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Trading costs of private debt[☆]

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ABSTRACT

We use institutional trade and dealer quote data to estimate transaction costs in the over-the-counter leveraged loan market. In the time series, we find an asymmetric response of transaction costs to loan market returns: negative market returns increase costs much more than positive returns decrease them. In the cross-section, our results support the inventory holding costs and adverse selection paradigms of price formation. As expected for a market without the governance role of securities laws and any regulatory oversight, the level of informed trading is high. Finally, liquidity is marginally priced in secondary market loan spreads, as predicted by classic asset pricing theory.

1. Introduction

While financial economists have extensively studied transaction costs in public securities markets, not much is known about the costs of trading in private (non-securities) markets.[1] This is even more worrying in view of the tremendous growth of institutional investors' allocations to private assets. According to McKinsey's Global Private Markets Review 2020, private market assets under management surpassed an all-time high of $6.5 trillion in 2019, up 10% year-on-year. In this paper, we use trade and dealer quote data to estimate actual trading costs for one of Wall Street's hottest private asset classes: institutional facilities (term loans) of leveraged loan packages traded over-the-counter (OTC).

The leveraged segment of the syndicated loan market represents an important source of funds for risky corporations and has witnessed remarkable growth after the financial crisis 2007–2009. As estimated by the Bank of England, at the end of 2018, there was $2.2 trillion in leveraged loans outstanding worldwide, of which around $1.8 trillion is held by non-bank institutions. The strong primary market presence of institutional investors such as collateralized loan obligations (CLOs) or loan mutual funds and exchange-traded funds (ETFs) fostered the establishment of a secondary market. While outside the radar of regulators and

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[1] Work examining the microstructure of private markets is recently emerging. For example, Albuquerque et al. (2018) and Nadauld et al. (2019) study liquidity provision in the secondary market for private equity fund stakes, and their findings suggest that certain theories of market microstructure broadly apply to this market as well.

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securities laws, the secondary market in the U.S. grew from an annual trading volume of $145 billion in 2003 to $743 billion in 2019 at an annual compound rate of 10.1%.

We assemble two different data sets that allow a comprehensive analysis of loan liquidity. The first one contains daily indicative dealer bid and ask quotes from Markit for a broad cross-section of facilities over the period from January 2008 to December 2016. To alleviate possible shortcomings of indicative quotes in OTC markets, and to measure trading costs using the prices actually obtained by investors, we additionally collect information on 141,575 trades executed by the most important leveraged loan investor group, CLOs. This trade data covers the period from July 2010 to December 2015.

We first look at systematic variation in loan liquidity at the market level and construct a liquidity index based on dealer quoted bid-ask spreads for facilities likely to be traded in the secondary market. The resulting time series comprises 468 weeks, from the first week of 2008 to the last week of 2016. Our primary interest here is to examine the collateral value or funding constraints view of liquidity that gained much attention after the financial crisis of 2007–2009. A key prediction of this theory is that liquidity suppliers who face capital constraints are less willing to make markets in assets that tie up more capital, especially at times when funding costs are high or capital constraints are more likely to be binding (e.g., Gromb and Vayanos, 2002; Gârleanu and Pedersen, 2007; Brunnermeier and Pedersen, 2009). In line with this prediction, we find that periods of general financial market turmoil (as proxied for by VIX changes) and heightened loan market price volatility go hand in hand with less liquidity. Deteriorating funding conditions of dealers (i.e., rising TED spreads) are also negatively associated with loan market liquidity.

Most importantly, we relate loan market price movements to liquidity and find an asymmetric response of liquidity to market returns: negative market returns decrease liquidity much more than positive returns increase liquidity. This finding is consistent with the theoretical predictions in the collateral-based models in Gârleanu and Pedersen (2007) and Brunnermeier and Pedersen (2009), and with the empirical evidence for stock markets in Chordia et al. (2001, 2002) and Hameed et al. (2010). By influencing the collateral value of dealer inventories, and, hence, dealer's funding constraints, loan price induced wealth changes affect market liquidity. This effect is asymmetric because it is exactly in down markets when liquidity providers are likely to hit their wealth or financing constraints.

While the capital constraints paradigm explains illiquidity during market stress with a supply effect, an alternative view predicts increased liquidity demand by panic sellers following market price declines (see Chen et al., 2010; Goldstein et al., 2017). To untangle supply from demand effects, we look at net flows into retail loan mutual funds and ETFs and we allow for a differential impact of excess buying and selling by loan funds as a response to flows. While buying demand by funds does not affect liquidity, outflows in turn are significantly associated with market-wide bid-ask spread increases, a finding in line with an asymmetric effect of liquidity demand. However, even after controlling for liquidity demand by fire sellers, the asymmetric effect of market returns on liquidity remains significant, emphasizing the separate role of liquidity supply in market declines.

We validate our findings through several robustness checks by using different liquidity indices constructed from dealer quote data provided by S&P's Leveraged Commentary and Data (LCD) unit. In particular, we verify that all of our results survive when we look at a much longer time series (944 weeks, from the last week of May 2002 to the first week of July 2020), restrict the index constituents to the top 15 facilities in terms of trading amount, or focus only on European facilities.

