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Well-connected short-sellers pay lower loan fees: A market-wide analysis☆

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ABSTRACT

High loan fees generate short-selling constraints and, therefore, reduce price efficiency. Despite the importance of loan fees, empirical evidence on their determinants is scarce. Using a market-wide deal-by-deal data set on the Brazilian equity lending market which uniquely identifies borrowers, brokers, and lenders, we are able to construct a proxy of search costs at the borrower–stock–day level. We find that—for the same stock, on the same day—borrowers with higher search costs pay significantly higher loan fees. Our results suggest that regulators should encourage the use of a centralized lending platform to reduce search costs in the lending market.

1. Introduction

A short-seller is constrained if the loan fee exceeds the expected fall in the stock price. High loan fees therefore generate short-selling constraints. Short-selling constraints are not desirable for two reasons: they cause stock overpricing (Danielsen and Sorescu, 2001; Jones and Lamont, 2002; Nagel, 2005; Chang, Cheng and Yu, 2007; Stambaugh, Yu and Yuan, 2012; Blocher, Reed and Van Wesep, 2013) and they reduce price efficiency (Asquith, Pathak and Ritter, 2005; Nagel, 2005; Cao, Dhaliwal, Kolasinski and Reed, 2007; Saffi and Sigurdsson, 2011; Engelberg, Reed and Ringgenberg, 2012; Boehmer and Wu, 2013). Despite these adverse effects of loan fees on the stock market, there is sparse empirical literature on the determinants of loan fees, mostly due to lack of data.[1] In this paper we use a unique data set to show that loan fees depend on borrower search costs.

Loan fees should be close to zero in a frictionless lending market with many lenders. Lenders have long investment horizons and do not care about short-term variations in stock prices (D'Avolio, 2002), so that lending a stock for a short period is costless. Competition among lenders

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[1] The equity lending market in the US and other countries is over-the-counter (OTC), with transactions usually only visible to the parties involved. As we discuss below, although the Brazilian lending market is also OTC, all loan deals must be registered at BM&FBOVESPA, which acts as the central counterpart. In this paper we use the BM&FBOVESPA market-wide data.

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would thus drive loan fees to zero. This is not observed in the data, however. Loan fees vary substantially over time and can be quite high (D'Avolio, 2002; Reed, 2013; Engelberg, Reed and Ringgenberg, 2013).

Duffie, Garleanu and Pedersen (2002, hereafter DGP) provide a model that explains why loan fees can be high. In their model borrowers face search costs that limit the frequency with which they can find lenders, allowing lenders to act as local monopolists and thereby charge positive loan fees. In this setting loan fees are increasing in borrower search costs. Another possibility for having high loan fees would be a market with a limited number of lenders and high shorting demand as shown in Blocher, Reed and Van Wesep (2013).

Kolasinski, Reed and Ringgenberg (2013, hereafter KRR) is the only paper which empirically studies the relationship between loan fees and search costs. They use proxies for search costs which vary across stocks and time, such as firm size, bid-ask spread, and measures of stock concentration among lenders. Consistent with the theoretical predictions in DGP, they find that both loan fee levels and loan fee dispersion are increasing in these stock-specific measures of search costs.[2] However, search costs are not just stock-specific: different borrowers should face different search costs when searching for the same stock. Consider two borrowers, A and B. Borrower A has very good relationships in the lending market: she is a good client of big brokers who in turn know many active lenders. By contrast, borrower B is connected to a single broker, who has few connections to active lenders. These two borrowers will face different search costs for the same stock.

The main contribution of this paper is to be the first to study the relationship between loan fees and search costs *at the borrower level*. We test two hypotheses: H1) the higher the search costs a borrower faces, the higher the loan fees she pays; and H2) the higher the search costs that borrowers face, the higher the loan fee dispersion among these borrowers. We find strong favorable evidence for both H1 and H2.

Measuring borrower-specific search costs is empirically challenging. As the earlier example suggests, one has to measure the importance of each lender in the market as well as the strength of the relationships between borrowers, brokers, and lenders. For that to be possible one needs to (i) observe all loan deals in the market and (ii) uniquely identify borrowers, brokers, and lenders over time. The data sets used so far in the literature allow neither (i) nor (ii). Our data set enables both (i) and (ii). Every transaction in the Brazilian lending market is cleared through BM&FBOVESPA, which keeps a record of all loan deals closed in Brazil. Our data set contains information on the loan quantity, loan fee, investor type, borrower ID, broker ID, and lender ID for all loan deals in the Brazilian stock market from January 2008 to July 2011.[3]

We construct our borrower-specific measure of search costs based on the DGP description of the lending market dynamics. In a typical transaction, a potential short-seller contacts her broker asking for a particular stock to borrow. The broker then searches for a potential lender of the stock. Hence, locating a stock will be easier for a borrower who has good relationships with brokers that, in turn, have good relationships with active lenders of the stock.

Based on that, we say that a borrower has low search costs if she is "well-connected" to brokers that are "well-connected" to active lenders. We say a borrower is well-connected to a broker if she is an important customer of the broker. We say a broker is well-connected to a lender if it is responsible for a high share in the loan deals of the lender. Since our data set allows us to follow each market participant through time, we are able to compute (a) how well-connected each borrower is to each broker, (b) how well-connected each broker is to each lender, and (c) how active each lender is in the lending market of each stock. From (a), (b), and (c) we calculate the *Borrower connection* (*BC*), a variable that is borrower-specific, stock-specific, and varies over time. The *BC* variable is constructed so that it is high when the borrower is well-connected to brokers which in turn are well-connected to active lenders of a stock. *BC* should therefore be *negatively* related to borrower search costs.

We perform a number of empirical exercises that relate *BC* to loan fees. We first run deal-by-deal panel regressions with loan fees on the left-hand side and *BC* on the right-hand side. We find that low-connected borrowers pay significantly higher loan fees. We also allow for nonlinear effects by separating borrowers into three groups (high-, medium-, and low-*BC*) and comparing the average loan fee in each group. We find that borrowers in the low-*BC* group pay 14.5% higher loan fees than borrowers in the high-*BC* group.

Second, we use direct measures of loan fee dispersion (loan fee standard deviation and range across deals for the same stock) to test whether loan fee dispersion is higher among low-connected borrowers. We find that loan fee standard deviation and loan fee range among borrowers in the low *BC*-group are, respectively, 46% and 135% higher than those among borrowers in the high-*BC* group.

Lastly, we refine the analysis by studying the in-broker variation of loan fees. We run the same regressions using only deals closed *within* a single broker—the largest one in terms of deals. The conclusions are the same as before: we find that on the same day, for the same stock, this single broker intermediates deals with different loan fees which are decreasing in borrower *BC*.

Importantly, all results are robust across subsamples. To account for unobserved borrower-specific effects that may correlate with both *BC* and loan fees, all regressions are run within subsamples of borrowers that share similar characteristics with respect to investor type, traded volume, and frequency of trades. In doing so, we estimate the effect of *BC* on loan fees across deals closed by similar bor-

[2] DGP's model does not predict loan fee dispersion, since it includes no heterogeneity among lenders and borrowers. As discussed by KRR, industrial organization models with sequential search produce price dispersion when there is heterogeneity among investors.

[3] The investor-type variable classifies borrowers as either "individuals" or "institutions." The ID variable in our data uniquely identify each market participant and is time-invariant. These IDs are "fake," i.e., anonymous.

rowers. Considering only institutions, we find that a low-*BC* institution pays an 8.5% higher loan fee than a high-*BC* institution. Considering only frequent borrowers, we find that a low-*BC* frequent borrower pays a 10.9% higher loan fee than a high-*BC* frequent borrower. Finally, considering only large borrowers, we find that a low-*BC* large borrower pays a 9.8% higher loan fee than a high-*BC* large borrower.

A borrower may have a high value of *BC* because of five different components: (i) she is connected to many brokers; (ii) she has strong relationships with her brokers; (iii) her brokers are connected to many lenders; (iv) her brokers have strong relationships with these lenders; and (v) these lenders have high market-shares. To assess the individual relevance of the five components, we then construct a flexible version of *BC*, which we name $BC(\gamma)$. In *BC*, all components (i) to (v) are active by construction, while in $BC(\gamma)$ these components can be switched off. Then, by regressing loan fees on $BC(\gamma)$, we let the data confirm the relevance of each one of the five components.

The estimation of $BC(\gamma)$ reveals that four out of the five components are indeed relevant in explaining loan fees. The only one that does not add explanatory power to *BC* is component (iii), the number of lenders that the borrower's brokers are connected to. The fact that the number of lenders is not relevant, while the number of brokers the borrower is connected to is relevant, is consistent with the idea that the stock lending market is less opaque for brokers than for borrowers—brokers intermediate loan deals frequently, updating their information set very often; borrowers, in turn, participate on the loan market occasionally. Hence, for borrowers, having access to a larger number of brokers is important to acquire updated information on loan fees, while the same is not necessary for brokers with respect to lenders.

The paper closest in purpose to ours is KRR. Using a unique data set involving 12 important lenders in the US market, KRR show that at high borrowing demand levels positive shocks to demand result in higher loan fees. They moreover show that the effect of borrowing demand on loan fees is greater for stocks associated with high levels of search costs, which is consistent with DGP. In doing so KRR inaugurate the empirical evidence of the effects of search costs on loan fees. Our paper continues this investigation. In addition to stock-specific search costs, we find that search costs at the borrower level are also important drivers of loan fees.

Engelberg, Reed and Ringgenberg (2013) also empirically investigate loan fees. They run predictive regressions to explain loan fees conditional on a number of variables such as past loan fees, institutional ownership, lending offers, and the federal funds rate. Their goal is to dynamically evaluate short-selling risks. Prado (2015) tests another implication of the DGP model, namely, that stock prices incorporate expected future lending income (i.e., the loan fee, acting as a dividend, increases the stock's price). She finds that institutions buy shares in response to an increase in loan fees, which is consistent with DGP.

This paper also relates to a more general literature on OTC markets. Duffie, Garleanu and Pedersen (2005, 2007) provide a theory of dynamic asset pricing that directly addresses search and bargaining in general OTC markets, with the goal of evaluating the effects of search frictions on asset prices. Another set of papers focuses on the "percolation" of information which is of common interest throughout OTC markets (Duffie and Manso, 2007; Duffie, Malamud and Manso, 2009; Duffie, Giroux and Manso, 2010). Zhu (2012) also presents a dynamic model of opaque OTC markets where sellers search for buyers. On the empirical side, Ang, Shtauber and Tetlock (2013) and Eraker and Ready (2015) study the stock returns of firms that trade on OTC markets. Our results suggest that opacity in OTC markets induces important search frictions that affect prices: market participants with higher search costs pay higher prices for the same asset. Regulators should therefore encourage the use of electronic trading platforms to reduce opacity and hence search costs in these markets.

This paper is organized as follows. Section 2 explains the Brazilian stock lending market and describes our data set. Section 3 documents the existence of loan fee dispersion. Section 4 specifies our measure of borrower-specific search costs. Section 5 presents the empirical results. Section 6 exhibits the effects of a lending platform on loan fees. Finally, Section 7 presents our concluding remarks.

2. Stock lending in Brazil

The securities lending market in Brazil is regulated by the Brazilian Securities Commission (CVM).[4] All transactions are mediated by BM&FBOVESPA-registered brokers, who are responsible for bringing together stock borrowers and stock lenders. All securities listed on the exchange are eligible for lending. Crucially for us, in Brazil *every* lending transaction must be registered in the BM&FBOVESPA lending system. This contrasts with most other lending markets, which are decentralized and in which data about lending deals are only partially available.

According to D'Avolio (2002) and Reed (2013), in the US the loan fee is implicitly given by the "rebate" rate when loans are cash-collateralized. The rebate rate is the interest rate that the lender pays the borrower in exchange for holding the cash-collateral; it is lower than the federal funds rate. The higher the difference between the rebate rate and the fed fund rate, the higher the implicit loan fee. If the borrower posts instead Treasury securities as collateral, she simply pays the lender an explicit loan fee. The average loan fee of an easily borrowed stock ranges between 0.05% and 0.25% per year. Stocks with high loan fees are called *specials*; their rebate rates may even be negative. Approximately 9% of stocks are specials, with an average loan fee of about 4.3% (D'Avolio, 2002). The overall average loan fee in the US is therefore 0.52%.[5]

All loan deals in Brazil are collateralized with Treasury securities.[6] Hence, there are no "rebate" rates and all

[4] The stock lending market in Brazil has grown substantially. During 2011, the last year in our data set, more than US$ 400 billion were loaned in over 1.4 million transactions, corresponding to one-third of the Brazilian market's total capitalization. In that year 290 different stocks were traded in the lending market.

[5] $0.52\% = 0.09 \times 4.3\% + 0.91 \times 0.15\%$.

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

Table 1
Number of borrowers and lenders by year.
This table shows the number of different borrowers and lenders in the lending market per year. The data set identifies each investor with a unique ID. An investor who closed both a borrowing and a lending deal in the same year is included in both columns. The last line considers only the first seven months of 2011.

Year	# of borrowers	# of lenders
2008	17,435	3,471
2009	22,166	3,416
2010	24,809	6,785
2011 (Jan.–Jul.)	16,515	8103

loan deals are negotiated in terms of explicit loan fees. In our sample the average loan fee, including all stocks (both specials and non-specials), is 2.75% per year—much higher than in the US.

One possible explanation for the higher Brazilian loan fees is the higher stock market volatility. According to DGP, given the existence of borrower search-costs, lenders are able to charge short sellers a loan fee that is equal to some fraction of the short-sellers' expected profit, which should be increasing in the expected volatility of the asset price. Hence, the higher the expected volatility, the higher the loan fee; Engelberg, Reed and Ringgenberg (2013) provides empirical evidence consistent with this. Indeed, stock market volatility is much higher in Brazil than in the US. During our sample period (January 2008–July 2011) the average implied volatility VIX for the US was 17.50% whereas in Brazil it was 23.72% (that is, about 35% higher).[7] The higher Brazilian risk-free rate may also contribute to the higher loan fees. Engelberg, Reed and Ringgenberg (2013) document that loan fees are proportional to the risk-free rate. Indeed, the ratios between loan fees and risk-free rates in Brazil and in the US are similar.[8]

2.1. Data set

We observe *all* of the 2,302,360 lending deals closed in the Brazilian stock market from January 2008 to July 2011. For each lending deal we have information on the loan quantity, loan fee, borrower type (institution or individual), borrower ID, broker ID, and lender ID. These ID variables uniquely and anonymously identify each market participant and are time-invariant. The numbers of distinct borrowers and lenders in the lending market are shown in Table 1. In 2008 there were 17,435 distinct borrowers and 3,471 distinct lenders. The number of investors increased over the subsequent years: there were 22,166 borrowers and 3,416 lenders in 2009; 24,809 borrowers and 6,785 lenders in 2010; and 16,515 borrowers and 8,103 lenders in the first seven months of 2011.

