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Short Selling, the supply side: are lenders price makers?

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Keywords: short selling; loan fee; lenders; public information.

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Abstract

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1. Introduction

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

It is widely accepted in the literature that high lending fees predict negative returns because high fees capture the negative information that short sellers, on the demand side, detain. We confirm that high lending fees predict negative returns. However, we argue that the supply side, where stock lenders provide supply for fees, also warrants attention. We disentangle the demand and supply shifts using Cohen et al.'s (2007) technique and then 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 specifically, we find that lenders decrease loan supply when they predict negative future returns. By that, we conclude that lenders are active, modifying loan fees and quantities independently of the changes in the demand side.

The traditional passive behavior of lenders is driven by limited information on borrowing demand in a nontransparent OTC market. In recent years, however, significant improvements in providing daily and intraday information on equity may have given a larger role and more bargaining power to lenders on the supply side. In Brazil, contrasting with most other lending markets, as a result of the local regulatory system, all lending deals must be registered in the B3 lending system. Reliable and frequently available information allows not only borrowers to locate securities faster but also lenders to observe demand and supply in a timely manner and charge more competitive prices (Duong et al., 2016). This peculiarity of the Brazilian market helps lenders to be active in Brazil.

The main conclusion of our study is that lenders are not price takers. Our results indicate that lenders decrease their lending offers when they predict negative future returns. Before we verify our second goal, we confirm the importance of new information in the market. We find that relevant announcements have significant impacts on securities prices and on investors' decisions to trade. Therefore, it seems useful to link them with supply curve to help understand if and how lenders use new information to modify their lending offers around announcements.

Since only relevant announcements affect securities prices, we separate different types of information into different categories, following B3's website. In general, there are many announcements containing non-relevant information, underestimating the importance of announcements in the market. Besides, by considering all news disclosed, it takes into account news that are not surprises to the market – which mitigates the impact on stock returns. Therefore, in our models, we choose to work only with relevant facts' announcements and economic-financial data announcements. Moreover, positive and negative news tend to affect securities prices in a different way; hence, news were considered positive if the difference between the stock return minus the expected stock return on day t is greater than zero and news were considered negative if this difference is lower than zero. In order to consider some news as neutral, we also run our models imposing a 1% bandwidth for positive and negative news.

By separating different categories and signals of announcements, we find that lenders do process news when they are released. More specifically, our results indicate that when lenders are informed with positive news they tend to increase their shorting supply – they decrease their restriction of shorting supply. In contrast, negative news tend to make lenders increase their restriction of shorting supply. Besides, our results also indicate that lenders are more responsive to economic-financial data announcements to modify their lending offers. It is worth mentioning that despite B3's website classify some news as relevant facts' announcements, they contain some information that may not provide a clear perspective of how stock returns will be in the next few days. On the other hand, the information of economic-financial data announcements seems clearer and easier to be understood by lenders. Overall, we conclude that lenders do process the information when it is released.

Taking all results together, our findings indicate that lenders are not price takers, since they change their lending offers when they predict negative future returns and they also use new information to modify supply conditions.

The use of the Brazilian stock market is justified by the external validity of the results. In addition to being one of the largest economies in the world and one of the most important markets among emerging countries, the Brazilian market has the same standards empirical facts for the equity lending market documented for the US and Europe. From a computational perspective, the size of the Brazilian market facilitates empirical analysis of the entire market at the deal-level (Chague et al., 2017b).

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

2. Literature review

In general, it is argued that short selling is an operation that contributes to the efficiency of market information (e.g., Saffi and Sigurdsson, 2010; Boehmer and Wu, 2013; among others). Several empirical studies argue that short selling is beneficial to the market because short sellers convey new negative information and perform a governance role in discovering profit manipulation and discouraging management of fraudulent activities (Duong et al. 2016). Massa et al. (2015) say that short selling encourages the release of private information by insiders, while Deng and Gao (2018) say that short selling plays an important role in monitoring the firm insiders.

Simultaneously, however, short selling is considered a dangerous operation and is prohibited in some countries, seen as an inherently speculative operation. For instance, in 2011, short selling was banned in some European countries, aiming to reduce volatility and to mitigate or stop the downward spiral in stock prices. However, Alves et al. (2016) found that the bans harmed liquidity and that bid-ask spread hiked after the implementation. They found that stocks subjected to the bans have exhibited a longer delay in the assimilation of negative common-wide information during the banning span, meaning that the regulation has failed to achieve its goals.

Anyhow, short selling is very common in the main economies, reaching a significant percentage of the volume of shares traded, e.g. 24% on NYSE and

31% on Nasdaq in 2005 (Diether et al., 2009). In Brazil, it is not different. In recent years, short selling responds, on average, for 25% of the volume of shares traded (Chague et al., 2017b).

Given the importance of the short market, there are numerous studies in the area, most focusing on the demand side of this market. In this context, it is widely accepted that lending fees capture information from short sellers. Engelberg et al. (2012) argue that the information advantage of short sellers lies on their ability to process publicly available information. Karpoff and Lou (2010) and Boehmer et al. (2015) find evidence that short sellers actually anticipate earnings surprises, financial misconducts, and analyst downgrades. Chague et al. (2017a) state that well-connected short sellers with low demand costs pay significantly lower lending fees. Chague et al. (2017a) show that short sellers, both individuals and institutions, get their earnings from their skills rather than from private information.

Kolasinski et al. (2013) argue that research costs in the capital loan market represent significant barriers to short sellers and that a reduction in barriers would be ideal for the best operation of this market. According to Kolasinski et al. (2013), the stock lending market remains relatively opaque, despite the increased accessibility of electronic networks, and claim that research costs can be reduced or possibly eliminated by the creation of a central reporting mechanism for sharing prices and loans availability. In this context, recent regulatory and market changes are giving potentially more bargaining power to lenders, placing them in a better position to manage their lending desks (Duong et al., 2016). As a result, lenders have responded eagerly to maximize income from their portfolios (SEC, 2014).

On the supply side of the market, Duong et al. (2016) state that high lending fees predict negative returns even after controlling for shorting demand, suggesting that there is an additional information component on the supply side. As suggested by Duffie et al. (2002), Duong et al. (2016) 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. (2016) conclude that, along with short sellers, lenders contribute to the price discovery process. However, their 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. Stocks that are impossible to short have an infinite shorting cost, yet the level of short interest is zero (Cohen et al., 2007).