We turn next to a cross-sectional analysis of liquidity and gauge actual trading costs by the effective half-spread (*EHS*), defined as the difference between the price at which a customer buy or sell order executes and the average dealer midquote posted on the day before the trade day. Loans are indeed expensive to trade, with mean and median *EHS* across our trade sample of 47.6 bps and 25.0 bps, respectively. However, the standard deviation is high at 64.4 bps. We examine various facility and trade characteristics likely to explain this cross-sectional variation in trade execution costs. The two main paradigms of market microstructure theory, the inventory holding costs and the adverse selection paradigm (Demsetz et al., 1968; Stoll, 1978; Ho and Stoll, 1981; Glosten and Milgrom, 1985) serve as the theoretical underpinning for our variable selection. In short, we find strong support for both theories. Price volatility, extreme past price movements, quoted bid-ask spreads, dealer coverage, facility size, past trading volume, average market valuation levels, and a facility's time on the market are all economically and statistically significantly associated with trading costs. Trade size exhibits an upward-sloping and almost exactly linear relation with trading costs.

The status of loans as non-securities and the privileged access of lenders to borrower private information raises significant adverse selection issues for traders. Indeed, a constellation of information parity between trading counterparties is rarely feasible in the loan market because borrowers agree to provide a continual stream of non-public, proprietary business information to their lending syndicates in exchange for a promise to keep that information confidential. Hence, by the very nature of the loan product, the sale of a loan from an existing lender to a new lender generally involves some degree of information asymmetry. In equilibrium, market makers should require extra bid-ask spreads to compensate for taking on such informational risk (e.g., Glosten and Milgrom, 1985).

To evaluate the relative contribution of adverse selection to trade execution costs, we decompose the effective spread (the total price impact) into two components: a permanent price impact (*PPI*) and a temporary price impact (*TPI*). Investors possessing superior information exert lasting pressure on prices, i.e., midquotes rise (fall) permanently after customer buys (sells). Because *PPI* estimates this permanent adjustment of dealer midquotes to the information content of trades, we consider it a measure of informed trading. The temporary price impact *TPI*, in turn, can be seen as a measure of the profit earned by the liquidity supplier on the trade.

As predicted, the loan market is exposed to a high degree of informed trading: midquotes move on average 30.1 (34.8) bps in the direction of the liquidity demander within 10 (20) days after the trade day. Stated differently, about two-thirds of the average effective spread (47.6 bps) represent adverse selection costs, and only one-third (12.7–17.5 bps) compensates the liquidity provider for inventory holding or order processing costs.[2] Hence, liquidity suppliers' gains, and therefore liquidity demanders' realized one-way trade execution costs, are on average in the order of 15 bps, much less than what is suggested by the effective spread. Furthermore, while informed trading harms liquidity, it benefits price discovery: dealer quotes for actively traded facilities likely represent informationally efficient prices. In line with this expectation, Addoum and Murfin (2020) find that publicly observable midquotes of syndicated loans reveal non-public information that predicts stock returns.

We also examine cross-sectional variation in the returns to liquidity provision (*TPI*) and the degree of informed trading, and identify determinants of this variation. For example, small trades in large and risky facilities with extreme past idiosyncratic returns, higher dealer coverage, and wider quoted spreads are generally more informed (higher *PPI*).

In the last part of the paper, we study a central prediction from asset pricing theory: illiquid assets should compensate investors through higher expected returns (or yield spreads) for transactions costs and liquidity risk [Amihud et al. (2005) provide a comprehensive survey]. The fact that sufficiently often two or more facilities issued by the same borrower trade simultaneously on the secondary market at different spreads and transaction costs allows us to dummy out credit risk by employing borrower × month fixed effects [see Dick-Nielsen et al. (2012) for a similar approach]. This way we can overcome the inherent endogeneity of liquidity and isolate the pricing of liquidity from the loan spread component due to credit risk. Our findings indicate that liquidity is marginally priced in secondary market spread-to-maturities (*STM*). For example, the effective (quoted) half-spread predicts an incremental 0.30 (1.83) bps increase in *STM* for a 1 bp increase in liquidity costs. However, in line with the dominant role of credit risk in driving bond yield spreads (e.g., Chen et al., 2007; Friewald et al., 2012), the borrower × month fixed effects are responsible for about 99.5% of the total explained variation in *STM*.

Studying the size and sources of trade execution costs in leveraged loans, and understanding the drivers of temporal and cross-sectional variation in these costs is important for several reasons. First, as argued above, leveraged loans play an increasingly important role in institutional investors' portfolios. Hence, a better awareness and understanding of the mechanisms of loan liquidity and trading not only fosters investors' reliance on the credit product itself and the market as a whole, it also improves loan portfolio management and, in the end, the allocation of investment capital.

Second, the fact that open-end loan mutual funds and ETFs fueled with retail investor money have become major buyers of leveraged loans has raised serious financial stability concerns among regulators and central bankers around the world.[3] The issue here is that ETFs and mutual funds are highly liquid instruments with short (mostly daily) redemption periods, meaning investors can enter and exit positions easily. Loans, in turn, are infrequently traded and face long settlement durations, typically exceeding ten or more business days. This liquidity mismatch and the associated first-mover advantage in an illiquid market could cause a "run-on-the-fund" phenomenon, as shown in Goldstein et al. (2017) for bond funds. In a downturn, when fund share redemptions gain momentum, a fund has to sell assets at heavy discounts as only a few market participants are still willing to trade in an illiquid market. The associated losses can provoke open-end mutual funds and ETFs to collapse by virtue of their incapacity to meet redemptions. Our paper informs this debate by enabling regulators, bankers, asset managers, and investors to identify loans and investment funds exposed to a heightened level of illiquidity.

