Does stock market illiquidity influence the cost of borrowing? Evidence from syndicated loans*

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Abstract

We find empirical evidence that firms with illiquid stock pay higher syndicated loan spreads. This result is invariant to multiple measurements of stock illiquidity, and is pronounced after we account for firm-level information opacity, a wide set of cross-sectional loan and firm features, as well as firm and year fixed effects. We, moreover, show that this result holds using a propensity-score matching difference-in-differences identification strategy. This strategy relies on an exogenous regulatory change in the minimum tick size of major United States exchanges, which improves the stock market liquidity but not firms' fundamentals. While stock illiquidity is shown to diminish the benefit to the loan recipient of a lending relationship, variation in information opacity does not substantively change this benefit. A rationale for these findings is that stock market illiquidity reduces the bargaining power of corporate borrowers, in the loan spread negotiating process, as it raises the cost of alternatively issuing equity. Our findings, thus, indicate that relative bargaining power plays a systematic role in determining syndicated loan spreads.

Keywords: Market illiquidity, information opacity, bargaining power, lending relationship, costs of borrowing

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1 Introduction

Stock market illiquidity can constrain a firm's capacity to avail of external financing. It is a critical component in successful initial public offerings (Corwin, Harris and Lipson, 2004) and in seasoned equity offerings (Stulz, Vagias and Van Dijk, 2013). Indeed, investment banks' fees are significantly lower for firms with more liquid stock (Butler, Grullon and Weston, 2005). Stock market liquidity can, furthermore, improve a firm's profitability, investment, value and productivity as well as substantively alter its dividend and capital structure decisions (Campello, Ribas and Wang, 2014; Zucchi, 2014), all of which can influence a firm's capacity to avail of external financing. In this paper, we address a natural question which arises as to whether there is an influence of stock market illiquidity on the cost of borrowing.

Using a large sample of syndicated loans covering 1,700 U.S. listed firms over the period 1988 to 2011, we empirically test whether stock market illiquidity affects the cost of syndicated loans. Our findings suggest that firms with less liquid stock pay significantly higher loan spreads, accounting for a wide variety of firm and loan features which pertain to loan spreads, as well as firm and year fixed effects. For instance, one percent widening in the bid-ask spreads translates into 13 basis points increase in the interest rates, which are roughly 7% of the sample mean ($6.68 \times 1.98/197.14$). A similar relationship is also evident when we study alternative stock market microstructure illiquidity measures including the closing effective spreads, Roll's (1984) effective spreads, the effective ticks (Goyenko, Holden and Trzcinka, 2009; Holden, 2009) , trading days with a zero returns measure (Lesmond, Ogden and Trzcinka, 1999) and the Amihud illiquidity ratio (Amihud, 2002).

One possible explanation of this stock illiquidity - loan spreads relationship is through information asymmetry (the adverse selection component of illiquidity). According to market microstructure theories, adverse selection is an important component of the bid-ask spread (e.g. Huang and Stoll, 1997). On the other hand, information asymmetry between lenders and borrowers has long been known to increase the cost of borrowing (e.g. Santos and Winton, 2008; Schenone, 2010; Bosch and Steffen, 2011)[1]. Indeed, Bharath, Dahiya, Saunders and Srinivasan (2011) use the first principal component of several microstructure adverse selection measures, and find it to explain loan spreads. Hence, in our study of the illiquidity - loan spreads relationship, we account for this information asymmetry effect in accordance with Bharath, Pasquariello and Wu (2009), with adaptation to our sample period. Our information asymmetry index (ASY) is the first component of a PCA decomposition of the following six variables: the adverse selection component of bid-ask spreads, the adverse selection component of Roll's (1984) effective spread (George, Kaul and Nimalendran, 1991), the return-volume coefficient of Llorente, Michaely, Saar and Wang (2002), the price impact measures of Amihud (2002), the modified Amihud, and the gamma coefficient of Pástor and Stambaugh (2003). We also account for the adverse selection component of bid-ask spread and Roll's (1984) effective spread (George, Kaul and Nimalendran, 1991) as standalone measures of information asymmetry. Our empirical results indicate that the

[1]For example, Santos and Winton (2008) find that banks exploit their private information about borrowers which have no access to public debt market, by charging higher spreads and raising more rates in recession. Using borrowers' initial public offer (IPO) as an information-releasing event, Schenone (2010) documents a drop in the mean interest rates after IPO. Bosch and Steffen (2011) find that the information effect of ratings on loan spreads is more pronounced to privately held firms, and is insignificant for exchange listed firms which have regular public information disclosures.

liquidity effect on loan spreads still holds even if we control for adverse selection, as reflected in a range of microstructure measures of information asymmetry.

We further identify the relationship between market illiquidity and loan spreads in a quasi-natural experiment. Around 2001, the three major U.S. stock exchanges reduced the minimum tick size from 1/16 dollar to 1 cent. This decimalisation event significantly improved the market liquidity (Bessembinder, 2003) and, critically, the improvement varied across firms. Similar to Fang, Tian and Tice (2014), we match firms on the *ex ante* propensity to receive a large liquidity shock from the decimalisation. We compare the *ex post* change in loan spreads of firms which experience large liquidity improvement due to decimalisation (treated group) with those which have similar propensity but do not receive such liquidity improvement (control group). Independent of the stock market illiquidity improvement, treated and control group loans are standardized on firm and loan level features. The results suggest that, albeit both treated and control groups witness an overall increase in loan spreads, firms receiving a large exogenous liquidity (positive) shock experience a significantly smaller increase (78 basis points less) than those without. This propensity-score matching difference-in-differences test enables us to identify a causal relationship between stock market illiquidity and loan spreads. Assessing the changes of loan spreads around decimalisation, when the borrowing firms receive heterogeneous levels of liquidity improvement due to this exogenous regulatory event, we confirm that stock market illiquidity leads to higher loan spreads.

Our main finding of the illiquidity - loan spreads relationship is consistent with Zucchi (2014), which argues for a positive firm-level internal (cash) and external (stock market) liquidity relation that cannot be matched with adverse selection. Zucchi (2014) models an internal-external liquidity loop, through which corporate liquidity and market liquidity stimulate each other. The external illiquidity limits firms' corporate policies, such as precautionary liquidity holding, financial constraints, investment decisions and, hence, corporate values. These consequences again discourage liquidity providers and further reduce the market liquidity. The model of Zucchi (2014) therefore provides formal insight on a channel which can link external illiquidity and, ultimately, those factors related to the capacity of a firm to borrow.

Lending relationships between borrowers and lenders have been found to influence the cost of borrowing, and this effect is closely related to the bargaining power and the information transparency of the borrowers. These arguments predict distinct and contradictory impacts of lending relationships on loan spreads. On the one hand, Boot and Thakor (1994) contend that intensified lender-borrower relationship diminishes information asymmetry between the lender and the borrower, and should hence reduce the borrowing costs. On the other hand, Sharpe (1990) predicts an increase in interest rate as lender-borrower relationship intensifies, since lenders' increasing monopoly allows them to exploit the private information about their captive customers (also see Santos and Winton, 2008). This monopoly scenario is limited, however, if the borrowing firms issue public debt (Diamond, 1991; Rajan, 1992). Saunders and Steffen (2011) note that public firms exhibit a negative association between relationship lending and loan spreads; while private firms exhibit the opposite association. Public firms are, hence, less likely to be "held up" due to having greater "bargaining power" vis-a-vis the relationship lenders. Following this line of argument, the less costly access to the equity market, the stronger is this negative association between relationship lending and loan spreads for public firms. One important cross-sectional variant with respect to the cost of capital on the equity market is the stock illiquidity (e.g. Amihud and Mendelson, 1986; Easley, Hvidkjaer and O' Hara, 2002; Butler, Grullon and Weston, 2005; Liu, 2006). Therefore, we test the effect of lending relationship on loan spreads conditioning on stock illiquidity.

We assess how stock market illiquidity influences the role of relationship lending. Our main finding, consistent with Boot and Thakor (1994), suggests that past relationship translates into about a 10 basis point reduction in the loan spreads. This benefit to the loan recipient is diminished if the recipient is illiquid in the stock market, but does not materially vary with variation in information asymmetry. This main finding is, hence, in line with Sharpe (1990) in that lenders can "hold up" their relationship borrowers and charge them with higher interest rates if the borrowers are more constrained with respect to external financing - higher stock market illiquidity. Our results are robust when we control for bond market access of the corporate borrower.

We contribute to the extant literature on the implications of stock market illiquidity. Most studies examine how stock illiquidity affects stock prices and corporate policy. We are the first, to the best of our knowledge, to provide evidence for the impact of stock illiquidity on loan spreads. It is interesting to show how market liquidity in one asset market affects the asset price (loan spreads) in another market of the same underlying firm. Furthermore, we not only show the positive association between stock illiquidity and the loan spreads paid by the borrower, but also establish a causal link by employing a quasi-natural experiment in which stock liquidity is prone to an exogenous shock.

This paper also adds to the literature on external financing. Traditional corporate finance literature argues firm might be constrained from external financing due to information asymmetry. This problem is particularly severe for mall and medium-sized enterprises. However, we show that even Compustat firms (usually large and publicly listed firms) whose information opacity is less of a problem, may be constrained due to a new channel of bargaining power when their stock liquidity is low. We show that such firms may have a lower bargaining power and hence pay higher interest rates relative to firms with liquid stocks.

The remainder of this paper is organised as follows. In Section 2 we develop our hypotheses tests. In Section 3 we present our methodology. A description of our data and our main empirical results are reported in Section 4. Section 5 concludes.

2 Hypotheses

Zucchi (2014) proposes a channel through which secondary stock market illiquidity constrains a firm's capacity to raise funds. The idea is that, in order to encourage stock investors' participation, a firm with illiquid stocks needs to promise an illiquidity premium which compensates for the costs associated with liquidity shocks that investors may unwind. The premium takes the form of larger payout rates, which further constrains the firm and makes outside funding more difficult. We extend the line of the reasoning and propose that the firm may be forced into a disadvantaged position when negotiating with banks which are major providers of external funds. Consequently, the firm with weaker bargaining power due to illiquid stocks may be charged of higher lending interest rates by the banks. Hence, we propose our first hypothesis:

H1: Firms with less liquid stock have higher costs of borrowing.

Information opacity of the firm may affect the cost of borrowing, given the classic information friction in the borrower-lender setting. On the other hand, information opacity may also enhance adverse selection, which is an important component of secondary market illiquidity (e.g. George, Kaul and Nimalendran, 1991; Huang and Stoll, 1997). Bharath, Dahiya, Saunders and Srinivasan (2011) find the information asymmetry estimated from market illiquidity can explain the loan spreads. Nevertheless, stock illiquidity can affect loan spreads through restraining financial constraints and diminishing bargaining power, in addition to the channel of information asymmetry (Zucchi, 2014). Therefore, we propose our second hypothesis:

H2: Firms with less liquid stock have higher costs of borrowing even controlling for information asymmetry.

