likely to receive information, as described in Section 8.2. In our baseline analyses, we focused on 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. The baseline definition of investors used is discussed in Section 4.1. In Columns 1 and 6, we require investors to buy or sell securities on average at least once a month instead of once a week (the number of investors increases to 714). In Columns 2 and 7, we require investors to borrow securities on average at least once a semester instead of once a month (the number of investors increases to 587). In Columns 3 and 8, we require investors to trade an average volume of at least R$50,000 considering the days the institution trades instead of R$100,000 (the number of investors increases to 512). In Columns 4 and 9, we require investors to trade at most 5 different stocks on the median day the institution trades instead of 10 (the number of investors decreases to 370). In Columns 5 and 10, we require investors to trade at more than 10 different stocks on the median day the institution trades instead of 10 (the number of investors decreases to 158). We compare how the trading behavior of clients differs from that of nonclients, before and after these alternative definitions of informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). $Clients$ is one for clients of the brokers and $EventDay$ is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for 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)	(5)	(6)	(7)	(8)	(9)	(10)
Alternative	trade once a month	short once a sem.	$AV >$ R$50k	5 stocks or less	$>$ 10 stocks	trade once a month 1	short once a sem.	$AV >$ R$50k	5 stocks or less	$>$ 10 stocks
Number of investors:	714 investors	587 investors	512 investors	370 investors	158 investors	714 investors	587 investors	512 investors	370 investors	158 investors
$Clients$	-0.001	0.008	0.003	0.037*	0.001	-0.017	-0.016	-0.024*	0.017	-0.021*
	(-0.03)	(0.49)	(0.20)	(1.87)	(0.21)	(-1.39)	(-1.31)	(-1.80)	-0.91	(-1.95)
$EventDay$	0.027	0.019	0.034*	0.041*	0.002	0.013	0.010	0.017	0.022	0.010
	(1.49)	(1.20)	(1.81)	(1.89)	(0.21)	(1.15)	(0.97)	(1.55)	-1.45	(1.28)
$Clients$ $\times EventDay$	-0.059**	-0.062**	-0.077***	-0.096***	-0.001	-0.037**	-0.039**	-0.042**	-0.051***	-0.010
	(-2.11)	(-2.22)	(-2.83)	(-3.35)	(-0.03)	(-2.20)	(-2.43)	(-2.55)	(-2.73)	(-0.67)
π	0.014	0.048***	0.027	0.012	0.043***	-0.009	0.009	-0.005	-0.001	0.004
	(0.70)	(2.31)	(1.22)	(0.42)	(2.69)	(-0.48)	(0.54)	(-0.29)	(-0.05)	(0.38)
$Clients \times \pi$	-0.122***	-0.151***	-0.134***	-0.127***	-0.069**	-0.085*	-0.091***	-0.082***	-0.087***	-0.065***
	(-4.07)	(-4.73)	(-4.55)	(-3.66)	(-2.57)	(-3.25)	(-3.87)	(-3.08)	(-2.79)	(-3.57)
$Constant$	-0.005	-0.016	-0.008	-0.007	-0.031***	0.015*	0.013*	0.011	0.005	-0.002
	(-0.48)	(-1.31)	(-0.76)	(-0.54)	(-3.27)	(1.97)	(1.79)	(1.52)	-0.59	(-0.33)
Event F.E.	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	11,232	11,232	11,232	11,232	10,345	11,232	11,232	11,232	11,232	10,345
Adj-R2	0.10	0.10	0.09	0.09	0.07	0.10	0.13	0.11	0.10	0.08

8.2 Alternative institutions likely to receive information

In Section 4.1, we define institutions that are likely to receive information from brokers after observing an informed securities lending event. Specifically, we require these institutions to (i) trade on average more than once a week, (ii) short sell on average more than once a month, (iii) trade an average volume above R$ 100,000 (US$ 29,325) per day, and (iv) have a median number of different stocks traded per day of 10 or fewer.

These criteria are designed to identify institutions that have access to securities lending information and can react quickly to capitalize on it. Next, we demonstrate that our results are robust to alternative definitions of these institutions. Table 12 presents the robustness estimates.

Trading less frequently. To focus on investors actively trading securities, our baseline analysis requires investors to trade at least once a week on average. However, our results remain robust when expanding the set to include less frequent traders. If we lower the threshold to once per month, the number of institutions likely to receive information increases to 714, and as shown in Columns 1 and 6 of Table 12, we still find a negative and significant β_3.

Borrowing securities less frequently. As discussed in Section 4.1, one important requirement for identifying institutions likely to receive information from a securities lending desk is that they must have had at least one open securities lending agreement in the previous month. This condition is crucial for two reasons. First, being a client of the securities lending desk grants direct access to information about informed securities lending events. Second, if we include investors who do not participate in securities lending at all, they would always be classified as nonclients across all events.

To test the robustness of this assumption, we relax criterion (ii) in Section 4.1, requiring that investors instead short sell at least once per semester on average. Under this more lenient definition, the number of investors likely to receive information increases from 463 to 587.

Columns 2 and 7 of Table 12 present the results under this broader definition. Since the expanded set includes more nonclients (who are less likely to have open securities lending agreements prior to an informed event), we expect weaker leakage results. Indeed, the point estimates in Columns 2 and 6 are lower in absolute value but remain statistically significant.

