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Short Selling, o lado da oferta: credores são ativos?

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

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RESUMO

É amplamente aceito na literatura que altas taxas de empréstimo de ações preveem retornos negativos, uma vez que altas taxas capturam as informações negativas de vendedores a descoberto, do lado da demanda. Tradicionalmente, o lado da oferta é visto como passivo, no qual os credores das ações agem como tomadores de preços. Estudos recentes, entretanto, mostram que essa passividade dos emprestadores não mais se perpetua. Diante dessa discussão, o presente estudo analisa o mercado de crédito acionário brasileiro e separa a curva de demanda da curva de oferta por *short* para entender o mecanismo de condução que liga o lado da oferta aos retornos acionários. Analisa-se, também, a relação da curva de oferta de *short* com novas informações e verifica-se como os credores reagem a uma nova informação no mercado. Nossos resultados indicam que os credores restringem a oferta de empréstimo de ações quando preveem retornos futuros negativos e que usam novas informações para alterar as condições de empréstimo, indicando que os credores não são tomadores de preço.

Palavras-chave: venda a descoberto; taxa de empréstimo.

Classificação JEL: G10, G12, G14.

ABSTRACT

It is widely accepted in the literature that high lending fees predict negative returns because high fees capture the negative information from short sellers, on the demand side. Traditionally, the supply side is seen as passive, in which stock lenders act as price takers. Recent studies, however, have shown that this passivity of lenders no longer perpetuates. Faced with this discussion, the present study analyze the Brazilian stock loan market and disentangles the shorting demand and shorting supply curve shifts in order to understand the driving mechanism linking the supply side and stock returns. We also link the shorting supply curve with new announcements and verify how lenders react to a new information in the market. Our results indicate that lenders decrease the loan supply when they predict negative future returns and that they use new information to change supply conditions, indicating that lenders are not price takers.

Keywords: short selling; loan fee.

JEL Classification: G10, G12, G14.

SUMMARY

LIST OF TABLES

1. Introduction

Traditionally, stock lending is seen as a passive activity in which lenders do not influence fees. Seeking to verify the veracity of this condition the objective of this paper is twofold. First, we want to verify if lenders are price makers. More specifically, we want to verify if lenders modify loans 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 new information to change their lending offers: do they process public information?

Numerous studies has documented that high lending fees predict negative returns because high fees capture the negative information from short sellers, on the demand side. In our first model, as expected, we confirmed that high lending fees predict negative returns. The results are presented in Table II and Table III. However, we argue that the supply side, where stock lenders provide supply for fees, also warrants attention. By applying a technique used in Cohen et al., (2007), our primary goal is to disentangle the demand and supply shifts in order to understand the driving mechanism linking the shorting supply and stock returns. The mechanism can be briefly explained as follows: when there is an increase in prices (loan fee) combined with a decrease in quantities, a supply shift inwards must have occurred[1]. The same idea is applied for the other possible shifts. 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, helping us to answer our main question. Our results, reported in Table IV and Table V, indicate that shorting supply has a statistically relevant relation with future stock returns. More specifically, our results indicate that lenders decrease the loan supply when they predict negative future returns. By that, we can conclude that lenders are active – i.e., lenders modify loan prices and quantities independently of the changes generated by the demand side.

The traditional passive behavior of lenders can be explained by limited information on borrowing demand in a nontransparent OTC market. In recent

[1] We assume that demand curves are not upward sloping and that supply curves are not downward sloping.

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 BM&FBOVESPA lending system. Reliable and frequently available information not only allows borrowers to locate securities faster but also allows lenders to observe demand and supply in real time and charge more competitive prices (Duong et al., 2016). This peculiarity of the Brazilian market is in favor of our results. In other words, the centralized lending 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. Our second goal consists in analyze how lenders predict that. However, before we verify our second goal, we want to confirm the importance of new information in the market. It is accepted that relevant announcements have significant impacts on securities prices and on investors' decisions to trade. The results are presented in Table VI. Having confirmed the importance of new information in the market, it seems useful to link them with supply curve to help us 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 BOVESPA's website. In general, there are many announcements containing non-relevant information, which underestimate 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; therefore, we were also concerned to classify them differently. 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.