According to Zucchi (2014), firms with illiquid stock have more corporate policy and financial constraints; hence these firms have lower bargaining power in the negotiation process, and are more likely to be *held up* by the relationship lenders. This is in line with Sharpe's (1990) prediction. In fact, some empirical studies provide implications in support of this argument. For example, Saunders and Steffen (2011) find that albeit loan spreads decrease as relationship intensifies for public firms, private firms pay higher loan spreads for relationship lenders. They also find that public firms listed on illiquid Small Cap/AIM stock market do not pay lower spreads compared to private firms. We hence propose our last hypothesis:

H3: Firms with less liquid stock benefit less from a past relationship with a lender than liquid firms.

3 Methodology

3.1 Measuring market illiquidity

Holden, Jacobsen and Subrahmanyam (2014) define market liquidity as "the ability to trade a significant quantity of a security at a low cost in a short time", which specifically points the three aspects of liquidity: cost, quantity and time. As liquidity is not directly observable, researchers have used a variety of proxies to measure liquidity. Some proxies are intuitive or heuristic, closely related to the three dimensions of liquidity; others are built based on theoretical models, such as price reversal and price impact of volume (Vayanos and Wang, 2012). In this study, we use six different illiquidity measures, namely, closing percent bid-ask (Chung and Zhang, 2014), closing effective spread, Roll's effective spreads (Roll, 1984), effective ticks (Goyenko, Holden and Trzcinka, 2009; Holden, 2009), number of zero-return days (Lesmond, Ogden and Trzcinka, 1999), and the Amihud illiquidity ratio (Amihud, 2002).

(i) **Closing percent bid-ask spread**

Liquidity is often measured by the bid-ask spread, which captures the cost dimension of liquidity. Many researchers rely on high-frequency databases such as NYSE Trade and Quote (TAQ); however, it is not only financially expensive and time-consuming to process large sample over a long period, it is also subject to errors mainly due to withdrawn quotes, and moreover, the spreads may vary substantially using different quote timing rules.[2] Recently, scholars in market microstructure studies have evaluated a variety of spread measures estimated from low-resolution data, and many of them well simulate high-frequency liquidity measures. For example, Corwin and Schultz (2012) derive a simple way to estimate bid-ask spread from daily *Ask/High* and *Bid/Low* prices from CRSP, which is highly correlated with TAQ based spread measure; and Chung and Zhang (2014) find that using daily *Bid* and *Ask* fields provided by the CRSP database, one can construct a spread measure, which has cross-section correlation with TAQ based spread of more than 0.9. We hence follow Chung and Zhang (2014) and calculate bid-ask spread $baspr_t$ as the average daily closing percent bid-ask spread during the time interval t:

$$baspr_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{Ask_i - Bid_i}{Mid_i}, i = 1, 2, \cdots, N_t, \tag{1}$$

where Mid_i is the midpoint of Ask_i and Bid_i, and N_t is the total number of days at time interval t.

(*ii*) **Closing percent effective spread**

However, given that many trades are executed between the best bid and ask price, an alternative measure of spread accounting for the "inside-spread" transactions is percent effective spread, defined as twice as the difference between the closing trade price and the closing bid-ask midpoint, as a proportion to the bid-ask midpoint, averaged over the time interval.

$$effspr_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\frac{2 \times |Prc_i - Mid_i|}{Mid_i}, i = 1, 2, \cdots, N_t. \tag{2}$$

(*iii*) **Roll's effective spread**

The autocovariance of returns reflects the ability of the market to revert from liquidity shocks. Roll (1984) develops theoretical framework that connects price reversal with spread. Let V_i be the unobservable fundamental value of the stock on day i, which follows a simple random walk, and the observed transaction price of stock is the fundamental value V_i plus half spread S:

$$V_i = V_{i-1} + e_i \text{ and } P_i = V_i \pm \frac{1}{2}S. \tag{3}$$

Combining two equations above, Roll (1984) proves that spread can be interpreted as twice as the square-root of the negative autocovariance of price change. We substitute positive serial autocovariance with zero in the same vein as Goyenko, Holden and Trzcinka (2009).

$$Roll = \begin{cases} 2\sqrt{-Cov(\Delta P_i, \Delta P_{i-1})} & \text{when } Cov(\Delta P_i, \Delta P_{i-1}) < 0, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

[2]See Holden and Jacobsen (2014) for a detailed discussion.

(*iv*) **Effective tick**

Goyenko, Holden and Trzcinka (2009) and Holden (2009) point out that it is possible to estimate effective spread from the end-of-day trade price cluster, given two assumptions: 1) the effective spread of one day is equal to the increment of price cluster on that day; 2) the daily closing price is uniformly distributed on the possible price increments.

Let N_j be the number of days where price cluster correspond to the jth spread s_j, where $j = 1, 2, \cdots, J$, and let F_j be the corresponding probability,

$$F_j = \frac{N_j}{\sum_{j=1}^{J} N_j}, j = 1, 2, \cdots, J. \tag{5}$$

The unconstrained probability U_j of the jth spread is

$$U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \cdots, J-1 \\ F_j - F_{j-1}, & j = J. \end{cases} \tag{6}$$

To control for unconstrained probability going below zero due to reverse price clustering, the constrained probability of the jth spread is calculated as:

$$C_j = \begin{cases} Min[Max\{U_j, 0\}, 1], & j = 1 \\ Min[Max\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} C_k], & j = 2, 3, \cdots, J. \end{cases} \tag{7}$$

And finally, the effective tick is calculated as the probability-weighted average spread divided by average price in time interval t

$$efftick_t = \frac{\sum_{j=1}^{J} C_j s_j}{\bar{P}_t} \tag{8}$$

The spread set $\{s_1, s_2, \cdots, s_J\}$ is dependent on the price grid, which is related to the minimum ticksize. In this paper, we infer the spread set based on the three minimum ticksize regimes:

$$\{s\} = \begin{cases} \$\frac{1}{8}, \$\frac{1}{4}, \$\frac{1}{2}, \$1, & \text{before year 1997,} \\ \$\frac{1}{16}, \frac{1}{8}, \$\frac{1}{4}, \$\frac{1}{2}, \$1, & \text{from year 1997 to 2000,} \\ \$0.01, \$0.05, \$0.1, \$0.5, \$1, & \text{from year 2001 onwards.} \end{cases}$$

(*v*) **Zero**

Another intuitive liquidity proxy that captures the cost aspect is introduced by Lesmond, Ogden and Trzcinka (1999). Calculated as the number of days with zero returns over total number of trading days, *zero* indicates the value of information relative to the transaction cost. When the transaction costs are high, traders will refrain from trading if the value of new information cannot over come the transaction cost. Therefore, in a limit order market, we will observe more zero-return days.[3] Let r_i and vol_i denote the return and trading

[3]Lesmond, Ogden and Trzcinka (1999) show that the effective number of zero-return days, which includes

volume (in shares) on day i during period t respectively, $zero$ can be interpreted as:

$$zero_t = \frac{N_t(r_i = 0)}{N_t}, i = 1, 2, \cdots, N_t. \tag{9}$$

(vi) **Amihud**

Amihud (2002) employs a market illiquidity measure as "the daily ratio of absolute stock return to its dollar volume". It calibrates the daily price change in response to one million U.S. dollars. Let r_i and $\$vol_i$ denote the return and dollar volume (in millions) on day i respectively, the Amihud illiquidity measure during period t is calculated as:

$$Amihud_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{|r_i|}{\$vol_i}, i = 1, 2, \cdots, N_t. \tag{10}$$

3.2 Measuring information asymmetry

Extensive market microstructure literature suggest that transaction cost mainly comes from three sources, order processing cost, inventory risk and adverse selection (e.g. Huang and Stoll, 1997). Based on the theoretical models and empirical implications, Bharath, Pasquariello and Wu (2009) construct an information asymmetry index from seven indicators,[4] which relate to adverse selection, informed trading or price impact. They show that this information asymmetry gauge has desirable properties as they are sensitive to corporate events and firm characteristics, as well as dynamic; in a later paper (Bharath, Dahiya, Saunders and Srinivasan, 2011), they also show a relation between this measurement and loan spread. Hence, we measure information asymmetry in accordance with Bharath, Pasquariello and Wu (2009), and we make slight adjustment to adapt to our sample period. Our information asymmetry index ASY is the first component of PCA decomposition of the following six variables: the adverse selection component of bid-ask spread and Roll's (1984) effective spread (George, Kaul and Nimalendran, 1991), the return-volume coefficient of Llorente, Michaely, Saar and Wang (2002), the price impact measures of Amihud (2002), its modification and Pástor and Stambaugh (2003).

(i) **Adverse selection**

George, Kaul and Nimalendran (1991) develop a simple model to decompose the quoted spread into an order processing cost component and an adverse selection component. Let R_{Ti} and R_{Bi} be the daily return calculated from closing transaction prices P_{Ti} and the subsequent bid quotes P_{Bi} respectively, the difference between the two, $RD_i = R_{Ti} - R_{Bi}$, can be used to estimate the order processing cost s_{sj} during month j,

the non-zero-return days due to bid-ask bounce, is closely related to the zero-return days reported by CRSP.

[4] These seven indicators are: the adverse selection portions of both the quoted and Roll's (1984) effective spread (George, Kaul and Nimalendran, 1991), the return-volume coefficient of Llorente, Michaely, Saar and Wang (2002), the probability of informed trading of Easley, Kiefer and O'Hara (1996), the price impact measures of Amihud (2002), Cooper, Groth and Avera (1985) and Pástor and Stambaugh (2003).

$$s_{2j} = 2\sqrt{-Cov(RD_i, RD_{i-1})} = \pi s_{qj}. \tag{11}$$

where s_{qj} is the observed quoted spread in month j (calculated as the daily average), and π is the unobservable proportion of the quoted spread due to order processing cost. An unbiased yearly measure of π can be estimated as $\hat{\pi} = \hat{\beta}_2$ from the following regression:

$$\hat{s}_{2j} = \alpha_2 + \beta_2 s_{qj} + \varepsilon_j. \tag{12}$$

Therefore, our yearly adverse selection component GKN can be calculated as $(1 - \pi)$ multiplied by the averaged daily bid-ask spread over the year *baspr*. Also, in line with Bharath, Pasquariello and Wu (2009), we also estimate $RGKN$ by substituting bid-ask spread with Rolls effective spread *Roll*:

$$GKN = (1 - \hat{\pi}) \cdot baspr, \tag{13}$$

$$RGKN = (1 - \hat{\pi}) \cdot Roll. \tag{14}$$

(ii) **Informed trading**

Based on the notion that returns accompanied by high volume tend to reverse themselves when speculative trading is insignificant and *vice versa*, Llorente, Michaely, Saar and Wang (2002) develop a model that implies the level of informed trading from return-volume relation. In the following regression, $C2$ is proportional to the level of informed trading:

$$R_{i+1} = C0 + C1 \cdot R_i + C2 \cdot ViRi + \varepsilon_{i+1} \tag{15}$$

where Ri is the daily return on day i, and V_i is the detrended log turnover,

$$V_i = ln(turnvr_i) - \frac{1}{200} \sum_{\tau=-200}^{-1} ln(turnvr_{i+\tau}). \tag{16}$$

A small constant 0.00000255 is added to turnover before taking the natural log to avoid the problem of zero daily trading volume.