Lower traded volumes. To focus on investors with more skin in the game, we required them to trade a relatively large volume per day on average. Specifically, we required them to trade an average volume above R$ 100,000 (US$ 29,325) per day. If we lower this figure to R$ 50,000, we expand the set to institutions likely to receive information increases to 512 and, as reported in Columns 3 and 8 of Table 12, we also find a negative and significant β_3.

Trading fewer securities. To exclude large funds and market makers, we initially restricted the sample to institutions with a median number of different stocks traded per day of 10 or fewer. As expected, tightening this restriction strengthens our estimates. If we further limit the sample to institutions trading at most 5 different securities per day, the set of institutions likely to receive information shrinks to 370, and as shown in Columns 4 and 9 of Table 12, the point estimates of β_3 become larger and remain statistically significant.

Trading many securities. Alternatively, we can examine institutions that trade a large number of different securities per day. This group includes market makers and index funds, for instance. If we consider institutions satisfying (i)-(iii) but trading more than 10 different stocks per day, the sample is restricted to 158 institutions.

We should not expect to observe information leakage among these institutions, as they are less likely to follow stock-picking strategies. Many of these institutions engage in factor investing, index fund management, or market making, which do not rely on broker-provided information about individual securities. Thus, estimating Equation (2) for this group serves as a placebo test. Given their investment strategies, we expect to find weaker or no evidence of information leakage. Columns 5 and 10 of Table 12 presents the results. As expected, the point estimates of β_3 is close to zero and statistically insignificant. Consistent with our analysis, we find no evidence of information leakage when we evaluate the trading behavior of institutions that are less likely to pursue stock-picking strategies.

8.3 Selective leakage

Di Maggio, Franzoni, Kermani, and Sommavilla (2019) document that brokers selectively disclose information, providing greater benefits to their most valuable clients. Our findings are consistent with this pattern.

Our dataset allows us to examine selective leakage in detail by analyzing differences across clients. Specifically, we test whether brokers leak information less frequently to lower-volume investors by re-estimating our main regression (Equation 2) on a subsample of the bottom 100 investors in terms of securities loan volume, out of 463 investors likely to receive information from brokers in our sample.

Consistent with the hypothesis that brokers selectively disclose information to their most valuable clients—as in Di Maggio, Franzoni, Kermani, and Sommavilla (2019)—we find no significant differences in the trading behavior of clients and nonclients on the event day when restricting the analysis to these lower-volume investors. The point estimates on the interaction term $Clients \times EventDay$ are smaller in absolute value and not statistically significant. We report these results in Table IA.5 in the Internet Appendix.

8.4 Other tests

Actual short sales In our main analysis, we examined how leakage affects both the long and short positions, by focusing on whether it leads them to reduce their exposure to the security in a lending event. Although we do not observe investors' entire portfolios, we can still test for leakage specifically among investors taking short positions.

We classified a sale as a short sale if the investor borrowed the stock through the securities lending market from the day before the sale until up to three days after the sale. We use this window because sales settle at $t+3$, whereas borrowings settle on the same day. Moreover, we measure $VShort$, which is the log of the volume shorted on each event-window day relative to the average over the previous seven days, and $NShort$, which captures the number of investors shorting the stock on each day, also relative to that same seven-day average. Finally, we implement our main empirical specification but using $VShort$ and $NShort$ instead of the imbalance measures. Consistent with our earlier findings, we observe an increase in shorting activity among clients of the brokers compared to nonclients on the event day. The results of this analysis are reported in Table IA.6 in the Internet Appendix.

Leakages after event day In this section, we investigate whether the observed leakage effects persist beyond the event day by extending our analysis window to include additional days after the event. We must note, however, that short-selling activity is incorporated daily to the publicly disclosed short interest, which we expect to weaker trading differences between clients and nonclients.

Table IA.7 in the Internet Appendix compares the behavior of $NImbalance$ and $VImbalance$ in the five days following the event to the five days preceding it. In this setup, the variable $After$ equals 1 for the five-day post-event period and 0 for the five-day pre-event period. To focus solely on post-event trading rather than include the event day itself, we exclude the event day from this new analysis.

Overall, the results are consistent with Table 5 in the Internet Appendix, again showing that clients reduce their buying activity more than nonclients in the days following the event, evidenced by a negative and significant interaction coefficient. Once the short interest data becomes public, some nonclients may also adjust their behavior, and a comparison with Table 5 is consistent with that interpretation. Specifically, the $After$ coefficients here are smaller than the corresponding coefficients for the event day in Table 5, and the interaction coefficients are less negative. This pattern indicates that public disclosure of short positions, likely via the short interest measure, may prompt nonclients to react as well, thereby weakening the relative difference between clients and nonclients.

Lead-lag effects and longer window to control for covement In our main analysis, we focus on a four-day window due to the exchange settlement period. However, we can also consider covariation in clients' trading behavior on a longer window. The advantage of the shorter window is that it captures trading comovement closer to the event day, whereas the advantage of a longer window is a potentially more precise estimate.

Table IA.8 in the Internet Appendix presents the results from expanding the event window to include the ten days before the event. This extended analysis also adds controls for lead-lag effects in trading since some institutions may react more quickly to common information than others. Despite these modifications, our findings remain largely unchanged.

Events without public information disclosures As discussed in Section 3.1, the disclosure of public information—such as earnings announcements—typically precedes informed securities lending events. Since these public events may serve as common signals for investors, we restrict our sample to events not surrounded by public information as a robustness exercise. Specifically, we exclude events with an earnings announcement or material fact disclosure within a 5-day window around the event day. This restricted sample includes 1,180 out of our baseline 1,404 informed securities lending events.