Several studies construct proxies for shorting supply and shorting demand and for equilibrium prices (e.g., rebate rates) and equilibrium quantities (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. Cohen et al. (2007) criticize the use of those proxies and propose a new empirical strategy, allowing them 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., prices) coupled with an increase in shares lent out (i.e., quantity) corresponds to an increase in shorting supply. This would be the same case of any decrease in price coupled with an increase in quantity. On the other hand, when the loan fees increase and the shares lent out decrease, it would be the case of a decrease in shorting supply. The same idea is applied to verify 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, Cohen et al. (2007) conclude that the relationship between high shorting costs and future negative returns is driven mainly by demand shifts than by supply shifts. The authors emphasize the importance of separating the demand and supply effects in order to understand the driving mechanism linking the shorting market and stock returns.

However, the identification strategy of Cohen et al. (2007) have some limitations. First, if there is a reduction in supply followed by a reduction in demand on a larger scale, they will observe a lower loan fee and lower quantity; therefore, they will not identify the supply shift at all. Moreover, their strategy does not differentiate between large and small shifts, which could matter if effects are increasing with the size of the shifts (Chague et al., 2014).

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 those stocks that are made available to lend are no different from the 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 a case of negative stock returns, 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. The results of 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 present relevant information and peculiarities about the stock loan market in Brazil. The Brazilian Securities Commission (CVM) regulates the securities lending market in Brazil. As a result of the regulatory system, all lending deals must be registered in the B3 lending system. The centralization of the Brazilian lending market contrasts with most other lending markets, which are decentralized and whose data about lending deals are only partially available. This peculiarity of the Brazilian market provides us a complete picture of lending activity for the whole market at a daily frequency.

Another peculiarity in the Brazilian lending market is that all loan deals are collateralized with Treasury securities,[4] so that all lending transactions are negotiated in terms of explicit loan fees. In the US market, for example, 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. The B3 provides a platform called BTC Securities Lending System where brokers electronically register their

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

offers. Usually, lenders place their shares for loan and borrowers can hit the offers. Even though it is also possible for borrowers to place their bids, this is not common. More than 99% of the offers come from lenders (Chague et al. 2014). Over-the-counter (OTC) deals are also possible. As the equity lending market in the US and other countries, the Brazilian lending market is mostly OTC. 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 peculiarity of the Brazilian market comes from the 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. As different investors have different income tax deductions, there was an opportunity for profit and borrowing stocks for a different reason 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 that law (Bonomo et al., 2017). Since 2015, with the repeal of the law, differences in taxes no longer exist.

3.1 Data set

We observe the universe of lending deals from January 2013 to December 2017 traded on the Brazilian stock lending market. For each lending deal, we have the information of the loan quantity and the loan fee. To create our variables related to stock returns (CumRet, AdjRet, Momentum and r_{-1}), this part of our data set goes from January 2012 to April 2018, since it includes lagged and forward stock returns.

Our paper constructs variables related to short selling activity. By using the entire data set, we implicitly assume that short selling is the major factor explaining why investors borrow a stock. This is in line with Clearstream (2014), which argues that despite stocks are borrowed for a number of reasons, such as voting, dividend arbitrage, funding trade, among others, the primary reason is for short selling.

We applied two filters on our data set. First, in order to avoid working with illiquid stocks, we restrict our data set to stocks that match the criteria used by the Brazilian Center for Research in Financial Economics (NEFIN) to calculate short interest:[5] (i) the stock is the most traded share of the firm; (ii) the stock was traded in more than 80% of the days in the previous year with volume greater than R$ 500,000 per day – in case the stock was listed in the previous year, the period considered goes from the listing day to the last day of the year; (iii) the stock was initially listed prior to December of year $t-1$. We end up with 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 received the interest on equity without paying taxes. While

[5] Available at the NEFIN webpage on http://www.nefin.com.br/short_interest.html (last access: 8th December 2019)

institutions profited by 15% of the interest on equity minus the loan fee, individuals received a higher fee. Considering that the loan fees were artificial around those days, we exclude two weeks before and one week after the ex-date. Since the tax arbitrage opportunity ends in 2014, we apply this filter only to 2013 and 2014. In order to avoid extremely high and artificial loan fees, we also drop from our data set 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 the risk-adjusted returns from NEFIN.[6]

Additionally, news and firms announcements are from B3's website.[7] We consider a couple of filters in order to better handle these data. First, we account only for the day of the announcement. It means that we flag days that have at least one announcement. The second filter relates to the official trading hours. Usually, the closing hour of the Brazilian stock market is 5 pm. However, between November and February, it changes to 6 pm. Taking into account the official hour, if the news was disclosed on day t after the closing hour, we are flagging the day $t + 1$. News that are disclosed on weekends and holidays are also assumed to be disclosed in the next trading day.

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[6] 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: 8th December 2019)

[7] The data were imported from the webpage: http://siteempresas.bovespa.com.br/consbov/InfoPerEventuaisBuscData.asp?site=C&ccvm=&razao=&acao=undefined. (last access: 8th December 2019)

Taking into account all filters mentioned above, we end up with 34,587 days flagged with at least one announcement. However, non-relevant news underestimate the relation between news and stock returns, distorting the relationship between news and shifts in lending supply curve. Accordingly, we create three different types of announcements based on B3's classifications. Type 1 encompasses only relevant facts' announcements. Type 2 includes news of economic-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 news tend to affect securities prices in a different way. We classify news 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 news to be negative if this difference is lower than zero. We obtain expected returns by means of:

$$Return_{i,t} = \alpha + \beta_1 MF_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 WML_{i,t} + e_{i,t}, \tag{1}$$

and then isolate the residual:

$$\hat{e}_{i,t} = Return_{i,t} - \hat{\alpha} + \hat{\beta}_1 MF_{i,t} - \hat{\beta}_2 SMB_{i,t} - \hat{\beta}_3 HML_{i,t} - \hat{\beta}_4 WML_{i,t}. \tag{2}$$

If there is an announcement on the day t and $\hat{e}_{i,t} > 0$, than we consider the news as positive. If there is an announcement on the day t and $\hat{e}_{i,t} < 0$, the news are considered as negative.[8]

[8] In order to consider some news as neutral, we also run our models imposing a 1% bandwidth for positive and negative news. In this case, news were considered as positive only if there is an announcement on the day t and $\hat{e}_{i,t} \geq 1\%$. Likewise, news we considered as negative only if there is an announcement on the day t and $\hat{e}_{i,t} \leq -1\%$.