Last, the special informational structure of the lender-borrower relationship and the high-risk nature of leveraged loans makes this asset class particularly suitable for stringent tests of theoretical paradigms of price formation (inventory concerns and asymmetric information). For example, the market maker capital constraints view of liquidity proposed by Gromb and Vayanos (2002) or Brunnermeier and Pedersen (2009), among others, predicts that for high-risk (i.e., capital-intensive) assets, liquidity provision should be sensitive to aggregate changes in inventory funding conditions. Similar, adverse selection plays more of a role in risky assets than in information-insensitive ones. As far as we known, our paper is the first to apply the main theories of market microstructure to the private loan market.

The remainder of the paper is organized as follows: In the next section, we characterize leveraged loans and describe how the secondary loan market works. In Section 3, we provide information on the loan quote and trade data. In Section 4, we investigate the time series and cross-sectional determinants of loan trading costs. We also look at the relative contribution of each source of illiquidity (adverse selection costs and inventory concerns), and offer evidence in line with the pricing of liquidity levels in loan spreads. Section 5 gives a summary and conclusions.

2. Institutional background

2.1. Leveraged loans

A syndicated loan is a commercial credit structured, arranged, and administered by one or several commercial or investment banks, known as arrangers or agents. In this paper, we look at the leveraged or noninvestment-grade segment of the syndicated loan market (i.e., loans to risky borrowers). Such leveraged loans are typically packaged into two broad structures: institutional

[2] To put this number into perspective, adverse selection risks are much less pronounced in public securities markets. Stoll (2000), for example, estimates the informational friction component of effective half-spreads to be typically on the order of 33%–45% for stocks listed on NYSE/AMSE and between 20% and 25% for stocks on Nasdaq.

[3] To cite just one example, in its September 2018 Quarterly Review, the Bank for International Settlements (BIS) puts it this way: "Moreover, given that mutual funds are a major buyer, mark-to-market losses could spur fund redemptions, induce fire sales and further depress prices. These dynamics may affect not only investors holding these loans, but also the broader economy by blocking the flow of funds to the leveraged credit market."

tranches and pro rata tranches. Institutional tranches comprise first- and second-lien, non-amortizing ("bullet"), fully-funded facilities (called term loans B, C, D, etc.) structured specifically for institutional investors like CLOs, mutual funds/ETFs, credit hedge funds, pension funds, and insurance companies. Pro rata debt includes unfunded revolving credit ("revolvers") and amortizing facilities (term loans A), which are packaged together and usually syndicated to banks. The institutional part of the U.S. leveraged loan market experienced a tremendous growth over the last decade, with institutional outstandings more than doubling since 2010, crossing the $1 trillion threshold for the first time at $1.006 trillion in April 2018, and catching up to the U.S. high-yield bond market.[4]

The most important investors in the institutional segment of the leveraged loan space are CLOs. Essentially, a CLO is a special-purpose vehicle similar to a managed closed-end fund, set up to hold and manage pools of leveraged loans (almost exclusively term loans B, C, etc.), and to a lesser extent high-yield bonds. These investments are financed through the issuance of several debt and (one or two) equity tranches that have rights to the collateral and payment stream, in descending order [(Taylor and Sansone, 2007) and Standard & Poor's (2013), among others, provide extensive details on the syndicated loan market]. According to data from LCD, the aggregate CLO share of institutional loan outstandings is currently around 70%, while the loan mutual funds and ETF market share oscillates between 10% and 15%.

2.2. How the secondary loan market works

The secondary leveraged loan market is exclusively an institutional market, operated by decentralized broker-dealers (trading desks). All trading takes place OTC, with most transactions concluded on an intermediated basis (i.e., trades pass through loan dealer desks located at large investment banks acting as lead arrangers or transfer agents for a given facility). The market generally lacks pre- and post-trade transparency. Hence, any potential trader cannot observe all dealer quotes in a central location or on a computer screen. Instead, the institution must call several dealers for quotes or subscribe to data vendors like Refinitiv LPC or Markit that broadcast near real-time bid and ask quotes aggregated across contributing dealers. As common for OTC markets, quotes are indicative, not firm.

Loan sales are legally structured as either assignments or participations. The major difference between these two transfer mechanisms is that in the former the lender disposes his loan commitment, with the new lender assuming a direct contractual relationship with the borrower, while within a participation the lender retains a contractual relationship with the borrower.[5] Due to this difference in legal structure, borrower (and sometimes agent) consent is usually required only for assignments, not participations.

Because loans are not standardized securities but individual contracts requiring extensive documentation, the anatomy of a loan trade is complex and time-consuming, involving several stages of exchange between the trade parties. In Section A in the Internet Appendix, we provide a typical time-line for a standard loan trade, highlighting the essential stages necessary to complete a trade. Not surprisingly, loan settlement durations are much longer compared to the standard of three business days in developed securities markets.

The private nature and limited transparency makes it difficult to assess the actual size of the secondary loan market. Available data collated by trading associations (the LSTA for the U.S. market and the LMA for the EMEA market) includes intermediated transactions but mostly neglects trades directly between seller and buyer without the involvement of one of the dealer banks contributing the data. Hence, the reported data is expected to underestimate actual traded volumes. Nevertheless, even with this caveat in mind, it is safe to say that the secondary loan market is on an exceptional growth path. According to LSTA data, the monthly U.S. trading volume increased by about 70% over our sample period, from $28.1 billion in July 2010 to $47.4 billion in December 2015.