Our results remain robust under this restriction, reinforcing the validity of our findings when excluding events potentially influenced by public disclosures. We present the estimates for this robustness check in Table IA.9 in the Internet Appendix, and our results remain unchanged.

9 Conclusion

In this paper, we examine how information from short sellers is transmitted to other investors. We find that a broker, intermediating a large securities lending agreement by 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.

A key question is why short sellers rely on brokers to share information rather than doing so themselves. While this question extends beyond the immediate scope of our paper, it presents an important avenue for future research. First, short sellers cannot easily prevent brokers from disseminating information. As discussed, we documented that information sharing accelerates price discovery, so it helps the short seller generate an event. Second, consistent with Ljungqvist and Qian (2016), short sellers may actually want to share information as widely as possible, and brokers can facilitate that. Third, a crucial argument in Ljungqvist and Qian (2016) is that the information must be "both credible and cannot be ignored." Since brokers operate in these markets long-term and have reputational concerns, they may serve as especially credible sources.

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Internet Appendix to "Information Leakage from Short Sellers"

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A Settlement timing at the Brazilian Exchange

When a security purchase transaction is executed between the buyer and the seller at date T, the details of the transaction are sent to the Central Counterparty (CCP). The CCP is the Brazilian exchange itself as it acts as an intermediary, ensuring both parties fulfill their obligations. The transaction is settled at $T + 3$, and the timing of the settlement process is as follows.[1]

- 10:00 AM - 2:00 PM: The clearinghouse processes the transfer of assets from the seller to the clearinghouse's settlement account at the exchange
- 2:00 PM to 3:49 PM: Confirmation of the availability of assets and final financial balances, along with the execution of procedures to resolve possible delivery failures.
- 3:50 PM: The clearinghouse makes the payments owed to creditor clients. It coordinates the delivery of assets against the simultaneous, final, and irrevocable payment of the financial amount, debiting its settlement account at the exchange central depository and crediting the creditor's deposit account.

Delivery failure. If by 2:00 PM the assets have not been deposited, the "failure handling" protocol is automatically triggered, as detailed in Section 8.1.5 of the Clearinghouse's Operational Procedures Manual. First, the clearinghouse compulsorily borrows the assets in the name of the buyer through the exchange's asset lending system, which is designed to be used in delivery failures. This ensures that buyers receive the assets in a timely manner, as the compulsory borrowing is settled on the same day. The compulsory borrowing takes place on a centralized lending platform specifically designed to handle delivery failures. The rates for compulsory borrowing are very high, typically spiking to 100 times and more than the usual rental rates during the key hours of the day. After the compulsory borrowing, a "repurchase order" is then issued by the clearinghouse on T+3 in favor of the buyer, who, in the meanwhile, is a security borrower. Once executed, the temporary compulsory borrowing ends and the buyer receives the shares on T+6. All expenses from the delivery failure, including price differences and lending fees from compulsory lending, are debited from the seller's account and credited to the buyer.

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[1] After 2018, new regulations in place reduced the settlement period to $T + 2$.

Delivery failure extends for multiple days. If the quantity available for compulsory borrowing is not sufficient, buyers will not receive the stock on the expected date, and further steps are taken, such as identifying all the buyers affected by the delivery failure and the establishment of a penalty for late delivery is imposed on the seller that amounts to 0.5% of the financial volume (limited to R$50,000), with additional penalties in the case multiple days are needed to resolve the delivery failure. (See Section 8.1.5.2 of the Clearinghouse's Operational Procedures Manual)

B Lending lees paid by short sellers when triggering an informed securities lending event.

In this section, we analyze the lending fee paid by a short seller on the agreement generating an informed securities lending event. On the one hand, the broker could charge higher lending fees to informed short sellers in exchange for not sharing information with other market participants. On the other hand, informed short sellers provide the broker with valuable information, which could lead the broker to charge a lower fee in return. Both channels are plausible, making examining the fees paid by the short sellers who generate these events worthwhile.

We begin with the following regression:

$$LoanFee_{t,s,b,i,c} = \lambda_{b,s,t} + \beta_1 EventBorrow_{t,s,b,i} + Controls + \epsilon_{t,s,b,i,c} \tag{IA.1}$$

where $LoanFee_{t,s,b,i,c}$ is the loan fee for contract c at time t for stock s, broker b, and short seller i. The variable $EventBorrow_{t,s,b,i}$ is a dummy equal to one if the borrowing contract was closed by short seller i, whose information was leaked on day t in stock s by broker b. We include broker–stock–day fixed effects ($\lambda_{b,s,t}$) to absorb all common factors at the broker–stock–day level. As control variables, we include $Retail_i$ (a dummy for retail short sellers), $Connections_i$ (the total number of broker connections of short seller i), and $\log(ContractVolume)_{t,s,b,i,c}$ (the log value of the contract volume). We report the estimates in Columns (1) through (4) of Table IA.1.

Broker–stock–day fixed effects allow us to interpret β_1 as the difference in fees paid by informed short sellers relative to other clients of the *same* broker, for the *same* stock on the *same* day. Across all four specifications, β_1 is statistically indistinguishable from zero; hence, we find no evidence that brokers charge either higher or lower fees on agreements that trigger an informed event. Moreover, the point estimates are not only statistically insignificant but also economically small, ranging from -0.5 to 4.6 basis points per year. We find the expected signs for our control variables: retail short sellers pay higher loan fees, short sellers interacting with multiple brokers pay lower fees, and larger lending agreements command higher fees.