By separating different categories and signals of announcements, our results indicate 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. Oppositely, 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 BOVESPA'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 can 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 rest of this dissertation is organized as follows. In Chapter 2, we present the literature review about the short-selling activity and its market. In Chapter 3, we present the Brazilian stock loan market highlighting its peculiarities and we also present the data set used. The empirical approach and results are presented in Chapter 4. Lastly, in Chapter 5, we conclude.

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, Huszár, Tan and Zhang, 2016). Massa, Zhang and Zhang (2015) say that short selling encourages the release of private information by insiders. Simultaneously, however, short selling is considered a dangerous operation and is prohibited in some countries, seen as an inherently speculative operation.

Short selling is very common in the main economies, reaching a significant percentage of the volume of shares traded, as shown by the North American market figures (24% on NYSE and 31% on Nasdaq) in 2005, reported by Diether, Lee and Werner (2009). In Brazil is not different. In recent years, on average, 25% of the volume of shares traded came from shares sold short (Chague, De-Losso and Giovannetti, 2017).

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

Kolasinski, Reed and Ringgenberg (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 own 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, Huszár, Tan and Zhang (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, Gârleanu and Pedersen (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. They concluded that, along with short sellers, lenders contribute to the price discovery process. However, the proxy used for shorting demand can be controversial. Even though a numerous studies already used short interest as a proxy, it seems to be a flawed metric, since 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, Pathak and Ritter (2005) combine both short interest and institutional ownership data to identify stocks with high shorting demand and low shorting supply. Cohen, Diether and Malloy (2007) criticize the use of those proxies and propose a new empirical strategy, which allows them to classify supply and demand shifts in the equity lending market. Using a novel 4-year panel data set (private data) 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 dummies 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, Diether and Malloy (2007) conclude that the relationship between high shorting costs and future negative returns is driven mainly by demand shifts than by supply shifts. In contrast with what they found, our results indicate that supply shifts also have an important relationship with future stock returns. More specifically, our results indicate that when lenders restrict their lending offers it precedes negative future stock returns. 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 can be a problem if the effects are increasing with the size of the shifts (Chague et al., 2014).

Kaplan, Moskowitz, and Sensoy (2013) studied the effect on stock prices after a supply shock of lendable shares. They found that exogenous changes in loan supply have significant effects on loan fees and quantities, but no adverse effects on security prices. In other words, the returns of those stocks that are made available to lend are no different from the other stocks, which suggests 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, Ferreira and Prado (2016) found that actively managed equity funds that lend securities underperform 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 securities lending market in Brazil is regulated by the Brazilian Securities Commission (CVM). As a result of the regulatory system, all lending deals must be registered in the BM&FBOVESPA lending system. Thus, the Brazilian lending market is centralized, contrasting with most other lending markets, which are decentralized and which 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 on daily frequency.

Another peculiarity in the Brazilian lending market is that all loan deals are collateralized with Treasury securities[2], which makes all lending transactions be 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 short seller interest – the “rebate” rate – 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 work as follows. The BM&FBOVESPA provides a platform called BTC Securities Lending System where brokers can register their offers directly in an electronic trading system. Usually, lenders place their shares for loan and borrowers can hit the offers. Even though is also possible for borrowers to place their bids, this is not common. More than 99% of the offers come from lenders (Chague, De-Losso, De Genaro and Giovannetti, 2014). Over-the-counter (OTC) deals is also a possibility for securities lending. As the equity lending market in the US and other countries, the Brazilian lending market is also 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 on daily frequency.

[2] The collateral is deposited at BM&FBOVESPA, which acts as the central counterpart to all lending transactions.

Another peculiarity of the Brazilian market comes from local tax legislation. Supported by a Brazilian law, 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 was using stock lending to take advantage of that law (Barbosa, Bonomo, Mello and Mota, 2018). From 2015 on, with the repeal of the law, differences in taxes no longer exist.