(iii) **Modified Amihud illiquidity ratio**

Enlighted by Amihud measure 10, we substitute the denominator daily trading volume $\$vol_i$ with daily turnover $turnvr_i$:

$$Amimod_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{|r_i|}{turnvr_i}, i = 1, 2, \cdots, N_t. \tag{17}$$

(*iv*) **Pastor-Stambaugh**

Built on the assumption that order flow induces greater return reversals when liquidity is lower, Pástor and Stambaugh (2003) measure the market liquidity during period t using the $\hat{\gamma}_t$ estimates from the following regression:

$$r^e_{i+1,t} = \theta_t + \phi_t r_{i,t} + \gamma_t \cdot sign(r^e_{i,t}) \cdot \$vol_{i,t} + \varepsilon_{i+1,t}, i = 1, 2, \cdots, N_t \tag{18}$$

where $r_{i,t}$ is the stock return on day i in period t, and $r^e_{i,t}$ is the excess return, which is measured as stock return $r_{i,t}$ minus CRSP value-weighted return $r^m_{i,t}$; $\$vol_{i,t}$ is the daily trading volume measured in million dollars. In this paper, a γ_t is calculated for each month (year) if there are more than 15 (180) positive volume days.

3.3 Control variables

We include a number of firm level controls that may affect the lending interest rates. First, we include firm size, as larger firms are less risky and more information transparent. Next, we control for leverage and ROA, as highly leveraged firms and less profitable firms are more likely to default. As for the firm specific controls that affect loss given default (LGD), we include net working capital (NWC) and tangible assets. Firms with more net working capital and a higher fraction of tangible assets are expected to lose less value in the event of default. We also control for Market-to-Book ratio (Firm MKTBOOK), an imperfect proxy of Tobin's Q, which is a ratio of the market value of a firm to its accounting value. We expect a firm with a higher Market-to-Book ratio to have lower spreads. Finally, we include industry dummies that classify borrowers into ten sectors based on 4-digit SIC codes, considering that loss given default (LGD) is strongly correlated with industry characteristics (Hertzel and Officer, 2012; James and Kizilaslan, 2014).

We also include several non-pricing loan features as they may reflect the default risks (Sufi, 2007). In specific, we include Facility Size and Maturity to proximate these features. The signs of their impact on loan spread are both ambiguous: large loans are likely to be associated with greater credit risk in the underlying project and lower liquidity, but could also be borrowed by larger firms which tend to have lower risks; it is similar in regard to maturity. Next, we use the number of lenders in a facility (No. of Lenders) and the number of facilities within a deal (No. of Facilities) to proxy the syndicated structure. To measure the liquidity exposure of each facility, we classify a loan as a line of credit (Revolver) or a term loan (Term Loan). Moreover, we include dummy variables that indicate whether a loan is senior (Senior) in the borrower's liability structure and whether the loan is secured by collateral (Secured). Seniority and collateral may reduce the lenders' loss in the event of borrower default and therefore reduce lending rates, however, the contractual arrangement may be required ex-ante to protect lenders towards specifically risky borrowers. Therefore, the relation between seniority, collateral and loan pricing is an empirical question. Last, we control for loan purpose dummies into five categories: Corporate Purpose, Debt Repayment, Takeover, Working Capital and Other.

In particular, we use the accounting information of the borrower from the fiscal year ending in the calendar year for loans made in calendar year. To eliminate the bias from outliers, we winsorise loan spreads, firm specific variables and borrowers' opacity measures at the 1 and 99 % levels. We include year dummies to capture time trends throughout the analysis as Santos and Winton (2008) have shown the business cycle effect on loan contracts.

3.4 Loan pricing model

Finally, our baseline loan pricing model is defined as follows:

$$LoanSpr_{f,l,t} = c + \beta Illiq_{f,t-1} + \sum_{m} \gamma_m Firm_{f,m,t-1} + \sum_{n} \theta_n Loan_{l,n,t} + \sum_{t} \delta_t T_t + \varepsilon_{f,l,t}, \tag{19}$$

where f, l, and t denote firm, loan and year, respectively. The dependent variable, $LoanSpr$, is the all-in-drawn spread in Dealscan which denotes an interest rate spread over LIBOR measured in basis points. It is a measure provided by Dealscan of overall costs of the loan, accounting for both one time and recurring fees. $Illiq$ is one of the market microstructure measures of firm's illiquidity; it can be one of bid-ask spread (baspr), effective spread (effspr), Roll's spread (Roll), effective tick (efftick), proportion of zero-return days (zero) and Amihud illiquidity ratio (Amihud). Moreover, we include the set of firm-level and loan-level control variables, $Firm$ and $Loan$. We also include year dummies T to control for year fixed effect. Lastly, $\varepsilon_{f,l,t}$ is the error term. We estimate the baseline loan pricing model by cross-sectional OLS regressions that pool together all valid observations. Robust standard errors are clustered at the firm level to correct for correlations across observations of a given firm.

4 Empirical analysis

4.1 Data

The data for this study come from LPC Dealscan, S&P Compustat and the Center for Research in Security Prices (CRSP) over the period between 1988 and 2011[5]. We exclude loans extended to US borrowers in financial industries (SIC codes 6000 to 6400, Finance and Insurance).

Dealscan is a database of loans provided by Thomson Reuters Loan Pricing Corporation, which covers most loans made to large publicly traded companies (Strahan, 1999). A deal is a loan contract agreed by the borrower and the lender(s), on a specific date of origination. Each deal is comprised of one or several facilities, or tranches, and they can vary significantly in the spreads (over LIBOR) due to different lender identities, collateral status and other contractual features. Dealscan provides detailed information about each facility, including borrower ID, deal active date, facility start date, facility end date, loan type, primary purpose, maturity, secured indicator, distribution method, senority indicator, deal amount, deal purpose, deal status, currency, exchange rate, sales at close, sales, institution type, public indicator, primary SIC; lenders ID, lender role, lead arranger credit indicator, number

[5]Before 1987, the coverage of Dealscan is uneven (see Strahan, 1999). We are indebted to Sudheer Chava and Michael Roberts who provide the link between Dealscan with Compustat until year 2011 (see Chava and Roberts, 2008).

of lenders, number of lead arrangers, number of participants, share of lead arranger(s), and all-in drawn spread over LIBOR. We treat facilities in each deal as different loans because spreads, identity of lenders and other contractual features often vary within a syndicated loan deal (see Carey and Nini, 2007; Focarelli, Pozzolo and Casolaro, 2008; Santos, 2011; Gaul and Uysal, 2013). Therefore, each observation in the regressions denoted by Eq. (19) corresponds to a syndicated loan facility.

Compustat collects annual report data of publicly listed American companies. By merging Dealscan with Compustat, we have detailed annual accounting information of the borrowers. Specifically, we obtain firms total asset, leverage ratio, return on assets (ROA), net working capital (NWC), tangible assets, market-to-book ratio (MTB) and the 4-digit SIC codes.

We rely on the CRSP database to calculate our market-based proxies for stock illiquidity and information asymmetry. In particular, we collect daily trade data over the year leading up to the facility activation date for borrowers listed in NYSE, AMEX and NASDAQ. For each stock, we record the closing ask/bid price, ask high/bid low price, last trade price, volume and shares outstanding. Ask high (bid low) records the highest (lowest) transaction price of the day; and if there is no trade, it returns the last bid (ask) price. Similarly, closing price records the last trade price if there are trades, and bid-ask midpoint if otherwise.

Finally, our sample consists of $10,877$ loans taken out by $1,779$ U.S. firms. All firm level variables are winsorised at the 1% and 99% levels. The definitions and data sources of all the variables are presented in the appendix Table A1, and the summary statistics and sample distribution are presented in Table 1 and 2.

[Please insert Table 1 and 2 about here.]

4.2 Empirical results

4.2.1 Baseline analysis

According to the theoretical link between market illiquidity and financial constraints, we expect to observe that market illiquidity provides additional explanatory power to the variance of loan spreads. To begin with, in Figure 1 we plot the average loan spread residuals in illiquidity deciles, from the most liquid to the least liquid. The loan spread residuals are calculated as the actual all-in-drawn spread minus the predicted spread from an OLS regression based on a set of control variables as described in Section 3.3[6]. The residuals capture the loan spread component which cannot be explained by these firm and loan features.

[Please insert Figure 1 about here.]

As shown in Figure 1, we observe a monotonic increasing trend of average loan spread residuals for all six measures of illiquidity. The mean all-in-drawn residuals for firms in the

[6]The regression is defined as:

$$LoanSpr_{f,l,t} = c + \sum_{m} \gamma_m Firm_{f,m,t-1} + \sum_{n} \theta_n Loan_{l,n,t} + \sum_{t} \delta_t T_t + \varepsilon_{f,l,t}.$$

least liquid decile is two to five times as much as those in the most liquid decile. Also, it is important to note that although the unit of *Average All-in-drawn Residuals* shown on the Y-axis is very close to zero (1×10^{-13} basis point), it does not necessarily indicate an infinitesimal effect. Because the residual loan spreads can take both positive and negative values, which can bring the mean towards zero. In the following paragraph, we test the magnitudinal marginal effect of illiquidity on loan spreads with multivariate models.

Next, we apply the baseline loan pricing model Eq. (19) to examine the impact of stock illiquidity on the costs of borrowing among U.S. public firms. In particular, we alternatively regress the all-in-drawn spreads on the six stock illiquidity measures, i.e., bid-ask spread (baspr), effective spread (effspr), Roll's effective spread (Roll), effective tick (efftick), proportion of zero-return days (zero) and Amihud ratio (Amihud). We also control for the set of firm and loan characteristics described in Section 3.3 as well as year dummies. The corresponding results are shown in Column (1) to (6) in Table 3[7].

[Please insert Table 3 about here.]

Column (1) suggests that firms with higher bid-ask spreads (baspr) in the stock market pay higher borrowing rates.One standard deviation widening in the bid-ask spreads translates into 13 basis points increase in the interest rates, which are 7% of the sample mean ($6.68 \times 13.23/197.14$). Using effective spread (effspr) in replace of bid-ask spreads, as shown in Column (2), we find similar results, but greater sensitivity (11.67). In Columns (3) and (4), we show that the coefficients of alternative effective spread measures, Roll's (1984) effective spread (Roll) and Goyenko, Holden and Trzcinka (2009) and Holden (2009) effective tick (efftick), are also positive and highly significant, consistent with the previous findings. Moreover, in Column (5) it suggests that borrowers with more zero-return days (zero) in the stock market are usually charged with higher loan spreads. When measuring market illiquidity as the price impact of one million dollar volume, in Column (6), the Amihud (2002) illiquidity measure shows a statistically significant (5%) and positive (3.72) coefficient, indicating that firms with greater stock market price impact are likely to pay higher interest rates in the syndicated loan market. Overall, across all six columns, these *illiquidity premia* are all economically and statistically significant. These results support our first hypothesis that externally illiquid firms have higher costs of borrowing.