2.3. What is special about trading loans?

While securities laws generally seek to reduce pre-trade information asymmetries by requiring disclosure of material information if the counterparties are on unequal footing, loans are not securities and securities laws (including antifraud and insider trading provisions) do not govern transactions in the secondary loan market. A constellation of information parity between trading counterparties is rarely feasible in the loan market because borrowers agree to provide a continual stream of non-public, proprietary business information to their lending syndicates in exchange for a promise to keep that information confidential. Some of that proprietary information is material and not intended by the borrower to be disseminated beyond the lending syndicate to the public, and may therefore potentially be classified as material non-public information under securities laws. Hence, by the very nature of the loan product, the sale of a loan from an existing lender to a new lender generally involves some degree

[4] The numbers cited in this section are sourced from LCD and refer to the U.S. leveraged loan market, for which more information is publicly available compared to syndicated lending in Europe, Middle East, and Africa (EMEA). Two different trade bodies, the Loan Syndications and Trading Association (LSTA) for the U.S., and the Loan Market Association (LMA) for the EMEA market, exist with the mission to "encourage liquidity in both the primary and secondary loan markets by promoting efficiency and transparency, as well as by developing standards of documentation and codes of market practice".

[5] Because offshore vehicles like CLOs or hedge funds suffer adverse tax consequences from buying loans directly in the primary market, a special transfer mechanism ("primary assignment") applies to the primary purchases of these important investor types. In a primary assignment, the lead arranger or transfer agent parks the desired loan on its books for some time after loan issuance, and subsequently transfers it to these investors through an assignment. Importantly, these primary assignments are primary purchases, not secondary market trades.

Table 1
Markit's loan market quotes. This table presents descriptive information for the facilities included in the loan market database from Markit for 2008–2016. Panel A provides information for all facilities included in the database. Panel B provides information for a subsample of Markit facilities assumed to be more extensively traded. For every year, the total number of observations and the number of facilities are presented. Additionally, the mean and median of the number of dealers providing quotes (*NumDealers*) and of the quoted spreads (*Quoted Spread*) are provided for each year. The quoted spread is the difference between the ask and bid quote and is measured in basis points.

			NumDealers		*Quoted Spread*	
Year	Observations	Facilities	Mean	Median	Mean	Median
Panel A: All Markit database facilities						
2008	1,738,684	9,420	1.357	1.000	252.173	200.000
2009	1,751,938	8,950	1.466	1.000	2,087.233	300.000
2010	1,670,252	9,567	2.122	1.000	8,104.022	200.000
2011	1,626,590	9,688	2.240	1.000	8,359.294	150.000
2012	1,675,969	9,706	2.156	1.000	1,282.913	133.400
2013	1,675,349	10,019	2.068	1.000	208.391	100.000
2014	1,633,071	9,825	1.966	1.000	200.847	87.500
2015	1,622,541	8,862	1.872	1.000	245.660	100.000
2016	1,521,422	8,959	1.812	1.000	269.094	100.000
Panel B: Facilities included in the liquidity index						
2008	135,100	524	6.113	5.000	227.041	195.000
2009	158,836	602	5.820	5.000	244.532	209.400
2010	220,344	850	6.131	5.000	160.380	143.700
2011	216,338	835	5.967	5.000	153.078	133.300
2012	244,746	946	5.417	5.000	140.797	112.500
2013	192,849	734	5.061	4.000	120.247	91.600
2014	170,453	647	5.420	5.000	83.197	66.700
2015	211,792	803	5.160	4.000	96.662	75.000
2016	192,922	773	4.723	4.000	118.427	87.500

of information asymmetry. To facilitate trading in the presence of potentially significant information asymmetries, loan market participants established a contractual disclaimer of reliance framework (known as "big boy" rule). This legal model allows some degree of information asymmetry between counterparties as of the trade date and protects purchase and sale transactions from being unwound at some future point by disgruntled counterparties. In sum, insider or informed trading is likely a more serious issue in the private loan market than the public securities markets. We investigate this point in Subsection 4.3.

3. Data and liquidity measures

3.1. Loan market quotes

We obtain daily average bid and ask quotes at the facility level from Markit for the period January 1, 2008 to December 31, 2016. Markit uses a proprietary algorithm to extract indicative OTC quotes from dealers making a market in a given facility. Quotes are parsed by Markit employees for consistency and averaged across dealers. These daily averages (and not the underlying quotes themselves) are available to Markit subscribers for a fee in near real-time. Dealers sourced by Markit usually come from the set of lead arrangers, transfer agents or administrative agents for the loan package at origination. While loan market investors widely use Markit quotes as a source of mark-to-market pricing, quotes are not without costs. Importantly, in most dealer (OTC) markets, posted quotes are typically indicative, representing just a starting point for bilateral negotiations between dealers and customers and not a binding commitment by a dealer to trade at his posted prices. Therefore, quotes may be stale and infrequently updated to new information.

In addition to these weaknesses, Panel A of Table 1 shows that among the broad cross-section of facilities (> 9,000) covered by Markit, more than 50% are quoted by just one dealer ($NumDealers = 1$), or no dealer at all.[6] Most of these single- or no-dealer facilities are infrequently traded term loans or even revolvers that typically do not trade at all. Hence, there are reasons to be concerned that a large fraction of quotes in the full Markit sample is uninformative about actual liquidity and trading costs. We address this important issue in Subsection 4.1.1 when we build an aggregate market liquidity index based on dealer bid-ask quotes.

[6] We identify matrix quotes as observations for which information on the number of dealers posting quotes is missing and quotes appear to be extremely stale over time. We set the *NumDealers* variable equal to zero in these cases. About 26% of the daily observations in the full sample represent matrix quotes. However, this number is likely to underestimate the real presence of matrix quotes because single-dealer quotes may sometimes result from matrix pricing, a prediction we cannot check directly.

