Short-selling, the supply side: Are lenders price makers?

Daniel de Sales Casula[†]
Rodrigo De-Losso[‡]

Abstract One widely accepted idea is that high lending fees predict negative returns, since high fees capture negative information held by short sellers on the demand side. Tradition sees the supply side as passive, with stock lenders acting as price takers. Recent evidence, however, shows that lenders are not truly passive. This paper analyzes the Brazilian stock loan market, disentangling shifts in the shorting supply and demand curves to understand the mechanism linking the supply side and stock returns. We also connect the shorting supply curve with news reports and verify how lenders react to new information. Our results indicate that lenders decrease the loan supply when they predict negative future returns and use new information to change supply conditions, indicating that lenders are not price takers.

Keywords: Short selling; Loan fee; Lenders; Public information.
JEL Code: G10, G12, G14.

1. Introduction

Short selling now comprises a significant volume of shares traded, increasing the importance of the short market. Most researchers in this area focus on the demand side of the market. Studies suggest that lending fees capture private information from short sellers, on the demand side. Meanwhile, stock lending (supply side) is usually considered not to influence lending fees.

Part of this passive behavior of lenders may be explained by the opacity of the market, that is, by the limited information on borrowing demand in a nontransparent OTC market. However, recent modernization of the securities lending market, with timely information and online platforms, has given lenders a better position to proactively price their lendable assets and manage supply (Duong et al., 2017).

Although most previous researchers on short sales argue that high lending fees predict negative returns, since high fees capture negative information held by short sellers, some recent authors (e.g., Duong et al., 2017) argue that high lending fees predict negative returns even after controlling for shorting

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[†]Federação Brasileira de Bancos, Brazil: danielcasula2@hotmail.com
[‡]FEA/USP, Brazil: delosso@usp.br

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demand. They suggest that an additional information component must exist on the supply side.

Following such debate, the goals of this paper are twofold. First, we want to verify whether lenders are price makers. More specifically, we want to verify whether lenders modify loan conditions (price and quantity) independently of changes generated by the demand side. Second, we want to see if lenders are informed and if they use public information to change their lending offers.

Using Brazilian data, we confirm that high lending fees predict negative stock returns. We argue that the supply side, where stock lenders provide supply for fees, also warrants attention. We disentangle the shifts in supply and demand using the technique of Malloy et al. (2005). Then we explore the effect of these shifts on future stock returns. Our results indicate that shorting supply has a statistically relevant relationship with future stock returns. More precisely, we find that lenders decrease loan supply when they predict negative future returns. Thus, we conclude that lenders are active; they modify loan fees and quantities after controlling for changes in the demand side.

For our second goal, we start by confirming the importance of new information in the market. We find that relevant announcements have significant impact on securities prices and on investors' decisions to trade. Therefore, it behooves us to relate announcements to the supply curve to help characterize whether and how lenders use new information to modify their lending offers.

Since only relevant information is likely to affect securities prices, we separate different types of announcements into categories, following B3's[1] classification. Many announcements contain irrelevant information, which could lead to an underestimation of announcements' impact on the market. Additionally, some announcements include news that is no surprise to the market—these would mitigate their overall impact on stock returns. Therefore, in our models, we consider only announcements of relevant facts and of economic-financial data.

Moreover, positive and negative announcements tend to affect securities prices differently. An announcement is said to be positive if the difference between the stock return minus the expected stock return on day t is greater than zero; and negative if the difference is less than zero. To include some announcements considered to be neutral, we also run our models with an interval imposed for positive and negative announcements.

By separating different categories and the sign of announcements, we find that lenders do process them when they are released. More specifically, when lenders are informed of positive news, they increase their shorting supply—

[1] Brazilian Stock Market.

decrease their restriction of shorting supply. By contrast, negative announcements induce lenders to increase restriction of shorting supply. Our results also indicate that lenders are more responsive to economic-financial data announcements to modify their offers. Despite B3 classification of announcements as relevant facts, some of their information may provide no clear perspective on stock returns. In contrast, information from economic-financial data announcements seems clearer and easier for lenders to understand. Overall, we conclude that lenders do process information when it is released.

Together, our findings indicate that lenders are not simply price takers. They change their lending offers when they predict negative future returns, and they also use new information to modify supply conditions.

Lastly, Brazil's regulatory structure contributes to this research question. In Brazil, all lending deals must be registered in the B3 lending platform. This is unlike most other lending markets. This unusual feature allows for a complete picture of lending activity for the whole market at a daily frequency. In addition, Brazil's market has the same standard empirical facts as the equity lending market documented in the US and Europe (Chague et al., 2019).

The rest of this paper is as follows. Section 2 discusses the literature on short selling activity and its market. Section 3 discusses the Brazilian stock loan market, highlighting its peculiarities, and the data set we use. Section 4 presents the empirical approach and results, and Section 5 concludes.

2. Literature review

Short selling is very common in advanced countries, comprising a significant percentage of the volume of shares traded, e.g. 24% on the NYSE and 31% on Nasdaq in 2005 (Diether et al., 2009). The practice is similar in Brazil. In recent years, short selling corresponds to 25% of the volume of shares traded (Chague et al., 2019).

Despite its widespread use, agents have mixed feelings about the implications of short selling. On one hand, some suggest that short selling improves the efficiency of market information (e.g., Saffi and Sigurdsson, 2011; Boehmer and Wu, 2013, among others). Along these lines, several empirical researchers argue that short selling is beneficial to the market. Short sellers convey new negative information. They even perform a governance role by uncovering profit manipulation and discouraging fraudulent activities (Duong et al., 2017). Additionally, Massa et al. (2015) suggest that short selling encourages insiders to release private information, and Deng and Gao (2018) say that short selling plays an important role in monitoring firm insiders.

On the other hand, some consider short selling a dangerous operation, seeing it as an inherently speculative. For instance, in 2011, some European countries banned short selling in an effort to reduce volatility and mitigate a downward spiral in stock prices. However, Alves et al. (2016) find that these bans hampered liquidity. Bid-ask spread increased following the bans' implementation. They find that stocks subject to the bans exhibit a longer delay in assimilating negative common-wide information over the course of the bans, meaning that these regulations have failed to achieve their goals.

Given the importance of the short market, researchers have devoted considerable attention to the practice, mostly focusing on the demand side of it. Lending fees are widely believed to capture information from short sellers. Engelberg et al. (2012) argue that the information advantage of short sellers lies in their ability to process publicly available information. Karpoff and Lou (2010) and Boehmer et al. (2020) find evidence that short sellers actually anticipate earnings surprises, financial misconduct, and analyst downgrades. Chague et al. (2017) argue that well-connected short sellers with low demand costs pay significantly lower lending fees. They show that short sellers, both individuals and institutions, profit from their skills rather than from private information.

Regarding market structure, Kolasinski et al. (2013) argue that research costs in the capital loan market represent significant barriers to short sellers, and that lowering barriers would improve the operation of this market. According to Kolasinski et al. (2013), the stock lending market remains relatively opaque, despite increased accessibility of electronic networks. These authors claim that research costs can be reduced or possibly eliminated by the creation of a central reporting mechanism for sharing prices and loan availability. Accordingly, recent regulatory and market changes give potentially more bargaining power to lenders, placing them in a better position to manage their lending desks (Duong et al., 2017). Lenders have responded eagerly to maximize income from their portfolios (SEC, 2014).