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., 2017).

3.1 Data Set

We observe all lending deals from January 2013 to December 2017 traded in the Brazilian stock lending market. As mentioned above, since the lending market is centralized, our data set provides us a complete picture of lending activity on a daily frequency for the whole market. For each lending deal, we have the information of the loan quantity and the loan fee.

Our paper constructs variables related to short-selling activity. By using the whole data set, we implicitly assume that short-selling is the major factor explaining why an investor borrow a stock. Our assumption is validated by the fact 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 (Clearstream, 2014).

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 matched the criteria used by

the Brazilian Center for Research in Financial Economics (NEFIN) to calculate short interest[3]. Therefore, we only use stocks following the eligibility criteria, which is composed of: (i) the stock is the most traded stock of the firm (the one with the highest traded volume during last year); (ii) the stock was traded in more than 80% of the days in year $t-1$ with volume greater than R$ 500,000.00 per day. In case the stock was listed in year $t-1$, 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 $t-1$. It is worth mentioning that some stocks do not obey the criteria in all years. In those years that the eligibility criteria is not fulfilled, the stocks are taken from the sample. We end up with 155 of the most liquid stocks of our period.

The second filter is as follows. Following the Brazilian law, 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 were artificially high. Individuals used to lend shares to financial institutions at a higher loan fee, since the institutions received the interest on equity and did not pay taxes. While 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, this filter is applied only in 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 also 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

[3] Available at the NEFIN webpage on http://www.nefin.com.br/short_interest.html

risk-factors[4] to calculate the risk-adjusted returns[5] from NEFIN. There is a detailed description on how the factors were computed in the centers' webpage.

Additionally, news events and companies announcements data set were obtained from BOVESPA's website[6]. We applied couple of filters in order to better use the data. First, we are taking into account only the day that the announcement was disclosed. It means that no matter if there is more than one announcement at the same day, we are just flagging the day that there is at least one announcement. The second filter is related to the legal hour of the market. 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 legal 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.

Taking into account all filters mentioned above, we end up with 34,587 days flagged with at least one announcement. However, non-relevant news can underestimate the relation between news and stock returns and distort the relationship between news and shifts in lending supply curve (our focus). Therefore, trying to better understand our findings, we create three different types of announcements based on different categories[7] previous classified by BOVESPA. Type 1 encompasses only relevant facts' announcements. Type 2 encompasses 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 the type.

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[4] Available at the NEFIN webpage on http://www.nefin.com.br/risk_factors.html

[5] To calculate risk-adjusted returns we took into account four risk factors: Market Factor (MF), SMB Factor, HML Factor and WML Factor.

[6] The data were imported from the webpage: http://siteempresas.bovespa.com.br/consbov/InfoPerEventuaisBuscData.asp?site=C&ccvm=&razao=&acao=undefined

[7] According to BOVESPA's website, the category Relevant Facts, our Type 1, encompasses announcements like acquisition of shares, shareholders' agreement, new projection of investments, among others. Our Type 2, announcements of Economic-financial data, encompasses financial statements, earnings releases, rating review and others.

Moreover, positive and negative news tend to affect securities prices in a different way; therefore, we were also concerned to classify them differently. 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. This difference can be understood as a shock or as an unexpected result. To obtain that, we regress the model:

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

and then we isolate the residual:

$$\hat{e}_{i,t} = Return_{i,t} - E_t[Return_{i,t}], \qquad (2)$$

where $Return_{i,t}$ is the stock return at the day t and $E_t[Return_{i,t}]$ is the expected return at the day t – the sum of the estimated parameters times the correspondent risk factor[8] plus the estimated intercept (for each stock and for every day t). If there is an announcement at the day t and $\hat{e}_{i,t} > 0$, than we consider the news as positive. If there is an announcement at the day t and $\hat{e}_{i,t} < 0$, the news are considered as negative.

Our sample contains 3,897 positive news flagged as Type 1 & 2, 1,769 positive news flagged as Type 1 and 2,365 positive news of Type 2. With regard to negative news, our sample contains 3,830 negative news flagged as Type 1 & 2, 1,676 as Type 1 and 2,350 negative news of Type 2.