Table 2
Summary statistics on liquidity measures. This table provides summary statistics on liquidity measures for the CLO trade sample from July 2010 to December 2015. The effective half-spread (*EHS*), the quoted half-spread (*QHS*), the temporary price impact (*TPI*), and the permanent price impact (*PPI*) are calculated using the samples from the regression models used to provide the results in columns (1) and (5) of Table 7. All four measures are denoted in basis points.

	N	Mean	Median	SD	P25	P75
EHS	141,575	47.566	25.000	64.370	11.100	55.000
QHS	141,575	41.438	34.400	25.987	25.000	50.000
$TPI(\Delta = 10)$	141,575	17.494	14.050	125.522	−13.000	50.000
$PPI(\Delta = 10)$	141,575	30.072	10.350	124.739	−9.300	47.500
EHS	141,083	47.574	25.000	64.397	11.100	55.000
QHS	141,083	41.442	34.400	25.958	25.000	50.000
$TPI(\Delta = 20)$	141,083	12.739	14.100	177.708	−29.150	62.500
$PPI(\Delta = 20)$	141,083	34.835	12.500	178.838	−19.950	64.550

3.2. Loan market trades

To circumvent possible shortcomings of indicative quotes in OTC markets, we construct a sample of actual secondary loan market transactions (i.e., the "trade sample") from the largest investor group: CLOs. By default, each CLO trustee report contains a section outlining the recent trading activity of the manager. We download all available trustee reports from the database CLO-i of Creditflux over the period July 2010 to December 2015, and extract the relevant trading information. In Section B in the Internet Appendix, we discuss the extensive cleaning and filtering process of the raw trade data. In short, we drop (1) trades with missing information on traded par amount, price or trade day, (2) transactions wrongly classified as secondary market trades (i.e., primary assignments, restructurings), (3) trades in facilities with no dealer quotes from Markit, (4) trades in instruments other than term loans (e.g., bonds, letters of credit, mezzanine tranches), or in facilities that cannot be clearly identified, and (5) trades with incomplete information on at least one of the explanatory variables outlined below. The final sample contains 141,575 secondary market trades of CLOs in term loans executed between July 2010 and December 2015.

In contrast to quoted spreads, the trade sample offers a way to measure trading costs using the prices actually obtained by the most important investor group in the leveraged loan market. Among other benefits, this makes it possible to verify whether indicative quoted bid-ask spreads indeed capture cross-sectional variation in transaction costs incurred by investors. We follow the market microstructure literature and gauge trading costs by the effective half-spread (*EHS*), defined as the difference between the price at which a customer buy or sell order executes and the average dealer midquote posted on the day before the trade day. Hence, we benchmark prices against one-day lagged midquotes (averaged across all dealers active in a given facility), implicitly assuming that average midquotes present an unbiased fundamental value proxy. This is a common assumption in the microstructure literature. However, if information dissemination and price formation occur more frequently (i.e., intra-daily), the reported effective spreads are likely systematically inflated. Our results on *EHS* must therefore be interpreted with this caveat in mind.

Formally, the *EHS* of a trade at price *P* in facility *i* at time *t* is defined as:

$$EHS_{it} = Q_{it}\left(P_{it} - M_{it-1}\right), \tag{1}$$

where Q is the trade direction indicator (1 for buyer-initiated and −1 for seller-initiated trades) and M is the pre-trade benchmark price (i.e., the one-day lagged average midquote). To establish a trade's direction, we again follow the extant market microstructure literature and sign trades using the algorithm proposed in Lee and Ready (1991). Specifically, we assume that a trade is buyer-initiated if the transaction price is above the previous day midquote, M_{t-1}, and seller-initiated if the price is below it. That is, $Q_t = 1$ if $P_t > M_{t-1}$, and $Q_t = -1$ if $P_t < M_{t-1}$.[7]

The first row in Table 2 reports mean and median *EHS* of 47.5 bps and 25.0 bps, respectively, for our sample of loan trades. Hence, by looking just at effective spreads, loans appear to be expensive to trade. However, as we show later, about two-thirds of the average effective spread represents adverse selection costs, and only one-third compensates the liquidity provider for inventory holding or order processing costs. Hence, effective spreads overestimate liquidity suppliers' gains, and therefore liquidity demanders' trading costs: average *realized* one-way trade execution costs are in the order of 15 bps, rather than 45 bps.

We can benchmark these numbers to other traded private debt instruments. The closest substitutes to leveraged loans, in terms of risk, cash flow profile and regulatory treatment are privately placed and non-registered, Rule 144A high-yield bonds. Jacobsen and Venkataraman (2018) employ price impact regressions and estimate average one-way trade execution costs of 12–14 bps for Rule 144A high-yield bonds (see Panel B in their Table 2). They also find that after the start of public dissemi-

[7] Since we only know the trade day and not the trade time, and because Markit quotes are unavailable intra-daily, we date-match trades to quotes, rather than time-match them. The 3,432 trades that take place exactly at the previous midquote are viewed as being initiated by the CLO (i.e., $Q_t = 1$ for CLO buys at M_{t-1}, $Q_t = -1$ for CLO sells at M_{t-1}). Our results remain qualitatively similar if we instead drop these trades or reverse their signing.

nation of trade information (through TRACE) in June 2014, trading costs for high-yield bonds decreased by 14% on average.[8] Furthermore, Han et al. (2018) report that following public registration of 144A bonds, effective bid-ask spreads narrow, by 12%–19%. These findings together with our results on the importance of adverse selection risks in the loan market imply that increased mandatory information disclosure (through public securities registration or trade reporting) could substantially lower effective spreads for traded loans.