Another approach is to include broker–stock–investor fixed effects to measure whether the broker charges different loan fees to the *same* short seller for the *same* stock around the leakage day relative to non-leakage days. Formally, we estimate:

$$LoanFee_{t,s,b,i,c} = \lambda_{b,s,i} + \beta_1 EventBorrow_{t,s,b,i} + Controls + \epsilon_{t,s,b,i,c} \tag{IA.2}$$

where $\lambda_{b,s,i}$ are broker–stock–investor fixed effects. We include $\log(ContractVolume)_{t,s,b,i,c}$ and

Table IA.1: Loan fees paid by the short sellers when triggering informed securities lending events

This table reports estimates from Equations (IA.1) and (IA.2), as described in Section 7.1, using securities lending data at the deal level. We regress $LoanFee_{t,s,b,i,c}$, the loan fee for contract c at time t for stock s, broker b, and short seller i on the following variables: $EventBorrow_{t,s,b,i}$ is one if the lending agreement closed by the short seller i triggered an informed securities lending event (defined in Section 3) on day t in stock s by broker b; $Retail_i$ is a dummy variable indicating whether i is a retail investor; $Connections_i$ represents the total number of broker connections of the investor i; $AvgFee_{t-1,s}$ the average loan fee for stock s on day $t-1$; $log(Volume_{t,s,b,i,c})$ is the log of the contract volume measured in US$ millions. Columns (1), (2), (3), and (4) have broker-stock-date fixed effects as in Equation (IA.1), and Columns (5), (6) and (7) broker-stock-investor fixed effects as in Equation (IA.2). Standard errors are double clustered by stock and date and are in parentheses. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

	Broker-stock-date FE				Broker-stock-investor FE		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$EventBorrow_{t,s,b,i}$	-0.005	0.042	0.046	0.022	-0.159	0.003	-0.001
	(-0.15)	(1.25)	(1.34)	(0.64)	(-1.50)	(0.14)	(-0.05)
$RetailDummy_i$		0.478***	0.421***	0.439***			
		(10.24)	(9.38)	(9.48)			
$Connections_i$			-0.005***	-0.006***			
			(-6.03)	(-6.56)			
$AvgFee_{t-1,s}$						0.940***	0.940***
						(48.51)	(48.49)
$log(Volume)_{t,s,b,i,c}$				0.019***			0.007*
				(4.57)			(2.16)
Fixed Effect	b-s-t	b-s-t	b-s-t	b-s-t	b-s-i	b-s-i	b-s-i
Adjusted R-squared	0.72	0.72	0.72	0.72	0.49	0.69	0.69
Observations	3,524,197	3,524,197	3,524,197	3,524,197	3,787,299	3,785,227	3,785,227

the average lending fee for stock s on day $t-1$ as control variables; the other controls used in the previous specification are absorbed by the fixed effects. We report these estimates in Columns (5) to (7) of Table IA.1. Again, β_1 remains statistically indistinguishable from zero. The point estimates, when controls are included, are not only statistically insignificant but also economically negligible, ranging from -0.1 to 0.3 bps per year. As before, the controls behave as expected: past loan fees strongly predict current fees and larger lending agreements incur higher fees.

Overall, we find that informed short sellers do not pay higher or lower borrowing fees when triggering informed securities lending events. One explanation is that the two opposing forces offset each other: the broker could charge higher lending fees from informed short sellers in exchange for not sharing information with other market participants or could charge a lower fee in exchange for the information provided by the short sellers. Another explanation is that brokers charge similar fees to similar securities lending agreements because any fee differential would be readily observable by regulators and could be characterized as a quid pro quo.

C Lending lees paid by clients likely receiving information

Another aspect of broker incentives is the fees paid by the clients receiving information. Our data allow us to compare how much investors pay when borrowing securities on event days. Specifically, for all securities lending agreements made by institutions likely to receive information (defined in Section 4.1), we run the following regression:

$$LoanFee_{t,s,b,i,c} = \lambda_{b,s,t} + \beta_1 Leakage_{t,s,b,i,c} + Controls + \epsilon_{t,s,b,i,c} \tag{IA.3}$$

where $LoanFee_{t,s,b,i,c}$ is the loan fee for contract c at time t for stock s, broker b, and short seller i. The variable $Leakage_{t,s,b,i,c}$ is a dummy indicating whether contract c is induced by information leakage. Specifically, $Leakage_{t,s,b,i,c}$ equals one if (i) there is an informed securities lending event one day t for security s through an agreement intermediated by broker b, (ii) contract c did not trigger the informed event, (iii) investor i sold the security s on the day of an event, (iv) investor i was not selling security s in the 15 days before the event, and (v) investor i borrowed the security s from broker b on the day of the sale (day t) or on the two subsequent days (days $t+1$ and $t+2$) of the leakage event. We include broker–stock–day fixed effects ($\lambda_{b,s,t}$) to absorb all common factors at the broker–stock–day level. We add the same control as those in Equation (IA.1). We report the estimates in Columns (1) through (3) of Table IA.2.