We apply two filters to our data set. First, because the main regressions in this paper use the standard deviation of loan fees for each stock in each week, we need a sufficiently large number of loan deals per stock per week. We therefore restrict our sample to liquid stocks in the lending market. We say a stock is liquid if it was loaned during every week of our sample. We end up with 55 stocks which jointly account for 1,417,964 loan deals. The second filter is as follows. According to Brazilian law the tax treatment of "interest on equity" differs by investor type: individual investors pay a tax rate of 15% while financial institutions are exempt. As a result, on days around the ex-date of interest on equity a tax arbitrage trade between individuals and financial institutions commonly occurs: (i) individuals lend shares to financial institutions at a higher loan fee; (ii) financial institutions receive the interest on equity and pay no taxes; (iii) financial institutions transfer to individuals the net value (i.e., excluding taxes) that individuals would receive from interest on equity; and (iv) individuals then receive a higher loan fee, while financial institutions profit by 15% of the interest on equity minus the loan fee. Since loan fees from these arbitrage deals are artificially high, we exclude all loan deals that were closed in a six-day window around the ex-date. The final sample encompasses 1,251,801 loan deals involving the 55 most liquid stocks.

3. Evidence of loan fee dispersion

Opaque markets are characterized by high search costs. This is the case for the stock lending market, which is OTC. As discussed by KRR, sequential search cost models predict that markets with high search costs exhibit high price dispersion. In this section we show that the Brazilian lending market has significant loan fee dispersion.

We measure loan fee dispersion as the standard deviation of the annualized loan fee of all deals for the same stock on a given day. Fig. 1 shows the time-series of this variable for the four stocks with the largest number of loan deals in our sample, namely, VALE5 (131,441 deals), PETR4 (107,263 deals), GGBR4 (78,916 deals), and BBDC4 (70,311). Each point in the figure corresponds to the loan fee dispersion in a given day. As can be seen, dispersion varies greatly during the period. Days with dispersion around 0.5% (per year) are common for the four stocks, and the variable often reaches 1% p.y., which is high when compared with the average loan fee levels reported in Table 2 for these stocks (VALE5: 0.47%; PETR4: 0.77%; GGBR4: 2.19%; BBDC4: 0.54%).

Fig. 2 and Table 2 show the time-series average of the loan fee dispersion for each stock in our sample. Stocks are alphabetically ordered. Note that average dispersion is high and varies across stocks.

Fig. 3 shows the cross-sectional average of the loan fee dispersion for each day in our sample. High dispersion is frequent in the Brazilian stock lending market.

4. Borrower-specific search costs

Our goal is to relate (i) the loan fee that a borrower pays to (ii) the search cost she faces when searching for the stock in the lending market. As shown by KRR, loan fee level and dispersion are increasing in various proxies

[7] Astorino, Chague, Giovannetti and Silva (2016) calculate the implied volatility for Brazil.

[8] The ratio in the US is 21% = 0.52%/2.5% (using 2.5% as the average federal funds rate). In Brazil, the ratio is 25% = 2.75%/10.9% (where 10.9% is the average Brazilian risk-free rate, the Selic rate, during our sample period).

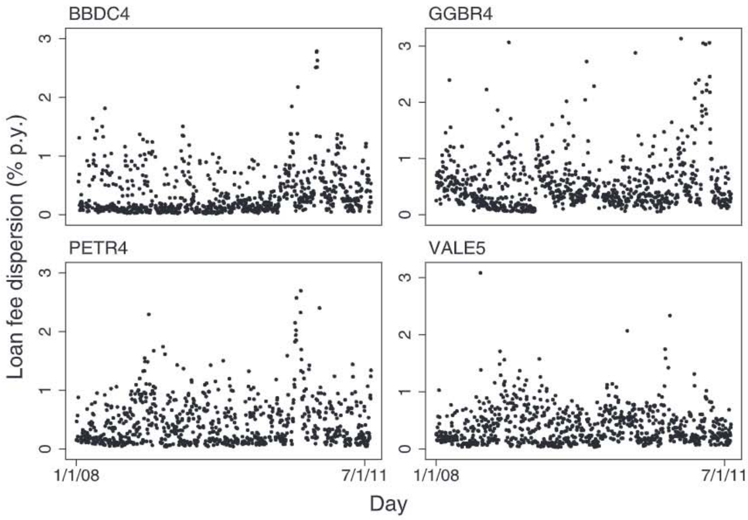

Fig. 1. Loan fee dispersion—four stocks. This figure shows the loan fee dispersion for the four stocks with the largest number of loan deals in our sample, namely, VALE5 (131,441 deals), PETR4 (107,263 deals), GGBR4 (78,916 deals), and BBDC4 (70,311). Loan fee dispersion is calculated as the standard deviation of the annualized loan fee in percentage points of all deals for the same stock on the same day. Each point in the figure is the loan fee dispersion of a day from January 2008 to July 2011.

for search costs. The proxies KRR use, however, are stock-specific (market capitalization, liquidity, and the fragmentation of its share lending market) and do not completely capture search costs at the borrower level. Our main contribution is to use a borrower-specific proxy for search cost.

Our measure of search cost relies on the idea that the stock lending market is a “relationship-based market,” as discussed in DGP and KRR. The typical lending transaction proceeds as follows. The borrower communicates to her broker(s) that she is looking for a particular stock to borrow. The broker then has to search for a potential lender of the stock. Based on such dynamics, we assume that a borrower has low search costs if she is “well-connected” to a broker who in turn is “well-connected” to active lenders. A borrower is well-connected to a broker if the borrower is an important customer of this broker. A broker is well-connected to a lender if the broker accounts for a high share of the lender’s loans.

We explain with an example. Investor *I* wants to borrow shares of stock XYZ. Investor *I* frequently borrows stocks (from any firm) with the intermediation of Broker *B*. Broker *B* is in turn responsible for a large share of the loans that Lender *L* makes (with respect to *all* stocks loaned by Lender *L*). Lender *L* is an active lender of stock XYZ. Will Investor *I* face high search costs in this case? We suppose not. In contrast, Investor *I* will face higher search costs if (i) Investor *I* is not an important client of Broker *B* and/or (ii) Broker *B* is responsible only for a small share of the loans that Lender *L* makes, and/or (iii) Lender *L* is a small lender of stock XYZ.

Since our detailed data set allows us to follow each market participant through time, we are able to compute (a) how well-connected each borrower is to each broker, (b) how well-connected each broker is to each lender, and (c) how active each lender is in the lending market of each stock. We use (a), (b), and (c) to calculate the search cost of each borrower. We now explain the details of this calculation.

4.1. Broker reach

To calculate the ability of broker i to locate a specific stock s to borrow on day t, which we call “Broker reach,” $BR_{i,\,s,\,t}$, we follow three steps. First, we measure the importance of each lender j in the lending market of stock s on day t by computing its Market share (MS) as

$$MS_{j,s,t} = \frac{shares_{j,s,t}}{total\ shares_{s,t}},$$

where $shares_{j,\,s,\,t}$ is the number of shares lent by lender j of stock s during the 90-day period[9] previous to day t, and $total\,shares_{s,\,t}$ is the total number of shares of stock s that were loaned in the same period.

We then quantify the strength of the relationship of broker i with lender j on day t as

$$BLR_{i,j,t} = \frac{deals_{i,j,t}}{total\ deals_{j,t}},$$

where BLR stands for “Broker–lender relationship,” $deals_{i,\,j,\,t}$ is the total number of loan deals closed, *considering allstocks*, between broker i and lender j in the 90-day period previous to day t, and $total\,deals_{j,\,t}$ is the total number of loan deals made by lender j in the same period. The assumption here is that if broker i recently closed many loan deals with lender j, then they have a good relationship. Note that measured this way the strength of the relationship between broker i and lender j is not stock-specific.

[9] The 90-day window was arbitrarily chosen and the first to be considered. All results are robust to 60-day and 120-day windows and are available upon request.

Table 2
Descriptive statistics by stock.
This table reports, stock by stock, the stock ticker, the average Loan Fee Dispersion (LFD), the standard deviation of the LFD, the daily average number of loan deals, and the average loan fee (% per year). We measure LFD as the standard deviation of the annualized loan fee of all deals for the same stock on a given day.

Ticker	Loan fee dispersion		Loan deals	
	Avg.	Std. dev.	Per day	Fee (in %)
AMBV4	0.32	0.58	58	0.65
BBAS3	0.61	1.24	80	1.04
BBDC4	0.43	0.43	113	0.54
BRAP4	0.25	0.33	26	0.74
BRKM5	0.55	0.45	49	1.88
BRML3	0.62	0.77	27	5.18
BRTO4	0.88	2.02	24	2.36
BTOW3	1.77	1.88	33	5.16
CCRO3	0.90	1.17	31	3.33
CESP6	0.91	0.80	25	1.72
CMIG4	0.69	0.58	66	2.07
CPFE3	0.86	0.61	48	4.82
CPLE6	0.60	0.49	29	2.20
CRUZ3	0.42	0.39	61	2.12
CSAN3	1.26	1.73	33	5.34
CSMG3	0.62	1.19	8	3.49
CSNA3	0.36	0.38	91	0.86
CYRE3	1.32	1.54	56	6.03
ELET3	0.62	0.84	22	1.90
ELET6	0.78	1.20	58	4.32
EMBR3	0.65	0.89	33	2.46
ENBR3	0.71	1.11	19	4.41
FFTL4	0.59	0.76	15	1.80
GFSA3	1.29	1.26	45	6.17
GGBR4	0.71	0.88	118	2.19
GOAU4	0.29	0.66	26	0.52
GOLL4	1.46	1.20	31	4.87
ITSA4	0.26	0.38	55	0.41
JBSS3	1.97	1.83	48	8.20
KLBN4	0.53	0.88	54	2.67
LAME4	0.80	0.76	66	3.28
LIGT3	0.99	1.32	42	4.64
LREN3	1.28	0.89	51	6.15
MRVE3	1.40	1.93	56	6.92
NATU3	1.06	0.97	67	6.25
PETR3	0.36	0.92	62	0.70
PETR4	0.62	0.95	154	0.77
RDCD3	1.49	1.62	71	7.20
RENT3	0.35	0.49	28	3.58
RSID3	1.13	1.40	44	4.87
SBSP3	0.83	1.24	22	2.50
SUZB5	0.50	0.49	22	2.38
TAMM4	1.38	1.28	29	3.57
TBLE3	0.40	0.38	26	2.13
TCSL4	1.11	1.21	44	5.24
TMAR5	1.14	1.32	19	4.38
TNLP3	0.56	0.73	12	2.25
TNLP4	0.87	0.73	59	3.42
TRPL4	0.44	0.50	19	1.81
UGPA4	0.33	0.88	25	1.05
USIM3	1.40	1.67	32	5.13
USIM5	0.44	0.37	92	1.26
VALE3	0.40	0.41	77	0.64
VALE5	0.42	0.33	169	0.47
WEGE3	0.76	0.80	23	3.76

Finally, the ability of broker i to locate stock s on day t is given by

$$BR_{i,s,t} = \sum_{j=1}^{J_{i,t}} BLR_{i,j,t} \times MS_{j,s,t},$$

where BR stands for "Broker reach" and $J_{i,t}$ denotes the total number of lenders broker i is connected to on day t.

$BR_{i,s,t}$ will be high for a broker that, on day t, has good relationships with important lenders of stock s. By construction, the cross-broker sum

$$\sum_{i=1}^{I_{k,t}} BR_{i,s,t}$$

is equal to one for any $s = 1, ..., S$ and every $t = 1, ..., T$, where $I_{k,t}$ denotes the total number of brokers borrower k is connected to on day t.

4.2. Borrower connection

If a borrower has good relationships with brokers with high BR on stock s, it should be easy for her to find the stock. That is, this well-connected borrower will have low search cost for this stock. Based on this idea we calculate the connection of borrower k with respect to stock s on day t , which we call "Borrower connection," $BC_{k,s,t}$, in two steps.

We first quantify the strength of the relationship between borrower k and each broker i on day t as

$$BBR_{k,i,t} = \frac{deals_{k,i,t}}{total\,deals_{i,t}},$$

where BBR stands for "Borrower–broker relationship," $deals_{k,i,t}$ is the number of loan deals (considering *any* stock) between borrower k and broker i in the 90-day period previous to day t, and $total\,deals_{i,t}$ is the total number of loan deals made by broker i in the same period.

The Borrower connection of borrower k with respect to stocks on day t is then

$$BC_{k,s,t} = 100 \times \left(\sum_{i=1}^{I_{k,t}} BBR_{k,i,t} \times BR_{i,s,t} \right). \tag{1}$$

We multiply the right-hand side by 100 so that $BC_{k,s,t}$ is expressed in percentage points. By construction, for any $s = 1, ..., S$ and at any $t = 1, ..., T$ the sum of $BC_{k,s,t}$ across all k borrowers for a given stock s and on given day t is equal to 100:

$$\sum_{k=1}^{K} BC_{k,s,t} = 100.$$

$BC_{k,s,t}$ is a time-varying and stock-specific variable which is decreasing in the search cost of borrower k: a high value means that the borrower has strong relationships with brokers with high reach, that is, with brokers which have strong relationships with active lenders of the stock. Fig. 4 presents a diagram that illustrates the steps involved in the construction of BC.[10]

[10] We could frame our measure within the theory of graphs and networks. Borrowers, brokers, and lenders are the nodes of the network. Brokers and lenders are connected through the variable *Broker lender relation* (a weighted edge) and the variable *Broker reach* is a measure of the centrality of brokers in the brokers–enders sub-network. Borrowers and brokers are connected through the variable *Borrower broker relation* (a weighted edge) and the variable *BC* is a measure of the centrality of bor-

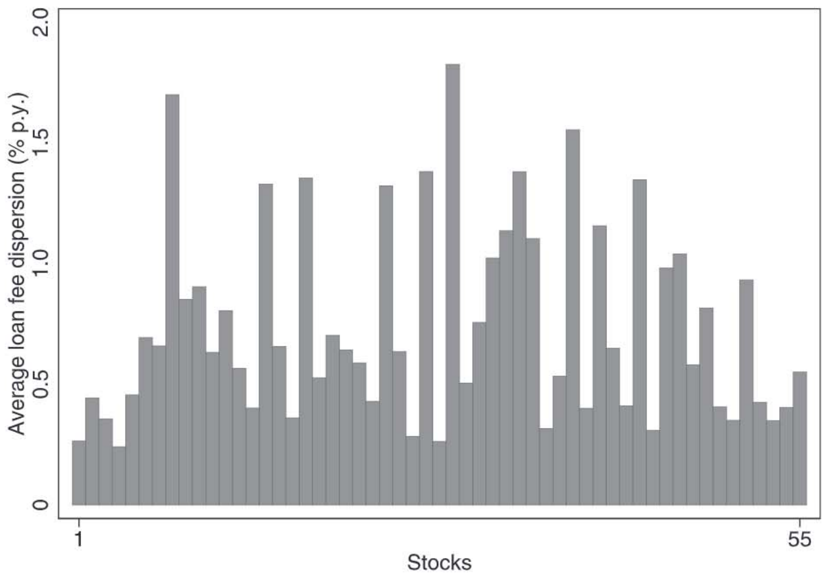

Fig. 2. Loan fee dispersion in the cross-section. This figure shows the time-series average of the loan fee dispersion for each stock in our sample. For each one of the 55 stocks in our sample we compute the average of its daily loan fee dispersion from January 2008 to July 2011. Loan fee dispersion is calculated as the standard deviation of the annualized loan fee in percentage points of all deals for the same stock on the same day. The 55 stocks are alphabetically ordered on the *x*-axis.