On the supply side of the market, Duong et al. (2017) state that high lending fees predict negative returns even after controlling for shorting demand. They suggesting that an additional information component exists on the supply side. They posit that lenders incorporate not only the past and current shorting demands, but also the expected future demand in their lending fees. Duong et al. (2017) conclude that, along with short sellers, lenders contribute to the price discovery process. However, these authors' proxy for shorting demand (short interest) is controversial—it actually represents the intersection of supply and demand. A low level of short interest may not indicate low shorting demand, since stocks that are impossible to short have an infinite shorting cost, coupled with a zero level of short interest (Malloy et al., 2005).

Several authors construct proxies for shorting supply, shorting demand, equilibrium price (e.g., rebate rate), and equilibrium quantity (e.g., short interest). Asquith et al. (2005) combine both short interest and institutional ownership data to identify stocks with high shorting demand and low shorting supply. Malloy et al. (2005) criticize the use of these proxies and propose a new empirical strategy to classify supply and demand shifts in the equity lending market. They proceed as follows: for a given security, a decrease in the stock loan fee (i.e., price) coupled with an increase in shares lent out (i.e., quantity) corresponds to an increase in shorting supply—any combination of a price reduction with an increase in quantity would cause a shift out of the supply curve. On the other hand, an increase in loan fees coupled with a decrease in shares lent out would point to a decrease in shorting supply. An analogous idea is applied to shorting demand shifts. Using this strategy, they construct dummy variables that encompass all four movements in loan prices and quantities.

Focusing on the universe of smalls stocks and identifying inwards and outwards supply and demand shifts for short, Malloy et al. (2005) conclude that the relationship between high shorting costs and future negative returns is driven mainly by demand shifts. The authors emphasize the importance of separating the supply and demand effects in order to understand the driving mechanism linking the shorting market and stock returns.

However, the identification strategy of Malloy et al. (2005) has its limitations. First, if a reduction in supply is followed by a reduction in demand on a larger scale, an observer will see a lower loan fee and lower quantity. Therefore, they will fail to identify the supply shift at all. Moreover, these authors' strategy does not distinguish between large and small shifts. This could matter if effects are increasing with the size of the shifts (Chague et al., 2014). We use their strategy; however, in our analysis it is enough to know which shift is preponderant in a period. This refinement obviates the limitations of the strategy.

Kaplan et al. (2013) study the effect on stock prices of a supply shock of lendable shares. They find that exogenous changes in loan supply have significant effects on loan fees and quantities, but no adverse effect on security prices. In other words, the returns of stocks that are made available to lend are no different from those of other stocks, suggesting that funds can lend out their stocks to earn lending fees without fearing negative consequences for the value of their holdings.

Overall, stock lending is an opportunity for lenders to generate additional income. By lending securities, lenders earn fees and the appreciation of loaned securities. In case of negative stock return, loan fees help lenders minimize their losses. However, Evans et al. (2017) find that actively managed equity funds that lend securities underperform, relative to similar funds that do not lend. This underperformance is concentrated among funds with investment restrictions (unable to sell stocks), which helps to explain why fund managers lend, rather than sell, stocks with high short selling demand. An alternative explanation is managers' overconfidence.

3. Stock loan market in Brazil

In this section, we examine features of the stock loan market in Brazil. The Brazilian Securities Commission (CVM) regulates the securities lending market in Brazil. Due to the regulatory system, all lending deals must be registered in the B3 lending system. Ready availability of data from the centralized Brazilian lending market contrasts with most other countries' markets, where data on lending deals is generally incomplete. This feature of the Brazilian market makes it possible for us to have a complete picture of lending activity for the whole market at a daily frequency.

Another feature in the Brazilian lending market is that all loan deals are collateralized with Treasury securities,[2] so that all lending transactions are negotiated in terms of explicit loan fees. In the US market, the loan fee is implicitly given by the "rebate" rate, which is the fee that the lender must pay back to the borrower of that stock. The borrower must leave collateral and, in turn, the lender pays the rebate rate to the short seller as interest on this collateral. The spread between the interest rate on cash funds and the rebate rate is often called the loan fee.

The lending system in Brazil works as follows. B3 provides a platform called BTC Securities Lending System where brokers electronically register their offers. Usually, lenders place their shares for loan and borrowers can hit the offers. Borrowers may also place their bids, but this is not a common practice. More than 99% of offers come from lenders (Chague et al., 2014). Over-the-counter (OTC) deals are also possible. Indeed the Brazilian lending market is mostly OTC, as are other lending markets in the US and other countries. In either case, electronic or OTC, the BTC registers the information for every deal. As a result, the BTC data set contains historical (order-by-order) information on the entire securities lending market in Brazil at a daily frequency.

Another unique feature of Brazil's market is its local tax legislation. Until August 2014, a difference in tax treatment of interest on equity between distinct investors generated a tax arbitrage opportunity. Individual investors used to pay a tax rate of 15% while financial institutions were exempt. Since in-

[2] The collateral is deposited in B3, which acts as the central counterpart to all lending transactions.

vestors have different income tax deductions, there was a chance to profit, and a reason to borrow stocks for reasons other than short selling. The difference in tax treatment was initially created to avoid double taxation. However, investors were using stock lending to take advantage of the law (Bonomo et al., 2017). In 2015, the repeal of the law eliminated differences in taxation.

3.1 Data set

We observe the universe of lending deals traded on the Brazilian stock lending market from January 2013 to December 2017. For each lending deal, we have information on the loan quantity and the loan fee. To create our variables related to stock returns, this part of our data set covers from January 2012 to April 2018, since it includes lagged and forward stock returns. These variables are: AdjRet (accumulated risk-adjusted return in percentage, from 1 to 6 weeks ahead), r_{-1} (last week return, in percentage) and momentum (return from week $t-52$ to $t-2$, in percentage).

This paper also constructs variables related to short selling activity. In using the entire data set, we implicitly assume that short selling is the major factor explaining why investors borrow a stock. This is consistent with Clearstream (2014), who argues that despite stocks being borrowed for numerous reasons, such as voting, dividend arbitrage, or funding trade, the primary reason is for short selling.

We apply two filters to our data set. First, to avoid working with illiquid stocks, we restrict our data to stocks that fulfill the criteria used by the Brazilian Center for Research in Financial Economics (NEFIN) to calculate short interest:[3] (i) the stock is the most traded share of the firm between ordinary and preferential shares;[4] (ii) the stock was traded on more than 80% of the days in the previous year with volume greater than R$ 500,000 per day — if the stock was listed in the previous year, the period considered extends from the listing day to the last day of the year; (iii) the stock was initially listed prior to December of year $t-1$. This gives us 155 stocks.