Table I, Panel A and Panel B, presents the summary statistics of the key variables used in the analysis from January 2013 to December 2017 traded in the Brazilian stock lending market. Panel A presents daily stats and Panel B presents average weekly stats.

[8] The risk factors are the same to calculate risk-adjusted return. Available at the NEFIN webpage on http://www.nefin.com.br/risk_factors.html

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 new information to change their lending offers: do they process public information?

As we already mentioned, numerous studies has documented that high lending fees predict negative returns because high fees capture the negative information from short sellers, on the demand side. In our first model, we want to confirm the hypothesis that high lending fees can predict negative future returns. However, our study focus on the supply side; therefore, we want to 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), our second test disentangles the demand and supply shifts in order to help us understand the driving mechanism linking the shorting supply and stock returns.

Before we explicitly check our second goal, we want to confirm the importance of new information in the market. It is accepted that relevant news have significant impacts on securities prices and on investors' decisions to trade; hence, it seems to be useful to link them with supply shifts to help us understand if lenders use new information to 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 public information is released. Three different types of announcements based on different categories previous classified by BOVESPA were created to proceed with the tests. 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 method[9] with fixed effects by stocks and week dummies as additional controls to test the return predictability of loan fees:

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

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

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

Table II and Table 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 support of the hypothesis that high loan fees can predict negative future returns, which is consistent with the literature.

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[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 habitual estimation procedures are 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 inconsistency 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 method with fixed effects by stocks 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.

[Table II and Table III is about here]

Our control variables are constructed following Boehmer et al. (2008) and Diether et al. (2009). We include variables that are related to long-term and short-term return predictability such as firm size, turnover, last week return and momentum. We also include bid-ask spread as a volatility control. 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 product of shares outstanding times price) in percentage. BAspread is the average bid-ask spread during the week, where bid-ask spread is the difference between the 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.

All those control variables are also used in the next section. It is worth mentioning that all coefficients for control variables are consistent with the findings reported in the literature. For example, as reported, large firms underperform smaller ones.

4.2 Demand and Supply Shifts in the Lending Market

The previous test confirmed us that high loan fees predict negative future returns, as we expected. There appear to be a consensus in the existing literature that lending fees capture information from short sellers. According to the literature, short sellers, on average, are skilled traders or have private information or even both. 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.

Our second test disentangles 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 apply a technique used in Cohen et al., (2007). The mechanism works as follows: 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. The same idea is applied to the four possible 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 at least a demand shift in has occurred, we flagged it as a dummy variable named DIN; at least a 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 clearly identify shifts in shorting demand and supply, and then explore the effect of these shifts on future stock returns, helping us to answer our main question.

We have run a panel regression method with fixed effects by stocks and week dummies as additional controls in order to verify the relationship between demand and supply shifts with future stock returns. Equation 5 exemplifies the model:

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

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 is about here]

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 clear signal of negative future returns.

Since our paper focus on the supply side, we should focus on β_1 and β_2. In contrast with some previous studies[10], Table IV indicates that the relation between accumulated raw returns and an inward shift in shorting supply (SIN) is negative and statistically significant from three to five weeks ahead. This result is crucial to help us answer our main question (are lenders price makers?). From β_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 negative and statistically related to this movement (SIN). Therefore, we can infer that lenders do modify loans conditions (price and quantity) independently of the changes generated by the demand side, which means that they are price makers.

As suggested by Duffie, Gârleanu and Pedersen (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 it was 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 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. Despite that β_1 is negative, it is not significant, meaning that lenders do not raise their profits by increasing loan fees and quantities.

By looking at β_1 and β_2, 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 direction with Evans, Ferreira and Prado (2016), which state that actively managed equity funds that lend securities underperform similar funds that do not lend but sell it. Besides, Evans et al. (2016) found that those results of underperformance is concentrated among funds with investment restrictions. Hence, one possible explanation for our

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

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 method 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 for us, Table V also shows a negative and statistically significant coefficient for SIN from the third week ahead, confirming our previous findings.