Our sample contains 3,897 positive Type 1 & 2 news, 1,769 positive Type 1 news and 2,365 positive Type 2 news. As for negative news, our sample contains 3,830 Type 1 & 2 news, 1,676 Type 1 news and 2,350 Type 2 news.

Panels A and B in Table I present the summary statistics of the key variables used in the analysis from January 2013 to December 2017 traded in the Brazilian stock lending market on the daily and weekly frequencies, respectively.

Table I – Descriptive statistics

Panel A – Daily stats

Variable	N	Mean	Standard Deviation	25^{th} percentile	Median	75^{th} 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

Panel A presents the summary daily statistics of the key variables used in the analysis from January 2013 to December 2017 traded in the Brazilian stock lending market. Loan fee 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 the 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. To create our variables related to stock returns, this part of our data set goes from January 2012 to April 2018.

Panel B – Average weekly stats

Variable	N	Mean	Standard Deviation	25^{th} percentile	Median	75^{th} 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
$CumRet_{i,1w}$ (%)	32,743	0.07	6.16	-2.86	0.00	2.78
$CumRet_{i,2w}$ (%)	32,743	0.13	8.69	-4.13	0.00	4.11
$CumRet_{i,3w}$ (%)	32,743	0.21	10.69	-5.11	0.00	5.10
$CumRet_{i,4w}$ (%)	32,743	0.29	12.47	-5.99	0.00	6.00
$CumRet_{i,5w}$ (%)	32,743	0.39	14.09	-6.76	0.00	6.81
$CumRet_{i,6w}$ (%)	32,743	0.50	15.68	-7.55	0.00	7.58

Panel B presents the summary the average weekly statistics of the key variables used in the analysis from January 2013 to December 2017 traded in the Brazilian stock lending market. Loanfee is the average loan fee (annualized) of the week, in percentage. Size is the weekly average of the natural logarithm of the value market. Turnover is the average weekly turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread during 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 last week return, in percentage. Momentum is the return from week $t-52$ to $t-2$, in percentage. $CumRet_{i,1:6w}$ is the accumulated raw returns from one to six weeks ahead, in percentage. To create our variables related to stock returns, this part of our data set goes from January 2012 to April 2018.

4. Empirical results

In this section, we explain the methodology used and present the results related to our two goals: (i) verify if lenders are price makers; (ii) check if lenders are informed and if they use public information to change their lending offers.

We first assess, in Section 4.1, the hypothesis that high lending fees can predict negative future returns. In Section 4.2, we verify if the relation between high loan fees and negative future returns is also driven by the supply side. By applying a technique used in Cohen et al. (2007), we disentangle the demand and supply shifts in order to help understand the driving mechanism linking the shorting supply and stock returns.

For our second goal, we start by confirming the importance of new information in the market. Relevant news have significant impacts 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 after the release of public information. We consider three different types of announcements based on B3 classification. Besides, we also separate positive from negative news since they tend to affect securities prices differently.

4.1 Loan fees and negative future returns

In this first model, we want to confirm the hypothesis that high lending fees can predict negative future returns. In Equation (3), we adopt a panel regression model[9] with stocks' fixed effects and week dummies as additional controls to test whether loan fees help predict future returns:

[9] By using dynamic panel models including lagged levels of the dependent variable as regressors, we are aware that it violates strict exogeneity, since the lagged dependent variable is necessarily correlated with the idiosyncratic error and, therefore, the estimators might be inconsistent. However, the estimation procedure is asymptotically valid when the number of observations in the time dimension gets large (Kiviet, 1995), which ensures our results. Besides, Nickell (1981) demonstrates that the bias of the estimator as N (tickers) goes to infinity is of order of 1/T, which may be quite small when T (time) gets large. OLS-FE is not a bad estimator as long as T is big. Anyhow, in order to eliminate any doubt, 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. The results are almost the same in terms of signal and significance, reinforcing our findings, and they are shown in the Appendix. The same idea is applied for all empirical tests.

$$CumRet_{i,1:6w} = \alpha + \beta_1 Loanfee_{i,w} + \beta_2 Size_{i,w} + \beta_3 Turnover_{i,w} + \beta_4 BAspread_{i,w} + \beta_5 r_{-1\ i,w} + \beta_6 Momentum_{i,w} + \varepsilon_{i,w}, \qquad (3)$$

where the dependent variable is accumulated raw returns in percentage, from one to six weeks ahead. In addition, the same model is used in Equation (4) but modifying the dependent variable for accumulated risk-adjusted returns in percentage, also from one to six weeks ahead.

$$AdjRet_{i,1:6w} = \alpha + \beta_1 Loanfee_{i,w} + \beta_2 Size_{i,w} + \beta_3 Turnover_{i,w} + \beta_4 BAspread_{i,w} + \beta_5 r_{-1\ i,w} + \beta_6 Momentum_{i,w} + \varepsilon_{i,w}. \qquad (4)$$

Our control variables are as in Boehmer et al. (2008) and Diether et al. (2009). We include variables that relate to return predictability such as firm size, turnover, last week return and momentum. Besides, short selling should increases in periods of uncertainty, since it is possible that short sellers 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 average loan fee (annualized) of the week, in percentage. Size is the weekly average of the natural logarithm of the value market. Turnover is the average weekly turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread during 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 last week return, in percentage. Momentum is the stock return from week $t-52$ to $t-2$, in percentage.

Tables II and III show a statistically significant negative relation between loan fees and future returns, captured by the negative coefficient on the *Loanfee* variable in both models. This finding provides evidence in favor of the hypothesis that high loan fees help predict negative future returns.