We end this section by highlighting that the decision to trade a facility is likely endogenous and depends on transaction costs. As shown in the second row of Table 2, the quoted half-spreads (*QHS*, i.e., the difference between the Markit ask and bid quote divided by two) among the facilities in our trade sample amount to 41.4 bps (mean) and 34.4 bps (median). The corresponding (unreported) numbers across all facilities covered by Markit (Table 1, Panel A) over the trade sample period (July 2010–December 2015) are significantly higher: 1,169.6 bps (mean) and 66.0 bps (median). Even our subsample of Markit facilities assumed to be widely traded (Table 1, Panel B, discussed below) depicts lower quoted liquidity (higher spreads) than the trade sample, with mean and median half-spreads of 62.0 bps and 49.0 bps, respectively. This suggests that the availability of quotes is a sign of marking demand rather than trading demand, and that only the liquid segment of the leveraged loan market is actively traded. Hence, our estimated effective spreads are not representative of a typical facility's liquidity.

4. Secondary market liquidity of leveraged loans

We split our empirical analysis into four subsections. We start by investigating potential sources of intertemporal variation in aggregate leveraged loan market liquidity. Our main result here is an asymmetric response of transaction costs to loan market returns: negative market returns increase costs much more than positive returns decrease them. This finding is consistent with the predictions in the collateral-based models of liquidity supply. Then, we look at cross-sectional variation and provide evidence supporting the inventory holding costs and adverse selection paradigms of price formation. To understand the relative importance of the key sources of illiquidity, we next estimate the contributions of adverse selection costs and inventory holding costs to illiquidity and price movements. In line with the private and unregulated nature of the secondary loan market, the level of informed trading is high: about two-thirds of the average effective spread represent adverse selection costs, and only one-third compensates the liquidity provider for inventory holding or order processing costs. Finally, we disentangle liquidity and credit risk non-parametrically, and find that liquidity is marginally priced in secondary market loan spreads, as predicted by classic asset pricing theory.

4.1. Time series determinants of liquidity

4.1.1. Main results

Much theoretical research looks at the role played by capital or funding constraints of the market making sector as a whole in causing liquidity dry-ups. While the exact details of the theoretical models in, for example Gromb and Vayanos (2002) or Brunnermeier and Pedersen (2009) differ, they all predict that liquidity suppliers who face capital constraints are less willing to make markets in assets that tie up more capital, especially at times when funding costs are high or capital constraints are more likely to be binding. The leveraged loan secondary market presents an ideal setting for testing this funding liquidity paradigm of liquidity supply because their high-risk nature lends leveraged loans exactly the status as capital-intensive assets for which liquidity provision should be particularly sensitive to aggregate changes in inventory funding conditions.

Similar to Hameed et al. (2010) and others (e.g., Chordia et al., 2001, 2002), who find that stock market movements do affect aggregate stock market liquidity, we consider the tightness of loan dealer capital constraints as being reflected in loan market returns (proxied for by the S&P/LSTA LL100 price index).[9] The idea is that a huge market-wide decline in loan prices reduces the aggregate collateral value of the loan dealer sector, further tightening their funding constraints, which ultimately feeds back as higher market illiquidity. This prediction is also in line with the finding in Comerton-Forde et al. (2010) that NYSE-specialist firms reduce their liquidity provision at times when they lose money on inventories.

As in Gârleanu and Pedersen (2011) or Nagel (2012), we proxy for the funding costs of dealer banks by the TED spread (the three-month Eurodollar deposit rate minus the three-month Treasury bill rate). In addition, market downs accompanied by rising volatility expectations lead to even more strains in funding conditions and corresponding increases in market illiquidity, as predicted by models in Gârleanu and Pedersen (2007) and Huang and Wang (2009). Accordingly, Nagel (2012) finds that both, market returns and the CBOE Volatility Index (VIX) of implied volatilities of S&P 500 Index options predict returns from liquidity provision in the stock market.

To apply the funding liquidity paradigm of liquidity supply to the loan market, we construct a weekly index of market-wide liquidity over the nine-year period from 2008 to 2016, 468 weeks in total. Since we want to study the dealer sector reaction to

[8] This decrease in liquidity cost for Rule 144A bonds coming from ex post trade reporting is consistent with results from earlier empirical studies on TRACE trade information dissemination for public corporate bonds introduced in July 2002. Bessembinder et al. (2006), for example, find larger half-spreads pre-TRACE for noninvestment-grade bonds (rated BB or lower) than for investment-grade bonds, 15.6 bps versus 12.9 bps. While trade execution costs dropped by 6.4 bps post-TRACE for the investment-grade sample, the author's results indicate a much larger increase in liquidity after TRACE for noninvestment-grade bonds.

[9] The S&P/LSTA Leveraged Loan 100 Index is a daily index for the U.S. market that consists of 100 facilities (mostly term loans, both amortizing and institutional) and intends to mirror the market-weighted performance of the largest institutional leveraged loans in an effort to reflect the most-liquid side of the market. The index is published by LCD, dates back to 2002, and the pricing source are average bid quotes from the LSTA/LPC mark-to-market service.