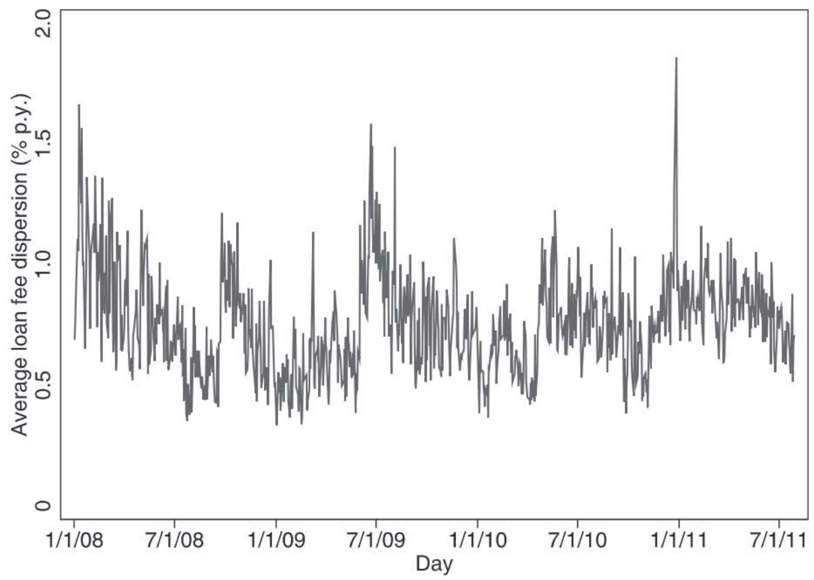

Fig. 3. Loan fee dispersion in the time-series. This figure shows the cross-sectional average of the loan fee dispersion for each day in our sample. For each trading day from January 2008 to July 2011, we compute the average of the loan fee dispersion across the 55 stocks in our sample. Loan fee dispersion is calculated as the standard deviation of the annualized loan fee in percentage points of all deals for the same stock on the same day.

We note that $BC_{k,s,t}$ is *not* the market share of the borrower on the stock. Consider for instance a short-seller that during the 90-day window did not borrow any stock *s*. She may still have a high $BC_{k,s,t}$ if she closed many deals on other stocks with brokers which have high Broker reach, *BR*, with respect to stock *s*. We further discuss the relation between *BC* and market share in Section 5.6.

To illustrate the dynamics of our main variable, Fig. 5 shows the time-series of *BC* of four arbitrary frequent borrowers on the four most liquid stocks in the lending market.

The top-left plot shows a borrower who had high connections at the beginning of the sample which then decreased over time. This pattern emphasizes the time-variability of *BC*. Note that the connections across the four

rowers in the whole network. A recent treatment of networks can be found in Newman (2010) and a discussion on recent applications of networks in finance can be found in Allen and Babus (2009).

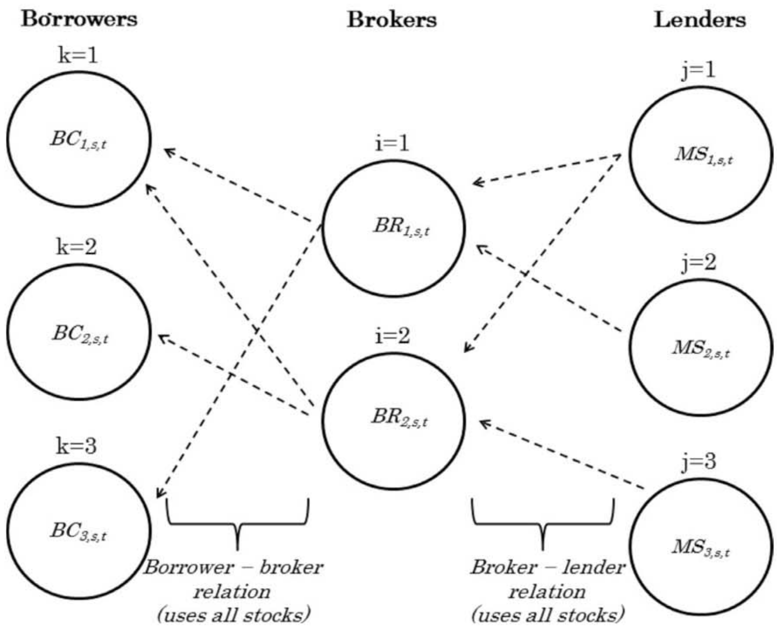

Fig. 4. Borrower connection diagram. This figure shows a diagram of the construction of the Borrower connection (*BC*) variable in a simplified lending market with three borrowers, two brokers and three lenders for a given stock *s*, on a given day *t*. First we measure the importance of each lender *j* in the lending market of stock *s* on day *t* as $MS_{j,s,t} = \frac{shares_{j,s,t}}{total\, shares_{s,t}}$, where *MS* stands for Market share, $shares_{j,\,s,\,t}$ is the number of shares lent by lender *j* of stock *s* during the 90-day period previous to day *t*, and $total\, shares_{s,\,t}$ is the total number of shares of stock *s* that were loaned in the same period. We then quantify the strength of the relationship of broker *i* with lender *j* on day *t* as $BLR_{i,j,t} = \frac{deals_{i,j,t}}{total\, deals_{j,t}}$, where *BLR* stands for Broker-lender relation, $deals_{i,\,j,\,t}$ is the total number of loan deals closed, *considering allstocks*, between broker *i* and lender *j* in the 90-day period previous to day *t*, and $total\, deals_{j,\,t}$ is the total number of loan deals made by lender *j* in the same period. We then compute the ability of broker *i* to locate stock *s* on day *t* as $BR_{i,s,t} = \sum_{j=1}^{J_{i,t}} BLR_{i,j,t} \times MS_{j,s,t}$. Next, we quantify the strength of the relationship between borrower *k* and each broker *i* on day *t* as $BBR_{k,i,t} = \frac{deals_{k,i,t}}{total\, deals_{i,t}}$, where *BBR* stands for Borrower–broker relation, $deals_{k,\,i,\,t}$ is the number of loan deals, *considering all stock*, between borrower *k* and broker *i* in the 90-day period previous to day *t*, and $total\, deals_{i,\,t}$ is the total number of loan deals made by broker *i* in the same period. Finally, the connection of borrower *k* with respect to stocks on day *t* is $BC_{k,s,t} = 100 \times \left(\sum_{i=1}^{I_{k,t}} BBR_{k,i,t} \times BR_{i,s,t}\right)$.

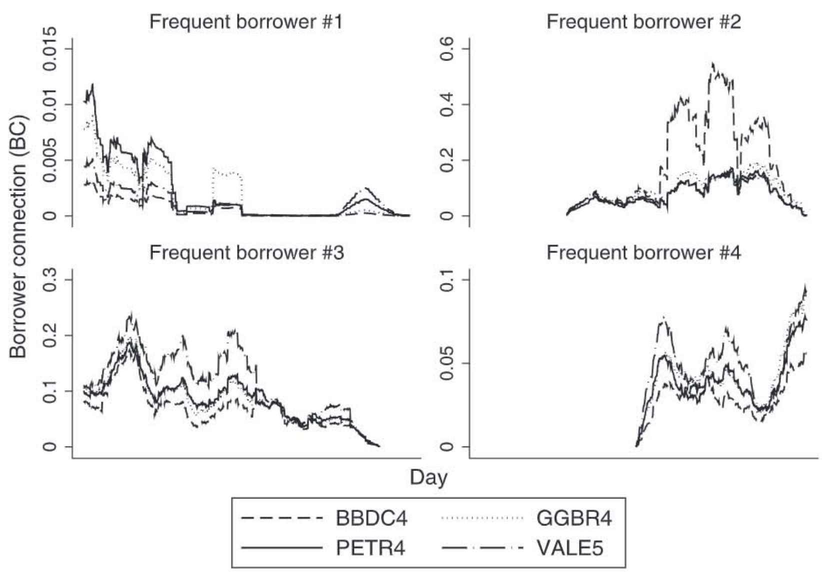

Fig. 5. Borrower connection. This figure shows the Borrower connection (*BC*) variable of four arbitrary frequent borrowers on four of the most liquid stocks in the lending market: Petrobras PN (PETR4), Bradesco PN (BBDC4), Gerdau PN (GGBR4) and Vale do Rio Doce PN (VALE5). The calculation of the variable *BC* is described in Section 4. *BC* is a time-varying (at the daily frequency) and stock-specific variable which it is decreasing in the borrower's search costs. A high value here means that the borrower has strong relationships with brokers which in turn have strong relationships with important lenders of the stock. The sample period is from July of 2008 to July 2011, and the frequency is daily.

Table 3
Loan deals and borrower connection by type of borrowers.

Panel A of this table shows descriptive statistics on the number of loan deals by borrower. Panel B shows descriptive statistics on the average Borrower connection (*BC*) within each borrower (across stocks and days). The calculation of the variable *BC* is described in Section 4. *BC* is a time-varying and stock-specific variable which is decreasing in the borrower's search costs. Here a high value means that the borrower has strong relationships with brokers which have strong relationships with important lenders of the stock. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers who traded in more than half of the weeks are frequent.

Panel A

Borrowers		Number of loan deals by borrower						
Type	N	Average	1st pct.	25th pct.	50th pct.	75th pct.	99th pct.	Max.
All	51,006	28	1	1	3	10	326	30,885
Individuals	45,097	9	1	1	3	9	21	3579
Institutions	5,909	167	1	2	7	34	3,484	30,885
Large	2,551	272	1	2	8	63	5,222	30,885
Frequent	364	1,750	142	354	722	1,676	18,942	30,885

Panel B

Borrowers		Average borrower connection within borrower						
Type	N	Average	1st pct.	25th pct.	50th pct.	75th pct.	99th pct.	Max.
All	51,006	0.003	0	0	0.00002	0.0002	0.064	3.86
Individuals	45,097	0.0006	0	0	0.00001	0.0001	0.009	1.28
Institutions	5,909	0.024	0	0	0.0001	0.004	0.449	3.86
Large	2551	0.040	0	0	0.0004	0.010	0.789	3.86
Frequent	364	0.168	0	0.007	0.066	0.149	1.817	3.86

stocks turn zero and nonzero at the same time. This highlights the difference between *BC* and market share: it takes a single deal on any stock during the past 90 days for the borrower to become connected with respect to all of the stocks that her broker can reach.

The top-right plot illustrates that *BC* indeed varies across stocks. This particular borrower is well-connected to brokers which, in turn, have strong relationships with important lenders of stock BBDC4. The borrowers represented in the lower plots further illustrate that *BC* does vary over time and across stocks.

4.2.1. Borrower connection by investor type

We observe 51,006 different borrowers who traded at least once between January 2008 and July 2011. We classify borrowers into the following types: individuals, institutions, large, and frequent. The distinction between individuals and institutions comes directly from the original data set. Out of the whole set of borrowers, 45,097 are individuals and 5,909 are institutions. The "large" and "frequent" types are defined as follows. We compute for each borrower the average volume across all her deals. We say that the top 5% borrowers are "large borrowers." We say moreover that borrowers who traded during more than half of the weeks are "frequent borrowers." Out of the whole set of borrowers, 2,551 are large borrowers and 364 are frequent borrowers. Table 3 exhibits some descriptive statistics on the number of loan deals and on the borrower connection, *BC*, for each type of borrower.

Considering all 51,006 borrowers, on average, 28 loan deals were made per borrower during the period. The number of deals of each borrower is highly left-skewed: the 1st, 25th, 50th, 75th, and 99th percentiles are, respectively, 1, 1, 3, 10, and 326 deals. The borrower with the greatest number of deals made 30,885 deals during the period. Considering only the 45,097 individual borrowers, the average borrower made nine deals and the percentiles are: 1 (1st), 1 (25th), 3 (50th), 9 (75th), and 21 (99th); the greatest individual borrower made 3,579 deals. Considering only the 5,909 institutional borrowers, the average borrower made 167 loan deals and the percentiles are 1 (1st), 2 (25th), 7 (50th), 34 (75th), and 3,484 (99th); the greatest institutional borrower made 30,885 deals. Considering only the 2,551 "large" borrowers," the average borrower made 272 deals and the percentiles are 1 (1st), 2 (25th), 8 (50th), 63 (75th), and 5,222 (99th); the greatest large borrower made 30,885 deals. Finally, considering only the 364 "frequent" borrowers, the average borrower made 1,750 deals and the percentiles are 142 (1st), 354 (25th), 722 (50th), 1,676 (75th) and 18,942 (99th); the greatest frequent borrower made 30,885 deals.

Table 3 also presents descriptive statistics for the *BC* variable (more precisely, for the borrower's *BC* average across time and stocks). The statistics show that the *BC* variable is also highly left-skewed. For all investors, the average *BC* is 0.003%, percentiles are 0 (1st), 0 (25th), 2×10^{-5}% (50th), 2×10^{-4}% (75th), and 0.064% (99th), and the maximum is 3.86%. Considering only individuals, the average *BC* is 6×10^{-4}%, percentiles are 0 (1st), 0 (25th), 1×10^{-5}% (50th), 1×10^{-4}% (75th), and 0.009% (99th), and the maximum is 1.28%. Considering only institutions, the average *BC* is 0.024%, percentiles are 0 (1st), 0 (25th), 1×10^{-4}% (50th), 0.004% (75th), and 0.449% (99th), and the maximum is 3.86%. Considering only large borrowers, the average *BC* is 0.04%, percentiles are 0 (1st), 0 (25th), 4×10^{-4}% (50th), 0.01% (75th), and 0.789% (99th), and the maximum is 3.86%. Finally, considering only frequent borrowers, the average *BC* is 0.168%, percentiles are

0 (1st), 0.007 (25th), 0.066% (50th), 0.149% (75th), and 1.817% (99th), and the maximum is 3.86%.

5. Empirical analysis

Our goal is to relate the loan fee that a borrower pays with the search costs she faces when looking for the stock in the lending market. We measure search costs via the borrower connection variable $BC_{k,s,t}$ introduced in the last section. This variable is borrower-specific, time-varying, and stock-specific. The higher $BC_{k,s,t}$ is, the lower the search costs of borrower k for stock s on day t are.

Since the lending market is OTC, borrowers need to locate lenders, which is costly in the presence of search frictions. Moreover, information on deals such as loan fees is not publicly disclosed. In this setting, theory predicts that borrower search costs affect loan fees. First, the magnitude of the loan fee is increasing in borrower search costs (see DGP). This follows from the "local" monopoly power lenders end up having due to the increasingly segmented market. Furthermore, since lenders may have different marginal costs and face different borrowing demands, higher search costs should also yield loan fee dispersion. We summarize these predictions into two testable hypotheses:

- Hypothesis 1 (H1): the higher the search cost that a borrower faces (i.e., the lower *BC*), the higher the loan fee she pays;
- Hypothesis 2 (H2): the higher the search cost that borrowers face (i.e., the lower *BC*), the higher the loan fee dispersion among these borrowers.

5.1. BC and loan fee level

Hypothesis H1 says that borrowers who face higher search costs pay higher loan fees. We test this first by running deal-by-deal panel regressions where the dependent variable is the loan fee (p.y., in %) paid by the borrower. The main explanatory variable is $BC_{k,s,t}$—borrower k's connection in the lending market for stock s on day t. The easier it is for borrower k to find stock s on day t, the higher the value of $BC_{k,s,t}$ is. We control the regressions for stock–day fixed-effects (dummy variables for each stock–day pair). Stock–day fixed-effects are important because, as shown by KRR, search costs can vary according to time-varying firm characteristics, such as firm size and stock illiquidity. Moreover, stock–day fixed effects also capture changes in the conditions of the lending market of each stock, such as daily shifts on demand and supply. Table 4 lays out the regression results.