Table II – Loan fee and negative future returns: Raw returns

	(1) $CumRet_{i,1w}$	(2) $CumRet_{i,2w}$	(3) $CumRet_{i,3w}$	(4) $CumRet_{i,4w}$	(5) $CumRet_{i,5w}$	(6) $CumRet_{i,6w}$
Loanfee	-0.0163	-0.0428*	-0.0410	-0.0536*	-0.0425	-0.0297
	(-1.02)	(-1.95)	(-1.59)	(-1.78)	(-1.18)	(-0.73)
Size	-1.180***	-2.309***	-3.649***	-5.044***	-6.468***	-7.780***
	(-7.00)	(-9.50)	(-12.06)	(-13.65)	(-15.06)	(-16.17)
Turnover	0.250	0.422*	0.316	0.299	0.204	0.286
	(1.39)	(1.92)	(1.33)	(1.16)	(0.62)	(0.91)
BAspread	0.0830	0.283	0.225	0.142	0.0375	-0.0564
	(0.70)	(1.15)	(0.90)	(0.55)	(0.17)	(-0.24)
r_{-1}	-0.0243	-0.0324	-0.00467	0.0461	0.0320	0.0288
	(-1.42)	(-1.35)	(-0.15)	(1.17)	(0.82)	(0.70)
Momentum	0.00332***	0.00586***	0.00881***	0.0118***	0.0148***	0.0175***
	(2.83)	(3.40)	(4.45)	(5.02)	(5.43)	(5.85)
Constant	16.48***	32.42***	51.54***	71.51***	91.95***	110.8***
	(6.44)	(8.73)	(11.15)	(12.68)	(14.06)	(15.09)
N° of Obs.	29,097	29,097	29,097	29,097	29,097	29,097
adj. R^2	0.212	0.226	0.241	0.259	0.274	0.292

This table presents the relationship between loan fees and stock returns. The dependent variable is accumulated raw returns in percentage, from one to six weeks ahead. Loanfee is the average loan fee (annualized) of the week, in percentage. Size is the weekly average of the natural logarithm of the value market. Turnover is the average weekly turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread during 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 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 and week dummies as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table III – Loan fee and negative future returns: Risk-adjusted returns

	(1) $AdjRet_{i,1w}$	(2) $AdjRet_{i,2w}$	(3) $AdjRet_{i,3w}$	(4) $AdjRet_{i,4w}$	(5) $AdjRet_{i,5w}$	(6) $AdjRet_{i,6w}$
Loanfee	-0.0291*	-0.0683***	-0.0838***	-0.107***	-0.111***	-0.116***
	(-1.94)	(-3.33)	(-3.50)	(-3.90)	(-3.47)	(-3.26)
Size	-0.816***	-1.533***	-2.423***	-3.350***	-4.262***	-5.118***
	(-5.17)	(-6.76)	(-8.94)	(-10.33)	(-11.74)	(-12.46)
Turnover	0.176	0.288	0.196	0.166	0.0987	0.195
	(1.05)	(1.36)	(0.87)	(0.69)	(0.33)	(0.68)
BAspread	0.156	0.452*	0.498**	0.532**	0.543**	0.515**
	(1.26)	(1.81)	(2.02)	(2.09)	(2.49)	(2.19)
r_{-1}	-0.0287*	-0.0476**	-0.0312	0.000989	-0.0297	-0.0403
	(-1.76)	(-2.18)	(-1.12)	(0.03)	(-0.83)	(-1.02)
Momentum	0.00155	0.00246	0.00408**	0.00549**	0.00689***	0.00875***
	(1.38)	(1.49)	(2.15)	(2.48)	(2.74)	(3.22)
Constant	11.34***	21.43***	34.13***	47.44***	60.60***	72.96***
	(4.73)	(6.18)	(8.24)	(9.59)	(10.95)	(11.64)
N° of Obs.	29,097	29,097	29,097	29,097	29,097	29,097
adj. R^2	0.016	0.027	0.036	0.046	0.055	0.063

This table presents the relationship between loan fees and risk-adjusted stock returns. The dependent variable is accumulated risk-adjusted returns in percentage, from one to six weeks ahead. Loanfee is the average loan fee (annualized) of the week, in percentage. Size is the weekly average of the natural logarithm of the value market. Turnover is the average weekly turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread during 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 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.

4.2 Demand and supply shifts in the lending market

There appear to be a consensus in the existing literature that lending fees capture information from short sellers. Short sellers are, on average, skilled traders and/or with private information. However, we want to verify if this relation between high loan fees and negative future returns is not only driven by the demand side. Our study indicates that the supply side also warrants attention.

We next disentangle the demand and supply shifts in order to verify if the supply side has an important relationship with future stock returns. To do that, we classify supply and demand shifts as in Cohen et al. (2007). For a given security, an increase in the stock loan fee (i.e., prices) coupled with an increase in shares lent out (i.e., quantity) corresponds to an increase in shorting demand. On the other hand, an increase in the stock loan fee coupled with a decrease in shares lent out would be the case of a decrease in shorting demand. The same idea is applied to verify shorting supply shifts. As pointed by the authors, we do not maintain that this is the only shift that occurred. However, when there is an increase in prices combined with an increase in quantities, a demand shift outwards must have occurred. Besides, we assume that demand curves are not upward sloping and that supply curves are not downward sloping.

Therefore, over the designated horizon (weeks), if there is an increase in the stock loan fee coupled with an increase in shares lent out, at least a demand shift out has occurred and we flagged it as a dummy variable named DOUT. If there is 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 SIN for those with at least a supply shift in. By classifying shifts in this way, we are able to identify shifts in shorting demand and supply, and then 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 in order to verify the relationship between demand and supply shifts with future stock returns:

$$CumRet_{i,1:6w} = \alpha + \beta_1 SOUT_{i,w} + \beta_2 SIN_{i,w} + \beta_3 DOUT_{i,w} + \beta_4 DIN_{i,w} + \beta_5 Size_{i,w} + \beta_6 Turnover_{i,w} + \beta_7 BAspread_{i,w} + \beta_8 r_{-1\,i,w} + \beta_9 Momentum_{i,w} + \varepsilon_{i,w}, \quad (5)$$

where the dependent variable is accumulated raw returns in percentage, from one to six weeks ahead. The control variables are the same mentioned in the previous section. The results are reported in Table IV.