In line with Equation (IA.1), the broker–stock–day fixed effects allow us to interpret β_1 as the difference in fees paid by informed short sellers compared to other clients of the *same* broker, trading the *same* stock on the *same* day. In all three specifications, β_1 is statistically indistinguishable from zero, suggesting no evidence of brokers charging higher or lower fees for agreements linked to an informed event. Furthermore, these point estimates are statistically insignificant and economically small, ranging between 2.5 and 3 basis points per year. As for our control variables, they have the expected signs: short sellers interacting with multiple brokers pay lower fees, while high-volume lending agreements correspond to higher fees.

We estimate the coefficient including broker–stock–investor fixed effects. Similar to Equation (IA.2), these fixed effects allow us to measure whether the broker charges different loan fees to the *same* short seller for the *same* stock around the leakage day relative to non-leakage days. Specifically, we estimate the following:

$$LoanFee_{t,s,b,i,c} = \lambda_{b,s,i} + \beta_1 Leakage_{t,s,b,i,c} + Controls + \epsilon_{t,s,b,i,c} \tag{IA.4}$$

where $\lambda_{b,s,i}$ are broker–stock–investor fixed effects. We add the same control as those in Equation (IA.2) and report the estimates in Columns (4) through (6) of Table IA.2. Although the t-statistics are larger in absolute value, β_1 remains statistically indistinguishable from zero. In other words, we find the clients receiving information from brokers do not pay higher or lower borrowing fees when borrowing event stock from the brokers on and immediately after an informed event.

Table IA.2: Loans fees after informed securities lending events for investors receiving information

This table reports estimates from Equations (IA.3) and (IA.4), as described in Section 7.2. The table presents the results of panel regressions of $LoanFee_{t,s,b,i,c}$, which represents the loan fee for contract c at time t for stock s, broker b, and short-seller i. The model includes the following variables: $LeakageDeal_{t,s,b,i}$ is set to one if the lending agreement was closed by an institution likely to receive information who actively benefited from the leakage by broker b by selling on the day of the leakage event and borrowing stock s on days t, $t+1$, or $t+2$; $AvgFee_{t-1,s}$ is the market average lending fee on day $t-1$ on stock s; $Connections_i$ represents the total number of broker connections of stock-picker i; $log(Volume_{t,s,b,i,c})$ is the log of the contract volume measured in US$ millions. Columns (1), (2), and (3) have broker-stock-date fixed effects as in Equation (IA.3), and Columns (4), (5), and (6) broker-stock-investor fixed effects as in Equation (IA.4). In this regression, we include all lending contracts where the borrowers were among the 463 institutions likely to receive to information (defined in Section 4.1). Standard errors are in parentheses and double clustered at stock and day. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

	Broker-stock-date FE			Broker-stock-investor FE		
	(1)	(2)	(3)	(4)	(5)	(6)
$LeakageDeal_{t,s,b,i}$	0.030	0.025	0.030	-0.451	-0.118	-0.120
	(0.69)	(0.59)	(0.69)	(-1.64)	(-1.48)	(-1.50)
$Connections_i$		-0.008**	-0.009***			
		(-3.35)	(-3.74)			
$AvgFee_{t-1,s}$					0.924***	0.924***
					(39.91)	(39.90)
$log(Volume)_{t,s,b,i,c}$			0.023***			0.008
			(3.44)			(1.70)
Fixed Effect	b-s-t	b-s-t	b-s-t	b-s-i	b-s-i	b-s-i
Adjusted R-squared	0.74	0.74	0.74	0.49	0.68	0.68
Observations	563,672	563,672	563,672	680,097	679,593	679,593

D Additional Tables and Figures

Figure IA.1: Distribution of informed securities lending events over time and across stocks

This figure illustrates the 1,404 informed securities lending events (defined in Section 3) over our sample period from 2015 to 2018 (923 trading days). Each row on the y-axis corresponds to one of the 96 stocks in our sample (sorted alphabetically by ticker), and every red mark indicates an occurrence of an informed lending event on that specific day.

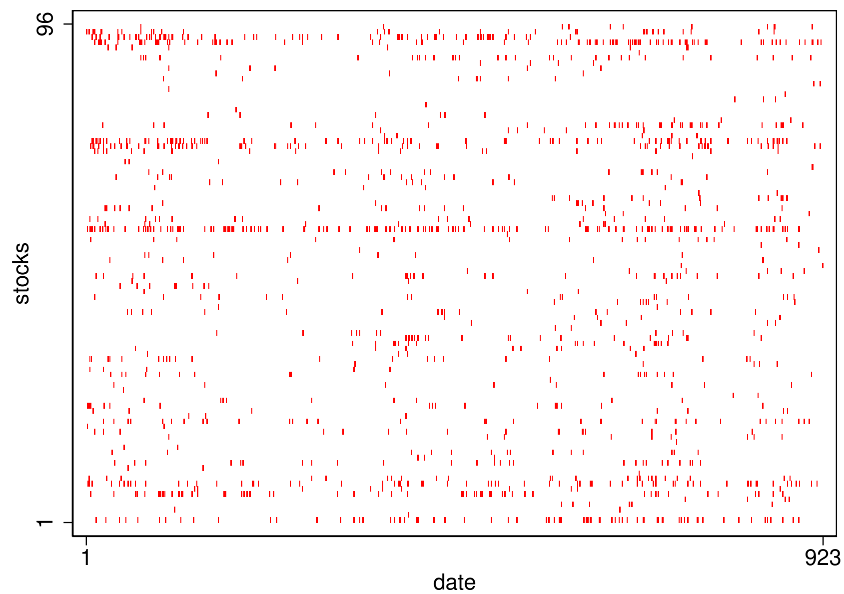

Figure IA.2: Volume share of institution likely to receive information

This figure shows the daily proportion of the trading volume by the institutions likely to receive information (defined in Section 4.1), 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 stock-day pair 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 across the institutions likely to receive information ($|q|_{sp}$). 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.