Column 2 of Table 4 shows the regression considering all deals from all borrowers. The number of observations (deals) is 1,251,801. The estimated coefficient of the variable *BC* is −0.105 and significant at the 1% level. This means that an increase of one percentage point in *BC* decreases the loan fee in 0.105 percentage points. To account for unobserved borrower-specific effects that may correlate with both *BC* and loan fees, we run this same regression within subsamples of borrowers that share similar characteristics with respect to investor type, traded volume, and frequency of trades. In doing so, we estimate the effect of *BC* on loan fees across deals closed by similar borrowers. The results are robust across subsamples.

Table 4
Loan fee level and borrower connection.

This table shows the estimates of deal-by-deal panel regressions with the loan fee as the dependent variable and Borrower connection (*BC*) as the main explanatory variable. The calculation of the variable *BC* is described in Section 4. *BC* is a time-varying (at the daily frequency) and stock-specific variable which is decreasing in the borrower's search costs. A high value here means that the borrower has strong relationships with brokers which have strong relationships with important lenders of the stock. Column 2 shows the estimates considering all deals in our sample. The other columns show the estimates for the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers who traded in more than half of the weeks are frequent. All regressions include stock–day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals	Institutions	Large	Frequent
BC	−0.105***	−0.082***	−0.081***	−0.091***
	(0.013)	(0.011)	(0.012)	(0.013)
Stock–day fixed-effects	Yes	Yes	Yes	Yes
N	1,251,801	912,579	641,744	605,916
$R^2 - adj$	0.83	0.84	0.84	0.85

Considering only institutions (Column 3), we have 912,579 deals in the regression. The *BC* coefficient is equal to −0.082, significant at the 1% level. Considering only large borrowers (Column 4), we have 641,744 deals in the regression. The estimate of *BC* coefficient is equal to −0.081, significant at the 1% level. Finally, considering only frequent borrowers (Column 5), we have 605,916 deals in the regression. The estimate of *BC* coefficient is equal to −0.091, significant at the 1% level.

The standard deviation of the variable *BC* is 1% within all types of borrowers, 1.2% within institutions, 1.4% within large borrowers, and 1.4% within frequent borrowers. The average loan fee is 2.6% within all types of borrowers, 2.7% for institutions, 2.7% for large borrowers, and 2.7% for frequent borrowers. Hence, considering the estimates of Table 4, we conclude that a one-standard-deviation increase in *BC*, for each restricted sample, generates a decrease in the loan fee relative to its mean equal to 4% (all borrowers), 3.6% (institutions), 4.2% (large borrowers), and 4.7% (frequent borrowers). However, a one-standard-deviation increase in *BC* is a very small increase given the highly right-skewed distribution of *BC*. We next show that grouping borrowers according to the value of their *BC* strengthens the effect of search costs on the loan fee levels.

5.1.1. Nonlinear effect

We allow for a nonlinear effect of *BC* on the loan fee by estimating three coefficients, one for each of the following groups: low-*BC*, medium-*BC*, and high-*BC*. The grouping is stock- and week-specific. Within each stock–week pair, we rank deals with respect to the borrowers' $BC_{k,s,t}$

Table 5
Loan fee level for high-, medium-, and low-connected borrowers.

This table presents estimates of nonlinear effects of *BC* on the loan fee. Within each stock–week pair, we rank deals with respect to the borrowers' *BC* and classify them into three groups: low-*BC* group if *BC* falls below the 50%-percentile, medium-*BC* group if it falls between the 50%- and the 90%-percentile, and high-*BC* group if it falls above the 90%-percentile. For each stock–week-group cell we compute the average loan fee across all deals. We then run panel regressions of this average loan fee on two dummy variables, *High* and *Low*. *High* takes value one if the cell refers to the high-*BC* group and zero otherwise. *Low* takes value one if the cell refers to the low-*BC* and zero otherwise. *BC* is a time-varying and stock-specific variable which is decreasing in the borrower's search costs. The calculation of the variable *BC* is described in Section 4. Column 2 in the Table shows the estimates considering all deals in our sample. Columns 3, 4, and 5 consider deals from samples restricted according to borrowers type: institutional, large and frequent. Classification between individuals and institutions comes directly from the original data set. To classify a borrower as large we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers who traded in more than half of the weeks are frequent. All regressions include stock and week fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals	Institutions	Large	Frequent
High	−0.153***	−0.157***	−0.189***	−0.213***
	(0.028)	(0.029)	(0.037)	(0.038)
Low	0.186***	0.060***	0.055**	0.066***
	(0.026)	(0.020)	(0.023)	(0.024)
Stock fixed-effects	Yes	Yes	Yes	Yes
Week fixed-effects	Yes	Yes	Yes	Yes
N	25,323	25,149	24,474	24,558
$R^2 - adj$	0.53	0.52	0.51	0.51

and then classify the borrowers as belonging to the low-*BC* group if $BC_{k,\,s,\,t}$ is below the 50%-percentile, to the medium-*BC* group if $BC_{k,\,s,\,t}$ is between the 50%- and the 90%-percentile, and to the high-*BC* group if $BC_{k,\,s,\,t}$ is above the 90%-percentile. We use these thresholds to account for the high left-skewness of *BC*, as shown in Table 3.

Within each stock–week-group cell, we compute the average loan fee across all deals. We then run panel regressions of this average loan fee within each cell on two dummy variables, *High* and *Low*. *High* has value one if the cell refers to the high-*BC* group and zero otherwise. *Low* has value one if the cell refers to the low-*BC* group and zero otherwise. All regressions include both stock and week fixed effects. Column 2 of Table 5 shows the results considering all borrowers. Columns 3 to 5 show the results considering groupings and regressing among institutions, large borrowers, and frequent borrowers.

Considering all borrowers (Column 2), there are 25,323 stock–week-type observations in the regression. The coefficient of the high-*BC* group is −0.153, significant at the 1% level. The coefficient for the low-*BC* group is 0.186, significant at the 1% level. This means that a low-*BC* borrower pays on average a 14.5% higher loan fee than a high-*BC* borrower.[11] Considering only institutions (Column 3), there are 25,149 stock–week-type observations in the regression. The coefficient of the high-*BC* group is −0.157, significant at the 1% level, and the coefficient relative to the low-*BC* group is 0.060, also significant at the 1% level. This means that a low-*BC* institution pays on average a 8.5% higher loan fee than a high-*BC* institution.[12] Considering only large borrowers (Column 4), there are 24,474 stock–week-type observations in the regression. The coefficient of the high-*BC* group is −0.189, significant at the 1% level, and the coefficient relative to the low-*BC* group is 0.055, also significant at the 5% level. This means that a low-*BC* large borrower pays on average a 9.8% higher loan fee than a high-*BC* large borrower.[13]

Finally, considering only frequent borrowers (Column 5), there are 24,558 stock–week-group observations in the regression. The coefficient relative to the high-*BC* group is −0.213, significant at the 1% level, and the coefficient of the low-*BC* group is 0.066, also significant at the 1% level. This means that a low-*BC* frequent borrower pays on average a 10.9% higher loan fee than a high-*BC* frequent borrower.[14] The effect of borrower search costs on the loan fee level is therefore very substantial across all groups. Note that connection matters even within large and frequent borrowers. We next study the relationship between borrower search costs and loan fee dispersion.

5.2. *BC* and loan fee dispersion

Hypothesis H2 says that the higher the search costs that borrowers face (i.e., the lower the *BC*), the higher the loan fee dispersion among these borrowers. To test this prediction, we use the weekly data set constructed in Section 5.1.1. Within each stock–week-type cell we compute two measures of loan fee dispersion: (i) the standard deviation of the loan fee and (ii) the range of the loan fee. We then run panel regressions of both variables on two dummy variables, *High* and *Low*, defined as in Section 5.1.1. As before, we first consider all borrowers and then restrict the sample to institutions, to large borrowers, and to frequent borrowers. All regressions include both stock and week fixed effects. The results are shown in Table 6.

Considering all borrowers (Columns 2 and 3), there are 25,252 stock–week-type observations in the regression. For the standard deviation measure (Column 2), the coefficient of the high-*BC* type is not significant, while the coefficient of the low-*BC* type is 0.246 and significant at the 1% level. For the range measure (Column 3), the coefficient of the high-*BC* type is −1.264, significant at the 1% level, and the coefficient of the low-*BC* type is 1.154, also significant at the 1% level. Considering only institutions (Columns 4 and 5), there are 25,097 stock–week-type observations in the regression. For the standard deviation measure (Column 4), the coefficient of the high-*BC* type is not significant, while the coefficient of the low-*BC* type is 0.10, significant at the 1% level. For the range measure (Column 5), the coefficient of the high-*BC* type is −0.977, significant at the 1% level,

[11] $14.5\% = \frac{0.186+0.153}{2.34}$, where 2.34 is the average loan fee across all deals closed by high-*BC* borrowers.

[12] $8.5\% = \frac{0.157+0.06}{2.57}$, where 8.5 is the average loan fee across all deals closed by high-*BC* institutions.

[13] $9.8\% = \frac{0.189+0.055}{2.50}$, where 2.50 is the average loan fee across all deals closed by high-*BC* large borrowers.

[14] $10.9\% = \frac{0.213+0.066}{2.55}$, where 2.55 is the average loan fee across all deals closed by high-*BC* frequent borrowers.

Table 6
Loan fee dispersion for high-, medium-, and low-connected borrowers.
This table presents estimates of the effect of Borrower connection (*BC*) on the loan fee dispersion. Within each stock–week pair we rank deals with respect to the borrowers' *BC* and classify them into three groups: low-*BC* group if *BC* falls below the 50%-percentile, medium-*BC* group if it falls between the 50%- and the 90%-percentile, and high-*BC* group if it falls above the 90%-percentile. For each stock–week-group cell, we compute two measures of loan fee dispersion: the standard deviation and the range of loan fees across all deals. We then run panel regressions of these dispersion measures on two dummy variables, *High* and *Low*. *High* takes value one if the cell refers to the high-*BC* group and zero otherwise. *Low* takes value one if the cell refers to the low-*BC* and zero otherwise. *BC* is a time-varying and stock-specific variable which it is decreasing in the borrower's search costs. The calculation of the variable *BC* is described in Section 4. Columns 2 and 3 in the Table show the estimates considering all deals in our sample. The other columns consider deals from samples restricted according to borrowers type: institutional, large, and frequent. Classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers who traded in more than half of the weeks are frequent. All regressions include stock and week fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals		Institutions		Large		Frequent	
	Std. dev.	Range	Std. dev.	Range	Std. dev.	Range	Std. dev.	Range
High	−0.016	−1.264***	0.027	−0.977***	0.043	−0.919***	0.018	−1.010***
	(0.025)	(0.096)	(0.023)	(0.079)	(0.027)	(0.074)	(0.029)	(0.085)
Low	0.246***	1.154***	0.100***	0.612***	0.012	0.156***	0.090***	0.489***
	(0.021)	(0.101)	(0.015)	(0.065)	(0.016)	(0.055)	(0.017)	(0.061)
Stock fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	25,252	25,252	25,097	25,097	24,474	24,474	24,558	24,558
$R^2 - adj$	0.25	0.33	0.22	0.29	0.21	0.25	0.21	0.28

and the coefficient of the low-*BC* type is 0.612, also significant at the 1% level.

Considering only large borrowers (Columns 6 and 7), there are 24,474 stock–week-type observations in the regression. For the standard deviation measure (Column 6), both the coefficients for the high-*BC* and for the low-*BC* types are not significant. For the range measure (Column 7), the coefficient of the high-*BC* type is −0.919, significant at the 1% level, and the coefficient of the low-*BC* type is 0.156, also significant at the 1% level. Finally, considering only frequent borrowers (Columns 8 and 9), there are 24,558 stock–week-type observations in the regression. For the standard deviation measure (Column 8), the coefficient of the high-*BC* type is not significant, while the coefficient of the low-*BC* type is 0.090, significant at the 1% level. For the range measure (Column 9), the coefficient of the high-*BC* type is −1.010, significant at the 1% level, and the coefficient for the low-*BC* type is 0.489, significant at the 1% level.

Using the loan fee standard deviation as the proxy for loan fee dispersion, we conclude that (i) among low-*BC* borrowers there is a higher loan fee dispersion than among medium- and high-*BC* borrowers; (ii) there is no difference in loan fee dispersions among medium- and high-*BC* borrowers; and (iii) there is no difference in dispersion across *BC* types when the sample is restricted to large borrowers.

For the unrestricted sample and for the restricted samples for institutions and frequent borrowers, the difference between the loan fee standard deviation among low-*BC* borrowers and that of other borrowers is 0.246% (unrestricted), 0.1% (institutions), and 0.09% (frequent borrowers). These numbers are economically significant: the average loan fee standard deviation is 0.53% (unrestricted), 0.53% (institutions), and 0.54% (frequent borrowers). Considering for instance the unrestricted sample, this means that the standard deviation among low-*BC* borrowers is 46% higher than the standard deviation among high-*BC* borrowers.[15]

Using the loan fee range as the proxy for loan fee dispersion, we conclude that (i) there is a higher loan fee dispersion among low-*BC* borrowers than among medium-*BC* borrowers and (ii) there is a higher loan fee dispersion among medium-*BC* borrowers than among high-*BC* borrowers. These results hold for all regressions. The difference between the loan fee range among low-*BC* borrowers and medium-*BC* borrowers is 1.154% (unrestricted), 0.612% (institutions), 0.156% (large borrowers), and 0.489% (frequent borrowers). The difference between the loan fee range among medium-*BC* borrowers and high-*BC* borrowers is 1.264% (unrestricted), 0.977% (institutions), 0.919% (large borrowers), and 1.010% (frequent borrowers). These numbers are economically significant: the average loan fee range is 1.79% (unrestricted), 1.78% (institutions), 1.79% (large borrowers), and 1.74% (frequent borrowers). Considering for instance the unrestricted sample, this means that the range among low-*BC* borrowers is 135% higher than the range among high-*BC* borrowers.[16] These estimates confirm that higher borrower search costs yield higher loan fee dispersions. As was the case for the average loan fee, the results still hold within borrower type. In particular, loan fee dispersion increases with search costs even among frequent borrowers.

5.3. Brokerage fees

In a lending transaction the borrower pays the loan fee plus a brokerage fee. In our regressions we considered the loan fee net of this brokerage fee. This is important because brokerage fee may be directly related to *BC*, since the

[15] $46\% = 0.25\%/0.53\%$.

[16] $135\% = (1.15\% + 1.26\%)/1.79\%$.

Table 7
Brokerage fee and borrowers connection.