The second filter is as follows. The tax treatment of interest on equity differs by investors' type, generating a tax arbitrage opportunity. As a result, on days around the ex-date of interest on equity, the loan fees are artificially high. Individuals could then lend shares to financial institutions at a higher loan fee, since the institutions receive interest on equity without paying taxes. While institutions profit by 15% of the interest on equity minus the loan fee, individuals receive a higher fee. Considering that the loan fees are artificial

[3] Available at the NEFIN webpage on `http://www.nefin.com.br/short_interest.html` - last access: February 15, 2021.

[4] Preferential shares, unlike those in the US, means only that their owner receives a dividend first.

around those days, we exclude observations two weeks before and one week after the ex-date. Since the tax arbitrage opportunity ended in 2014, we apply this filter only to 2013 and 2014. To avoid extremely high and artificial loan fees, we also exclude from our data deals with loan fees above the 99th percentile of our sample.

Our data set comes from different investment platforms. From Economatica, we match our loan data to historical equity prices (adjusted by inplits, splits and dividend payouts), market value, trading volume and shares outstanding. The average bid-ask spread comes from Bloomberg. We obtain the risk factors to calculate risk-adjusted returns from NEFIN.[5]

Additionally, announcements are from B3. Certain filters help us better handle these data. First, we account for the days of announcements only, meaning that we flag days that have at least one announcement. The second filter relates to the official trading hours, since Brazil observed Daylight Saving Time throughout the period under analysis.[6] The usual closing hour of the Brazilian stock market is 5 p.m., but it changed to 6 p.m. between November and February. Therefore, if announcements were disclosed on day t after the closing hour, we flag the day $t+1$. Announcements disclosed on weekends and holidays are also assumed to be disclosed on the next trading day.

Taking into account all filters mentioned above, we have 34,587 stock day observations flagged with at least one announcement. However, irrelevant announcements lead to an underestimation of the relation between new information and stock returns, distorting the relationship between announcements and shifts in the lending supply curve. Accordingly, we create three different types of announcements based on B3's classifications. Type 1 encompasses only announcements of relevant facts. Type 2 includes announcements of economic and financial data. Lastly, Type 1&2 combines these two previous categories, meaning that the day t will be flagged if there is at least one announcement disclosed, regardless of the type.

Moreover, positive and negative information tend to affect securities prices in different ways. We classify announcements as positive if the difference between the stock return minus the expected stock return on day t is greater than zero. In turn, we consider announcements to be negative if this difference is less than zero. We obtain expected returns by means of

$$\text{Return}_{i,t} = \alpha_i + \beta_{1i}\text{MF}_{i,t} + \beta_{2i}\text{SMB}_{i,t} + \beta_{3i}\text{HML}_{i,t} + \beta_{4i}\text{WML}_{i,t} + e_{i,t}, \quad (1)$$

[5]To calculate risk-adjusted returns we account for the following risk factors: market factor (MF), SMB factor, HML factor and WML factor. See NEFIN's webpage: http://www.nefin.com.br/risk_factors.html - last access: February 15, 2021.

[6]Since April 2019, DST is no longer in use in Brazil.

and then isolate the residual:

$$\hat{e}_{i,t} = \text{Return}_{i,t} - \hat{\alpha}_i - \hat{\beta}_{1i}\text{MF}_{i,t} - \hat{\beta}_{2i}\text{SMB}_{i,t} - \hat{\beta}_{3i}\text{HML}_{i,t} - \hat{\beta}_{4i}\text{WML}_{i,t}. \quad (2)$$

If an announcement was made on day t and $\hat{e}_{i,t} > 0$, then we consider the announcement as positive. If an announcement was on day t and $\hat{e}_{i,t} < 0$, the announcement is considered to be negative.[7] Our sample contains 3,897 positive Type 1&2 announcements, 1,769 positive Type 1, and 2,365 positive Type 2. As for negative announcements, our sample contains 3,830 Type 1&2, 1,676 Type 1 and 2,350 Type 2.

Tables 1 and 2 present the summary statistics of key variables from January 2013 to December 2017 traded on the Brazilian stock lending market on daily and weekly frequencies, respectively. At the daily level, the loan fee is, on average, 2.67% (median 1.00%), which is very close to that reported by Chague et al. (2017). This figure is much higher than in the US, for example. One possible explanation is the high stock market volatility in Brazil, seen in the high standard deviation. The median risk-adjusted return is –0.01%, which we expect, while the natural logarithm of the value market (size) is, on average, 15.52, with quite low dispersion. In addition to the logarithm effect, the low standard deviation reflects our restricted data set; since we avoid working with illiquid stocks, we mostly observe large companies—stocks that match the criteria used by NEFIN. The average turnover is 0.48%, while the average bid-ask spread is 0.40%.

Table 2, in turn, presents average weekly stats, which align better with the methodology used in the next sections—following Malloy et al. (2005). Overall, the statistics are similar to those presented in Table 1. For example, average weekly loan fee is 2.77% (median 1.20%), not much different from the daily average. From weekly adjusted-risk returns, the dispersion expands as we increase the number of weeks, as expected.

4. A closer look at the shorting supply

We first assess, in Section 4.1, the hypothesis that high lending fees predict negative future returns. In Section 4.2, we verify whether the relation between high loan fees and negative future returns is also driven by the supply side. Applying a technique used by Malloy et al. (2005), we disentangle the demand and supply shifts, in order to help understand the driving mechanism linking the shorting supply and stock returns.

[7] To consider some announcements as neutral, we also run our models imposing an interval (−1%, 1%). Under this definition, an announcement is positive if it is made on day t and $\hat{e}_{i,t} \geqslant 1\%$. In turn, an announcement is negative if it occurs on day t and $\hat{e}_{i,t} \leqslant -1\%$. Other intervals are also considered.

Table 1
Descriptive statistics - Daily stats

Variable	N	Mean	Standard Deviation	25th percentile	Median	75th percentile
LoanFee (%)	124,524	2.67	4.37	0.27	1.00	3.00
Size	159,143	15.52	1.48	14.60	15.47	16.43
Turnover (%)	150,858	0.48	0.87	0.15	0.29	0.54
BAspread (%)	162,422	0.40	1.12	0.12	0.19	0.35
AdjRet (%)	151,068	0.04	2.37	−1.10	−0.01	1.11

This table presents summary daily statistics of key variables of trades on the Brazilian stock lending market from January 2013 to December 2017. LoanFee is the value-weighted loan fee (annualized) of the day, in percentage. Size is the natural logarithm of the value market. Turnover is composed of trading volume divided by market cap, in percentage. BAspread is the average daily bid-ask spread, where bid-ask spread is the difference between the closing daily ask price and bid price, relative to the average of the daily bid and ask prices, in percentage. AdjRet is the risk-adjusted return that takes into account risk factors (MF, SMB, HML, and WML), in percentage.

For our second goal, we start by confirming the importance of new information in the market. Relevant announcements have significant impact on securities prices and on investors' decisions to trade; hence, it seems useful to link them with supply shifts to help understand if lenders modify their lending offers around announcements. Section 4.3 verifies the importance of relevant announcements on stock returns.