[Table V is about here]

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

4.3 The importance of Relevant Announcements

We can conclude from the previous tests that lenders are not price takers. Our results indicate that lenders decrease their lending offers when they predict negative future returns. Our second goal consists in analyze how lenders predict that. We want to check if lenders are informed and if they use new information to modify their lending offers: do they process public information? By doing that, we suggest that lenders convey material information through their acts around the arrival of new information in the market.

However, before we answer the question above, we want to confirm the importance of new information in the market. It is accepted that relevant facts

have significant impacts on securities prices and on investors' decisions to trade. To confirm that, we regress a panel regression with fixed effect by stocks 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. In the analysis here, we are only considering Type 1 & 2 news, since we understand them as a set of relevant announcements. However, in the Appendix, Table XI, we show that the same results are found we when analyze Type 1 and Type 2 announcements separately. 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 $\hat{e}_{i,t} < 0$.

[Table VI is about here]

Table VI indicates that on days with relevant announcements releases, there is an increase in stocks' returns volatility. As expected, there is a strong positive and statistically relevant relation between positive news and stock return at the day t. The same happens when we check 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 to be useful to link them with supply shifts in (SIN) – the relevant shift from the supply side in the previous test – to help us understand if and how lenders use new information to modify their lending offers around announcements.

4.4 Do Lenders better process Public Information?

The previous section confirmed us the importance of new information on the market. Besides, Section 4.2 informed us that lenders restrict their lending offers when they predict negative future returns. In this final section, we want to verify if lenders restrict their lending offers after the public information is released. In other words, we want to analyze explicitly our second goal, which is verify if lenders are informed and if they use new information to change their lending offers – do they process public information?

In order to verify if and how lenders restrict their lending offers after the public information is available, we proceed as follows. We run a panel regression method with fixed effect by stocks and dummies for days as additional controls:

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

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. $PositiveNews_{i,t:t+1}$ is a dummy variable which is equal to one at the day t and $t+1$ if there is at least one positive news disclosed at the day t. One can understand that the day and the next trading day is enough for the new information be absorbed by the market. This idea comes from 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 day, $t+1$, and that there is no significant effect at the day $t+2$. The same idea is applied for negative news. $NegativeNews_{i,t:t+1}$ is a dummy variable which is equal to one at the day t and $t+1$ if there is at least one negative news disclosed at the day t.

As already mentioned before, we also separate different types of information into different categories, following BOVESPA's website. Type 1 encompasses only relevant facts' announcements like acquisition of shares, shareholders' agreement, new projection of investments, among others. Type 2 encompasses announcements of Economic-financial data such as financial statements, earnings releases, rating review and others.

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. The second model encompasses only Type 1 news, with 1,769 positive news and 1,676 negative news disclosed. The last model is about Type 2 announcements, containing 2,365 positive news and 2,350 negative news of this type.

From Equation 8 we might expect $\beta_1 < 0$ and $\beta_2 > 0$. To make it clear, imagine a situation where a positive information is released. By construction, it tends to generate a positive stock return – as already proven in Section 4.3. Therefore, lenders should increase their lending offers, since they would profit from the positive return plus the loan fee. In this case, one can 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 tends to generate a negative stock return. Therefore, following Evans et al. (2016), 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 is about here]

The first model in Table VII, encompassing Type 1 & 2 announcements, indicates that positive news tends to affect SIN in a negative way. In other words, a positive news at the day t contributes in a negative way (reduces the probability) to 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, since they would 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.

Oppositely, also in the first model in Table VII, we can 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. A negative news tends to decrease the stock return. Therefore, following Evans et al. (2016), lenders should sell their stocks instead of lending them, which increases 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 announcements are not statistically relevant to affect the shorting supply curve (SIN). It is worth mentioning that despite the name (relevant facts), Type 1 announcements include some information that may not be easily related to future stock returns by lenders, which may explain the result above. However, the third model shows that the relation of Type 2 news and SIN are statistically relevant. The interpretation is the same as the first model. Besides, note that, in both signals of news (positive and negative), the effects of Type 2 announcements on SIN are stronger and more relevant (mainly in 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.