Turning to the control variables, it shows in Table 3 that the most of the coefficients are statistically different from zero and have expected signs. In specific, we find that large firms, more profitable firms and firms with higher net working capital tend to pay lower interest rate, whereas highly leveraged firms are charged higher loan spreads. The coefficients of tangible assets and the market-to-book ratio, however, are not significantly different from zero. In terms of loan-specific features, we find that loans with more lenders, larger size and longer maturity are associated with lower interest rates; credit lines (revolver) and senior loans (dummy senior) are also cheaper. Nevertheless, loans with greater number of facilities and secured by collaterals are charged at higher loan spreads; this is likely because risky firms are more often requested to provide collaterals. The coefficients of control variables give support to the overall credibility of our baseline model.

[7] We also alternatively regress the loan spreads on the three information opacity measures, i.e., GKN, RGKN and ASY, in replace of illiquidity measures. We report these latter regression coefficients in Column (1) to (3) in Appendix Table A2. These results are comparable to Bharath, Dahiya, Saunders and Srinivasan (2011).

Hence, Table 3 provides empirical evidence that firms' illiquidity in the stock market are positively and significantly associated with firms borrowing cost. However, one may argue that this relationship might be driven by information asymmetry, since adverse selection is an important component of stock market illiquidity (e.g. Huang and Stoll, 1997). Moreover, there might be omitted variables that drive both stock illiquidity and loan spreads. In the following section, we conduct a series of robustness tests to account for information asymmetry, default risk and firm fixed effects.

4.2.2 Robustness tests of baseline regressions

In this section, we apply a battery of robustness tests (i) to distinguish the effect of market illiquidity from information asymmetry (the adverse selection component of illiquidity); (ii) to show that our results are not driven by imperfect control of firms' default risk; and (iii) to control for the potential endogeneity problem due to omitted variables in the baseline specification (that unobserved time-invariant firm characteristics drive both firms' stock illiquidity and loan spreads). We focus our discussion on bid-ask spread measure of illiquidity[8], as presented in Panel A of Table 4. The robustness tests are applied in a similar way to the other five illiquidity measures, and we report these results in Panel B to F of Table 4.

[Please insert Table 4 about here.]

In Panel A of Table 4, the first column shows the baseline pooled OLS estimates as in the previous section. In Columns (2) to (4), we respectively add an information opacity measure GKN, RGKN and ASY, to control for the effect of information asymmetry. The coefficient of the bid-ask spread remains positive and highly significant (at 1% level) through (2) to (4), confirming that the connection between firms' market illiquidity and borrowing costs cannot be explained by information asymmetry. Turning the magnitude of this coefficient, in Column (2) the coefficient of bid-ask spread is 3 unit larger than that in Column (1), which coincides with a negative and significant coefficient of GKN (-3.52). This can be caused by the multicollinearity between baspr and GKN, where the latter is a component of the former. The coefficients of bid-ask spread in Column (3) and (4) are similar to that in Column (1), with insignificant coefficients on the information asymmetry measures, RGKN and ASY.

The second robustness test is in regard to the potential imperfect control of default risk. We include credit ratings from Standard & Poor in Column (5), despite that our sample size is halved, as about 50% of the loans are taken out from firms which are not rated by S&P. In particular, we adopt the S&P domestic long term issuer credit rating. The variable S&P rating takes value of 1 if the firm has AAA rating; and the value increases as the rating deteriorates; the highest value is 17 for ratings below B-. Thus "good" firms take a lower value, whereas firms with higher default risk take greater values. We find that one notch downgrade of S&P rating is related to about 19 basis points rise in the interest rates, which is consistent with our expectation that firms of higher default risk pay higher interest rates.

[8]We focus on the bid-ask spread because based on the empirical comparison between TAQ-based spread and a variety of low-frequency liquidity measures, Chung and Zhang (2014) find that the simple CRSP-based spread provide a better approximation.

Despite the significant impact of credit ratings on loan spreads, the coefficient of the bid-ask spread measure is positive and significant at the 1% level. The adverse selection index (ASY) remains insignificant as in Column (4). Nevertheless, the coefficients of some of the firm-level control variables alter drastically. For example, coefficient of firm size switches from significantly negative in the previous regressions to significantly positive, and those of leverage ratio and ROA become insignificant. It implies that the S&P Rating variable has captured a large portion of the variance explained by these three variables.

Lastly, although one caveat may arise if our specification is prone to, if any, unobserved firm factors, for instance, CEO management, we take care of this omitted variable bias by estimating a firm fixed effects model and showing that the pricing patterns hold. Specifically, we restructure the data set into panel data in which we have $f = firm$ as the cross section unit and $l = loan$ as the time series unit. We estimate a firm fixed effects model, allowing for arbitrary correlation between the unobserved borrower effect and the observed explanatory variables. The identification comes from variations in stock illiquidity and loan spreads within the same firm. In particular, we compare loan spreads of the same firm across different loans when stock illiquidity differ before the loan origination. The ASY measure of information opacity is also included in the fixed effect model specification to control for information asymmetry. As it shows in Column (6), the coefficient of the bid-ask spread measure is quantitatively alike as in Column (4); and the coefficient of ASY becomes positive and statistical significant at the 10% level.

Turning to the other five illiquidity measures, as shown in Panel B to F, the results are similar to that of bid-ask spread. Therefore, to sum up, the results in Table 4 are consistent with the previous empirical findings, as well as theoretical expectations. It supports that our findings are robust to information asymmetry, default risk and omitted firm-level features.

4.2.3 Decimalisation, illiquidity and loan spreads

In the previous section, we show that the stock secondary market illiquidity is related to higher borrowing costs in the syndicated loan market, and this relation is robust when we control for information asymmetry, default risk and firm fixed effects. To further establish the causality, and to illustrate that this relationship is not driven by omitted variables, in this section, we apply the propensity-score matching difference-in-differences (PSM DiD) approach in the context of an exogenous liquidity shock. It has been demonstrated in many studies that *decimalisation*[9], the regulation change taken place around 2001 in the major U.S. stock exchanges, significantly improved the market liquidity (e.g. Bessembinder, 2003; Furfine, 2003). This exogenous shock provides a quasi-natural experiment to examine the impact of liquidity (Fang, Tian and Tice, 2014). The PSM DiD approach has several advantages. First, it rules out the potential omitted variables which drive both illiquidity and loan spreads. Secondly, it strengthens our argument of a causal relationship between market illiquidity and cost of loans. Lastly, the propensity score matching reduces the effect of unobserved firm traits between treated and control groups that contribute to explaining the differences in loan spreads. Our research design is similar to that of Fang, Tian and Tice (2014).

[9]Prior to 2001, the minimum tick size for quotes and trades on the three major U.S. exchanges was \$1/16. Over the period of August 28, 2000 to April 9, 2001, NYSE, NYSE MKT (then AMEX) and NASDAQ reduced the minimum tick size to 1 cent.

Firstly, we calculate the change in the average bid-ask spread before and after the year of decimalisation, i.e., year 2001. Firms that do not have bid-ask spread observations between 2000 and 2002 are excluded. This leaves us with 1,638 firms. Then we sort the firms by the change of the average bid-ask spread in the ascending order; the top one third are regarded as the *treated group*, as they experience the greatest reduction in bid-ask spread; the bottom one third are considered as the *control group*, as they witness the smallest reduction in bid-ask spread. Firms that neither fall into the *treated group* nor the *control group* are disregarded. Hence we are left with 1,092 firms.

Secondly, we select a subset of firms which have taken out loans both in the year before and after the decimalisation, i.e., year 2000 and 2002. There are 179 firms that satisfy this condition. Noticing that many of the firms have borrowed more than one loans with non-identical loan characteristics in the same year, we hence use a new method to select a pair of most comparable loans for each firm (one before and one after the year of decimalisation). A natural approach for the selecting process would be matching loans by features, such as the number of lenders, the number of facilities, facility size, maturity, revoler/term loan, whether secured by collaterals and seniority status. However, very few loans are identical in all these features. Therefore we use a new collective method in matching. This method has two steps. In the first step we pool all the loans borrowed by the sample firms in both 2000 and 2002, and we regress loan spreads (all-in-drawn) on the same set of firm and loan control variables as in Equation (19) but exclude the illiquidity variables. The second step involves calculating the fitted (predicted) loan spreads from the estimation in the first step, and based on which we select the pair of loans for each firm that have the nearest fitted (predicted) loan spreads.

Thirdly, we merge the bid-ask spread (and the treatment indicator 0 or 1) with the paired loans, which gives us 198 loans (99 firms), of which 110 are treated. We use the logit model to calculate the propensity score of a firm's likelihood to receive the treatment, i.e., large liquidity improvement. The explanatory variables include the bid-ask spread, firm size, return on assets (ROA), net working capital (NWC) and market-to-book ratio (MTB) before the year of decimalisation. Then, using the propensity score, we match each *treated* firm with the nearest neighbouring *control* firm according to the score, and we test if the difference in the change of loan spreads of the matched treated group and the control group are significantly different from zero. We illustrate the results in Table 5.

[Please insert Table 5 about here.]

In Table 5, Panel A shows the summary statistics of our sample at each filtering stage as stated above. Panel B presents the logit model estimates, with robust standard errors adjusted for heteroskedasticity. The estimates suggest that the likelihood of getting the treatment (large liquidity improvement due to decimalisation) is positively related to the bid-ask spread and firm size in the year prior to decimalisation. Overall, the model captures 27% of the variance, as indicated by the pseudo-R^2. Using the predicted likelihood from Panel B, we perform propensity score matching, where each *treated* firm (i.e., large liquidity improvement) is matched, with replacement, to an *untreated* firm (i.e., small liquidity improvement) with the closest propensity score. We call the former *treated* group and the latter *control* group. To show that our matching method is reliable, first, we apply the same logit model on the post-match sample. As shown on the right-hand side of Panel B, the coefficients on bid-ask spread and firm size have lost their significance at 5% level, and the pseudo-R^2 is reduced to 0.07. Furthermore, in Panel C, we report the mean differences and standardised bias (Rosenbaum and Rubin, 1985) of the logit model regressors for the *treated* group and the *control* group, both before and after matching. The results show that the sample means of all variables are not significantly different at 5% level between the *treated* and *control* groups post-match, and that all the absolute standardised biases are smaller than 20%, as the rule of thumb according to Rosenbaum and Rubin (1985) in the post-match sample.

Finally, we report the change in loan spreads (all-in-drawn) around the decimalisation in Panel D. From the left to the right, we respectively report the mean and standard deviation of the change in loan spreads for (1) all firms, (2) treated firms, (3) control firms and (4) difference between treated and control firms. As shown, the average loan spread increases by 56 basis points after decimalisation, but it is not statistically significant. The average increase for treated firms (17 basis points) is much lower than that for control firms (95 basis points). Again, these are not statistically significant. One explanation for the overall increase in loan spreads is that the decimalisation coincides with the burst of dot-com bubble [10], which increases the overall default risk in the economy. Most importantly, the mean DiD estimator is negative (-78 basis points) and significant at 5% level. It suggests that in the year subsequent to decimalisation, firms experiencing large liquidity improvement receive on average 49 basis points decrease in loan spread compared to those without much liquidity change. Hence, our PSM DiD analysis strongly supports our argument that market liquidity does influence firms' financial constraints and the cost of loans.