Lastly, Section 4.4 verifies if lenders modify their lending offers following the release of public information. We consider three different types of announcements based on B3's classification. We also separate positive from negative announcements, since they tend to affect securities prices differently.

4.1 Loan fees and negative future returns

In this first model, we want to test the hypothesis that high lending fees predict negative future returns. In Equation (3), we adopt a panel regression model with stocks' fixed effects and week dummies as additional controls to test whether loan fees help predict future returns:

$$\begin{aligned}\text{AdjRet}_{i,1:6w} = \alpha + \beta_1 \text{LoanFee}_{i,w} + \beta_2 \text{Size}_{i,w} + \beta_3 \text{Turnover}_{i,w} + \\ \beta_4 \text{BAspread}_{i,w} + \beta_5 r_{-1i,w} + \beta_6 \text{Momentum}_{i,w} + \delta_i + \gamma_w + \varepsilon_{i,w},\end{aligned} \tag{3}$$

where the dependent variable is the accumulated risk-adjusted return in percentage, with $w = 1,\ldots,6$ (from 1 to 6 weeks). Robust standard errors are clustered across both weeks and stocks. We take weekly data because it better fits with the methodology used in the next section.

Table 2
Descriptive statistics - Average weekly stats

Variable	N	Mean	Standard Deviation	25th percentile	Median	75th percentile
LoanFee (%)	29,332	2.77	4.31	0.37	1.20	3.16
Size	31,973	15.51	1.49	14.59	15.47	16.42
Turnover (%)	31,972	0.48	0.80	0.17	0.32	0.56
BAspread (%)	32,626	0.40	1.09	0.12	0.19	0.36
r_{-1} (%)	32,743	0.05	4.19	−1.93	0.00	1.97
Momentum (%)	32,743	6.83	52.97	−21.00	2.12	27.95
$\text{AdjRet}_{i,1w}$ (%)	32,743	0.21	5.23	−2.24	0.00	2.44
$\text{AdjRet}_{i,2w}$ (%)	32,743	0.41	7.31	−3.09	0.05	3.64
$\text{AdjRet}_{i,3w}$ (%)	32,743	0.61	8.89	−3.70	0.22	4.61
$\text{AdjRet}_{i,4w}$ (%)	32,743	0.81	10.25	−4.10	0.31	5.45
$\text{AdjRet}_{i,5w}$ (%)	32,743	1.01	11.46	−4.60	0.46	6.25
$\text{AdjRet}_{i,6w}$ (%)	32,743	1.20	12.63	−4.97	0.59	6.92

This table presents the average weekly statistics of key variables of trades on the Brazilian stock lending market from January 2013 to December 2017. LoanFee is the average loan fee (annualized), in percentage. Size is the average of the natural logarithm of the value market. Turnover is the average turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread, where bid-ask spread is the difference between the closing daily ask price and bid price, relative to the average of the daily bid and ask prices, in percentage. r_{-1} is last-week return, in percentage. Momentum is the return from week $t-52$ to $t-2$, in percentage. $\text{AdjRet}_{i,1:6w}$ is the accumulated risk-adjusted returns from one to six weeks, in percentage. To create our variables related to stock returns, this part of our data set extends from January 2012 to April 2018.

Our control variables follow those of Boehmer et al. (2008) and Diether et al. (2009). We include variables related to return predictability such as firm size, turnover, last week return, and momentum. Short selling should increases in periods of uncertainty, since short sellers may step in as opportunistic risk bearers during periods of increased uncertainty. Since this increased uncertainty could be caused by asymmetric information or a wider divergence of opinion, we also include bid-ask spread as a control variable. LoanFee is the weekly average loan fee (annualized), in percentage. Size is the weekly average of the natural logarithm of the value market. Turnover is the weekly average turnover (trading volume divided by market cap), in percentage. BAspread is the average bid-ask spread for the week, where bid-ask spread is the difference between the closing daily ask price and bid price, relative to the average of the daily bid and ask prices, in percentage. r_{-1} is the last week return, in percentage. Momentum is the stock return from week $t-52$ to $t-2$, in percentage. δ_i is the individual effect (time-invariant) while γ_w are week dummies (time-specific intercept).

Table 3 is consistent with results of previous studies of short selling in

Table 3
Loan fee and negative future returns

	(1) $\text{AdjRet}_{i,1w}$	(2) $\text{AdjRet}_{i,2w}$	(3) $\text{AdjRet}_{i,3w}$	(4) $\text{AdjRet}_{i,4w}$	(5) $\text{AdjRet}_{i,5w}$	(6) $\text{AdjRet}_{i,6w}$
LoanFee	−0.029*	−0.068***	−0.084***	−0.11***	−0.11***	−0.12***
	(−1.940)	(−3.330)	(−3.500)	(−3.90)	(−3.47)	(−3.26)
Size	−0.816***	−1.533***	−2.423***	−3.35***	−4.26***	−5.12***
	(−5.170)	(−6.760)	(−8.940)	(−10.33)	(−11.74)	(−12.46)
Turnover	0.176	0.288	0.196	0.17	0.10	0.20
	(1.050)	(1.360)	(0.870)	(0.69)	(0.33)	(0.68)
BAspread	0.156	0.452*	0.498**	0.53**	0.54**	0.52**
	(1.260)	(1.810)	(2.020)	(2.09)	(2.49)	(2.19)
r_{-1}	−0.029*	−0.048**	−0.031	0.00	−0.03	−0.04
	(−1.760)	(−2.180)	(−1.120)	(0.03)	(−0.83)	(−1.02)
Momentum	0.002	0.002	0.004**	0.01**	0.01***	0.01***
	(1.380)	(1.490)	(2.150)	(2.48)	(2.74)	(3.22)
Constant	11.340***	21.430***	34.130***	47.44***	60.60***	72.96***
	(4.730)	(6.180)	(8.240)	(9.59)	(10.95)	(11.64)
Nº of Obs.	29.097	29.097	29.097	29.10	29.10	29.10
adj. R^2	0.016	0.027	0.036	0.05	0.06	0.06

This table presents the relationship between loan fees and risk-adjusted stock returns, measured at weekly intervals. The dependent variable is the accumulated risk-adjusted return in percentage, with $w = 1, \ldots, 6$ (from 1 to 6 weeks). LoanFee is the average loan fee (annualized), in percentage. Size is the average of the natural logarithm of the value market. Turnover is the average turnover (trading volume divided by the market cap), in percentage. BAspread is the average bid-ask spread, where bid-ask spread is the difference between the daily closing bid price and ask price, relative to the average of the daily bid and ask prices, in percentage. r_{-1} is last-week return, in percentage. Momentum is the return from week $t-52$ to $t-2$, in percentage. The period is January 2013 to December 2017. T-statistics are in parentheses. The estimation includes stocks' fixed effect and week dummies as additional controls. Standard errors are robust. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

other markets. Its main result shows a statistically significant negative relation between loan fees and future returns, captured by the negative coefficient of the LoanFee variable. This evidence favors the hypothesis that high loan fees help predict negative future returns. We can now check whether this relation is driven by the supply or the demand side, or both.