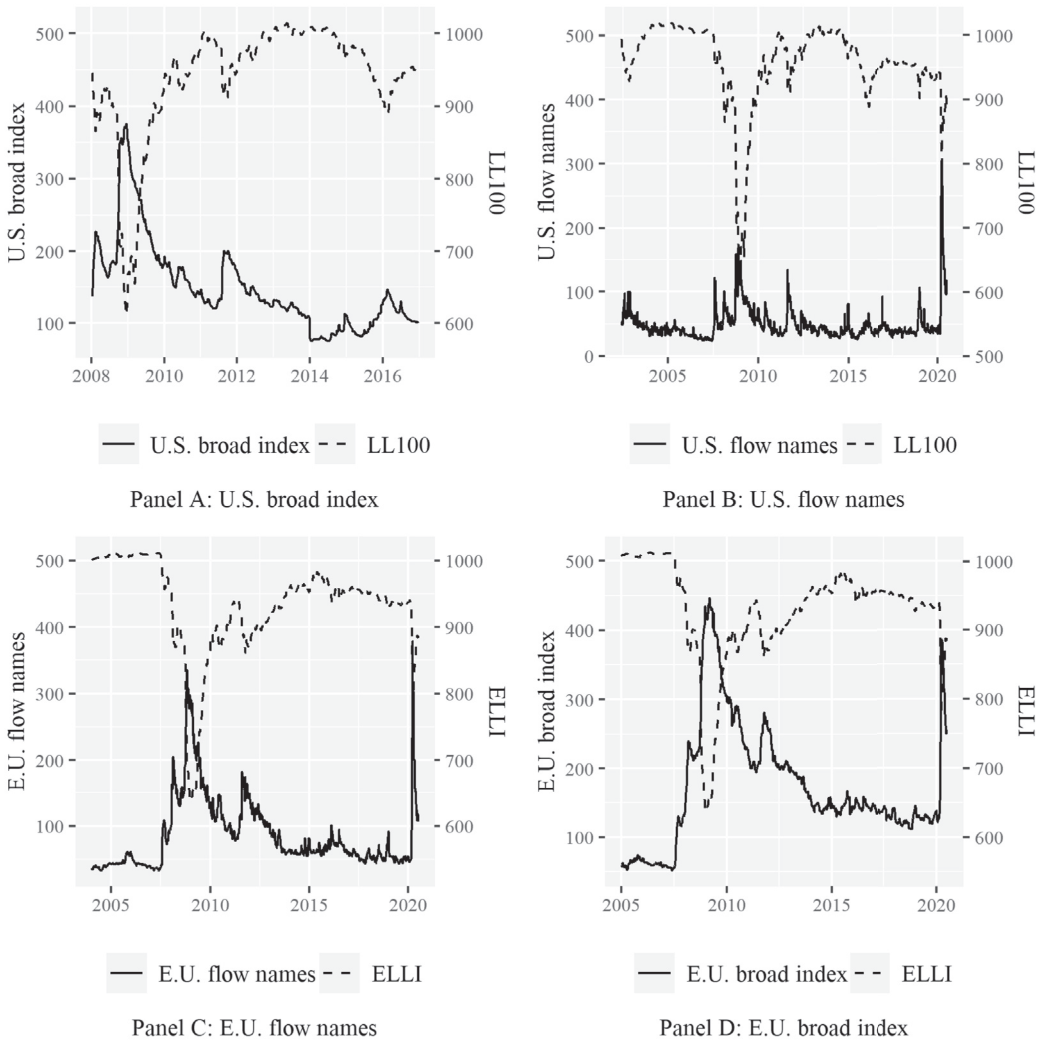

Fig. 1. Comparison of market-average liquidity and market price index level. This figure shows the evolution of the weekly market average bid-ask spreads (in basis points) together with the weekly average levels of the market price indices. Panel A and Panel B compare the U.S. broad index and the U.S. flow names composite with the LL100 price index, Panel C and Panel D compare the E.U. flow names and the E.U. broad secondary market composites with the ELLI price index.

changes in financing conditions, we base the index on our Markit dealer quotes sample that also has a longer time series than the trade sample. In particular, at the beginning of each year, we select all institutional facilities that have (1) two or more dealers providing quotes at any point during the year, and (2) at least one daily average bid-ask spread in each calendar week of the year. We impose these two restrictions to focus on the liquid segment of the leveraged loan market.[10] The daily averages of the index constituents' quoted bid-ask spreads are aggregated to obtain weekly equally-weighted average spreads. This liquidity index is reformulated each year and the number of index constituents during a typical year is 746. Panel B of Table 1 gives additional information on index constituents over time, and Fig. 1 (Panel A) depicts the evolution of the index together with the LL100 price index level. Importantly, quoted illiquidity steadily decreases from a peak of 376.0 bps in December 2008 to about 100 bps at the end of our sample period. As might be expected, liquidity *levels* co-vary strongly with market trends, the correlation between the liquidity index and the LL100 price index level is −0.9.

Although level-to-level correlations are revealing, week-to-week *changes* in liquidity provide a more stringent test of the capital constraints paradigm. Specifically, the weekly relative change in the market-average quoted bid-ask spread is regressed on (1) the concurrent price return of the LL100 index, (2) contemporaneous weekly relative changes in the TED spread and the VIX index, (3) the simultaneous weekly relative change in the aggregate U.S. secondary loan market trading volume, and (4) the

[10] The first restriction ensures that we exclude all facilities with matrix quotes and infrequently or non-traded facilities (e.g., revolvers). All of our results remain qualitatively unchanged if we set the minimum requirement to three dealers posting quotes.