Panel A of this table shows the estimates of deal-by-deal panel regressions of brokerage fee on Borrower connection (*BC*). Brokerage fee is the fee in % p.y. paid by borrower in the loan deal. *BC* is a time-varying and stock-specific variable which is decreasing in the borrower's search costs. The calculation of the variable *BC* is described in Section 4. Panel B presents estimates of nonlinear effects of *BC* on brokerage fee. Within each stock–week pair we rank deals with respect to the borrowers *BC* and classify them into three groups: low-*BC* group if *BC* falls below the 50%-percentile, medium-*BC* group if it falls between the 50%- and the 90%-percentile, and high-*BC* group if it falls above the 90%-percentile. For each stock–week-group cell we compute the average brokerage fee across all deals. We then run panel regressions of this average brokerage fee on two dummy variables, *High* and *Low*. *High* takes value one if the cell refers to the high-*BC* group and zero otherwise. *Low* takes value one if the cell refers to the low-*BC* and zero otherwise. Column 2 of both Panels shows the estimates considering all deals in our sample. Columns 3, 4, and 5 consider deals from samples restricted according to borrowers type: institutional, large, and frequent. Classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we do the following. We compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers that traded in more than half of the weeks are frequent. All regressions include stock–day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A				
	All deals	Institutions	Large	Frequent
BC	−0.035***	−0.014***	−0.010***	−0.013***
	(0.005)	(0.002)	(0.001)	(0.002)
Stock–day fixed-effects	Yes	Yes	Yes	Yes
N	1,251,801	912,579	641,744	605,916
$R^2 - adj$	0.13	0.14	0.14	0.15

Panel B				
	All deals	Institutions	Large	Frequent
High	−0.034***	−0.017***	−0.018***	−0.023***
	(0.005)	(0.005)	(0.005)	(0.005)
Low	0.158***	0.050***	0.030***	0.052***
	(0.006)	(0.005)	(0.004)	(0.005)
Stock fixed-effects	Yes	Yes	Yes	Yes
Week fixed-effects	Yes	Yes	Yes	Yes
N	25,258	25,103	24,479	24,562
$R^2 - adj$	0.187	0.084	0.078	0.080

broker may charge lower fees from more important borrowers. Thus, including the brokerage fee in the loan fee would pollute our analysis. However, understanding how brokerage fee and search costs relate to each other is important in itself: high brokerage fees constrain short-sellers by increasing the costs of borrowing.[17] Panel A of Table 7 shows the results of the deal-by-deal panel regressions where the dependent variable is the brokerage fee (p.y., in %) paid by the borrower and the explanatory variable is *BC*. In Panel B we allow for a nonlinear effect of *BC* on brokerage fees by grouping borrowers into the high-, medium-, and low-*BC* groups as in Section 5.1. We compute the average brokerage fee within each stock–week-group cell. We then run panel regressions of this average brokerage fee within each cell on the two group dummy variables.

The results in Table 7 are consistent with the idea that brokers charge lower fees from high-*BC* borrowers. In Panel A, the coefficients of the *BC* variable are always negative and statistically significant at the 1% level across all samples. Panel B shows that low-*BC* borrowers pay higher brokerage fees than medium- and high-*BC* borrowers. Moreover, medium-*BC* borrowers pay higher brokerage fees than high-*BC* borrowers. Again, the results hold across all samples.

5.4. Loan fee level vs. loan fee dispersion across stocks

KRR argue that search costs can be stock-specific. For example, it should be relatively costly to search for small cap and illiquid stocks in the lending market. It is therefore interesting to compare loan fee dispersion and loan fee level across the stocks in our sample. If search costs vary at the stock-level, then these two variables should be positively related in the cross-section of stocks.

Fig. 6 shows a scatter-plot of the stock fixed effects estimated in Column 2 of Table 5 and in Column 2 of Table 6. It clearly shows that stocks with higher loan fee dispersion also have higher loan fee level. This is in line with the results shown in Table 8 of KRR.

In Section 5.8 we further analyze the relation between loan fee level and loan fee dispersion with variables such as firm size, liquidity, specialness, and lending concentration.

5.5. Inside the top broker

We have so far have been measuring loan fee dispersion as the standard deviation and range of the loan fees within stock–day pairs (in Section 3) and within stock–week pairs (in Section 5.2). In this section we refine these measures by calculating them within a single broker. Consistent with our previous findings, we find that (i) different borrowers pay different loan fees in deals done with the same broker (same stock, same day) and (ii) these differences are related to borrower search costs.

Fig. 7 shows all of the 91 brokers in our sample sorted according to the number of deals closed during the entire period. The biggest broker is responsible for 195,512 loan deals, twice the number of deals closed by the second-biggest broker (93,966). This volume of data suffices to analyze loan fee dispersion inside this *single* top broker.

We first document the existence of loan fee dispersion by computing the standard deviation of loan fees within stock–day pairs using only deals closed inside the top broker. Fig. 8 reports the time-series average of the daily loan fee dispersion for each stock. Fig. 9 reports the cross-sectional average of the loan fee dispersion for each day. Both figures show that even inside the same broker there is significant loan fee dispersion. Moreover, loan fee dispersion varies considerably both in the cross-section and in the time-series, consistent with the results in Section 3.

[17] In our sample, the average brokerage fee is 0.22% p.y. and the median brokerage fee is 0.05% p.y. Considering only deals closed by frequent borrowers the average is 0.14% p.y. and the median is zero. Considering only deals closed by institutions and large borrowers we get similar numbers, the average is 0.15% p.y. and the median is zero.

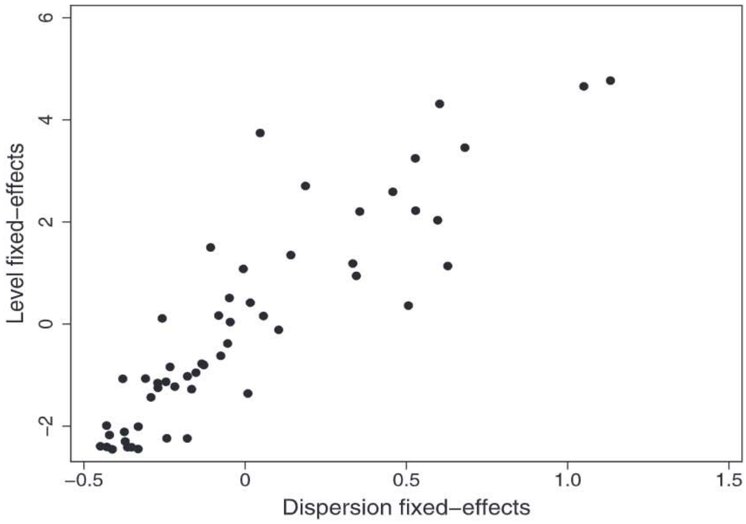

Fig. 6. Level fixed-effect vs. dispersion fixed-effect. This figure shows the scatter-plot between the level fixed-effect and the dispersion fixed-effect of each one of the 55 stocks in our sample. The level fixed-effect is the stock fixed-effect estimated in Table 5. The dispersion fixed-effect is the stock fixed-effect estimated in Table 6.

Table 8
Inside the top broker: Loan fee and borrower connection.

This table shows the estimates of deal-by-deal panel regressions with the loan fee as the dependent variable. All regressions consider only deals intermediated by the top broker. The top broker is the broker with the highest number of deals closed in the entire sample. Columns 2, 4, 6 and 8 have Borrower connection (*BC*) as the explanatory variable. The calculation of the variable *BC* is described in Section 4. *BC* is a time-varying (at the daily frequency) and stock-specific variable, and it is decreasing in the search costs of the borrower. A high value of this variable means that the borrower has strong relationships with brokers with strong relationships with important lenders of the stock. Columns 3, 5, 7, and 9 include past volatility and past return as control variables. Past volatility is the standard deviation of stock returns on the past 5 days. Past return is the stock return on the last 5 days. Columns 2 and 4 show the estimates considering all deals in our sample. The other columns show the estimates for the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we do the following. We compute the average volume across all deals within each borrower and rank borrowers according to this. Then, we say that the top-5% are large borrowers. Finally, we say that borrowers that traded in more than half of the weeks are frequent. All regressions include stock and day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals		Institutions		Large		Frequent	
BC	−0.199***	−0.195***	−0.155***	−0.151***	−0.129***	−0.126***	−0.123***	−0.125***
	(0.067)	(0.069)	(0.049)	(0.048)	(0.048)	(0.046)	(0.043)	(0.042)
Past volatility		0.144**		0.170*		0.200**		0.113**
		(0.065)		(0.083)		(0.088)		(0.051)
Past return		-0.002		0.010		0.012		−0.001
		(0.005)		(0.007)		(0.009)		(0.009)
Stock fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	195,512	195,512	25,901	25,901	14,739	14,739	15,335	15,335
$R^2 - adj$	0.59	0.59	0.57	0.58	0.58	0.58	0.61	0.61

We now run regressions of loan fee level and loan fee dispersion on *BC*.[18] We first test whether the loan fee level is decreasing in *BC* in a deal-by-deal regression. We then test whether loan fee dispersions are higher in groups of low-*BC* borrowers.

Table 8 shows the results of the loan fee level regressions. Columns 2 and 3 show the estimates considering all deals closed inside the top broker (a total of 195,512 observations). In Column 2 the coefficient of the *BC* variable is −0.199, significant at the 1% level. This means that an increase of one percentage point in *BC* decreases the loan fee level by 0.199 percentage points. Column 3 shows that these results remain the same after controlling for past volatility and past return.

Columns 4 and 5 show the estimates considering deals from institutions closed inside the top broker (a total of 25,901 observations). In Column 4, the coefficient of variable *BC* is −0.155 and significant at the 1% level. In Column 5, the results remain after we control for past volatility and past return. Columns 6 and 7 show the estimates considering deals from large borrowers closed inside the top broker (a total of 14,739 observations). In Column 6, the coefficient of variable *BC* is −0.129 and significant at the 1% level. In Column 7, it becomes −0.126. Finally, Columns 8 and 9 show the estimates considering deals from frequent

[18] Although the regressions in this section include only the deals closed by the top broker, *BC* is a market-wide variable, computed using the *full* sample, as in Section 4.

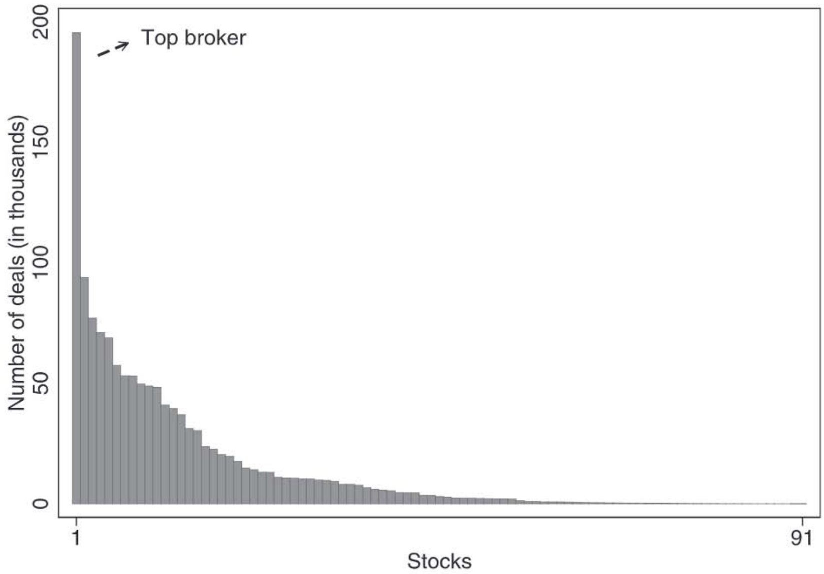

Fig. 7. Number of loan deals by brokers. This figure shows the number of lending deals intermediated by each broker during January 2008 and July 2011. The 91 brokers are sorted on the *x*-axis according to the total number of deals.

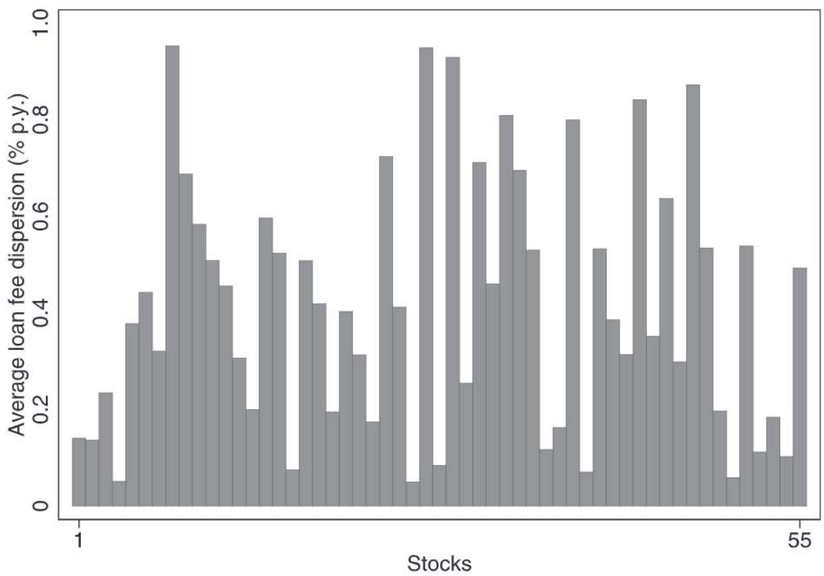

Fig. 8. Inside the top broker: loan fee dispersion in the cross-section. This figure shows the time-series average of the loan fee dispersion inside the top broker for each stock in our sample. For each one of the 55 stocks in our sample, we compute the average of its daily loan fee dispersion from January 2008 to July 2011. Loan fee dispersion is calculated as the standard deviation of the annualized loan fee in percentage points of all deals intermediated by the top broker for the same stock on the same day. The 55 stocks are alphabetically ordered on the *x*-axis. The top broker is the broker with the highest number of closed deals in the entire sample.

borrowers closed inside the top broker (a total of 15,335 observations). In Column 8, the coefficient of variable *BC* is −0.123 and significant at the 1% level. In Column 9, it becomes −0.125.

Table 9 presents the results for the loan fee dispersion regressions. The regressions are the same ones shown in Table 6, but with the dependent variables constructed with only the deals closed inside the top broker. Columns 2 and 3 show the estimates considering all borrowers (a total of 5,421 stock–week-type observations). For the standard deviation measure (Column 2), the coefficient relative to the high-*BC* type is−0.168, significant at the 1% level, and the coefficient relative to the low-*BC* type is 0.002, not significant. For the range measure (Column 3), the coefficient relative to the high-*BC* type is −1.355, significant at the 1% level, and the coefficient relative to the low-connected type is −0.025, but not significant.

Considering only institutions (Columns 4 and 5), there are 4,021 stock–week-type observations in the regression. Using the standard deviation measure (Column 4), the coefficient of the high-*BC* type is −0.221, significant at the 1% level, and the coefficient of the low-*BC* type is 0.067,

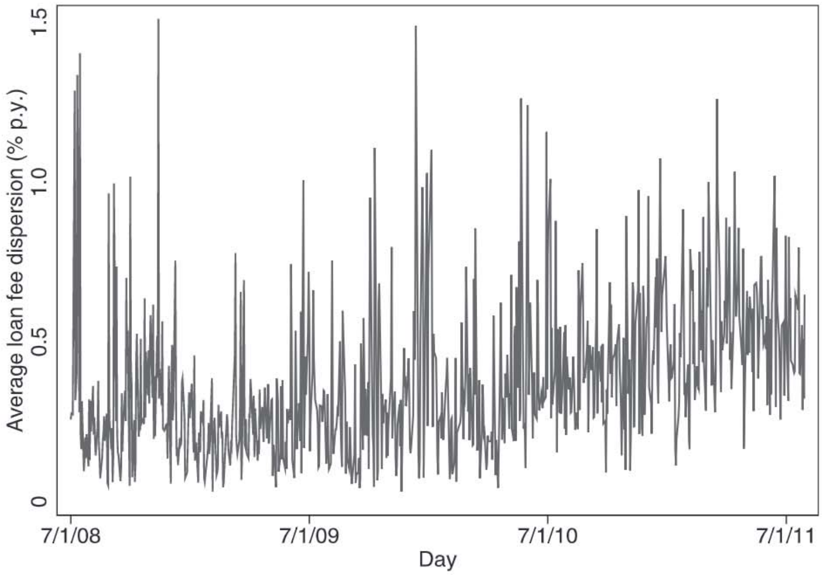

Fig. 9. Inside the top broker: loan fee dispersion in the time-series. This figure shows the cross-sectional average of the loan fee dispersion inside the top broker for each day in our sample. For each trading day from January 2008 to July 2011, we compute the average of the loan fee dispersion across the 55 stocks in our sample. Loan fee dispersion is calculated as the standard deviation of the annualized loan fee in percentage points of all deals intermediated by the top broker for the same stock on the same day. The top broker is the broker with the highest number of deals closed in the entire sample.