4.2 Supply and demand shifts in the lending market

An apparent consensus among experts is that lending fees capture information from short sellers. Short sellers are often known as skilled traders and/or those with private information (Chague et al., 2014). Nevertheless, we want to verify if such a relation between high loan fees and negative future returns is driven not only by the demand side, but also by the supply side. Our results indicate that the supply side also deserves attention.

We next disentangle the supply and demand shifts to verify whether the supply side has an important relationship with future stock returns. To do this, we classify supply and demand shifts in the manner of Malloy et al. (2005). For a given security, an increase in the stock loan fee (i.e., price) coupled with an increase in shares lent out (i.e., quantity) corresponds to an increase in shorting demand. On the other hand, a decrease in the stock loan fee coupled with a decrease in shares lent out indicates a decrease in shorting demand. We apply an analogous procedure to verify shorting supply shifts. We cannot confirm that this is the only shift that occurred, as those authors indicate. However, when an increase in price is coupled with an increase in quantity, a demand shift outwards must have occurred. We assume that demand curves are not upward sloping and that supply curves are not downward sloping. Overall, with this technique, we can isolate shorting supply from shorting demand and verify whether the supply side has any significant relationship with stock returns.

We work with weekly data since it best captures trends of price and quantity movements. Daily variations can be too erratic, which would impair our analysis. We also consider the median duration of a shorting deal in Brazil, which is over two weeks (Chague et al., 2019).

Therefore, over the designated time horizon (week), if an increase in the stock loan fee is coupled with an increase in shares lent out, a demand shift out has occurred, and we flag it as a dummy variable named DOUT. If we record at least one demand shift in, we flag it as a dummy variable named DIN. Similarly, if there is at least one supply shift out, SOUT; and at least one supply shift in, SIN. By classifying shifts in this way, we can identify shifts in shorting supply and demand, and explore the effect of these shifts on future stock returns.

We run a panel regression model with stocks' fixed effects and week dummies as additional controls, to verify the relationship between supply and demand shifts with future stock returns:

$$\begin{aligned}\text{AdjRet}_{i,1:6w} = \alpha + \beta_1\text{SOUT}_{i,w} + \beta_2\text{SIN}_{i,w} + \beta_3\text{DOUT}_{i,w} + \beta_4\text{DIN}_{i,w}\\ +\beta_5\text{Size}_{i,w} + \beta_6\text{Turnover}_{i,w} + \beta_7\text{BAspread}_{i,w} + \beta_8 r_{-1i,w}\\ +\beta_9\text{Momentum}_{i,w} + \delta_i + \gamma_w + \varepsilon_{i,w},\end{aligned} \tag{4}$$

where the dependent variable is the accumulated risk-adjusted return in percentage, with $w = 1,...,6$. The control variables are those listed in the previous section. Robust standard errors are clustered across both weeks and stocks. Results are reported in Table 4.

The only difference between Equations (3) and (4) is that we replace LoanFee by the four dummies movements (SOUT, SIN, DOUT, and DIN). It is not a straightforward decomposition (nor an exactly perfect one). Instead, the idea is to apply specific clippings to better understand the problem: to verify whether the supply or demand side, or both, has an important relationship to future stock returns. To check the week movement, we must look at the variation of the loan fee for the week, which is the price movement. More precisely, as mentioned in Section 4.1, over the designated horizon (week), if an increase in the stock loan fee is coupled with an increase in shares lent out, a demand shift out has occurred, and we flag it as a dummy variable named DOUT—we apply an analogous idea to the other movements. Therefore, we are actually considering loan fees to assemble the dummies.

Even after controlling for size, turnover, bid-ask spread, last-week return, and momentum, Table 4 shows a statistically significant negative relation between demand shift outward and future returns, captured by the negative coefficient of the DOUT variable from the third week ahead. This result indicates that short sellers increase the shorting demand when they predict negative future returns. This is consistent with results of previous studies. An increase in demand by short is typically interpreted as a signal of negative future return.

Table 4 also shows a negative and statistically significant coefficient for SIN from the third week ahead, meaning that the accumulated stock return is negative after lenders restrict their short offers. Therefore, from $\hat{\beta}_2$, we infer that lenders restrict their short offers when they predict a negative future return. This means that lenders are indeed price makers; they modify loan conditions (price and quantity) independently of changes generated by the demand side. If the supply side were not important, the coefficient should be nonsignificant.

Duong et al. (2017) posit that lenders incorporate not only the past and current shorting demands, but also the expected future demand, into their lending fees. If this were the case, when lenders predict an increase in future

Table 4
Supply and demand shifts in the lending market

	(1) $\text{AdjRet}_{i,1w}$	(2) $\text{AdjRet}_{i,2w}$	(3) $\text{AdjRet}_{i,3w}$	(4) $\text{AdjRet}_{i,4w}$	(5) $\text{AdjRet}_{i,5w}$	(6) $\text{AdjRet}_{i,6w}$
SOUT	–0.020	–0.222	–0.224	–0.301	–0.35	–0.32
	(–0.170)	(–1.410)	(–1.170)	(–1.370)	(–1.41)	(–1.15)
SIN	–0.118	–0.211	–0.476**	–0.555**	–0.59**	–0.48*
	(–0.990)	(–1.300)	(–2.420)	(–2.490)	(–2.37)	(–1.76)
DOUT	–0.112	–0.207	–0.401**	–0.501**	–0.66***	–0.59**
	(–0.950)	(–1.310)	(–2.070)	(–2.290)	(–2.66)	(–2.17)
DIN	–0.069	–0.250	–0.224	–0.261	–0.38	–0.25
	(–0.590)	(–1.610)	(–1.150)	(–1.210)	(–1.56)	(–0.94)
Size	–0.788***	–1.443***	–2.325***	–3.215***	–4.09***	–4.88***
	(–5.260)	(–6.780)	(–9.130)	(–10.650)	(–12.03)	(–12.88)
Turnover	0.158	0.232	0.127	0.096	0.03	0.12
	(0.990)	(1.150)	(0.600)	(0.420)	(0.11)	(0.45)
BAspread	0.127	0.410*	0.399*	0.471**	0.45**	0.47**
	(1.120)	(1.880)	(1.820)	(2.080)	(2.20)	(2.22)
r_{-1}	–0.024	–0.042**	–0.027	0.002	–0.04	–0.04
	(–1.560)	(–2.050)	(–1.010)	(0.060)	(–1.00)	(–1.05)
Momentum	0.001	0.002	0.003*	0.005**	0.01**	0.01***
	(1.240)	(1.280)	(1.830)	(2.200)	(2.53)	(2.92)
Constant	10.910***	19.940***	32.510***	45.230***	58.07***	69.49***
	(4.770)	(6.130)	(8.360)	(9.850)	(11.23)	(12.05)
Nº of Obs.	31.790	31.790	31.790	31.790	31.79	31.79
Adj. R^2	0.015	0.026	0.034	0.044	0.05	0.06

This table presents the relationship between supply and demand shifts, measured at a weekly frequency, with accumulated risk-adjusted stock returns. The dependent variable is the accumulated risk-adjusted return in percentage, with $w = 1,\dots,6$ (from 1 to 6 weeks). SOUT is a dummy variable for an outward supply shift. SIN is a dummy variable for an inward supply shift. DOUT in a dummy variable for an outward demand shift. DIN is a dummy variable for an inward demand shift. Size is the average natural logarithm of the market value. Turnover is the average turnover (trading volume divided by market cap), in percentage. BAspread is the average bid-ask spread, where bid-ask spread is the difference between the closing daily bid price and ask price, relative to the average of the daily bid and ask prices, in percentage. r_{-1} is last-week return, in percentage. Momentum is the return from week $t-52$ to $t-2$, in percentage. The period is January 2013 to December 2017. T-statistics are in parentheses. The estimation includes stocks' fixed effect and week dummies as additional controls. Standard errors are robust. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

shorting demand, they should increase their lending offers and raise loan fees in order to generate an additional income. An increase in supply followed by an increase in demand may result in higher fees and quantities. This is the case if the coefficient of SOUT is negative. We do find a negative coefficient, although $\hat{\beta}_1$ is not statistically significant.