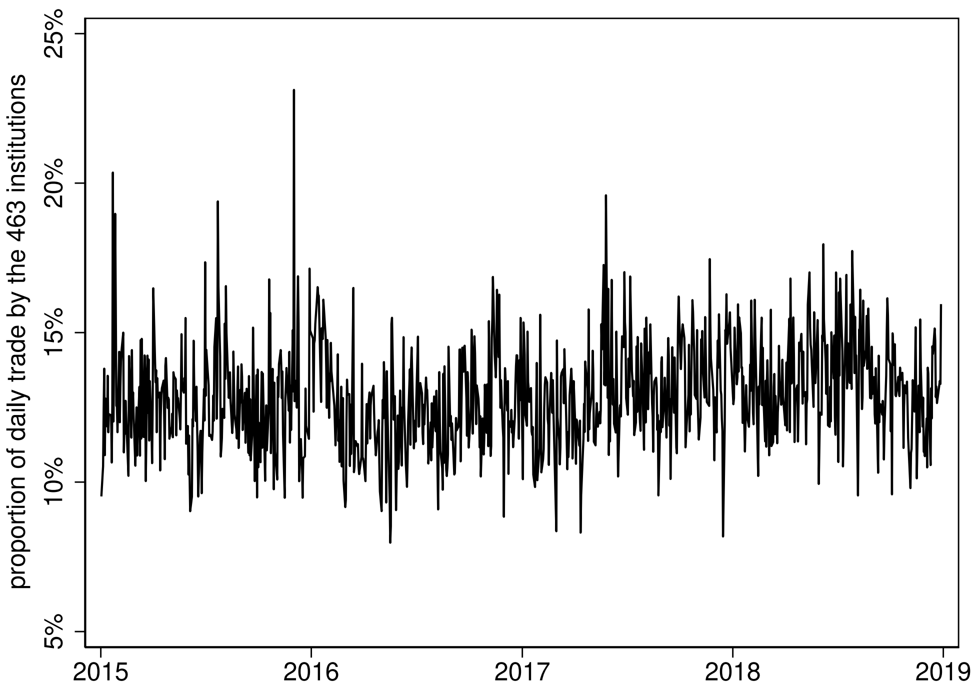

Figure IA.3: Distribution of the selling activity by the short seller generating informed securities lending events.

This figure shows, for each informed securities lending event (defined in Section 3), the distribution of the event stock's selling activity by the short seller who initiated that event. Specifically, it presents heat maps illustrating the short seller's daily selling activity during the 3 days leading up to the event and on the event day itself. The measure of selling activity is the variable π (see Section 4.3), defined as the volume sold by the short seller on a given day divided by the total volume sold across the 4-day period.

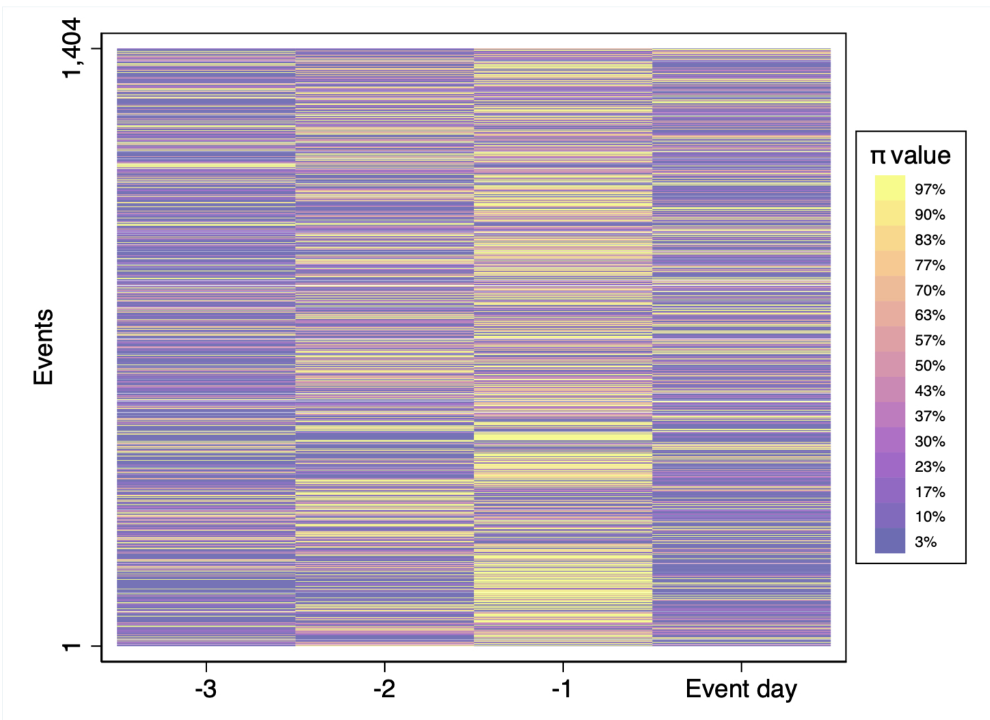

Table IA.3: Distributions of $VImbalance$ and $NImbalance$

This table presents descriptive statistics for the trading imbalance variables for clients and nonclients: $VImbalance^{c}_{\nu,t}$, $VImbalance^{n}_{\nu,t}$, $NImbalance^{c}_{\nu,t}$, and $NImbalance^{n}_{\nu,t}$. The definitions of these imbalance measures, along with the criteria for classifying clients and nonclients, can be found in Section 4.2. We focus on the imbalances observed from 10 trading days before an informed securities lending event (see Section 3) through the event day itself. Columns 1, 2, and 3 report the number of observations, mean, and standard deviation, respectively. Columns 4 and 8 display the minimum and maximum observed values, while Columns 5, 6, and 7 present the 25th, 50th, and 75th percentiles, respectively.