4.2.4 Illiquidity, information asymmetry and past lending relationships

Researchers in banking and finance have long been interested in the impact of relationship lending. In Sharpe (1990), theory suggests relationship lending results in higher loan spreads, as relationship lenders are more likely to "hold-up" their captive customers; nonetheless, Boot and Thakor (1994) predict that repeated lending reduces the information asymmetry between lenders and borrowers, and should therefore lowers the interest rates. Both theories are supported by evidence mixed in the empirical literature. One study which is most relevant to our paper is by Saunders and Steffen (2011), who suggest that the information asymmetry channel dominates the impact of relationship lending on loan spreads among public firms, as public firms are less likely to be "held up" by their relationship lenders. Following their findings, we postulate that despite that public firms generally pay lower loan spreads to relationship lenders, borrowers with illiquid stock benefit less from past lending relationship. Hence, we construct a dummy variable *rel*, which takes the value of one if the borrowing firm has taken a loan within five years from the same lead lender, and zero otherwise.

We include this relationship dummy *rel* and its interaction with one of the illiquidity measures, $rel \times illiq$, into our baseline loan pricing model denoted by Eq.(19) similar to Bharath, Dahiya, Saunders and Srinivasan (2011). We present the regression results in Table 6 Panel A. In Each column, we report the coefficients (and standard errors) from the pooled OLS regressions using bid-ask spread (baspr), effective spread (effspr), Roll's effective spread (Roll), effective tick (efftick), proportion of zero-return days (zero) and Amihud

[10] During 1997 to 2000, the equity value of the Internet related firms rose rapidly, with a climax on 10 March 2000 (NASDAQ reached 5,132.52), but then collapsed, with many firms losing most of their market value.

illiquidity ratio (Amihud) as explanatory variable, respectively. For comparison purpose, we then replace the illiquidity measure with one of the information opacity measures, and the results are included in Table 6 Panel B. In each column we report the coefficients using adverse selection component of bid-ask spread (GKN), that of Roll's effective spread (RGKN) and information asymmetry index (ASY). We also include the interaction between relationship and three additional measures of information opacity, namely, firm size, dummy variable indicating the firm is without S&P rating (*no rating*), and dummy indicating the firm does not issue corporate bonds (*no bond*). The first two measures *no rating* and *no bond* are suggested by Bharath, Dahiya, Saunders and Srinivasan (2011); the last one, *no bond*, which takes the value of one if the company does not issue corporate bonds within five years before the loan initiation date, and zero otherwise, are believed to be positively related to information asymmetry and negatively associated with bargaining power vis-à-vis lenders.

[Please insert Table 6 about here.]

In both Panel A and B of Table 6, the coefficient of relationship dummy is negative and significant throughout all specifications, except for Column (4) in Panel B where the coefficient is negative but insignificant. This is consistent with Bharath, Dahiya, Saunders and Srinivasan (2011), and it indicates that past relationship reduces the borrowing costs for repeated borrowers, ranging from 7 to 12 basis points according to the model specification. The negative relationship dummy coefficient can be explained by Boot and Thakor (1994), as past relationship reduces the information asymmetry between the lender and the borrower, lowering the adverse selection risk and the due diligence and monitoring costs faced by the lender, and thus reduces the loan spreads.

In the six models using illiquidity measure (shown in Column 1 to 6 of Panel A) as one of the explanatory variables, the coefficients of the illiquidity measures are ubiquitously positive and statistically significant; their magnitudes are also comparable to those shown in Table 3. It indicates that the inclusion of lending relationship does not alter our findings of the positive link between illiquidity and loan spreads. Furthermore, the three models using information opacity measure as an independent variable (shown in Column 1 to 3 of Panel B) suggest a positive relationship between adverse selection and loan spreads, which is similar to that of Bharath, Dahiya, Saunders and Srinivasan (2011) both in terms of magnitude and statistical significance.

Turning to the interaction terms, in Panel A, except Amihud illiquidity ratio which is insignificant, all coefficients of $rel \times illiq$ are unanimously positive and statistically significant. It implies a "illiquidity premium" charged by relationship lenders, which supports our Hypothesis 3 that borrowing firms with less liquid stock benefit less from lending relationship. In Panel B, the coefficients of $rel \times opac$ are generally statistically insignificant; nevertheless, we do find consistent signs on $rel \times RGKN$, $rel \times ASY$, $rel \times firm\ size$ and $rel \times no\ rating$ with Bharath, Dahiya, Saunders and Srinivasan (2011). Hence, we argue that firms with illiquid stock, although public traded, are faced with higher costs and more limited financing capacity in the capital market; these firms are therefore more dependent on debt financing, so the relationship lenders can exploit these borrowers and charge higher rates. Our finding is consistent with Santos and Winton (2008) and Zucchi (2014).

One may argue that the corporate bond market serves as an alternative source of external financing in complementary to bank loans and capital market. Therefore, we add an additional variable, bond issuance (bond), which equals to one if a company has issued corporate bond within five years before the loan initiation date, and equals to zero otherwise. We also include the interactions of bond issuance and each of our illiquidity measures, $bond \times illiq$, as well as the triple interaction of bond, relationship and illiquidity, $rel \times bond \times illiq$. We report these results in Table 7.

[Please insert Table 7 about here.]

As it shows in Table 7, past relationship results in a reduction of 9 to 12 basis point of loan spreads, with the coefficients remaining negative and significant across all model specifications. Bond issuance is associated with 3 to 20 basis point reduction of loan spreads; however it is only significant in the first three models (Column 1 to 3). The reduction in loan spreads is slightly reverted if a firm both has a past relationship with the lead lender and has issued corporate bond within five years prior to the loan initiation date, as the coefficients of $rel \times bond$ are mostly positive but **not** significantly different from zero statistically. The coefficients of all the six illiquidity measures are positive and significant, and the magnitudes of which are very similar to those from our baseline regressions reported in Table 3, confirming the positive link between market illiquidity and loan spreads.

Turning to the interactions, except for Roll's effective spread (Roll) and Amihud illiquidity ratio (Amihud), the coefficients of the interactions of relationship with illiquidity measures, $rel \times illiq$, are positive and significant at 90% or higher confidence level. Also, the magnitude of these coefficients are very similar to those reported in Panel A of Table 6. It further confirms our finding that firms with less liquid stock benefit less from lending relationships. The coefficients of the interactions of bond issuance with illiquidity measures, $bond \times illiq$, are mostly insignificantly different from zero, with the sole exception of $bond \times Roll$, which is positive and significant at the 95% level. The coefficients of the triple interaction terms, $rel \times bond \times illiq$, are generally statistically insignificant, although in Column (2) the coefficient of $rel \times bond \times effspr$ is marginally significant at 90% confidence level. In sum, Table 7 shows that the inclusion of bond issuance dummy does not alter our findings about past lending relationship and stock illiquidity. Despite the literature which find that access to the corporate bond market can improve information transparency and bargaining power of the borrowing firm; we do not find this dummy variable significantly influence the impact of illiquidity on loans spreads, and the role of lending relationship.

5 Conclusion

In this study, we discuss the role of stock illiquidity in determining a firm's borrowing costs. Taking a large sample of U.S. listed firms from 1987 to 2011, we construct a set of illiquidity measures, and we discuss their impact on the cost of loans in conjecture with information opacity, past lending relationship and causality. Our measurements of illiquidity include bid-ask spread, effective spread, Roll's (1984) effective spread, effective tick (Holden, 2009; Goyenko, Holden and Trzcinka, 2009), proportion of zero-return days and Amihud (2002) illiquidity ratio. Our findings are three-fold.

First, we find that firms with illiquid stock pay significantly higher interest rates in the syndicated loan market. This relationship is robust to the control of firm and loan characteristics, information asymmetry, firms' credit rating, and firm fixed effects. Second, by analysing the changes of loan spreads around the year of *decimalisation*, we identify the causal relationship between market illiquidity and loan spreads using the propensity-score matching difference-in-difference method. Furthermore, studying market illiquidity in conjecture with past lending relationship, we further illustrate that stock illiquidity diminishes the benefit of relationship lending, which according to Boot and Thakor (1994), should reduce the information asymmetry and hence the loan spreads.

To the best of our knowledge, this paper is the first to examine the connection between stock market illiquidity and the financing cost in the syndicated loan market. Our findings provide indirect empirical support to Zucchi (2014), who establishes a direct theoretical link between external and internal liquidity which cannot be explained by adverse selection. Our study also contributes to the broad discussion of the role of relationship lending.

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Table 1 Summary Statistics

This table provides summary statistics of a variety of loan and borrowing firm features. Panel A reports the key features of loan facilities. *All in Drawn* is the all-inclusive cost of a loan measured in basis points; *facility size* is the natural log of a loan facility amount, measured in million dollars; *maturity* is the natural log of maturity, in years; *revolver, term loan, secured, senior* are dichotomous variables, which take the value of one if true, and zero otherwise. Panel B reports key features of borrowing firms. *firm size* is the natural log of total asset in million dollars; *leverage* is the ratio of total liability to total asset; *ROA* and *NWC* refer to return on asset and net working capital (as a percentage of total asset) respectively; *tangibles* is the ratio of tangible asset to total asset; *MTB* is the market to book ratio. Panel C gives a description of our selected measures of illiquidity and information asymmetry. Note that all samples observations in Panel B and C are winsorised at 1% and 99% level. Finally, Panel D summarises the four dummy variables, *relationship*, *bond*, *no bond* and *no rating*, which stand for lending relationship within past five years, corporate bond issuance, no corporate bond issuance and S&P ratings unavailability respectively. The last row of Panel D reports the summary statistics of the indicator of actual S&P ratings. The definitions of these variables are listed in Appendix Table A1.