Overall, our results indicate that when lenders predict negative future returns, instead of raising loan fees, they restrict their short offers and probably sell their stocks. Our finding aligns with that of Evans et al. (2017), who state that actively managed equity funds that lend securities underperform similar funds that do not lend but sell them. Additionally, Evans et al. (2017) find that underperformance is concentrated among funds with investment restrictions. Hence, one possible explanation for our findings is that, if no restrictions are imposed, and lenders predict negative future returns, lenders do not raise their offers and fees but sell their stocks.

4.3 The importance of relevant announcements

Our results so far indicate that lenders decrease their lending offers when they predict negative future returns. Our second goal is to analyze how lenders predict that. We check whether lenders are informed, and whether they use public information to change their lending offers. In so doing, we suggest that lenders convey material information through their behavior around the arrival of new information in the market.

We start by confirming the importance of new information in the market. Relevant announcements have significant impact on securities prices and on investors' decisions to trade. To verify this, we estimate a panel regression model with stocks' fixed effect and dummies for days as additional controls:

$$R_{i,t:t+2} = \alpha + \beta_1 \text{PositiveNews}_{i,t} + \beta_2 \text{NegativeNews}_{i,t} + \delta_i + \gamma_t + \varepsilon_{i,t}, \quad (5)$$

where the dependent variable, risk-adjusted return in percentage for stock i, varies from day t to day $t+2$, with t the day of the announcement. $\text{PositiveNews}_{i,t}$ is a dummy variable, which is equal to one if at least one announcement is disclosed on the day t and $\hat{e}_{i,t} > 0$ (the difference between the stock return minus the expected stock return on day t is greater than zero, as shown in Equation (2)). Similarly, $\text{NegativeNews}_{i,t}$ is a dummy variable which is equal to one if at least one announcement is disclosed on day t and $\hat{e}_{i,t} < 0$. δ_i is the (time-invariant) individual effect and γ_t is the time-specific intercept.

We next separate different types of information into categories, following B3's classification. Type 1 encompasses only announcements of relevant facts, including acquisition of shares, shareholder agreements, and new investment projections, among others. Type 2 involves announcements of economic-financial data such as financial statements, earnings releases, and rating reviews. Type 1&2 includes both types.

Table 5 indicates that on days with relevant announcement releases, stock return increases. As expected, the relation between positive announcements and stock return on day t is strongly positive and statistically significant. The same is true for negative announcements. The relation between negative announcements and stock return on day t is strongly negative statistically significant. The effects of announcements of both types (positive and negative) on stock returns also appear to spill over to the next trading day, $t+1$, although at less significant levels. However, no statistically significant effect occurs on day $t+2$. This suggests that the market fully absorbs the new information by that point.

Therefore, since new information in the market affects securities prices, it seems useful to link them with supply shifts inwards (SIN)—the relevant shift from the supply side in Equation (4)—to help understand whether and how lenders use new information to modify their lending offers around announcements.

4.4 Do lenders better process public information?

Our findings so far indicate the importance of announcements on the market and show that lenders restrict their lending offers when they predict negative future returns. Next, we verify whether lenders restrict their lending offers after the release of public information. In other words, we want to confirm if lenders are informed, and if they use new information to change their lending offers.

In order to verify if and how lenders restrict their lending offers after new public information is available, we proceed as follows. We run a panel regression model with stocks' fixed effects and day dummies as additional controls:

$$\begin{aligned} \mathrm{SIN}_{i,t} = \alpha &+ \beta_1 \mathrm{PositiveNews}_{i,t:t+1} \\ &+ \beta_2 \mathrm{NegativeNews}_{i,t:t+1} + \delta_i + \gamma_t + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

where $\mathrm{SIN}_{i,t}$ is a dummy variable for an inward supply shift for the day, equal to one if an increase in loan fee coupled with a decrease in quantity occurs on day t. $\mathrm{PositiveNews}_{i,t:t+1}$ and $\mathrm{NegativeNews}_{i,t:t+1}$ are dummy variables that equal one on day t and $t+1$ if at least one positive/negative announcement is made on day t. We restrict our attention to the day of disclosure and the next trading day, given the evidence in Section 4.3, that an announcement affects

Table 5
Impact of relevant news on stock returns

	Type 1&2			Type 1			Type 2		
	$R_{i,t}$	$R_{i,t+1}$	$R_{i,t+2}$	$R_{i,t}$	$R_{i,t+1}$	$R_{i,t+2}$	$R_{i,t}$	$R_{i,t+1}$	$R_{i,t+2}$
PositiveNews$_{i,t}$	2.41***	0.11**	–0.04	2.84***	0.13	–0.10	2.15***	0.11*	–0.01
	(45.71)	(2.03)	(–0.91)	(29.69)	(1.42)	(–1.40)	(40.91)	(1.88)	(–0.29)
NegativeNews$_{i,t}$	–2.09***	–0.24***	0.04	–2.24***	–0.24***	0.03	–2.08***	–0.24***	0.06
	(–49.23)	(–5.00)	(0.84)	(–31.45)	(–2.85)	(0.34)	(–40.95)	(–4.39)	(1.09)
Constant	–0.09	–0.06	–0.06	–0.06	–0.06	–0.06	–0.10	–0.06	–0.06
	(–0.79)	(–0.52)	(–0.58)	(–0.52)	(–0.52)	(–0.58)	(–0.96)	(–0.56)	(–0.58)
Nº of Obs.	151,068	151,064	150,910	151,068	151,064	150,910	151,068	151,064	150,910
R^2	0.05	0.00	0.00	0.03	0.00	0.00	0.03	0.00	0.00
Nº of Positive News	3,897	3,897	3,897	1,769	1,769	1,769	2,365	2,365	2,365
Nº of Negative News	3,830	3,830	3,830	1,676	1,676	1,676	2,350	2,350	2,350

This table presents the impact of positive and negative announcements on stock returns. The dependent variable is risk-adjusted returns, by percentage, from day t to $t+2$. PositiveNews$_{i,t}$ is a dummy variable equal to one if at least one positive announcement is disclosed on day t. NegativeNews$_{i,t}$ is a dummy variable equal to one if at least one negative announcement is disclosed on day t. Announcements are considered positive if the difference between the stock return on day t minus the expected stock return on day t is greater than zero, and considered negative if this difference is less than zero. The first three models encompass announcements of categories Type 1 and Type 2, containing 3,897 days of positive and 3,830 days of negative announcements of at least one type. Type 1 models encompass only announcements of relevant facts, with 1,769 positive and 1,676 negative announcements disclosed. Type 2 models encompass only announcements of economic-financial data, resulting in 2,365 positive and 2,350 negative announcements of this type. The period is January 2013 to December 2017. T-statistics are in parentheses. We regress a panel regression with stocks' fixed effect and dummies for days as additional controls. Standard errors are robust. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

the stock return on day t, spills over to the next trading day, $t+1$, and has no statistically significant effect on day $t+2$.