Table IV – Demand and supply shifts in the lending market: Raw returns

	(1) $CumRet_{i,1w}$	(2) $CumRet_{i,2w}$	(3) $CumRet_{i,3w}$	(4) $CumRet_{i,4w}$	(5) $CumRet_{i,5w}$	(6) $CumRet_{i,6w}$
SOUT	0.0284	-0.125	-0.165	-0.235	-0.400	-0.358
	(0.23)	(-0.75)	(-0.80)	(-1.00)	(-1.50)	(-1.22)
SIN	-0.0642	-0.125	-0.354*	-0.413*	-0.509*	-0.343
	(-0.51)	(-0.71)	(-1.68)	(-1.74)	(-1.89)	(-1.17)
DOUT	-0.0572	-0.132	-0.350*	-0.459**	-0.686**	-0.614**
	(-0.46)	(-0.78)	(-1.68)	(-1.96)	(-2.54)	(-2.08)
DIN	-0.0598	-0.211	-0.243	-0.277	-0.476*	-0.370
	(-0.48)	(-1.26)	(-1.17)	(-1.20)	(-1.79)	(-1.30)
Size	-1.136***	-2.166***	-3.462***	-4.780***	-6.144***	-7.405***
	(-7.12)	(-9.55)	(-12.25)	(-14.00)	(-15.38)	(-16.71)
Turnover	0.234	0.387*	0.268	0.260	0.179	0.267
	(1.36)	(1.84)	(1.19)	(1.06)	(0.57)	(0.89)
BAspread	0.0517	0.249	0.147	0.114	-0.0315	-0.0868
	(0.47)	(1.16)	(0.66)	(0.50)	(-0.16)	(-0.42)
r_{-1}	-0.0194	-0.0285	-0.000934	0.0467	0.0265	0.0293
	(-1.19)	(-1.26)	(-0.03)	(1.25)	(0.70)	(0.74)
Momentum	0.00311***	0.00538***	0.00776***	0.0105***	0.0134***	0.0158***
	(2.78)	(3.28)	(4.08)	(4.67)	(5.18)	(5.59)
Constant	15.80***	30.13***	48.64***	67.43***	87.29***	105.4***
	(6.50)	(8.69)	(11.25)	(12.94)	(14.34)	(15.59)
Nº of Obs.	31,790	31,790	31,790	31,790	31,790	31,790
adj. R^2	0.205	0.221	0.236	0.253	0.266	0.285

This table presents the relationship between demand and supply shifts with future stock returns. The dependent variable is accumulated raw returns in percentage, from one to six weeks ahead. SOUT is a dummy variable for an outward supply shift in the week. SIN is a dummy variable for an inward supply shift in the week. DOUT in a dummy variable for an outward demand shift in the week. DIN in a dummy variable for an inward demand shift in the week. Size is the weekly average of the natural logarithm of the value market. Turnover is the average weekly turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread during 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 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.

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

In Table IV we see that the relationship between accumulated raw returns and an inward shift in shorting supply (SIN) is negative and statistically significant from three to five weeks ahead, in contrast with some previous studies.[10] This result is crucial to help answer whether lenders are price makers. From $\hat{\beta}_2$, we can infer that lenders restrict their short offers when they predict a negative future return. In other words, this result states that the accumulated stock return from three to five weeks after lenders restrict their short offers are significantly negative. This means that lenders are indeed price makers, modifying loan

[10] See Cohen et al. (2007), for example.

conditions (price and quantity) independently of the changes generated by the demand side.

As suggested by Duffie et al. (2002), Duong et al. (2016) posit that lenders incorporate not only the past and current shorting demands, but also the expected future demand in their lending fees. If this were the case, when lenders predict an increase in future shorting demand, they should increase their offers and raise loan fees in order to generate an additional income. The increase in supply followed by an increase in demand may result in higher fees and quantities. This would be the case of finding a negative and statistically significant coefficient of SOUT, which is not found in our results. Although $\hat{\beta}_1$ is negative, it is not significant, meaning that lenders do not raise their profits by increasing loan fees and quantities.

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 goes in the same direction as Evans et al. (2017), which state that actively managed equity funds that lend securities underperform similar funds that do not lend but sell it. Besides, Evans et al. (2017) found that underperformance is concentrated among funds with investment restrictions. Hence, one possible explanation for our findings is that, if there is no restriction and lenders predict negative future returns, lenders will not raise their offers and fees but sell their stocks.

In addition, the same model is used in Equation (6) but modifying the dependent variable for accumulated risk-adjusted returns in percentage, also from one to six weeks ahead:

$$AdjRet_{i,1:6w} = \alpha + \beta_1 SOUT_{i,w} + \beta_2 SIN_{i,w} + \beta_3 DOUT_{i,w} + \beta_4 DIN_{i,w} + \beta_5 Size_{i,w} + \beta_6 Turnover_{i,w} + \beta_7 BAspread_{i,w} + \beta_8 r_{-1\,i,w} + \beta_9 Momentum_{i,w} + \varepsilon_{i,w}. \quad (6)$$

The results are even more favorable with what was mentioned above. Table V also shows a negative and statistically significant coefficient for DOUT, as expected. But more importantly, Table V also shows a negative and statistically significant coefficient for SIN from the third week ahead, confirming our previous findings.