Table 9
Inside the top broker: Loan fee dispersion for high-, medium-, and low-connected borrowers.

This table presents estimates of the effect of Borrower connection (*BC*) on the loan fee dispersion. All regressions consider only deals intermediated by the top broker. The top broker is the broker with the highest number of deals closed in the entire sample. Within each stock–week pair we rank deals with respect to the borrowers *BC* and classify them into three groups: low-*BC* group if *BC* falls below the 50%-percentile, medium-*BC* group if it falls between the 50%- and the 90%-percentile, and high-*BC* group if it falls above the 90%-percentile. For each stock–week-group cell we compute two measures of loan fee dispersion: the standard deviation and the range of loan fees across all deals. We then run panel regressions of these dispersion measures on two dummy variables, *High* and *Low*. *High* takes value one if the cell refers to the high-*BC* group and zero otherwise. *Low* takes value one if the cell refers to the low-*BC* and zero otherwise. *BC* is a time-varying and stock-specific variable which is decreasing in the search costs of the borrower. The calculation of the variable *BC* is described in Section 4. Columns 2 and 3 in the table show the estimates considering all deals in our sample. The other columns consider deals from samples restricted according to borrowers type: institutional, large, and frequent. Classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers that traded in more than half of the weeks are frequent. All regressions include stock and week fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals		Institutions		Large		Frequent	
	Std. dev.	Range	Std. dev.	Range	Std. dev.	Range	Std. dev.	Range
High	−0.168***	−1.355***	−0.221***	−1.239***	−0166***	−0.820***	−0.150***	−0.889***
	(0.023)	(0.115)	(0.049)	(0.119)	(0.051)	(0.074)	(0.051)	(0.091)
Low	0.002	−0.025	0.067**	0.065	0.042	−0.017	0.093***	0.067
	(0.019)	(0.077)	(0.031)	(0.069)	(0.031)	(0.049)	(0.023)	(0.042)
Stock fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed-effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,421	5,421	4,021	4,021	2,908	2,908	3,431	3,431
$R^2 - adj$	0.26	0.29	0.17	0.17	0.12	0.25	0.14	0.12

significant at the 5% level. Using the range measure (Column 5), the coefficient of the high-*BC* type is −1.239, significant at the 1% level, and the coefficient of the low-*BC* type is 0.065, but not significant. Considering only large borrowers (Columns 6 and 7), there are 2,908 stock–week-type observations. Using the standard deviation measure (Column 6), the coefficient of the high-*BC* type is −0.166, significant at the 1% level, and the coefficient of the low-*BC* type is 0.042, not significant. Using the range measure (Column 7), the coefficient of the high-*BC* type is −0.820, significant at the 1% level, and the coefficient of the low-*BC* type is −0.017, but not significant.

Finally, considering only frequent borrowers (Columns 8 and 9), there are 3,431 stock–week-type observations in the regression. For the standard deviation measure (Column 8), the coefficient relative to the high-*BC* type is −0.150, significant at the 1% level, and the coefficient of the low-*BC* type is equal to 0.093, also significant at the 1% level. For the range measure (Column 9), the coefficient of the high-*BC* type is −0.889, significant at the 1% level, and the coefficient of the low-*BC* type is 0.067, but not significant. These results show that borrowers with different search costs pay different loan fees in deals closed even inside the *same* broker. We take

Table 10
Borrower connection vs. borrower market share.
This table shows deal-by-deal panel regressions of borrower market share (*share*) on Borrower connection (*BC*). *share* is the lending market share of borrower *k* with respect to stock *s* in the 90-day window previous to day *t*. It is calculated as the ratio between the quantity borrowed by *k* and total quantity borrowed in the market. *BC* is also a time-varying and stock-specific variable which is decreasing in the borrower's search costs. The calculation of the variable *BC* is described in Section 4. Column 2 shows the estimates considering all deals in our sample. Columns 3, 4, and 5 consider deals from samples restricted according to borrowers type: institutional, large and frequent. Classification between individuals and institutions comes directly from the original data set. To classify a borrower as large we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers that traded in more than half of the weeks are frequent. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals	Institutions	Large	Frequent
BC	1.444***	1.325***	1.174***	1.166***
	(0.003)	(0.004)	(0.004)	(0.004)
Constant	0.801***	1.201***	1.886***	1.603***
	(0.003)	(0.005)	(0.007)	(0.006)
N	1,251,801	912,579	641,744	605,916
$R^2 - adj$	0.16	0.17	0.11	0.12

this as a strong evidence in favor of hypotheses H1 and H2.

5.6. BC and borrower market share

Let $share_{k,s,t}$ be the market share of borrower k with respect to stock s in the 90-day window previous to day t. Recall that $BC_{k,\ s,\ t}$ measures how costly it is for borrower k to search for stock s on day t. This section discusses the relation between $BC_{k,\ s,\ t}$ and $share_{k,\ s,\ t}$ and shows that $share_{k,\ s,\ t}$ explains neither loan fee levels nor loan fee dispersions. Hence, $BC_{k,\ s,\ t}$ encompasses more information than the borrower market share $share_{k,\ s,\ t}$

The following example illustrates how these two variables differ. Consider an investor who during the last 90 days borrowed a large volume of firm A's stock from a large broker. During this period the borrower called the broker almost every day searching for stock A, and closed large loan deals. Assume that today this same borrower calls the broker, but now searching for stock B. Although the borrower has closed no deals on stock B in the last 90 days, it is likely to be relatively easy for him to search for stock B: she is after all a good client of the broker, which is therefore high motivation to do a good job looking for stock B among its clients. In other words, the borrower's search cost on stock B is not just a function of his market share in the stock.

Although conceptually different, $BC_{k,\ s,\ t}$ and $share_{k,\ s,\ t}$ should be positively related to each other: both should be high for active borrowers. To confirm this intuition we run $share_{k,\ s,\ t}$ on $BC_{k,\ s,\ t}$ using our deal-by-deal data set. We first use the full sample and then restrict it to institutions, to large borrowers, and to frequent borrowers. Table 10 displays the results. The estimates show that the relation between $BC_{k,\ s,\ t}$ and $share_{k,\ s,\ t}$ is, as expected, positive and highly significant.

Although *BC* and *share* are positively related, *BC* should contain more relevant information to explain the loan fee level and dispersion, as explained in the example above. We test this by running deal-by-deal regressions of the loan fee level as the dependent variable, using both *share* and *BC* on the right-hand side.

The results in Table 11 are clear. In every regression *BC* remains significant and negatively related to the loan fee levels even after controlling for *share*.

5.7. Decomposing BC

According to expression (1), the variation in *BC* comes from five different sources (components):

- Component (i) – the number of brokers borrower k is connected to at time t (as measured by I);
- Component (ii) – the strengths of the relationships between borrower k and her brokers at time t (as measured by *BBR*);
- Component (iii) – the number of lenders borrower k's brokers are connected to at time t (as measured by J);
- Component (iv) – the strengths of the relationships of borrower k's brokers with their lenders at time t (as measured by *BLR*); and
- Component (v) – the market-shares on stock s of the lenders that are connected to borrower k's brokers at time t (as measured by *MS*).

The regression of loan fees on *BC* does not allow one to understand which of these five components matter and which do not in explaining loan fees. To assess the individual relevance of the five components, we construct a new variable $BC(\gamma)$ which is a flexible version of *BC*. In *BC*, all components (i)–(v) are active by construction, while in $BC(\gamma)$ these components can be switched off. Then, by regressing loan fees on $BC(\gamma)$, we let the data decide which components do not matter and should be switched off.

The variable $BC(\gamma)$ is parameterized by $\gamma = \left(\gamma^{i,ii}, \gamma^{iii,iv}, \gamma^{i}, \gamma^{ii}, \gamma^{iii}, \gamma^{iv}, \gamma^{v}\right) \in \{0, 1\}^7$. Each parameter switches on or off—by taking the value of 1 or 0—the component(s) denoted in the superscript. For instance, if $\gamma^{i,ii} = 1$ then both components (i) and (ii) are on, but if $\gamma^{i,ii} = 0$ then both components (i) and (ii) are off. Likewise, if $\gamma^{v} = 1$ then component (v) is on, but if $\gamma^{v} = 0$ then component (v) is off.

Notably, $BC(\gamma)$ has more parameters (seven) than components (five). The additional parameter $\gamma^{i,\ ii}$ is needed to allow for both components (i) and (ii) to be active and, at the same time, to preserve the functional form of *BC*; this could not be achieved by setting both $\gamma^{i} = 1$ and $\gamma^{ii} = 1$, as can be seen in the formula below. The same applies to $\gamma^{iii,\ iv}$ with respect to components (iii) and (iv).

We define $BC(\gamma)$ as

$$BC_{k,s,t}(\gamma) = 100 \times \sum_{i=1}^{I_{k,t}} \left\{ \left[\gamma^{i,ii} BBR_{k,i,t} + \gamma^{i} + \gamma^{ii} \frac{BBR_{k,i,t}}{I_{k,t}} + \left(1 - \gamma^{i} - \gamma^{ii} - \gamma^{i,ii}\right) \frac{1}{I_{k,t}} \right] BR_{i,s,t}(\gamma) \right\} \quad (2)$$

where

Table 11
Borrower connection and market share.
This table shows the estimates of deal-by-deal panel regressions with the loan fee as the dependent variable. Columns 2, 4, 6, and 8 have borrower market share (*share*) as the explanatory variable. *share* is the lending market share of borrower *k* with respect to stock *s* in the 90-day window previous to day *t*. It is calculated as the ratio between the quantity borrowed by *k* and total quantity borrowed in the market. Columns 3, 5, 7, and 9 also include the Borrower connection (*BC*) as explanatory variable. The calculation of the variable *BC* is described in Section 4. *BC* is also a time-varying (at the daily frequency) and stock-specific variable which is decreasing in the borrower's search costs. A high value here means that the borrower has strong relationships with brokers which have strong relationships with important lenders of the stock. All columns include past volatility and past return as control variables. Past volatility is the standard deviation of stock returns on the past 5 days. Past return is the stock return on the last 5 days. Columns 2 and 3 show the estimates considering all deals in our sample. The other columns show the estimates for the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers that traded in more than half of the weeks are frequent. All regressions include stock–day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals		Institutions		Large		Frequent	
Borrower market share	−0.011***	0.003	−0.002	0.009***	−0.001	0.010***	−0.004	0.009***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
BC		−0.109***		−0.092***		−0.092***		−0.102***
		(0.015)		(0.014)		(0.019)		(0.016)
Stock–day fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,251,801	1,251,801	912,579	912,579	641,744	641,744	605,916	605,916
$R^2 - adj$	0.84	0.85	0.86	0.86	0.86	0.86	0.86	0.87

$$BR_{i,s,t}(\gamma) = \sum_{j=1}^{J_{i,t}} \Bigg\{ \Bigg[\gamma^{iii,iv} BLR_{i,j,t} + \gamma^{iii} + \gamma^{iv} \frac{BLR_{i,j,t}}{J_{i,t}} + \left(1-\gamma^{iii}-\gamma^{iv}-\gamma^{iii,iv}\right)\frac{1}{J_{i,t}} \Bigg] \times \left[\gamma^{v} MS_{j,s,t} + \left(1-\gamma^{v}\right)\overline{MS}\right] \Bigg\} \tag{3}$$

and $\overline{MS}$ is a constant (the average market share in the sample). We impose that $\left(1-\gamma^{i}-\gamma^{ii}-\gamma^{i,ii}\right) \in \{0,1\}$ and $\left(1-\gamma^{iii}-\gamma^{iv}-\gamma^{iii,iv}\right) \in \{0,1\}$. From restriction $\left(1-\gamma^{i}-\gamma^{ii}-\gamma^{i,ii}\right) \in \{0,1\}$, it follows that ($\gamma^{i,ii}$, γ^{i}, γ^{ii}) is equal to either (1, 0, 0), or (0, 1, 0), or (0, 0, 1), or (0, 0, 0). The same follows from restriction $\left(1-\gamma^{iii}-\gamma^{iv}-\gamma^{iii,iv}\right) \in \{0,1\}$.

Since there are 5 components to be switched on or off, there are $32 = 2^5$ possible cases for $BC(\gamma)$. Table 12 presents them all. To clarify the relation between γ and the 32 cases, we go through some of them:

- $\gamma = (1,1,0,0,0,0,1)$: Since $\gamma^{iii,iv} = \gamma^{v} = 1$ and $\gamma^{iii} = \gamma^{iv} = 0$, we have that $BR_{i,s,t}(\gamma) = BR_{i,s,t}$. Then, since $\gamma^{i,ii} = 1$ and $\gamma^{i} = \gamma^{ii} = 0$, $BC(\gamma) = BC$. In this case, all components (i) to (v) are switched on.
- $\gamma = (0,0,1,0,0,0,0)$: Since $\gamma^{iii,iv} = \gamma^{iii} = \gamma^{iv} = \gamma^{v} = 0$, we have that $BR_{i,s,t}(\gamma) = \overline{MS}$ is constant. Then, since $\gamma^{i,ii} = \gamma^{ii} = 0$ and $\gamma^{i} = 1$, we have that $BC(\gamma) = 100 \times I_{k,t} \times \overline{MS}$. In this case, all variation in $BC(\gamma)$ comes from $I_{k,t}$, that is, only component (i) is switched on.
- $\gamma = (0,0,0,1,0,0,0)$: Since $\gamma^{iii,iv} = \gamma^{iii} = \gamma^{iv} = \gamma^{v} = 0$, we have that $BR_{i,s,t}(\gamma) = \overline{MS}$ is constant. Then, since $\gamma^{i,ii} = \gamma^{i} = 0$ and $\gamma^{ii} = 1$, we have that $BC(\gamma) = 100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} BBR_{k,i,t} \times \overline{MS}$. In this case, all variation in $BC(\gamma)$ comes from $BBR_{k,i,t}$ (the effect of $I_{k,t}$ becomes null when $BBR_{k,i,t}$ is averaged out across $I_{k,t}$). As such, only component (ii) is switched on.
- $\gamma = (0,0,0,0,0,0,1)$. Since $\gamma^{iii,iv} = \gamma^{iii} = \gamma^{iv} = 0$ and $\gamma^{v} = 1$, we have that $BR_{i,s,t}(\gamma) = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} MS_{j,s,t}$. Furthermore, since $\gamma^{i,ii} = \gamma^{i} = \gamma^{ii} = 0$, we have that $BC(\gamma) = 100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} [\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} MS_{j,s,t}]$. In this case, all variation in $BC(\gamma)$ comes from component (v).
- $\gamma = (1,0,0,0,0,1,1)$. Since $\gamma^{iii,iv} = \gamma^{iii} = 0$ and $\gamma^{iv} = \gamma^{v} = 1$, we have that $BR_{i,s,t}(\gamma) = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} BLR_{i,j,k} MS_{j,s,t}$. Furthermore, since $\gamma^{i,ii} = 1$, we have that $BC(\gamma) = 100 \times \sum_{i=1}^{I_{k,t}} BBR_{k,i,t} [\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} BLR_{i,j,k} MS_{j,s,t}]$. In this case, only component (iii) is off.