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 information is released. This result helps us to confirm the previous findings that lenders are not price takers, since they use new 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 concluded 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. Oppositely, 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. 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 can 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. Therefore, we argue that the supply side, where stock lenders provide supply for fees, also warrants attention.

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Table I – Descriptive Stats

Table I, Panel A and Panel B, presents the summary statistics of the key variables used in the analysis from January 2013 to December 2017 traded in the Brazilian stock lending market. Panel A presents daily stats and Panel B presents average weekly stats.

Panel A – Daily stats: 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 product of shares outstanding times price, in percentage. BAspread is the average daily bid-ask spread, where bid-ask spread is the difference between the daily ask price and bid price, relative to the average of the daily bid and ask prices, in percentage.

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

Panel B – Average weekly stats: 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 product of shares outstanding times price) in percentage. BAspread is the average bid-ask spread during the week, where bid-ask spread is the difference between the 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.

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
$CumRet_{i,1w}$ (%)	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

Table II – Loan fee and Negative Future Returns: raw 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 product of shares outstanding times price) in percentage. BAspread is the average bid-ask spread during the week, where bid-ask spread is the difference between the 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 time period is January 2013 to December 2017. T-statistics are in parentheses. The estimation includes fixed effect by stocks and week dummies as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$CumRet_{i,1w}$	$CumRet_{i,2w}$	$CumRet_{i,3w}$	$CumRet_{i,4w}$	$CumRet_{i,5w}$	$CumRet_{i,6w}$
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

Table III – Loan fee and Negative Future Returns: risk-adjusted 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 product of shares outstanding times price) in percentage. BAspread is the average bid-ask spread during the week, where bid-ask spread is the difference between the 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 time period is January 2013 to December 2017. T-statistics are in parentheses. The estimation includes fixed effect by stocks and week dummies as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(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

Table IV – Demand and Supply Shifts in the Lending Market: raw 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 product of shares outstanding times price) in percentage. BAspread is the average bid-ask spread during the week, where bid-ask spread is the difference between the 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 time period is January 2013 to December 2017. T-statistics are in parentheses. The estimation includes fixed effect by stocks and week dummies as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(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

Table V – Demand and Supply Shifts in the Lending Market: risk-adjusted 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 product of shares outstanding times price) in percentage. BAspread is the average bid-ask spread during the week, where bid-ask spread is the difference between the 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 time period is January 2013 to December 2017. T-statistics are in parentheses. The estimation includes fixed effect by stocks and week dummies as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(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

Table VI – The Impact of Relevant 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. In this table, we are showing only Type 1 & 2 announcements, combining relevant facts' announcements and news of economic-financial data. Our sample contains 3,897 days with positive news and 3,830 days with negative news of this type. The time period is January 2013 to December 2017. T-statistics are in parentheses. We regress a panel regression with fixed effect by stocks and dummies for days as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)
	$R_{i,t}$	$R_{i,t+1}$	$R_{i,t+2}$
PositiveNews$_{i,t}$	2.409***	0.105**	-0.0394
	(45.71)	(2.03)	(-0.91)
NegativeNews$_{i,t}$	-2.093***	-0.242***	0.0379
	(-49.23)	(-5.00)	(0.84)
Constant	-0.0860	-0.0575	-0.0644
	(-0.79)	(-0.52)	(-0.58)
N° of Obs.	151,068	151,064	150,910
R^2	0.046	0.002	0.002
Nº of Positive News	3,897	3,897	3,897
Nº of Negative News	3,830	3,830	3,830

Table VII – The Impact of News on SIN

$SIN_{i,t}$ 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 time period is January 2013 to December 2017. T-statistics are in parentheses. We regress a panel regression with fixed effect by stocks and dummies for days as additional controls. Standard errors are robust. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	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

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 habitual estimation procedures are 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 consistency of the estimators, we adopt the same panel regression method with fixed effects by stocks 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 three tables – A1, A2 and A3.