Table V – Demand and supply shifts in the lending market: Risk-adjusted returns

	(1) $AdjRet_{i,1w}$	(2) $AdjRet_{i,2w}$	(3) $AdjRet_{i,3w}$	(4) $AdjRet_{i,4w}$	(5) $AdjRet_{i,5w}$	(6) $AdjRet_{i,6w}$
SOUT	-0.0195	-0.222	-0.224	-0.301	-0.348	-0.316
	(-0.17)	(-1.41)	(-1.17)	(-1.37)	(-1.41)	(-1.15)
SIN	-0.118	-0.211	-0.476**	-0.555**	-0.590**	-0.482*
	(-0.99)	(-1.30)	(-2.42)	(-2.49)	(-2.37)	(-1.76)
DOUT	-0.112	-0.207	-0.401**	-0.501**	-0.662***	-0.594**
	(-0.95)	(-1.31)	(-2.07)	(-2.29)	(-2.66)	(-2.17)
DIN	-0.0685	-0.250	-0.224	-0.261	-0.382	-0.249
	(-0.59)	(-1.61)	(-1.15)	(-1.21)	(-1.56)	(-0.94)
Size	-0.788***	-1.443***	-2.325***	-3.215***	-4.093***	-4.884***
	(-5.26)	(-6.78)	(-9.13)	(-10.65)	(-12.03)	(-12.88)
Turnover	0.158	0.232	0.127	0.0959	0.0296	0.122
	(0.99)	(1.15)	(0.60)	(0.42)	(0.11)	(0.45)
BAspread	0.127	0.410*	0.399*	0.471**	0.445**	0.473**
	(1.12)	(1.88)	(1.82)	(2.08)	(2.20)	(2.22)
r_{-1}	-0.0244	-0.0423**	-0.0268	0.00223	-0.0353	-0.0398
	(-1.56)	(-2.05)	(-1.01)	(0.06)	(-1.00)	(-1.05)
Momentum	0.00133	0.00200	0.00333*	0.00467**	0.00602**	0.00751***
	(1.24)	(1.28)	(1.83)	(2.20)	(2.53)	(2.92)

Constant	10.91***	19.94***	32.51***	45.23***	58.07***	69.49***
	(4.77)	(6.13)	(8.36)	(9.85)	(11.23)	(12.05)
N° of Obs.	31,790	31,790	31,790	31,790	31,790	31,790
adj. R^2	0.015	0.026	0.034	0.044	0.053	0.062

This table presents the relationship between demand and supply shifts with accumulated risk-adjusted stock returns. The dependent variable is accumulated risk-adjusted returns in percentage, from one to six weeks ahead. SOUT is a dummy variable for an outward supply shift in the week. SIN is a dummy variable for an inward supply shift in the week. DOUT in a dummy variable for an outward demand shift in the week. DIN in a dummy variable for an inward demand shift in the week. Size is the weekly average of the natural logarithm of the value market. Turnover is the average weekly turnover (trading volume divided by the market cap) in percentage. BAspread is the average bid-ask spread during 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 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.

Therefore, our findings suggest two conclusions. First, when lenders predict negative future returns, instead of raising loan fees they probably sell their stocks – they restrict their lending offers. Second, since lenders modify their lending offers conditions, we conclude that lenders are not, by no means, price takers.

4.3 The importance of relevant announcements

Our previous findings indicate that lenders decrease their lending offers when they predict negative future returns. Our second goal consists in analyze how lenders predict that. We check if lenders are informed and if they use public information to change their lending offers. By doing that, we suggest that lenders convey material information through their acts around the arrival of new information in the market.

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

$$R_{i,t:t+2} = \alpha + \beta_1 PositiveNews_{i,t} + \beta_2 NegativeNews_{i,t} + \varepsilon_{i,t}, \qquad (7)$$

where the dependent variable is risk-adjusted return in percentage for stock i and it varies from the day t to the day $t+2$, being t the day of the announcement. The variable $PositiveNews_{i,t}$ is a dummy variable, which is equal to one if there is at least one announcement disclosed at 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). Similarly, the variable $NegativeNews_{i,t}$ is a dummy variable which is equal to one if there is at least one announcement disclosed at the day t and $\hat{e}_{i,t} < 0$.

We next separate different types of information into different categories, following B3's website. Type 1 encompasses only relevant facts' announcements including acquisition of shares, shareholders' agreement, new projection of investments, among others. Type 2 involves announcements of economic-financial data such as financial statements, earnings releases, rating review and others. Type 1 & 2 includes both types.

Table VI – The impact of relevant news on stock returns

	Type 1 & 2 $R_{i,t}$	Type 1 & 2 $R_{i,t+1}$	Type 1 & 2 $R_{i,t+2}$	Type 1 $R_{i,t}$	Type 1 $R_{i,t+1}$	Type 1 $R_{i,t+2}$	Type 2 $R_{i,t}$	Type 2 $R_{i,t+1}$	Type 2 $R_{i,t+2}$
$PositiveNews_{i,t}$	2.409***	0.105**	-0.0394	2.835***	0.129	-0.0960	2.145***	0.113*	-0.0148
	(45.71)	(2.03)	(-0.91)	(29.69)	(1.42)	(-1.40)	(40.91)	(1.88)	(-0.29)
$NegativeNews_{i,t}$	-2.093***	-0.242***	0.0379	-2.240***	-0.242***	0.0270	-2.076***	-0.237***	0.0569
	(-49.23)	(-5.00)	(0.84)	(-31.45)	(-2.85)	(0.34)	(-40.95)	(-4.39)	(1.09)
Constant	-0.0860	-0.0575	-0.0644	-0.0558	-0.0575	-0.0642	-0.104	-0.0617	-0.0646
	(-0.79)	(-0.52)	(-0.58)	(-0.52)	(-0.52)	(-0.58)	(-0.96)	(-0.56)	(-0.58)
N° of Obs.	151,068	151,064	150,910	151,068	151,064	150,910	151,068	151,064	150,910
R^2	0.046	0.002	0.002	0.027	0.002	0.002	0.025	0.002	0.002

	Type 1 & 2	Type 1	Type 2
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 positive and negative news on stock returns. The dependent variable is risk-adjusted returns in percentage, from the day t to $t+2$. $PositiveNews_{i,t}$ is a dummy variable which is equal to one if at least one positive announcement is disclosed at day t. $NegativeNews_{i,t}$ is a dummy variable which is equal to one if at least one negative announcement is disclosed at day t. News 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 news are considered negative if this difference is lower than zero. The first three models encompass news of the categories Type 1 and Type 2, containing 3,897 days of positive news and 3,830 days of negative news of at least one type. Type 1 models encompass only relevant facts' announcements with 1,769 positive news and 1,676 negative news disclosed. Type 2 models encompass only news of economic-financial data, totalizing 2,365 positive news and 2,350 negative news 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.