Panel A: Loan features

	No. of Obs.	Mean	Std. Dev.	Min.	25th pct.	Median	75th pct.	Max.
All in Drawn	10,877	197.141	145.071	0.625	87.500	175.000	275.000	1655.000
no. of lenders	10,877	9.233	9.168	1.000	3.000	7.000	13.000	118.000
no. of facilities	10,877	1.788	1.109	1.000	1.000	1.000	2.000	12.000
facility size	10,877	4.899	1.571	−2.303	3.912	5.011	5.991	10.309
maturity	10,877	1.178	0.682	−2.485	1.012	1.427	1.609	3.135
revolver	10,877	0.729	0.445	0.000	0.000	1.000	1.000	1.000
term loan	10,877	0.245	0.430	0.000	0.000	0.000	0.000	1.000
secured	10,877	0.649	0.477	0.000	0.000	1.000	1.000	1.000
senior	10,877	0.998	0.041	0.000	1.000	1.000	1.000	1.000

Panel B: Firm features

	No. of Obs.	Mean	Std. Dev.	Min.	25th pct.	Median	75th pct.	Max.
firm size	10,877	6.828	1.718	2.988	5.594	6.795	7.964	10.663
leverage	10,877	0.302	0.203	0.000	0.155	0.286	0.416	1.006
ROA	10,877	0.132	0.084	−0.146	0.088	0.127	0.174	0.407
NWC	10,877	0.154	0.185	−0.359	0.020	0.130	0.271	0.651
tangibles	10,877	0.732	0.381	0.064	0.437	0.718	0.997	1.832
MTB	10,877	1.685	0.887	0.697	1.127	1.419	1.909	5.781

Panel C: Illiquidity and Information asymmetry

	No. of Obs.	Mean	Std. Dev.	Min.	25th pct.	Median	75th pct.	Max.
baspr	10877	1.564	1.983	0.000	0.183	0.923	2.165	20.544
effspr	10877	1.025	1.363	0.048	0.227	0.505	1.239	15.295
Roll	10877	1.569	1.377	0.000	0.743	1.173	1.899	15.540
efftick	10877	0.601	1.276	0.007	0.046	0.175	0.633	40.000
zero	10877	7.378	8.809	0.000	1.212	3.258	10.557	64.953
Amihud	10877	0.444	2.047	0.000	0.001	0.008	0.082	52.612
GKN	10363	0.912	1.681	−0.037	0.000	0.129	1.285	21.392
RGKN	10363	0.632	0.886	0.000	0.000	0.345	0.938	11.209
ASY	10363	−0.033	2.410	−9.605	−0.402	−0.393	−0.337	59.564

Panel D: Others

	No. of Obs.	Mean	Std. Dev.	Min.	25th pct.	Median	75th pct.	Max.
rel	10,877	0.373	0.484	0.000	0.000	0.000	1.000	1.000
bond	10,877	0.274	0.446	0.000	0.000	0.000	1.000	1.000
rating	10,877	0.530	0.499	0.000	0.000	1.000	1.000	1.000
S&P rating	5,769	10.852	3.091	1.000	9.000	11.000	13.000	17.000

Table 2 Summary of loan distribution by category

In Panel A to C, we report the loan facility distribution by three categories, namely, year, loan purpose and industry. Within each panel, we respectively record the number of loan facilities borrowed from lenders with or without a pre-exiting lending relationship (Column 1 and 2), by corporate bond issuers or non-corporate bond issuers (Column 3 and 4), and by firms with and without S&P credit ratings (Column 5 and 6).

Panel A: Calendar time distribution of loans

	Relationship		Bond Issuer		S&P Rating	
Year	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
1988	2	61	3	60	36	27
1989	16	59	10	65	57	18
1990	23	58	7	74	66	15
1991	20	62	8	74	61	21
1992	47	70	25	92	83	34
1993	57	101	36	122	97	61
1994	88	125	54	159	131	82
1995	94	160	64	190	154	100
1996	142	267	118	291	243	166
1997	166	323	128	361	294	195
1998	138	326	100	364	258	206
1999	133	357	110	380	231	259
2000	224	474	161	537	360	338
2001	212	473	228	457	281	404
2002	160	566	206	520	343	383
2003	234	497	214	517	329	402
2004	366	512	251	627	353	525
2005	426	513	300	639	365	574
2006	350	389	207	532	299	440
2007	331	470	228	573	285	516
2008	201	231	113	319	230	202
2009	123	184	94	213	147	160
2010	161	284	131	314	201	244
2011	348	253	187	414	204	397

Panel B: Purpose distribution of loans

	Relationship		Bond Issuer		S&P Rating	
Year	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Corporate Purpose	1355	1681	1018	2018	1243	1793
Debt Repayment	632	1126	386	1372	973	785
Takeover	621	1301	596	1326	743	1179
Working Capital	385	1074	402	1057	602	857
Others	1069	1633	581	2121	1547	1155

Panel C: Industry distribution of borrowing firms

	Relationship		Bond Issuer		S&P Rating	
Year	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture Forestry Fishing	7	18	11	14	10	15
Construction	36	65	10	91	59	42
Finance Insurance RealEstate	20	37	7	50	37	20
Manufacturing	1624	2939	1310	3253	2163	2400
Mining	432	478	264	646	481	429
Retail Trade	431	674	292	813	511	594
Services	615	1197	318	1494	1044	768
Transportation Communication Electric Gas Sanitary Services	682	1009	654	1037	423	1268
Others	215	398	117	496	380	233

Figure 1 Average loan spread residuals by illiquidity deciles

This figure displays the average value of loan spread (*all-in-drawn*) residuals by illiquidity deciles from low to high. The loan spread residuals (all-in-drawn residuals) are the residuals from a pooled OLS estimates, where we regress (all-in-drawn) loan spread on a set of firm features, loan features, borrower industry dummies, loan purpose dummies and year dummies. The firm features include firm size, leverage, return on asset, net working capital, tangible assets and market-to-book ratio. The loan features include number of lenders, number of facilities, facility size, maturity as well as binary indicators for revolver, term loan, collateral and seniority.

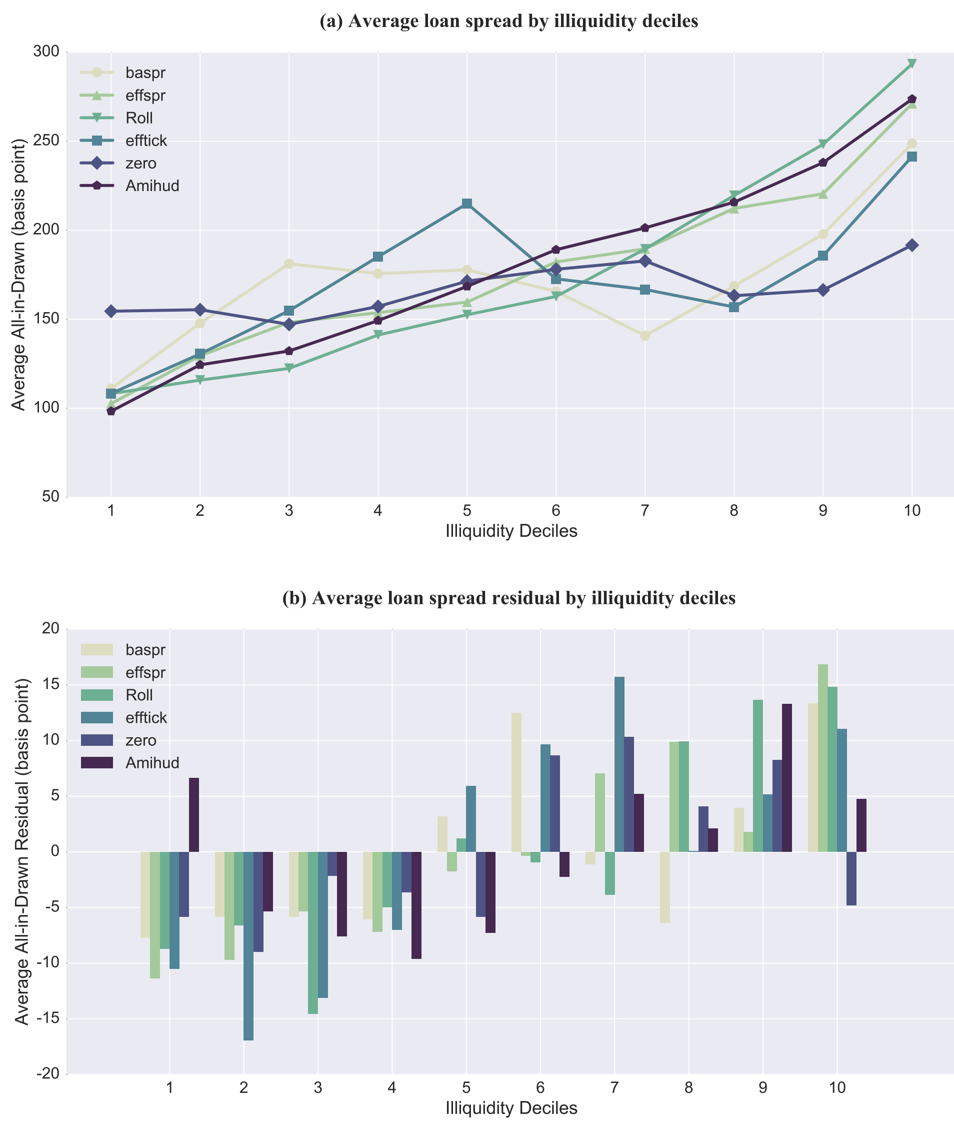

Table 3 Pooled OLS regression estimation

This table presents in each column the coefficient of one of our illiquidity measures along with the control variables estimated from Eq.(19). The definitions of the variables are listed in Appendix Table A1. In all specifications, we run cross-sectional OLS regressions that pool together all observations. The dependent variable is the all-in-drawn spreads of loan facilities. Standard errors are adjusted for clustering at the borrower level and reported below in parentheses. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
baspr	6.683***					
	(1.360)					
effspr		11.673***				
		(1.790)				
Roll			10.113***			
			(1.540)			
efftick				13.579***		
				(2.621)		
zero					0.889***	
					(0.307)	
Amihud						3.724**
						(1.708)
firm size	−7.702***	−6.369***	−7.513***	−7.696***	−8.830***	−9.286***
	(1.830)	(1.841)	(1.783)	(1.816)	(1.831)	(1.777)
leverage	69.591***	67.459***	69.891***	68.648***	72.838***	74.539***
	(9.107)	(9.025)	(9.003)	(9.098)	(9.136)	(9.016)
ROA	−242.554***	−235.221***	−231.101***	−234.379***	−249.307***	−248.384***
	(25.435)	(25.306)	(25.058)	(25.051)	(25.182)	(25.482)
NWC	−39.998***	−39.540***	−41.687***	−40.808***	−44.022***	−43.369***
	(10.240)	(10.123)	(9.996)	(10.184)	(10.172)	(10.231)
tangibles	2.159	2.632	2.068	2.892	2.463	2.161
	(4.998)	(5.005)	(4.973)	(5.050)	(5.003)	(5.014)
MTB	−1.761	−1.820	−3.001*	−2.419	−2.235	−3.071*
	(1.830)	(1.803)	(1.770)	(1.824)	(1.819)	(1.793)
no. of lenders	−1.057***	−1.055***	−1.040***	−1.028***	−1.014***	−1.058***
	(0.169)	(0.169)	(0.166)	(0.17)	(0.170)	(0.171)
no. of facilities	10.060***	9.848***	10.091***	9.917***	9.865***	9.889***
	(2.047)	(2.015)	(2.003)	(2.040)	(2.068)	(2.040)
facility size	−9.532***	−9.280***	−9.334***	−9.461***	−10.000***	−9.846***
	(1.525)	(1.530)	(1.521)	(1.526)	(1.492)	(1.528)
maturity	−5.468**	−5.183**	−5.666**	−5.408**	−5.949**	−5.844**
	(2.442)	(2.440)	(2.443)	(2.435)	(2.422)	(2.448)
revolver	−64.398***	−64.634***	−64.468***	−64.101***	−64.037***	−64.167***
	(9.752)	(9.774)	(9.706)	(9.859)	(9.830)	(9.807)
term loan	−3.829	−4.024	−3.734	−3.481	−3.098	−3.359
	(10.105)	(10.125)	(10.060)	(10.207)	(10.175)	(10.161)
secured	82.254***	82.294***	81.410***	82.551***	82.770***	83.018***
	(3.105)	(3.090)	(3.075)	(3.114)	(3.138)	(3.133)
senior	−247.653***	−247.121***	−244.632***	−247.678***	−251.217***	−249.766***
	(47.155)	(47.345)	(46.787)	(47.514)	(46.550)	(46.701)
constant	485.100***	471.095***	485.626***	484.980***	500.562***	514.324***
	(55.976)	(55.951)	(54.289)	(54.778)	(56.683)	(54.424)
dummy year	Yes	Yes	Yes	Yes	Yes	Yes
dummy loan purpose	Yes	Yes	Yes	Yes	Yes	Yes
dummy industry	Yes	Yes	Yes	Yes	Yes	Yes
no. of observations	10877	10877	10877	10877	10877	10877
no. of firms	1779	1779	1779	1779	1779	1779
R-square	0.550	0.552	0.552	0.541	0.557	0.547