To understand which of the five components matter in explaining loan fees, we run our deal-by-deal regression of loan fees on $BC(\gamma)$:

$$LoanFee_{d,k,s,t} = \beta BC_{k,s,t}(\gamma) + \alpha_{s,t} + \epsilon_{d,s,t}\,. \tag{4}$$

We emphasize that this regression nests the original regression of loan fees on *BC*. Indeed, when $\gamma = (1,1,0,0,0,0,1)$ we have *BC* as the explanatory variable. By estimating γ, we let the data decide which of the five components matter in explaining loan fees and which do not. In other words, we let the data decide what is the optimal functional form of *BC* concerning the relevance of its components.

The estimation of regression (4) is done by minimizing the sum of the squared residuals considering the domain given by $\beta \in \mathbb{R}$ and the 32 cases for γ presented in Table 12. Since the elements of γ are binary, the significance of the parameters are calculated using bootstrap.[19] The results are shown in Table 13. In Columns 2, 4, 6, and 8, regression (4) is estimated restricting $\gamma = (1,1,0,0,0,0,1)$. This is the original regression of loan fees on *BC*. In Columns 3, 5, 7, and 9, the unrestricted regression is estimated.

[19] We obtain 1,000 estimates for (β, γ) and compute the percentage of the samples that each parameter in vector γ is estimated to be zero. This percentage is the *p*-value of the test $H_0 : \gamma = 0$, $H_1 : \gamma = 1$. To respect the clustering by stock used in the regressions throughout the paper, the bootstrap is performed by sampling with replacement across stock-blocks.

Table 12
Relevant cases for $BC(\gamma)$.
This table shows all 32 relevant cases for $BC(\gamma)$, see equation (2). Column 1 shows all the relevant parameter vectors. Column 2 shows the components that are being switched on. There are 5 different components: (i) the number of brokers a borrower is connected to; (ii) the strength of her relationships with these brokers; (iii) the number of lenders that her brokers are connected to; (iv) the strength of the relationships of her brokers with these lenders; and (v) the market share of these lenders. Column 3 shows the resulting expression for $BC(\gamma)$.

$(\gamma^{i,\,ii}, \gamma^{iii,\,iv}, \gamma^{i}, \gamma^{ii}, \gamma^{iii}, \gamma^{iv}, \gamma^{v})$	Components switched on	$BC(\gamma)$
(1, 1, 0, 0, 0, 0, 1)	(i), (ii), (iii), (iv), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(0, 1, 0, 1, 0, 0, 1)	(ii), (iii), (iv), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(0, 1, 1, 0, 0, 0, 1)	(i), (iii), (iv), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[\sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(1, 0, 0, 0, 0, 1, 1)	(i), (ii), (iv), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(1, 0, 0, 0, 1, 0, 1)	(i), (ii), (iii), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(1, 1, 0, 0, 0, 0, 0)	(i), (ii), (iii), (iv)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(1, 0, 0, 0, 1, 0, 0)	(i), (ii), (iii)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times J_{i,t} \times \overline{MS}\right]$
(1, 0, 0, 0, 0, 1, 0)	(i), (ii), (iv)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(1, 0, 0, 0, 0, 0, 1)	(i), (ii), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 1, 0, 1, 1, 0)	(i), (iii), (iv)	$100 \times \sum_{i=1}^{I_{k,t}} \left[\sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(0, 0, 1, 0, 1, 0, 1)	(i), (iii), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[\sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 1, 0, 0, 1, 1)	(i), (iv), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(0, 0, 0, 1, 1, 1, 0)	(ii), (iii), (iv)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(0, 0, 0, 1, 1, 0, 1)	(ii), (iii), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 0, 1, 0, 1, 1)	(ii), (iv), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(0, 1, 0, 0, 0, 0, 1)	(iii), (iv), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[\sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(1, 0, 0, 0, 0, 0, 0)	(i), (ii)	$100 \times \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \overline{MS}\right]$
(0, 0, 1, 0, 1, 0, 0)	(i), (iii)	$100 \times \sum_{i=1}^{I_{k,t}} \left[J_{i,t} \times \overline{MS}\right]$
(0, 0, 1, 0, 0, 1, 0)	(i), (iv)	$100 \times \sum_{i=1}^{I_{k,t}} \left[\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(0, 0, 1, 0, 0, 0, 1)	(i), (v)	$100 \times \sum_{i=1}^{I_{k,t}} \left[\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 0, 1, 1, 0, 0)	(ii), (iii)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \sum_{j=1}^{J_{i,t}} \left(\overline{MS}\right)\right]$
(0, 0, 0, 1, 0, 1, 0)	(ii), (iv)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(0, 0, 0, 1, 0, 0, 1)	(ii), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[BBR_{k,i,t} \times \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 0, 0, 1, 1, 0)	(iii), (iv)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[\sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(0, 0, 0, 0, 1, 0, 1)	(iii), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[\sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 0, 0, 0, 1, 1)	(iv), (v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} MS_{j,s,t}\right)\right]$
(0, 0, 1, 0, 0, 0, 0)	(i)	$100 \times I_{k,t} \times \overline{MS}$
(0, 0, 0, 1, 0, 0, 0)	(ii)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left(BBR_{k,i,t} \overline{MS}\right)$
(0, 0, 0, 0, 1, 0, 0)	(iii)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left(J_{i,t} \times \overline{MS}\right)$
(0, 0, 0, 0, 0, 1, 0)	(iv)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(BLR_{i,j,t} \overline{MS}\right)\right]$
(0, 0, 0, 0, 0, 0, 1)	(v)	$100 \times \frac{1}{I_{k,t}} \sum_{i=1}^{I_{k,t}} \left[\frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \left(MS_{j,s,t}\right)\right]$
(0, 0, 0, 0, 0, 0, 0)	none	$100 \times \overline{MS}$

Table 13
Panel-regression of loan fees on $BC(\gamma)$.

This table shows the estimates of the deal-by-deal panel regression $LoanFee = \beta \times BC(\gamma) + \epsilon$. The estimated parameters are $\beta \in \mathbb{R}$ and $\gamma = (\gamma^{i,ii}, \gamma^{iii,iv}, \gamma^{i}, \gamma^{ii}, \gamma^{iii}, \gamma^{iv}, \gamma^{v})$, where $\gamma \in \{0, 1\}^7$. The main explanatory variable in the regression is $BC(\gamma)$, which is a flexible version of BC. By setting each of its parameters to 1 or 0, the five components of BC are switched on or off. These components are: (i) the number of brokers a borrower is connected to; (ii) the strength of her relationships with these brokers; (iii) the number of lenders that her brokers are connected to; (iv) the strength of the relationships of her brokers with these lenders; and (v) the market share of these lenders. If $(\gamma^{i,ii}, \gamma^{iii,iv}, \gamma^{i}, \gamma^{ii}, \gamma^{iii}, \gamma^{iv}, \gamma^{v}) = (1, 1, 1, 0, 0, 0, 0, 1)$, we have that $BC(\gamma) = BC$. Columns 2, 4, 6, and 8 present the results of regressions of loan fees on $BC(\gamma)$ under this restriction. Columns 3, 5, 7, and 9 presents the results of the unrestricted regressions. Columns 2 and 3 show the estimates considering all deals in our sample. The other Columns show the estimates for the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we do the following. We compute the average volume across all deals within each borrower and rank borrowers according to this. Then, we say that the top-5% are large borrowers. Finally, we say that borrowers that traded in more than half of the weeks are frequent. All regressions include stock–day fixed-effects. Bootstrapped standard errors for the estimates of β are presented in parentheses. For the estimates of γ, we present in brackets the proportion of the bootstrapped samples (1,000) in which the parameter estimate was equal to 0. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All Deals		Institutions		Large		Frequent	
β	−0.105***	−0.399***	−0.082***	−0.378***	−0.081***	−0.377***	−0.091***	−0.397***
	(0.013)	*(0.034)*	*(0.011)*	*(0.009)*	*(0.012)*	*(0.009)*	*(0.013)*	*(0.009)*
$\gamma^{i,\ ii}$		1***		1***		1***		1***
		[0.00]		*[0.00]*		*[0.00]*		*[0.00]*
γ^{i}		0		0		0		0
		[1.00]		*[1.00]*		*[1.00]*		*[1.00]*
γ^{ii}		0		0		0		0
		[1.00]		*[1.00]*		*[1.00]*		*[1.00]*
$\gamma^{iii,\ iv}$		0		0		0		0
		[1.00]		*[1.00]*		*[1.00]*		*[1.00]*
γ^{iii}		0		0		0		0
		[1.00]		*[1.00]*		*[1.00]*		*[1.00]*
γ^{iv}		1**		1***		1***		1***
		[0.04]		*[0.00]*		*[0.00]*		*[0.00]*
γ^{v}		1***		1***		1***		1***
		[0.00]		*[0.00]*		*[0.00]*		*[0.00]*
Stock–day fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,251,801	1,251,801	912,579	912,579	641,744	641,744	605,916	605,916

The results across all samples (all deals, deals from institutions, large, and frequent borrowers) are qualitatively the same. With respect to which of the components of *BC* matter, we conclude that components (i), (ii), (iv), and (v) are relevant in explaining loan fees. Parameters $\gamma^{i,\ ii}$, γ^{iv}, and γ^{v} are statistically equal to one. Component (iii), in turn, does not add explanatory power to *BC*, given that the optimal choice was to set $\gamma^{iii,iv} = 0$ and $\gamma^{iii} = 0$. Accordingly, we conclude that (a) to measure how well-connected a borrower is to brokers, both the number of her brokers—component (i)—and the strength of her relationship with her brokers—component (ii)—matter; and (b) to measure how well-connected a broker is to the supply side of the lending market, the strength of its relationship with lenders matters—component (iv)—and the market-share of these lenders, while the number of lenders the broker is connected to is unimportant.

The overall conclusion of the paper is that "borrowers that are *well-connected* to *good brokers* pay lower loan fees." After opening *BC*, we can say that for a borrower to be *well-connected* it is necessary for her to have strong relationships with many brokers. In turn, for a broker to be *good* (with respect to a specific stock) it is sufficient for it to have a strong relationship with *one* lender with high market-share. The fact that the number of brokers is relevant, while the number of lenders is not, is consistent with the idea that the stock lending market should be more opaque for borrowers than for brokers. Indeed, brokers intermediate loan deals frequently, updating their information set very often. Borrowers, in turn, participate on the loan market occasionally. Hence, for borrowers, having access to a larger number of brokers is important to acquire updated information on loan fees.

5.7.1. *Comparing the importance of components (i) and (ii)*

The estimation of $BC(\gamma)$ shows that both components (i) and (ii) matter in explaining loan fees. In this section we compare their importance. First, we double-sort our sample across two dimensions. In one dimension, we divide deals into two groups: deals closed by borrowers connected to only one broker ($I_{k,t} = 1$) and deals closed by borrowers connected to more than one broker ($I_{k,\ t} > 1$). In a second dimension, we divide the deals, day by day, into three groups (terciles) according to the borrower's average connection strength ($\overline{BBR}_{k,t}$). As a result, deals are classified into six different (I, $\overline{BBR}$) pairs: (1, low), (1, medium), (1, high), (>1, low), (>1, medium), (>1, high). For each of the six different pairs, we then compute the average loan fee within each pair. To exclude stock–day fixed effects we use the residual of the regression of loan fees on stock–day dummies. Fig. 10 shows four graphs, one for each of the subsamples (all deals, institutions, large, and frequent).

Consistent with the results in the previous section, the graphs in Fig. 10 show that loan fees decrease along both dimensions. However, being connected to more than one broker is relatively more important. Indeed, in all subsamples, the average loan fee in the (1, high) pair is significantly higher than the average loan fee in the (>1, low) pair. Moreover, since the line for $I > 1$ is flatter in all samples considered, we conclude that $\overline{BBR}$ is less important for

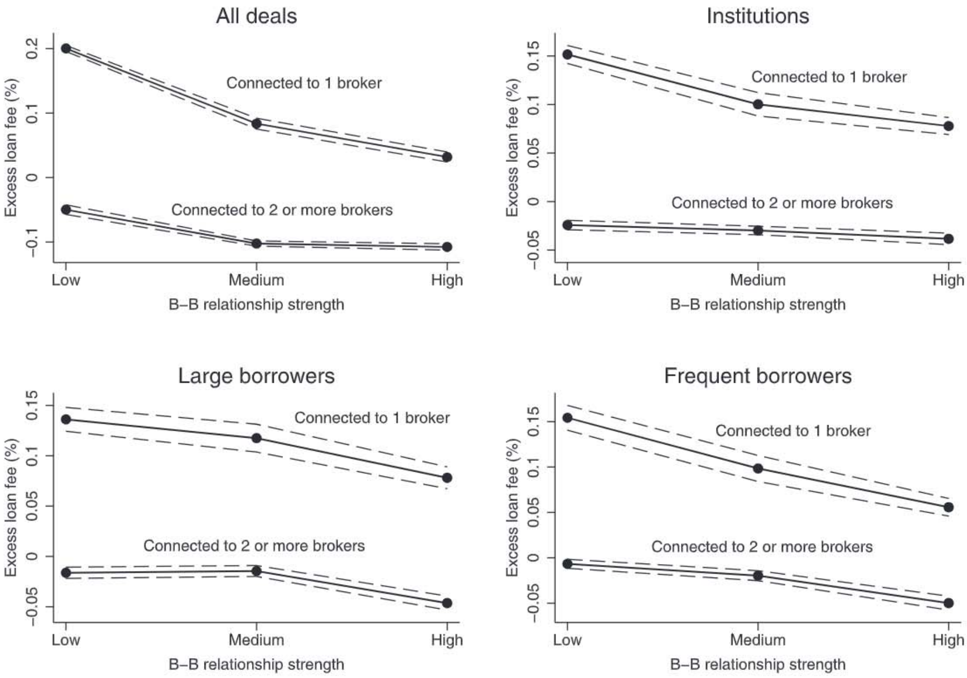

Fig. 10. Average loan fees: Double-sort across $I_{k,t}$ and $\overline{BBR}_{k,t}$. Deals are double-sorted across the number of brokers a borrower is connected with ($I_{k,t}$) and across the borrower's average connection strength ($\overline{BBR}_{k,t}$). Along $I_{k,t}$, deals are divided into two groups: borrowers connected to only 1 broker ($I_{k,t} = 1$) and borrowers connected to more than 1 broker ($I_{k,t} > 1$). Along $\overline{BBR}_{k,t}$, deals are divided daily into terciles: low, medium and high-$\overline{BBR}_{k,t}$. Then, for all possible (I, $\overline{BBR}$) pairs, we compute the average loan fee across all deals within each pair. To exclude stock–day fixed effects we use the residual of the regression of loan fees on stock–day dummies to compute the average. The dotted lines show +/− 2 standard-deviation bands around the average loan fee. The top-left graph considers all deals in our sample. The other graphs are based on the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we do the following. We compute the average volume across all deals within each borrower and rank borrowers according to this. Then, we say that the top-5% are large borrowers. Finally, we say that borrowers that traded in more than half of the weeks are frequent.

borrowers connected to more than one broker. To further compare the effects of I and $\overline{BBR}$ on loan fees, we run a deal-by-deal regression of loan fees on these variables and their interaction. We standardize both variables to allow for a direct comparison of the coefficients. The estimated coefficients in Table 14 show that both variables explain loan fees. Consistent with Fig. 10, the coefficients of $I_{k,t}$ are about twice as large as those of $\overline{BBR}_{k,t}$. This confirms that the number of brokers a borrower has a relationship with is qualitatively more important than the strength of this borrower's relationships with these brokers.