Table VI indicates that on days with relevant announcements releases, there is an increase in stock return. As expected, there is a strong positive and statistically relevant relation between positive news and stock return at the day t. The same happens for negative news. There is a strong negative and statistically relevant relation between negative news and stock return at the day t. More interestingly, note that, in both types (positive and negative) of news, the effect of an announcement on stock return appears to spillover to the next trading day, $t + 1$, although less significant. However, there is no statistically relevant effect on the day $t + 2$, suggesting that the market has already absorbed the new information.

Therefore, since new information in the market influences securities prices, it seems useful to link them with supply shifts in (SIN) – the relevant shift from the supply side in the previous test – to help understand if 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 new information on the market and that lenders restrict their lending offers when they predict negative future returns. In what follows, we verify if lenders restrict their lending offers after the release of public information. In other words, we want to confirm whether 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 effect and day dummies as additional controls:

$$SIN_{i,t} = \alpha + \beta_1 PositiveNews_{i,t:t+1} + \beta_2 NegativeNews_{i,t:t+1} + \varepsilon_{i,t}, \quad (8)$$

where $SIN_{i,t}$ is a dummy variable for an inward supply shift in the day, which is equal to one if an increase in loan fees coupled with a decrease in quantity has occurred at the day t. $PositiveNews_{i,t:t+1}$ and $NegativeNews_{i,t:t+1}$ are dummy variables that take to one on the day t and $t+1$ if there is at least one positive/negative news on the day t. We restrict to the day of disclosure and the next trading given the evidence in Section 4.3, which states that the effect of an announcement on stock return occurs at the day t, appears to spillover to the next trading day, $t+1$, and that there is no significant effect at the day $t+2$.

The first model encompasses news of types 1 and 2, containing 3,897 days of positive news and 3,830 days of negative news of at least one type. The second model contemplates only Type 1 news, with 1,769 positive news and 1,676 negative news. The last model is about Type 2 announcements, containing 2,365 positive news and 2,350 negative news of this type.

In Equation (8) we expect $\beta_1 < 0$ and $\beta_2 > 0$. Suppose there is a positive news. 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, one expect a decrease in SIN (shorting supply in), i.e., a decrease in the restriction of shorting supply – it would be the case of a negative coefficient for β_1. On the other hand, a 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). It would be the case of a positive coefficient for β_2.

Table VII – The impact of news on SIN

	Type 1 & 2 $SIN_{i,t}$	Type 1 $SIN_{i,t}$	Type 2 $SIN_{i,t}$
$PositiveNews_{i,t:t+1}$	-0.00762*	-0.00791	-0.00978*
	(-1.82)	(-1.30)	(-1.86)
$NegativeNews_{i,t:t+1}$	0.00872**	-0.00119	0.0114**
	(1.99)	(-0.19)	(2.06)
Constant	0.0961***	0.0963***	0.0965***
	(5.27)	(5.28)	(5.28)
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 news on the supply curve. $SIN_{i,t}$ is a dummy variable for an inward supply shift in the day, which is equal to one if an increase in loan fees coupled with a decrease in quantity has occurred at the day t. $PositiveNews_{i,t:t+1}$ is a dummy variable which is equal to one at the day t and $t+1$ if there is at least one positive announcement disclosed at the day t. $NegativeNews_{i,t:t+1}$ is a dummy variable which is equal to one at the day t and $t+1$ if there is at least one negative announcement disclosed at the day t. News 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 news are considered negative if this difference is lower than zero. The first model encompasses news of the categories Type 1 and Type 2, containing 3,897 days of positive news and 3,830 days of negative news of at least one type. Type 1 encompasses only relevant facts' announcements with 1,769 positive news and 1,676 negative news disclosed. Type 2 encompasses only news of economic-financial data, totalizing 2,365 positive news and 2,350 negative news 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 first model in Table VII, with Type 1 & 2 announcements, indicates that positive news tends to affect SIN in a negative way. In other words, a positive news in the day t reduces the probability of a restriction in shorting supply happens. This result goes in direction with what was mentioned above. A positive news tend to increase the stock return. Therefore, lenders should increase their lending offers to profit with the increase in 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, we see that negative news tend to affect SIN in a positive way. In other words, negative news increase the probability of a restriction in shorting supply. This result also goes in direction with what was mentioned above. Negative news tend to decrease stock return. Lenders should then sell their stocks instead of lending them, increasing the restriction of shorting supply (higher SIN).

The second model in Table VII encompasses only Type 1 news. 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. It is worth mentioning that despite the name (relevant facts), Type 1 announcements include information that does not relate to future stock returns. However, the third model shows that the relation of Type 2 news and SIN are statistically relevant. Besides, note that the effects of Type 2 announcements on SIN are stronger and more relevant, especially for negative news. It suggests that lenders are more responsive to economic-financial data announcements to modify their lending offers. One possible explanation, as already mentioned, would be that relevant facts' announcements do not give a clear perspective of how stock returns will be in the next few days. On the other hand, the information of economic-financial data announcements might be clear and easy to be understood by lenders.

As a robustness test, we also run the same panel regression model but considering a 1% bandwidth for positive and negative news. The idea behind it is to classify some news as neutral. In this case, news are considered as positive only if there is an announcement on the day t and $\hat{e}_{i,t} \geq 1\%$. Likewise, news are considered as negative only if there is an announcement on the day t and $\hat{e}_{i,t} \leq -1\%$.

Table VIII – The impact of news on SIN – 1% bandwidth

	Type 1 & 2 $SIN_{i,t}$	Type 1 $SIN_{i,t}$	Type 2 $SIN_{i,t}$
$PositiveNews_{i,t:t+1}$	-0.00779*	-0.0107	-0.00816
	(-1.66)	(-1.58)	(-1.37)
$NegativeNews_{i,t:t+1}$	0.0119**	0.00104	0.0141**
	(2.41)	(0.15)	(2.27)
Constant	0.0962***	0.0962***	0.0965***
	(5.27)	(5.28)	(5.29)
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 news on the supply curve. $SIN_{i,t}$ is a dummy variable for an inward supply shift in the day, which is equal to one if an increase in loan fees coupled with a decrease in quantity has occurred at the day t. $PositiveNews_{i,t:t+1}$ is a dummy variable which is equal to one at the day t and $t+1$ if there is at least one positive announcement disclosed at the day t. $NegativeNews_{i,t:t+1}$ is a dummy variable which is equal to one at the day t and $t+1$ if there is at least one negative announcement disclosed at the day t. News are considered positive if the difference between the stock return on day t minus the expected stock return on day t is greater or equal to one percent and news are considered negative if this difference is lower or equal to minus one percent. The first model encompasses news of the categories Type 1 and Type 2, containing 3,090 days of positive news and 3,085 days of negative news of at least one type. Type 1 encompasses only relevant facts' announcements with 1,422 positive news and 1,343 negative news disclosed. Type 2 encompasses only news of economic-financial data, totalizing 1,867 positive news and 1,915 negative news 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.