Table 4 Robustness tests

We presents the estimates of a series of robust tests on each of our illiquidity measures in Panel A to F respectively. In each Panel, Column (1) reports the coefficient estimation of the baseline OLS regression as Eq. (19). In column (2) to (4), we report the estimates controlling for the information opacity measure GKN, RGKN and ASY respectively. In Column (5) we add S&P ratings, and column (6) presents fixed effect estimates. The coefficients of the control variables are suppressed from reporting. The definitions of the variables are listed in Appendix Table A1. In all specifications except for column (6), we run cross-sectional OLS regressions that pool together all valid observations. The dependent variable is the all-in-drawn spreads of loan facilities. Standard errors are adjusted for clustering at the borrower level. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

Panel A: Robust tests on bid-ask spread

	(1)	(2)	(3)	(4)	(5)	(6)
baspr	6.683***	9.805***	6.468***	7.228***	12.154***	7.019***
	(1.360)	(1.812)	(1.540)	(1.504)	(2.792)	(1.522)
GKN		−3.524**				
		(1.667)				
RGKN			2.311			
			(2.374)			
ASY				−0.199	−1.835	2.896*
				(1.572)	(4.134)	(1.541)
SP rating					19.002***	
					(1.044)	
firm fixed effect	No	No	No	No	No	Yes
no. of observations	10,877	10,363	10,363	10,363	5,645	10,363
no. of firms	1,779	1,737	1,737	1,737	934	1,737
R-square	0.550	0.555	0.555	0.557	0.681	0.430

Panel B: Robust tests on effective spread

	(1)	(2)	(3)	(4)	(5)	(6)
effspr	11.673***	13.662***	12.387***	14.244***	25.830***	13.258***
	(1.790)	(1.947)	(1.978)	(2.001)	(4.867)	(2.250)
GKN		−1.011				
		(1.379)				
RGKN			1.619			
			(2.350)			
ASY				−1.764	−5.453	1.897
				(1.623)	(4.149)	(1.520)
SP rating					18.563***	
					(1.044)	
firm fixed effect	No	No	No	No	No	Yes
no. of observations	10,877	10,363	10,363	10,363	5,645	10,363
no. of firms	1,779	1,737	1,737	1,737	934	1,737
R-square	0.552	0.557	0.557	0.558	0.684	0.432

Panel C: Robust tests on Roll's effective spread

	(1)	(2)	(3)	(4)	(5)	(6)
Roll	10.113***	10.121***	10.113***	10.859***	13.507***	9.056***
	(1.540)	(1.610)	(1.726)	(1.645)	(2.487)	(1.719)
GKN		1.154				
		(1.310)				
RGKN			1.147			
			(2.342)			
ASY				−0.670	0.643	2.835**
				(1.515)	(3.658)	(1.432)
SP rating					18.649***	
					(1.034)	
firm fixed effect	No	No	No	No	No	Yes
no. of observations	10,877	10,363	10,363	10,363	5,645	10,363
no. of firms	1,779	1,737	1,737	1,737	934	1,737
R-square	0.552	0.557	0.557	0.557	0.681	0.431

Continued on next page

Table 4 – *Continued from previous page*

Panel D: Robust tests on effective tick

	(1)	(2)	(3)	(4)	(5)	(6)
efftick	13.579∗∗∗	13.663∗∗∗	12.635∗∗∗	14.118∗∗∗	16.194∗∗∗	15.180∗∗∗
	(2.621)	(2.973)	(2.946)	(2.797)	(6.100)	(2.732)
GKN		0.407				
		(1.409)				
RGKN			3.134			
			(2.315)			
ASY				−0.154	1.218	2.556∗
				(1.501)	(4.020)	(1.391)
SP rating					19.213∗∗∗	
					(1.050)	
firm fixed effect	No	No	No	No	No	Yes
no. of observations	10,877	10,363	10,363	10,363	5,645	10,363
no. of firms	1,779	1,737	1,737	1,737	934	1,737
R-square	0.551	0.555	0.556	0.555	0.679	0.432

Panel E: Robust tests on zero

	(1)	(2)	(3)	(4)	(5)	(6)
zero	0.889∗∗∗	0.775 ∗ ∗	0.787 ∗ ∗	0.870 ∗ ∗	1.124 ∗ ∗	0.474
	(0.307)	(0.340)	(0.330)	(0.338)	(0.520)	(0.345)
GKN		2.368∗				
		(1.380)				
RGKN			6.066∗∗∗			
			(2.240)			
ASY				2.058	3.365	4.856∗∗∗
				(1.503)	(3.906)	(1.471)
SP rating					19.547∗∗∗	
					(1.055)	
firm fixed effect	No	No	No	No	No	Yes
no. of observations	10,877	10,363	10,363	10,363	5,645	10,363
no. of firms	1,779	1,737	1,737	1,737	934	1,737
R-square	0.547	0.553	0.554	0.553	0.678	0.427

Panel F: Robust tests on Amihud illiquidity ratio

	(1)	(2)	(3)	(4)	(5)	(6)
Amihud	3.724 ∗ ∗	3.286	3.128	3.760	22.884∗∗∗	3.291
	(1.708)	(2.074)	(2.037)	(2.466)	(6.178)	(2.339)
GKN		2.099				
		(1.302)				
RGKN			5.729∗∗∗			
			(2.185)			
ASY				0.859	−5.789	3.829∗∗∗
				(1.780)	(5.394)	(1.477)
SP rating					19.489∗∗∗	
					(1.056)	
firm fixed effect	No	No	No	No	No	Yes
no. of observations	10,877	10,363	10,363	10,363	5,645	10,363
no. of firms	1,779	1,737	1,737	1,737	934	1,737
R-square	0.547	0.553	0.553	0.553	0.680	0.427

Table 5 Propensity score matching difference-in-differences estimation

This table presents the empirical results of the propensity score matching difference-in-difference analysis. The treatment is defined as the top tertile liquidity improvement as a result of *decimalisation* in stock exchanges; and control is defined the bottom tertile liquidity improvement. Panel A summarises the subsample used for PSM-DiD analysis at each filtering stage. Panel B reports the logit regression estimates. Panel C reports the mean and percentage bias of unmatched and matched samples. Panel D reports the average difference in loan spread (all-in-drawn) before and after the *decimalisation* on the first row; and on the second row, the numbers in parentheses in are standard errors. The definitions of the variables are listed in Appendix Table A1. ⋆ denotes coefficients significantly different from zero at the 5% levels, and † denotes absolute standardised bias greater than 20%, respectively.

Panel A: Summary statistics

	Pre-match by fitted	Post-match by fitted	In treated group: top tertile of liquidity improvement	In control group: bottom tertile of liquidity improvement	Total
No. of firms	179	179	55	44	99
No. of loans	579	358	110	88	198

Panel B: Logit regression estimation

	Pre-match by propensity				Post-match by propensity			
	Coefficient	Std Err	t-stat	p-value	Coefficient	Std Err	t-stat	p-value
baspr	0.735⋆	0.193	3.803	0.000	0.001	0.128	0.009	0.993
firm size	0.309⋆	0.180	1.721	0.085	0.016	0.152	0.104	0.917
ROA	0.319	2.865	0.111	0.911	−4.859	2.891	−1.681	0.093
NWC	−1.144	1.456	−0.786	0.432	1.197	1.482	0.808	0.419
MTB	0.013	0.206	0.062	0.950	0.667	0.387	1.722	0.085
constant	−3.814⋆	1.683	−2.266	0.023	−0.581	1.597	−0.364	0.716
No. of Observations	99				No. of Observations	110		
Pseudo R2:	0.27				Pseudo R2:	0.07		

Panel C: Balancing test

	Pre-match by propensity				Post-match by propensity			
	Treated	Control	Difference	% bias	Treated	Control	Difference	% bias
baspr	4.116	2.094	2.022⋆	104.2†	4.116	4.307	−0.191	−9.8
firm size	6.454	6.243	0.211	13.5	6.454	6.335	0.119	7.6
ROA	0.109	0.123	−0.014	−14.9	0.109	0.124	−0.015	−16.4
NWC	0.120	0.215	−0.095⋆	−48.4†	0.120	0.111	0.009	4.8
MTB	1.489	2.292	−0.802⋆	−54.6†	1.489	1.276	0.214	14.5

Panel D: Difference-in-difference estimation

	Mean Difference (after - before)	Mean Treatment Difference (after - before)	Mean Control Difference (after - before)	Mean DiD Estimator (treat - control)
AllinDrawn (bps)	56.03	17.23	94.82	-77.60⋆
	(121.54)	(68.94)	(148.33)	(39.10)

Table 6 Pooled OLS regression on relationship

From Column (1) to (6) in Panel A (Panel B), we alternatively present the coefficient of one of our illiquidity measures (information opacity measures), along with those of the relationship dummy and its interactions with illiquidity (information opacity) estimated from the following regression:

Panel A Column (1) to (6):

$$LoanSpr_{f,l,t} = c + \alpha_r rel_{f,t} + \beta_i Illiq_{f,t-1} + \beta_{ir} rel_{f,t} \times Illiq_{f,t-1} + \sum_m \gamma_m Firm_{f,m,t-1} + \sum_n \theta_n Loan_{l,n,t} + \sum_t \delta_t T_t + \varepsilon_{f,l,t},$$

Panel B Column (1) to (3):

$$LoanSpr_{f,l,t} = c + \alpha_r rel_{f,t} + \beta_o Opac_{f,t-1} + \beta_{or} rel_{f,t} \times Opac_{f,t-1} + \sum_m \gamma_m Firm_{f,m,t-1} + \sum_n \theta_n Loan_{l,n,t} + \sum_t \delta_t T_t + \varepsilon_{f,l,t},$$