The first model encompasses announcements of Types 1 and 2, with 3,897 days of positive and 3,830 days of negative announcements of at least one type. The second model consists exclusively of Type 1, with 1,769 positive and 1,676 negative announcements. The last model has only Type 2, containing 2,365 positive and 2,350 negative announcements.

In Equation (6) we expect $\beta_1 < 0$ and $\beta_2 > 0$. Suppose a positive announcement is made; then, by construction, it generates a positive stock return. As a result, lenders should increase their lending offers to profit from the positive return plus the loan fee. In this case, we expect a decrease in SIN, i.e., a decrease in the restriction of shorting supply—finding a negative coefficient for β_1. On the other hand, negative information generates a negative stock return. Following Evans et al. (2017), lenders should sell their stocks instead of lending them, which tends to increase the restriction of shorting supply (higher SIN)—resulting in a positive coefficient for β_2.

The first model in Table 6, with Type 1&2 announcements, indicates that positive news tends to affect SIN in a negative way. In other words, a positive announcement on day t reduces the probability of a restriction in shorting supply. This result aligns with the expectations we mentioned above: a positive announcement tends to increase the return; therefore, lenders should increase their lending offers to profit with a higher stock return plus the loan fee. An increase in lending offers can be understood as a decrease in the restriction of shorting supply.

In contrast, negative announcements tend to affect SIN in a positive way. In other words, negative news increases the probability of a restriction in shorting supply. This result is also consistent with our expectations—negative announcements tend to decrease stock return. Lenders should then sell their stocks instead of lending them, which increases the restriction of shorting supply (higher SIN).

The second model in Table 6 encompasses only Type 1 announcements. When we restrict our analysis to this type, the impact of announcements on the shorting supply curve (SIN) are not statistically significant at the usual levels. Despite the label (relevant facts), Type 1 announcements may include information that does not relate to future stock returns. However, the third model shows that the relation between Type 2 announcements and SIN is statistically relevant. The effects of Type 2 announcements on SIN are stronger and more relevant, especially for negative news. This suggests that lenders are especially responsive to economic-financial data announcements, and modify their lending offers accordingly. One possible explanation, as already men-

Table 6
Impact of announcements on SIN

	$SIN_{i,t}$		
	Type 1&2	Type 1	Type 2
$PositiveNews_{i,t:t+1}$	–0.008*	–0.008	–0.010*
	(–1.820)	(–1.300)	(–1.860)
$NegativeNews_{i,t:t+1}$	0.009**	–0.001	0.011**
	(1.990)	(–0.190)	(2.060)
Constant	0.096***	0.096***	0.097***
	(5.270)	(5.280)	(5.280)
Nº of Obs.	163,006	163,006	163,006
R^2	0.012	0.012	0.012
Nº of Positive News	3,897	1,769	2,365
Nº of Negative News	3,830	1,676	2,350

This table presents the impact of announcements on the supply curve. $SIN_{i,t}$ is a dummy variable for an inward supply shift, equal to one when an increase in loan fee is coupled with a decrease in quantity on day t. $PositiveNews_{i,t:t+1}$ is a dummy variable, equal to one on days t and $t+1$ if at least one positive announcement is disclosed on day t. $NegativeNews_{i,t:t+1}$ is a dummy variable, equal to one on days t and $t+1$ if at least one negative announcement is disclosed on day t. Announcements are considered positive if the difference between the stock return on day t minus the expected stock return on that day is greater than zero. Announcements are considered negative if this difference is less than zero. The first model encompasses announcements of the Types 1 and 2, with 3,897 days of positive and 3,830 days of negative announcements of at least one type. Type 1 encompasses only announcements of relevant facts, with 1,769 positive and 1,676 negative announcements disclosed. Type 2 encompasses only announcements of economic-financial data, resulting in 2,365 positive and 2,350 negative announcements. The period extends from January 2013 to December 2017. T-statistics are in parentheses. We regress a panel regression with stocks' fixed effect and dummies for days as additional controls. Standard errors are robust. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

tioned, is that announcements of relevant facts may give no clear perspective on stock returns. On the other hand, information in economic-financial data announcements is clearer and more easily understood by lenders.

As a robustness test, we run the same panel regression model again, while considering some announcements to be neutral. In this case, we classify announcements as positive if an announcement is made on day t and $\hat{e}_{i,t} \geqslant 1\%$. We consider them to be negative, in turn, if an announcement is made on day t and $\hat{e}_{i,t} \leqslant -1\%$. A return 1 percentage point above or below the stock's expected return on a given day may indicate that the announcement had some effect—i.e., that the announcement is not neutral. Considering this interval considered neutral, we are left with 3,090 positive Type 1&2 announcements,

Table 7
Impact of announcements on SIN - non-neutral announcements

	$\text{SIN}_{i,t}$		
	Type 1&2	Type 1	Type 2
$\text{PositiveNews}_{i,t:t+1}$	–0.008*	–0.011	–0.008
	(–1.660)	(–1.580)	(–1.370)
$\text{NegativeNews}_{i,t:t+1}$	0.012**	0.001	0.014**
	(2.410)	(0.150)	(2.270)
Constant	0.096***	0.096***	0.097***
	(5.270)	(5.280)	(5.290)
Nº of Obs.	163.006	163.006	163.006
R^2	0.012	0.012	0.012
Nº of Positive News	3.090	1.422	1.867
Nº of Negative News	3.085	1.343	1.915

This table presents the impact of business announcements on the supply curve. $\text{SIN}_{i,t}$ is a dummy variable for an inward supply shift, equal to one if an increase in loan fees is coupled with a decrease in quantity on day t. $\text{PositiveNews}_{i,t:t+1}$ is a dummy variable, equal to one on days t and $t+1$ if at least one positive announcement is disclosed on day t. $\text{NegativeNews}_{i,t:t+1}$ is a dummy variable, equal to one on days t and $t+1$ if at least one negative announcement is disclosed on day t. Announcements are considered positive if the difference between the stock return on day t minus that day's expected stock return is greater than or equal to 1%. Announcements are considered negative if this difference is less than or equal to -1%. The first model encompasses announcements Types 1 and 2, with 3,090 days of positive and 3,085 days of negative announcements of at least one type. Type 1 includes only announcements of relevant facts, with 1,422 positive and 1,343 negative announcements disclosed. Type 2 includes only announcements of economic-financial data, resulting in 1,867 positive and 1,915 negative announcements. The period is January 2013 to December 2017. T-statistics are in parentheses. We perform a panel regression with stocks' fixed effect and dummies for days as additional controls. Standard errors are robust. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

1,422 positive Type 1, and 1,867 positive Type 2. As for negative announcements beyond the threshold, the sample contains 3,085 Type 1&2, 1,343 Type 1, and 1,915 Type 2.