	obs. (1)	mean (2)	std. (3)	min. (4)	pct 25 (5)	pct 50 (6)	pct 75 (7)	max (8)
$VImbalance^{c}$	15,444	-0.02	0.73	-1	-0.79	0	0.73	1
$VImbalance^{n}$	15,444	0.01	0.61	-1	-0.52	0	0.53	1
$NImbalance^{c}$	15,444	-0.01	0.60	-1	-0.40	0	0.33	1
$NImbalance^{n}$	15,444	0.02	0.40	-1	-0.23	0	0.28	1

Table IA.4: Information leakage in restricted events

This table presents difference-in-differences regression estimates following Equation 2. Informed securities lending events are defined in Section 3, but we only consider informed securities lending events in which there is at least one client who had not sold the stock in the 15 days preceding the event but did sell on the event day. This restricts the number of events to 549 events. This restriction reduces the number of events from 1,404 to 1,180. Client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the event day itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). *Clients* is one for clients of the brokers and *EventDay* is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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	0.034	0.034	0.002	0.002
	(1.30)	(1.30)	(0.12)	(0.12)
EventDay	0.038	0.038	0.027	0.027
	(1.17)	(1.17)	(1.63)	(1.64)
Clients $\times$ *EventDay*	-0.306***	-0.306***	-0.248***	-0.248***
	(-4.81)	(-4.81)	(-6.90)	(-6.90)
π	0.040	0.042	0.003	0.008
	(1.30)	(1.36)	(0.14)	(0.35)
Clients $\times$ π	-0.115***	-0.115***	-0.061**	-0.061***
	(-2.83)	(-2.83)	(-2.05)	(-2.05)
Constant	-0.025	-0.026*	0.003	0.002
	(-1.23)	(-1.80)	(0.18)	(0.17)
Event F.E.		✓		✓
Obs	4,392	4,392	4,392	4,392
Adj-R2	0.02	0.10	0.03	0.12

Table IA.5: Leakage to low-volume investors

This table presents difference-in-differences regression estimates following Equation 2. Informed securities lending events are defined in Section 3. When constructing the imbalance measures for clients and nonclients, we only consider a subsample of the institutions likely to receive information, described in Section 4.1. Specifically, we restrict the sample to the 100 institutions with the lowest volume in securities lending, as discussed in Section 8.3. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the day of the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). *Clients* is one for clients of the brokers, and *EventDay* is one for the day of an informed securities lending event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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	-0.001	-0.001	-0.023	-0.023
	(-0.04)	(-0.04)	(-1.59)	(-1.59)
EventDay	0.003	0.004	0.009	0.009
	(0.12)	(0.16)	(0.39)	(0.42)
Clients × *EventDay*	-0.030	-0.030	-0.027	-0.027
	(-1.03)	(-1.03)	(-1.01)	(-1.01)
π	-0.045	-0.037	-0.037	-0.029
	(-1.45)	(-1.09)	(-1.35)	(-1.03)
Clients × π	0.016	0.016	0.010	0.010
	(0.54)	(0.54)	(0.35)	(0.35)
Constant	0.022	0.019**	0.040***	0.038***
	(1.55)	(2.06)	(3.03)	(4.07)
Event F.E.		✓		✓
Obs	11,232	11,232	11,232	11,232
Adj-R2	0.01	0.04	0.01	0.04

Table IA.6: Leakage effects on short-selling activity

.

This table presents difference-in-differences regression estimates following Equation 2. Informed securities lending events are defined in Section 3, while client and nonclient institutions likely to receive information are defined in Section 4.1. We use clients' and nonclients' actual short-selling activity during the 3 days prior to the event and the day of the event itself as dependent variables. We classified a sale as a short sale if the investor borrowed the stock through the securities lending market from the day before the sale until up to three days after the sale. The dependent variable $VShort$ is the log of the volume shorted on each day for the security event relative to the average of the previous seven days, whereas the dependent variable $NShort$is the number of investors shorting the stock on each day, also relative to that same seven-day average. $Clients$ is one for clients of the brokers and $EventDay$ is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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.