In this case, we have 3,090 positive Type 1 & 2 news, 1,422 positive Type 1 news and 1,867 positive Type 2 news. As for negative news, this sample contains 3,085 Type 1 & 2 news, 1,343 Type 1 news and 1,915 Type 2 news.

The results in Table VIII are qualitatively and economically the same as shown in Table VII. The only difference is the loss of significance of positive news of Type 2. However, all signals remain the same and negative news of Type 2 remains significant, which reinforces our results.

Overall, we can conclude that lenders do process the information when it is released. Besides, we can infer that economic-financial data announcements (Type 2) are the ones that influence shorting supply conditions after the release of the information. This result helps to confirm the previous findings that lenders are not price takers, since they use public information to modify supply conditions.

5. Conclusion

The main conclusion of our study is that lenders are not price takers. Our results indicate that lenders decrease their lending offers when they predict negative future stock returns. One possible explanation for our findings is that, when lenders predict negative returns, they restrict their short offers and probably sell their stocks.

We also find that lenders use new information to modify their lending offers. By separating different categories and signals of announcements, our results indicate that when lenders are informed with positive news they tend to increase their shorting supply – they decrease their restriction of shorting supply.

In turn, negative news make lenders increase their restriction of shorting supply. Besides, our results also indicate that lenders are more responsive to economic-financial data announcements to modify their lending offers. By that, we suggest that lenders convey material information through their acts around the arrival of new information in the market.

Taking all results together, we conclude that lenders are not price takers, since they change their lending offers when they predict negative future returns and they also use new information to modify supply conditions. Accordingly, we argue that the supply side, where stock lenders provide supply for fees, also warrants attention.

Appendix

In Chapter 4, we mentioned the possible problem with estimators when we applied 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 gets large (Kiviet, 1995), which ensures our results. In order 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. The results are almost the same in terms of signal and significance, reinforcing our findings, and they are shown in the next two tables.

Table IX – Loan fee and negative future returns: modified control variable

	(1) $AdjRet_{i,1w}$	(2) $AdjRet_{i,2w}$	(3) $AdjRet_{i,3w}$	(4) $AdjRet_{i,4w}$	(5) $AdjRet_{i,5w}$	(6) $AdjRet_{i,6w}$
Loanfee	-0.0275*	-0.0647***	-0.0792***	-0.102***	-0.105***	-0.108***
	(-1.83)	(-3.13)	(-3.29)	(-3.67)	(-3.24)	(-3.01)
Size	-0.773***	-1.490***	-2.295***	-3.145***	-3.994***	-4.787***
	(-5.35)	(-7.15)	(-9.14)	(-10.55)	(-11.89)	(-12.54)
Turnover	0.176	0.325	0.251	0.266	0.158	0.278
	(1.04)	(1.52)	(1.11)	(1.09)	(0.52)	(0.93)
BAspread	0.169	0.478*	0.535**	0.586**	0.605***	0.588**
	(1.36)	(1.91)	(2.16)	(2.28)	(2.75)	(2.49)
VolRet	-0.0231	-0.132**	-0.118*	-0.150*	-0.0766	-0.120
	(-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)
N° of Obs.	29,084	29,084	29,084	29,084	29,084	29,084
adj. R^2	0.016	0.027	0.035	0.046	0.055	0.063

This table is the same as Table III with a unique difference: instead of last week return and momentum, we choose to use past-week return volatility (the standard deviation of the week) as a control. VolRet is the standard deviation of the last-week return. T-statistics are in parentheses. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A.2 – Demand and supply shifts in the lending market: modified control variable

	(1) $AdjRet_{i,1w}$	(2) $AdjRet_{i,2w}$	(3) $AdjRet_{i,3w}$	(4) $AdjRet_{i,4w}$	(5) $AdjRet_{i,5w}$	(6) $AdjRet_{i,6w}$
SOUT	-0.0315	-0.233	-0.226	-0.297	-0.349	-0.319
	(-0.27)	(-1.49)	(-1.18)	(-1.35)	(-1.41)	(-1.16)
SIN	-0.115	-0.209	-0.467**	-0.559**	-0.560**	-0.453*
	(-0.97)	(-1.29)	(-2.38)	(-2.51)	(-2.26)	(-1.66)
DOUT	-0.127	-0.218	-0.403**	-0.497**	-0.671***	-0.604**
	(-1.08)	(-1.38)	(-2.08)	(-2.27)	(-2.69)	(-2.20)
DIN	-0.0676	-0.247	-0.215	-0.261	-0.355	-0.221
	(-0.58)	(-1.59)	(-1.10)	(-1.21)	(-1.45)	(-0.83)
Size	-0.751***	-1.417***	-2.232***	-3.053***	-3.868***	-4.611***
	(-5.42)	(-7.17)	(-9.37)	(-10.89)	(-12.21)	(-13.00)
Turnover	0.158	0.268	0.180	0.190	0.0662	0.183
	(0.97)	(1.32)	(0.84)	(0.83)	(0.23)	(0.65)
BAspread	0.143	0.439**	0.434*	0.519**	0.502**	0.541**
	(1.23)	(1.98)	(1.93)	(2.23)	(2.42)	(2.48)
VolRet	-0.0154	-0.120**	-0.110*	-0.141*	-0.0350	-0.0761
	(-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)
N° of Obs.	31,765	31,765	31,765	31,765	31,765	31,765
adj. R^2	0.015	0.026	0.034	0.044	0.053	0.062

This table is the same as Table V with a unique difference: instead of last week return and momentum, we choose to use past-week return volatility (the standard deviation of the week) as a control. VolRet is the standard deviation of the last-week return. T-statistics are in parentheses. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

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