Conducting the panel regression without an interval around zero, in practice includes noise in the announcements signal. The threshold separates the Brownian component (noise) near zero from the informational component with higher values. Moreover, with a 1% interval, about 80% of announcements are considered. Results, in Table 7, are qualitatively and economically the same as those shown in Table 6, except for a loss of significance of positive announcements of Type 2. However, the signs remain the same, and negative announcements of Type 2 still produce significant effects. These details lend further credibility to our results.[8]

Overall, we conclude that lenders do process relevant business information when it is released. Additionally, we can infer that economic-financial data announcements (Type 2), in particular, influence shorting supply conditions after their release. These patterns help confirm the previous findings that lenders are not merely price takers, since they use public information to modify supply conditions.

5. Conclusion

This study's main conclusion is that lenders are not price takers. Our results indicate that lenders decrease their lending offers when they predict negative future stock returns. A possible explanation is that, when lenders predict negative returns, they restrict their short offers and instead may sell their stocks.

We also find that lenders use new information to modify their lending offers. After separating announcements into categories and by sign, results indicate that when lenders are informed with positive news they tend to increase their lending offers to profit from the positive return plus the loan fee—they decrease their restriction of shorting supply. Negative announcements, in contrast, induce lenders to further restrict shorting supply, probably selling their stocks. Interestingly, our results also indicate that lenders are more responsive to economic-financial data announcements, and modify their lending offers accordingly. Thus, we suggest that lenders convey material information through their actions around the arrival of new information in the market.

Taking all of these results together, we conclude that lenders actually are not price takers, since they change their lending offers when they predict negative future returns, and, further, they use new information to modify supply conditions. Consequently, we argue that the supply side, in which stock lenders provide supply for fees, deserves further attention.

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[8]Results are not economically different for other threshold levels. For instance, if we instead consider the interval (-0.5%, 0.5%), around 90% of the announcements appear beyond the thresholds, and results remain the same, in sign and statistical significance.

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A. Additional tables

In Section 4, we mention the possible problem with estimators when we apply dynamic panel models including lagged levels of the dependent variable as regressors. However, the estimation procedure is asymptotically valid when the number of observations in the time dimension grows large (Kiviet, 1995), which bolsters our results. To eliminate any doubt about the estimators' bias, we adopt the same panel regression model with stocks' fixed effects and week dummies as additional controls, but modifying our control variables. Instead of last-week return and momentum (lagged dependent variable), we choose to use past-week return volatility (the standard deviation of the week) as a control. Results are nearly identical in terms of sign and significance, which reconfirms our findings. These results appear in Table A1 and Table A2.

Table A1
Loan fee and negative future returns: Modified control variable

	(1) $\text{AdjRet}_{i,1w}$	(2) $\text{AdjRet}_{i,2w}$	(3) $\text{AdjRet}_{i,3w}$	(4) $\text{AdjRet}_{i,4w}$	(5) $\text{AdjRet}_{i,5w}$	(6) $\text{AdjRet}_{i,6w}$
LoanFee	−0.03*	−0.06***	−0.08***	−0.10***	−0.11***	−0.11***
	(−1.83)	(−3.13)	(−3.29)	(−3.67)	(−3.24)	(−3.01)
Size	−0.77***	−1.49***	−2.30***	−3.15***	−3.99***	−4.79***
	(−5.35)	(−7.15)	(−9.14)	(−10.55)	(−11.89)	(−12.54)
Turnover	0.18	0.33	0.25	0.27	0.16	0.28
	(1.04)	(1.52)	(1.11)	(1.09)	(0.52)	(0.93)
BAspread	0.17	0.48*	0.54**	0.59**	0.61***	0.59**
	(1.36)	(1.91)	(2.16)	(2.28)	(2.75)	(2.49)
VolRet	−0.02	−0.13**	−0.12*	−0.15*	−0.08	−0.12
	(−0.50)	(−2.30)	(−1.76)	(−1.96)	(−0.86)	(−1.25)
Constant	10.68***	20.89***	32.24***	44.40***	56.48***	67.90***
	(4.85)	(6.55)	(8.39)	(9.73)	(11.00)	(11.62)
Nº of Obs.	29,084	29,084	29,084	29,084	29,084	29,084
adj. R^2	0.02	0.03	0.04	0.05	0.06	0.06

Table A2
Supply and demand shifts in the lending market: Modified control variable

	(1) $\text{AdjRet}_{i,1w}$	(2) $\text{AdjRet}_{i,2w}$	(3) $\text{AdjRet}_{i,3w}$	(4) $\text{AdjRet}_{i,4w}$	(5) $\text{AdjRet}_{i,5w}$	(6) $\text{AdjRet}_{i,6w}$
SOUT	−0.03	−0.23	−0.23	−0.30	−0.35	−0.32
	(−0.27)	(−1.49)	(−1.18)	(−1.35)	(−1.41)	(−1.16)
SIN	−0.12	−0.21	−0.47**	−0.56**	−0.56**	−0.45*
	(−0.97)	(−1.29)	(−2.38)	(−2.51)	(−2.26)	(−1.66)
DOUT	−0.13	−0.22	−0.40**	−0.50**	−0.67***	−0.60**
	(−1.08)	(−1.38)	(−2.08)	(−2.27)	(−2.69)	(−2.20)
DIN	−0.07	−0.25	−0.22	−0.26	−0.36	−0.22
	(−0.58)	(−1.59)	(−1.10)	(−1.21)	(−1.45)	(−0.83)
Size	−0.75***	−1.42***	−2.23***	−3.05***	−3.87***	−4.61***
	(−5.42)	(−7.17)	(−9.37)	(−10.89)	(−12.21)	(−13.00)
Turnover	0.16	0.27	0.18	0.19	0.07	0.18
	(0.97)	(1.32)	(0.84)	(0.83)	(0.23)	(0.65)
BAspread	0.14	0.44**	0.43*	0.52**	0.50**	0.54**
	(1.23)	(1.98)	(1.93)	(2.23)	(2.42)	(2.48)
VolRet	−0.02	−0.12**	−0.11*	−0.14*	−0.04	−0.08
	(−0.35)	(−2.25)	(−1.71)	(−1.93)	(−0.40)	(−0.83)
Constant	10.34***	19.67***	31.17***	42.87***	54.58***	65.31***
	(4.89)	(6.52)	(8.56)	(10.02)	(11.31)	(12.08)
Nº of Obs.	31.77	31.77	31.77	31.77	31.77	31.77
adj. R^2	0.02	0.03	0.03	0.04	0.05	0.06