	$VShort$		$NShort$	
	(1)	(2)	(3)	(4)
$Clients$	-0.221*	-0.221*	-0.202***	-0.202***
	(-1.93)	(-1.93)	(-3.51)	(-3.51)
$EventDay$	0.246**	0.245**	0.056	0.056
	(2.08)	(2.08)	(1.55)	(2.35)
$Clients \times EventDay$	0.366**	0.366**	0.137**	0.137**
	(2.12)	(2.12)	(2.37)	(2.37)
π	0.525**	0.512**	0.266	0.258
	(2.53)	(2.58)	(4.28)	(3.99)
$Clients \times \pi$	1.399***	1.399***	0.496***	0.497***
	(4.80)	(4.80)	(4.86)	(4.86)
$Constant$	1.858***	1.861***	1.689***	1.211***
	(19.98)	(28.17)	(36.51)	(40.95)
Event F.E.		✓		✓
Obs	11,232	11,232	11,232	11,232
Adj-R2	0.01	0.14	0.01	0.15

Table IA.7: Leakage effects up to 5 days after informed securities lending events

This table presents the estimates of difference-in-differences regressions robustness discussed in Section 8.4. Informed securities lending events are defined in Section 3, while client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 5 days prior to the event and the 5 days after the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). *Clients* is one for clients of the brokers and *EventDay* is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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	0.003	0.004	-0.013	-0.013
	(0.28)	(0.28)	(-1.20)	(-1.20)
After	0.015*	0.015*	0.001*	0.011
	(1.72)	(1.67)	(1.68)	(1.61)
Clients $\times$ *After*	-0.037**	-0.037**	-0.030**	-0.030**
	(-2.19)	(-2.19)	(-2.12)	(-2.12)
π	0.006	0.002	-0.023	-0.027
	(0.27)	(0.10)	(-1.27)	(-1.48)
Clients $\times$ π	-0.162***	-0.162***	-0.119***	-0.119***
	(-4.73)	(-4.73)	(-4.12)	(-4.12)
Constant	-0.001	-0.001	0.020**	.021***
	(-0.06)	(-0.03)	(2.51)	(3.57)
Event F.E.		✓		✓
Obs	28,080	28,080	28,080	28,080
Adj-R2	0.01	0.07	0.01	0.07

Table IA.8: Leakage effects in informed securities lending events, controlling for comovement with longer window and lead-lag effects

This table presents the estimates of difference-in-differences regressions robustness discussed in Section 8.4. Informed securities lending events are defined in Section 3, while client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 10 days prior to the event and the event itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). $Clients$ is one for clients of the brokers and $EventDay$ is one for the day of the informed event. π is defined in Section 4.3, and it is the day-by-day proportion of the total volume sold in the centralized stock market during the event window by the short seller responsible for the informed event. We also include lead and lag values of π. 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	0.003	-0.019*	-0.019*
	(0.22)	(0.18)	(-1.82)	(-1.75)
$EventDay$	0.031*	0.031*	0.009	0.017
	(1.80)	(1.68)	(0.91)	(1.48)
$Clients \times EventDay$	-0.073***	-0.076***	-0.043***	-0.051***
	(-2.84)	(-2.71)	(-2.79)	(-3.00)
π	0.024	0.029	-0.013	-0.014
	(0.85)	(1.04)	(-0.69)	(-0.78)
$Clients \times \pi$	-0.179***	-0.187***	-0.120***	-0.120***
	(-4.76)	(-4.96)	(-3.82)	(-3.86)
$lag\ \pi$		-0.001		-0.029
		(0.01)		(-1.44)
$Clients \times lag\ \pi$		0.005		0.028
		(0.14)		(0.74)
$lead\ \pi$		-0.018		-0.017
		(-0.63)		(-0.84)
$Clients \times lead\ \pi$		0.034		0.012
		(0.86)	(-1.25)	(0.41)
$Constant$	-0.005	-0.004	0.019***	.021***
	(-0.62)	(-0.47)	(3.63)	(3.42)
Event F.E.	✓	✓	✓	✓
Obs	30,888	28,080	30,888	28,080
Adj-R2	0.07	0.07	0.08	0.08

Table IA.9: Leakage effects in informed securities lending events with no public information disclosure

This table presents the estimates of difference-in-differences regressions robustness discussed in Section 8.4. Informed securities lending events are defined in Section 3, but we restrict to a subsample of events without earnings announcement or material fact disclosure within a 5-day window around the event day. This restriction reduces the number of events from 1,404 to 1,180. Client and nonclient institutions likely to receive information are defined in Section 4.1. We compare how the trading behavior of clients differs from that of nonclients, before and after these informed events. The imbalance measures discussed in Section 4.2 are the dependent variables, and this specification includes, for each informed event, imbalance measures for clients and nonclients during the 3 days prior to the event and the event day itself. $VImbalance$ goes from -1 (all volume traded on the selling side) to $+1$ (all volume traded on the buying side) and $NImbalance$ also goes from -1 (when all institution sell) to $+1$ (when all institutions buy). $Clients$ is one for clients of the brokers and $EventDay$ is one for the day of the informed event. π is defined in Section 4.3 and it is the day-by-day proportion of the total volume sold in the centralized stock market, during this four-day period, by the short seller responsible for the informed 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)
$Clients$	0.016	0.016	-0.014	-0.014
	(0.79)	(0.79)	(-0.91)	(-0.91)
$EventDay$	0.021	0.022	0.017	0.017
	(0.96)	(0.94)	(1.29)	(1.47)
$Clients \times EventDay$	-0.069**	-0.069**	-0.058***	-0.058***
	(-2.25)	(-2.25)	(-3.23)	(-3.23)
π	0.042	0.039	-0.003	-0.002
	(1.48)	(1.41)	(-0.13)	(-0.12)
$Clients \times \pi$	-0.135***	-0.135***	-0.072***	-0.072***
	(-3.88)	(-3.88)	(-2.65)	(-2.65)
$Constant$	-0.015	-0.014	0.008	0.008
	(-1.04)	(-1.08)	(0.95)	(0.89)
Event F.E.		✓		✓
Obs	9,440	9,440	9,440	9,440
Adj-R2	0.01	0.09	0.01	0.10