Table VIII – A1

Table VIII 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.

	(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

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IX – A2

Table IX is the same as Table IV 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.

	(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	0.0174	-0.136	-0.161	-0.223	-0.395	-0.352
	(0.14)	(-0.81)	(-0.79)	(-0.95)	(-1.48)	(-1.20)
SIN	-0.0585	-0.119	-0.343	-0.417*	-0.487*	-0.321
	(-0.46)	(-0.68)	(-1.63)	(-1.75)	(-1.81)	(-1.09)
DOUT	-0.0720	-0.145	-0.350*	-0.454*	-0.698**	-0.627**
	(-0.57)	(-0.85)	(-1.69)	(-1.94)	(-2.58)	(-2.11)
DIN	-0.0560	-0.205	-0.231	-0.276	-0.455*	-0.349
	(-0.45)	(-1.22)	(-1.11)	(-1.20)	(-1.72)	(-1.22)
Size	-1.030***	-1.995***	-3.179***	-4.352***	-5.576***	-6.743***
	(-6.94)	(-9.38)	(-11.99)	(-13.69)	(-14.97)	(-16.20)
Turnover	0.252	0.454**	0.373	0.421*	0.304	0.426
	(1.43)	(2.13)	(1.62)	(1.69)	(0.92)	(1.35)
BAspread	0.0690	0.289	0.196	0.181	0.0580	0.0192
	(0.61)	(1.33)	(0.86)	(0.77)	(0.28)	(0.09)
VolRet	-0.0197	-0.114**	-0.116*	-0.125	-0.0149	-0.0475
	(-0.43)	(-1.99)	(-1.72)	(-1.59)	(-0.16)	(-0.49)
Constant	14.15***	27.59***	44.36***	60.93***	78.46***	95.19***
	(6.26)	(8.49)	(10.90)	(12.51)	(13.78)	(14.94)
N° of Obs.	31,765	31,765	31,765	31,765	31,765	31,765
adj. R^2	0.204	0.221	0.236	0.252	0.265	0.284

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table X – A3

Table X 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.

	(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

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table XI – A4

Table XI is the same as Table VI but extending the results for Type 1 and Type 2 announcements.

	Type 1 & 2 $R_{i,t}$	Type 1 & 2 $R_{i,t+1}$	Type 1 & 2 $R_{i,t+2}$
PositiveNews$_{i,t}$	2.409***	0.105**	-0.0394
	(45.71)	(2.03)	(-0.91)
NegativeNews$_{i,t}$	-2.093***	-0.242***	0.0379
	(-49.23)	(-5.00)	(0.84)
Constant	-0.0860	-0.0575	-0.0644
	(-0.79)	(-0.52)	(-0.58)
N° of Obs.	151,068	151,064	150,910
R^2	0.046	0.002	0.002

	Type 1 $R_{i,t}$	Type 1 $R_{i,t+1}$	Type 1 $R_{i,t+2}$
PositiveNews$_{i,t}$	2.835***	0.129	-0.0960
	(29.69)	(1.42)	(-1.40)
NegativeNews$_{i,t}$	-2.240***	-0.242***	0.0270
	(-31.45)	(-2.85)	(0.34)
Constant	-0.0558	-0.0575	-0.0642
	(-0.52)	(-0.52)	(-0.58)
N° of Obs.	151,068	151,064	150,910
R^2	0.027	0.002	0.002

	Type 2 $R_{i,t}$	Type 2 $R_{i,t+1}$	Type 2 $R_{i,t+2}$
PositiveNews$_{i,t}$	2.145***	0.113*	-0.0148
	(40.91)	(1.88)	(-0.29)
NegativeNews$_{i,t}$	-2.076***	-0.237***	0.0569
	(-40.95)	(-4.39)	(1.09)
Constant	-0.104	-0.0617	-0.0646
	(-0.96)	(-0.56)	(-0.58)
N° of Obs.	151,068	151,064	150,910
R^2	0.025	0.002	0.002

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	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