Panel B Column (4) to (6):

$$LoanSpr_{f,l,t} = c + \alpha_r rel_{f,t} + \beta_{or} rel_{f,t} \times Opac_{f,t-1} + \sum_m \gamma_m Firm_{f,m,t-1} + \sum_n \theta_n Loan_{l,n,t} + \sum_t \delta_t T_t + \varepsilon_{f,l,t}.$$

Illiq (*Opac*) denotes one of our illiquidity measures (information opacity measures) illustrated on the header row, whereas all other denotations are the same with Eq.(19). The coefficients of the control variables, γ_m, θ_n and δ_t are suppressed from reporting. In Column (4) of Panel B, since our opacity measure *firm size* is also a control variable, we hence do not suppress reporting the coefficient and standard error of *firm size*. The definitions of the variables are listed in Appendix Table A1. In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. Standard errors are adjusted for clustering at the borrower level, and are reported in parentheses. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

Panel A: Illiquidity and relationship lending

	(1)	(2)	(3)	(4)	(5)	(6)
illiq=	baspr	effspr	Roll	efftick	zero	Amihud
rel	−10.728***	−11.912***	−12.143***	−9.889***	−10.714***	−7.686***
	(2.630)	(2.515)	(3.038)	(2.294)	(2.610)	(2.049)
illiq	6.176***	10.698***	9.376***	12.763***	0.779**	3.657**
	(1.365)	(1.797)	(1.620)	(2.643)	(0.313)	(1.732)
rel×illiq	2.409*	5.455***	3.080*	4.242**	0.435**	−0.221
	(1.254)	(1.932)	(1.800)	(2.154)	(0.218)	(2.320)
no. of observations	10,877	10,877	10,877	10,877	10,877	10,877
no. of firms	1,779	1,779	1,779	1,779	1,779	1,779
R-square	0.551	0.553	0.553	0.548	0.551	0.548

Panel B: Information opacity and relationship lending

	(1)	(2)	(3)	(4)	(5)	(6)
opac=	GKN	RGKN	ASY	firm size	no rating	no bond
rel	−9.136***	−7.046***	−8.016***	−14.405***	−6.934***	−11.300***
	(2.395)	(2.611)	(2.028)	(0.109)	(0.007)	(0.000)
opac	2.860**	7.251***	2.678*	−10.551***		
	(1.407)	(2.485)	(1.492)	(0.000)		
rel×opac	1.496	−1.433	−0.697	0.916	−2.414	4.867
	(1.535)	(2.865)	(2.379)	(0.458)	(0.528)	(0.136)
no. of observations	10,363	10,363	10,363	10,877	10,877	10,877
no. of firms	1,737	1,737	1,737	1,779	1,779	1,779
R-square	0.551	0.553	0.553	0.547	0.557	0.547

Table 7 Pooled OLS regression on relationship and bond issuance

From Column (1) to (6), we alternatively present the coefficient of one of our illiquidity measures, along with those of the relationship dummy, bond issuance dummy, the interactions with illiquidity and control variables estimated from the following regression:

$$
\begin{aligned}
LoanSpr_{f,l,t} = & \; c + \alpha_r rel_{f,t} + \alpha_b bond_{f,t} + \alpha_{rb} rel_{f,t} \times bond_{f,t} \\
& + \beta_i Illiq_{f,t-1} + \beta_{ir} rel_{f,t} \times Illiq_{f,t-1} + \beta_{ib} bond_{f,t} \times Illiq_{f,t-1} + \beta_{irb} rel_{f,t} \times bond_{f,t} \times Illiq_{f,t-1} \\
& + \sum_m \gamma_m Firm_{f,m,t-1} + \sum_n \theta_n Loan_{l,n,t} + \sum_t \delta_t T_t + \varepsilon_{f,l,t}.
\end{aligned}
$$

Illiq denotes one of our six illiquidity measures shown on the header row, whereas all other denotations are the same with Eq.(19). The definitions of the variables are listed in Appendix Table A1. In all specifications, we run cross-sectional OLS regressions that pool together all valid observations. Standard errors are adjusted for clustering at the borrower level, and are reported in parentheses. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

illiq=	(1) baspr	(2) effspr	(3) Roll	(4) efftick	(5) zero	(6) Amihud
rel	−12.429***	−12.579***	−13.319***	−11.103***	−12.565***	−8.617***
bond	−9.485*	−9.401*	−20.193***	−6.773	−5.322	−3.377
rel × bond	7.47	0.226	7.888	4.445	6.392	2.976
illiq	5.983***	10.624***	8.541***	12.697***	0.751**	3.753**
rel × illiq	2.611**	4.459**	2.762	4.124*	0.493**	−0.443
bond × illiq	3.807	5.945	12.801**	4.046	24.642	−3.079
rel × bond × illiq	−1.658	12.669*	−0.917	3.788	−12.772	33.389
dummy year	Yes	Yes	Yes	Yes	Yes	Yes
dummy loan purpose	Yes	Yes	Yes	Yes	Yes	Yes
dummy industry	Yes	Yes	Yes	Yes	Yes	Yes
no. of observations	10877	10877	10877	10877	10877	10877
no. of firms	1779	1779	1779	1779	1779	1779
R-square	0.551	0.554	0.554	0.552	0.548	0.548

Appendix

Table A1 Variable definitions

This table provides the definitions and sources of all the variables used in this analysis.

Variable	Definition	Source
Loan features		
AllinDrawn	The All-in-Drawn spread is an interest rate spread over LIBOR measured in basis points for each dollar drawn from the loan.	LPC Dealscan
no. of lenders	Number of lenders in a facility	LPC Dealscan
no. of facilities	Number of facilities in a syndicated deal	LPC Dealscan
facility size	Natural log of facility amount in million dollars	LPC Dealscan
maturity	Natural log of loan maturity in years	LPC Dealscan
revolver	Binary indicator which takes the value of 1 if the loan is a credit line, and 0 otherwise.	LPC Dealscan
term loan	Binary indicator which takes the value of 1 if the loan is a term loan, and 0 otherwise.	LPC Dealscan
secured	Binary indicator which takes the value of 1 if the loan is secured by collateral, and 0 otherwise.	LPC Dealscan
senior	Binary indicator which takes the value of 1 if the loan has seniority, and 0 otherwise.	LPC Dealscan
Borrowing firm features		
firm size	Natural log of firm total assets in million dollars	Compustat
leverage	Sum of long term and short term debt over total assets	Compustat
ROA	Return on assets	Compustat
NWC	Net working capital over total assets	Compustat
tangibiles	Tangible assets over total assets	Compustat
MTB	Market to book ratio	Compustat
Illiquidity and information asymmetry		
baspr	The difference between ask-price and bid-price, as a percentage of the quoted bid-ask midpoint.	CRSP
effspr	Twice as the difference between trade price and quoted bid-ask midpoint, as a percentage of the bid-ask midpoint.	CRSP
Roll	Square root of twice as the negative first order autocovariance of returns.	CRSP
efftick	Probability weighted price clusters.	CRSP
zero	Number of zero-return days as a percentage of the total number of trading days	CRSP
Amihud	Price impact of a million dollar volume.	CRSP
GKN	Adverse selection component of percent bid-ask spread.	CRSP
RGKN	Adverse selection component of Roll's effective spread.	CRSP
rel	Binary indicator which takes the value of 1 if the borrowing firm has taken a syndicated loan within five years from the same lead lender, and 0 otherwise.	LPC Dealscan
bond	Binary indicator which takes the value of 1 if the borrowing firm has issued corporate bond before loan initiation date, and 0 otherwise. We also use *no bond* to refer the opposite.	SDC Platinum
rating	Binary indicator which takes the value of 1 if the borrowing firm has issued corporate bond before loan initiation date, and 0 otherwise. We also use *no rating* to refer the opposite.	SDC Platinum
S&P rating	Credit rating from S&P, which takes the value of 1 if the firm has AAA rating, and the value increases as the rating deteriorates, with highest value 17 for ratings below B-.	Compustat

Table A2 Pooled OLS regression estimation on information opacity measures

From Column (1) to (3), we alternatively present the coefficient of one of our information opacity measures, along with those of the control variables estimated from the following regression:

$$LoanSpr_{f,l,t} = c + \beta Opac_{f,t-1} + \sum_m \gamma_m Firm_{f,m,t-1} + \sum_n \theta_n Loan_{l,n,t} + \sum_t \delta_t T_t + \varepsilon_{f,l,t}.$$

Opac represents one of our information opacity measures shown on the header row, whereas all other denotations are the same with Eq.(19). The definitions of the variables are listed in Appendix Table A1. In all specifications, we run cross-sectional OLS regressions that pool together all observations. Standard errors are adjusted for clustering at the borrower level, and are reported in parentheses. ***, **, * denote coefficients significantly different from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)
opac=	GKN	RGKN	ASY
GKN	3.234∗∗		
	(1.336)		
RGKN		6.950∗∗∗	
		(2.228)	
ASY			2.672∗
			(1.494)
firm size	−9.620∗∗∗	−9.670∗∗∗	−9.558∗∗∗
	(1.815)	(1.802)	(1.828)
leverage	74.472∗∗∗	74.104∗∗∗	75.026∗∗∗
	(9.47)	(9.414)	(9.464)
ROA	−252.116∗∗∗	−250.138∗∗∗	−251.832∗∗∗
	(27.219)	(27.093)	(27.182)
NWC	−42.301∗∗∗	−42.478∗∗∗	−42.383∗∗∗
	(10.625)	(10.475)	(10.631)
tangibles	4.728	4.828	4.637
	(5.152)	(5.133)	(5.193)
MTB	−3.687∗	−4.065∗∗	−4.018∗∗
	(1.999)	(1.971)	(1.984)
no. of lenders	−1.068∗∗∗	−1.065∗∗∗	−1.080∗∗∗
	(0.174)	(0.172)	(0.175)
no. of facilities	10.223∗∗∗	10.314∗∗∗	10.109∗∗∗
	(2.093)	(2.063)	(2.103)
facility size	−9.804∗∗∗	−9.761∗∗∗	−9.697∗∗∗
	(1.541)	(1.539)	(1.555)
maturity	−6.078∗∗	−6.098∗∗	−5.925∗∗
	(2.482)	(2.477)	(2.507)
revolver	−64.172∗∗∗	−64.710∗∗∗	−64.023∗∗∗
	(10.06)	(10.061)	(10.089)
term loan	−1.495	−1.97	−1.377
	(10.348)	(10.356)	(10.385)
secured	82.454∗∗∗	82.408∗∗∗	82.703∗∗∗
	(3.199)	(3.186)	(3.201)
senior	−229.985∗∗∗	−229.408∗∗∗	−231.000∗∗∗
	(48.352)	(48.532)	(48.362)
constant	495.781∗∗∗	496.722∗∗∗	500.819∗∗∗
	(56.055)	(55.897)	(55.558)
dummy year	Yes	Yes	Yes
dummy loan purpose	Yes	Yes	Yes
dummy industry	Yes	Yes	Yes
no. of observations	10,363	10,363	10,363
no. of firms	1,737	1,737	1,737
R-square	0.552	0.553	0.552