5.8. Stock-specific proxies for search costs

Stock liquidity, firm size, and other stock-specific variables are typically associated with hard-to-borrow stocks and as such are used as proxies for search costs (for instance, in KRR). In this section, we show that these variables are indeed good proxies. We run two sets of regressions. First, we run stock–day panel regressions of loan fee level and loan fee dispersion on these variables. We find that small stocks, for instance, present higher loan fee level and dispersion. Second, we run deal-by-deal panel regressions to see if the effect of BC on loan fees changes when conditioning on these variables. We find that the effect of BC on loan fees is stronger for small stocks and other proxies.

Table 14
Relative importance of $I_{k,t}$ and $\overline{BBR}_{k,t}$.

This table shows the estimates of deal-by-deal panel regressions of loan fees on $I_{k,t}$, $\overline{BBR}_{k,t}$ and their interaction. $I_{k,t}$ is the total number of brokers that borrower k is related with (i.e., closed at least one deal in the last 90 days). $\overline{BBR}_{k,t}$ is the average (across brokers) of $BBR_{k,i,t}$, which is the *Borrower-broker relation* and is measured by the ratio between the number of loan deals (considering *any*stock) between borrower k and broker i in the 90-day period previous to day t. Column 2 shows the estimates considering all deals in our sample. The other columns show the estimates for the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large, we do the following. We compute the average volume across all deals within each borrower and rank borrowers according to this. Then, we say that the top-5% are large borrowers. Finally, we say that borrowers that traded in more than half of the weeks are frequent. All regressions include stock–day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals	Institutions	Large	Frequent
$I_{k,t}$	−0.139***	−0.092***	−0.097***	−0.112***
	(0.014)	(0.011)	(0.012)	(0.015)
$\overline{BBR}_{k,t}$	−0.040***	−0.039***	−0.046***	−0.071***
	(0.011)	(0.014)	(0.015)	(0.019)
$I_{k,t} \times \overline{BBR}_{k,t}$	−0.008	−0.040***	−0.057***	−0.060***
	(0.013)	(0.014)	(0.016)	(0.017)
Stock–day fixed- effects	Yes	Yes	Yes	Yes
N	1,251,801	912,579	641,744	605,916
$R^2 - adj$	0.84	0.86	0.86	0.87

Table 15
Stock-specific determinants of loan fee and loan fee dispersion.
Panel A of this table shows the estimates of stock–day panel regressions of daily average loan fee on size (the natural log of the market capitalization), illiquidity (the bid-ask closing price spread), stock volatility (the past 5-day standard deviation of stock returns) and volume concentration (a Herfindahl index of all lender's market share on the stock on the previous 90 days). Panel B shows the estimates from stock–day panel regressions of daily standard deviation of loan fee on the same proxies and on a dummy if the stock is special (stocks are ranked every day according to their average loan fee; stocks that fall in the top quintile are called specials) and its interaction with volume concentration. All regressions include day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Loan fee level						
Log(market cap)	−0.024***					−0.022***
	(0.005)					(0.005)
Bid-ask spread		0.611**				0.263
		(0.230)				(0.163)
Stock volatility			0.600***			0.515***
			(0.151)			(0.136)
Volume concentration				3.985		1.840
				(2.880)		(2.355)
Day fixed-effects	Yes	Yes	Yes	Yes		Yes
N	29,849	29,651	29,849	29,849		29,651
$R^2 - adj$	0.11	0.01	0.05	0.01		0.14
Panel B: Loan fee dispersion						
Log(market cap)	−0.004***					−0.002***
	(0.001)					(0.000)
Bid-ask spread		0.072*				0.001
		(0.042)				(0.024)
Stock volatility			0.166***			0.092***
			(0.027)			(0.015)
Volume concentration				0.522	0.484	0.338
				(0.564)	(0.301)	(0.269)
Special dummy					1.478***	1.413***
					(0.202)	(0.192)
Vol. con. × special dummy					−2.298*	−2.307*
					(1.315)	(1.244)
Day fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	29,849	29,651	29,849	29,849	29,849	29,651
$R^2 - adj$	0.04	0.01	0.04	0.01	0.23	0.24

Panel A in Table 15 shows the estimates from stock–day panel regressions of daily average loan fee on size (the natural log of the market capitalization), illiquidity (the bid-ask closing price spread), stock volatility (the past five-day standard deviation of stock returns), and volume concentration (a Herfindahl index of all lenders' market share on the stock in the previous 90 days). Panel B shows the estimates from stock–day panel regressions of daily standard deviation of loan fee on the same proxies and on a dummy if the stock is special (stocks are ranked every day according to their average loan fee; stocks that fall in the top quintile are called specials) and its interaction with volume concentration.

The significance of the coefficients in Columns 2, 3, and 4 in Panel A of Table 15 indicates that stocks that are volatile, illiquid, and from small firms have higher loan fees. Furthermore, Columns 2, 3, and 4 in Panel B show that these stock characteristics are also associated with higher loan fee dispersion. When all variables are included, the illiquidity proxy becomes insignificant. Columns 6 and 7 in Panel B show that for special stocks, loan fee dispersion is also higher, and that this effect is higher if the lending volume is dispersed across lenders. These findings are in line with the evidence presented by KRR for the US (see their Table 7).

Next, we analyze if the effect of *BC* on loan fees is more pronounced for hard-to-borrow stocks. We do so by including in our main deal-by-deal regression interactions of *BC* with dummy variables to test for heterogeneous effects of *BC* on loan fees. We consider four different dummies, one for each of the hard-to-borrow proxies: specialness, size, illiquidity, and volatility. The specialness dummy is constructed by ranking stocks on each day according to their daily average loan fee. We then set the dummy to one for the deals on the stocks in the top quintile. For the other dummies, the same procedure is used—for size, we rank the stocks by market capitalization; for volatility, by the last five-day volatility of returns; and for illiquidity, by the closing bid-ask spread of the stock price.

As expected, the results in Table 16 show that for hard-to-borrow stocks the effect of *BC* on loan fees is stronger. Except for the illiquidity dummy, all interaction terms are negative and statistically significant. In Column 2, the coefficient on *BC* is −0.07 and the coefficient on *BC* × *special* is −0.18, which implies that the overall partial effect of *BC* on loan fee is −0.25 for special stocks. For small firms and volatile stocks, Columns 3 and 4, the overall partial effect is −0.16. We emphasize that although for hard-to-borrow stocks the effect of *BC* is stronger, its effect on other stocks continues to be negative and statistically significant. Taken together, these results justify the use of size, volatility, specialness, and, less clearly, illiquidity, as proxies for search costs.

Table 16
Interactions of *BC* with stock-specific search-cost proxies.
This table shows the estimates of deal-by-deal panel regressions of loan fees on BC and interaction of BC with four different dummies: specialness, size, illiquidity, and volatility. The specialness dummy is constructed by ranking stocks on each day according to their daily average loan fee. We then set the dummy to one for the deals on the stocks in the top quintile. For the other dummies, the same procedure is used—for size, we rank the stocks by market capitalization; for volatility, by the last five-day volatility of returns; and for illiquidity, by the closing bid-ask spread of the stock price. All regressions include stock–day fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

BC	−0.070***	−0.096***	−0.090***	−0.104***	−0.057***
	(0.008)	(0.013)	(0.011)	(0.014)	(0.008)
BC × special	−0.180***				−0.171***
	(0.029)				(0.027)
BC × small		−0.067**			−0.051*
		(0.029)			(0.027)
BC × vol			−0.074***		−0.038***
			(0.015)		(0.012)
BC × illiquid				−0.011	0.005
				(0.013)	(0.015)
Stock–day fixed effects	Yes	Yes	Yes	Yes	Yes
N	1,251,801	1,251,801	1,251,801	1,251,801	1,251,801
$R^2 - adj$	0.85	0.85	0.85	0.85	0.85

6. Further discussion

As shown by many authors, short-selling constraints reduces price efficiency by excluding information from price (Asquith, Pathak and Ritter, 2005; Nagel, 2005; Cao, Dhaliwal, Kolasinski and Reed, 2007; Saffi and Sigurdsson, 2011; Engelberg, Reed and Ringgenberg, 2012; and Boehmer and Wu, 2013). As was highlighted by KRR, it follows that the result that search costs affect loan fees does have important policy implications. A regulator could improve price efficiency in the stock market by reducing search costs. A natural way to reduce search costs is to reduce the opacity of the lending market. This could be done for instance via an electronic screen where lending offers are seen by all borrowers. In this section we present preliminary evidence that a lending electronic screen reduces both loan fee levels and loan fee dispersion.

In Brazil lending transactions can occur in two ways. Most loan transactions are closed OTC (in our sample, 90% of the lending volume is OTC). Alternatively, lenders can place shares for loan directly into an online system where brokers, representing borrowers, can electronically hit the offers.[20] Chague, De-Losso, De Genaro and Giovannetti (2014) use this feature of the Brazilian market to identify supply and demand shifts in the lending market and then estimate their effects on stock prices.

The more lending offers are placed on the screen, the more information the borrower has about current market conditions, and so the less opaque the lending market becomes. We measure opacity by computing for each stock–week pair the proportion $screen_{s,t}$ of the number of shares placed for loan on the electronic screen among the total number of shares loaned during that week. The numerator of $screen_{s,t}$ measures how active the screen is during the week in terms of the quantity of loan offers. The denominator of $screen_{s,t}$ measures how active the whole lending market is during the week. The lower $screen_{s,t}$ is, the more opaque the lending market for stock s in week t is.

[20] Only brokers have access to this electronic screen.

The variable $screen_{s,t}$ significantly varies both in the cross-section and in the time-series. However, the reasons behind these variations are not clear. In what follows we directly relate loan fee level and dispersion to $screen_{s,t}$. Since the variation in $screen_{s,t}$ might not be exogenous, we acknowledge that this exercise provides only preliminary evidence on the effect that an active lending platform could have on loan fee levels. We regress (i) the standard deviation of loan fees within each stock–week pair on the $screen_{s,t}$ variable, (ii) the range of loan fees within each stock–week pair on the $screen_{s,t}$ variable, and (iii) the average loan fee within each stock–week pair on the $screen_{s,t}$ variable. We standardize the $screen_{s,t}$ variable within each firm in order to purge it of stock-specific characteristics and to allow a better interpretation of the results. As usual, we first consider all deals (from all types of borrowers) and then we restrict the sample to deals from institutions, deals from large borrowers, and deals from frequent borrowers. Table 17 presents the results.

Considering all deals, we find that during weeks when the number of lending offers on the screen is one standard deviation higher than the average, the standard deviation of loan fees across deals is 0.057% lower, the range of loan fees is 0.441% lower, and the average loan fee is 0.193% lower, all significant at the 1% level. Considering deals only from institutions, the corresponding coefficients are 0.049% for the standard deviation, 0.394% for the range, and 0.187% for the average loan fee, all significant at the 1% level. Considering deals only from large borrowers, the coefficients are 0.054% for the standard deviation, 0.365% for the range, and 0.190% for the average loan fee, all significant at the 1% level. Finally, considering deals only from frequent borrowers, the coefficients are 0.049% for the standard deviation, 0.371% for the range, and 0.187% for the average loan fee, all significant at the 1% level. These estimates indicate that an active electronic screen in the lending market can reduce both loan fee levels and loan fee dispersion. Regulators should therefore consider the use of such platforms to reduce opacity and hence search costs in the lending market, which would increase price efficiency in the overall stock market.

Table 17
Loan fee level and dispersion vs. loan activity through screen.

This table show the estimates of panel regressions with *screen* as the explanatory variable. *screen* is the proportion of the number of shares placed for loan on the electronic screen to the total number of shares lent in the week. The numerator of *screen* measures how active the screen is in the week in terms of quantity of loan offers. The denominator of *screen* measures how active the lending market is in the week. The lower the *screen*, the more opaque is the lending market for the stock in the week. *screen* is standardized within stocks. Columns "Level" have as the dependent variable the average loan fee across all deals within each stock–week-pair. Columns "Std. dev." have as the dependent variable the standard deviation of loan fee across all deals within each stock–week-pair. Columns "range" have as the dependent variable the range of loan fee across all deals within each stock–week-pair. The first top three columns show the estimates considering all deals in our sample. The other columns show the estimates for the restricted samples according to the borrower type. Each borrower in our sample is classified into the following types: individuals, institutions, large, and frequent. The classification between individuals and institutions comes directly from the original data set. To classify a borrower as large we compute the average volume across all deals within each borrower and rank borrowers according to this. We then say that the top-5% are large borrowers. We say that borrowers that traded in more than half of the weeks are frequent. All regressions include week fixed-effects. Standard errors are presented in parentheses and are clustered by stock. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

	All deals			Institutions		
	Std. dev.	Range	Level	Std. dev.	Range	Level
Screen	−0.057***	−0.441***	−0.193***	−0.049***	−0.394***	−0.187***
	(0.012)	(0.072)	(0.051)	(0.012)	(0.066)	(0.051)
Week fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	8,388	8,396	8,396	8,382	8,393	8,393
$R^2 - adj$	0.04	0.04	0.03	0.04	0.04	0.03
	Large			**Frequent**		
	Std. dev.	Range	Level	Std. dev.	Range	Level
Screen	−0.054***	−0.365***	−0.190***	−0.049***	−0.371***	−0.187***
	(0.0127)	(0.063)	(0.053)	(0.012)	(0.058)	(0.052)
Week fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
N	8,348	8,371	8,371	8,356	8,386	8,386
$R^2 - adj$	0.04	0.04	0.03	0.04	0.05	0.03

7. Concluding remarks

This study yields empirical evidence regarding the effects of borrower-specific search costs on equity loan fees. We introduce a measure of search cost that is based on borrowers' connections and thus view the lending market as a relationship-based market. The degree of the borrower connectedness is calculated using a unique data set that comprises all loan deals in the Brazilian market from January 2008 to July 2011. For each deal we have information on the loan quantity, the loan fee, the borrower type, the borrower ID, the broker ID, and the lender ID.

Our empirical results confirm DGP's prediction that higher search costs result in higher loan fees. These results are robust to different specifications of search costs and still hold when the sample is restricted to institutions, to large borrowers, and to frequent borrowers. Our results extend the findings by KRR that document stock-specific search costs as important determinants of loan fees. Since higher loan fees and loan fee dispersion increase the costs and the risks of short-selling, an important policy implication is that a reduction of search costs in the lending market is very desirable. As KRR point out, this can be directly achieved by implementing a centralized trade platform. We contribute to this discussion by documenting the effect that the proportion of lending offers placed on the Brazilian electronic lending platform has on loan fees.

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