Table 3

Time series regressions of weekly liquidity changes. This table reports the results of OLS time series regressions of changes in the market-average quoted bid-ask spread. The dependent variable is the week-to-week change (in basis points) in the liquidity index from the first week of January 2008 to the last week of December 2016. The explanatory variables are the weekly changes (in basis points) in: the U.S. secondary loan market trading volume (Δ*Trade Volume*), the VIX (Δ*VIX*), and the TED spread (Δ*TED*). *Market Return* is the price return of the S&P/LSTA Leveraged Loan 100 Index (in basis points), and (*Market Return*) is the proxy for loan market volatility. Net fund inflows resp. outflows in $ million are represented by max[0, *Net Flow*] resp. min[0, *Net Flow*]. In the regressions for columns (2) and (4), the market return and its volatility proxy are replaced by the positive market return (max [0, *Market Return*]) and the negative market return (min [0, *Market Return*]). Columns (1) and (2) show the results for the concurrent liquidity changes. Columns (3) and (4) show the results for next week's liquidity changes, i.e., all explanatory variables are lagged by one week with the additional inclusion of the lagged dependent variable on the right-hand side. Newey-West standard errors are reported in parentheses; the number of lags is automatically selected according to Newey and West (1994). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Concurrent liquidity change		Next-week's liquidity change	
	(1)	(2)	(3)	(4)
Intercept	−109.141***	−109.141***	−42.674**	−42.674**
	(20.604)	(20.604)	(20.753)	(20.575)
Δ*Trade Volume*	4.379**	4.379**	7.847***	7.847***
	(2.126)	(2.126)	(1.985)	(1.835)
max[0, *Net Flow*]	0.017	0.017	−0.010	−0.010
	(0.017)	(0.017)	(0.017)	(0.017)
min[0, *Net Flow*]	−0.145***	−0.145***	−0.107***	−0.107***
	(0.027)	(0.027)	(0.037)	(0.037)
Market Return	−1.397***		−0.746***	
	(0.282)		(0.189)	
max[0, *Market Return*]		−0.269		−0.534**
		(0.209)		(0.212)
min[0, *Market Return*]		−2.526***		−0.958***
		(0.544)		(0.332)
|*Market Return*|	1.128***		0.212	
	(0.300)		(0.202)	
Δ*VIX*	0.048***	0.048***	0.069***	0.069***
	(0.012)	(0.012)	(0.018)	(0.018)
Δ*TED*	0.031*	0.031*	0.014	0.014
	(0.017)	(0.017)	(0.018)	(0.018)
One-week lagged liquidity change			0.102	0.102
			(0.068)	(0.069)
Observations	468	468	467	467
Adjusted R^2	0.474	0.474	0.297	0.297

concurrent loan market volatility (measured by the absolute return on the LL100).

While the capital constraints paradigm explains illiquidity during market stress with a supply effect, an alternative view predicts increased liquidity demand by panic sellers following market price declines. For example, Chen et al. (2010) and Goldstein et al. (2017) show that investors in mutual funds holding illiquid assets face "run-on-the-fund-incentives" and that, as a result, outflows from such funds are highly sensitive to asset price drops. Such outflow-induced fire selling by funds in market downs could exhaust liquidity as in the theoretical model of Campbell et al. (1993) when dealers demand extra compensation for accommodating excess selling pressure by liquidity traders. To untangle supply from demand effects, we look at net flows (in $ millions) into retail loan mutual funds and ETFs.[11] These flows proxy for aggregate order imbalances of institutional investors in the leveraged loan market. To allow for a differential impact of excess buying and selling by loan funds as a response to flows, we split net fund flows into positive (i.e., net inflows) and negative (i.e., net outflows) parts, and include both as separate regressors. Time series regression results with Newey-West standard errors are reported in Table 3.

Consistent with previous studies examining stock market liquidity, we find in column (1) in Table 3 that periods of general financial market turmoil (as proxied for by VIX changes) go hand-in-hand with less loan market liquidity. A standard deviation (or 11.69%) increase in the VIX is associated with a 0.56% rise in the average quoted bid-ask spread. This is over and above the positive level effect of loan market volatility (the absolute value of the LL100 return) on quoted spreads, a result consistent with increased loan price fluctuations causing a decrease in liquidity due to increased adverse selection and/or inventory risk. Hence, in line with theoretical paradigms of liquidity supply (adverse selection, inventory risk, and capital constraints), loan dealers require a larger compensation for counterbalancing the increased funding costs and the risk of providing liquidity when the market deteriorates. The positive and (marginally) significant coefficient on the TED spread change also highlights the important

[11] We obtained a monthly time series of aggregate net flows into loan mutual funds and loan ETFs from LCD. In addition, the LSTA provided us with a monthly series of aggregate U.S. secondary loan market trading volumes. We transformed both series into a weekly frequency by using cubic splines.

role of dealer funding conditions for loan market liquidity.

As predicted, the effect of liquidity demand is asymmetric: if funds face one standard deviation ($676.5 million) higher outflows in a given week, the average bid-ask spreads increase by almost 1% from last week's level, or by about 28% of the standard deviation of week-to-week spread changes. This is consistent with the idea that excessive selling by retail accounts forces capital-constrained dealers to finance larger inventories. In contrast, the buying demand by funds does not significantly affect liquidity. Interestingly, changes in aggregate market trading volumes have a separate and significant positive impact on spreads. A possible explanation could be that irrespective of any imbalances in trade direction, larger trading volumes make it more difficult for dealers to control their optimal inventory and, hence, induce them to respond by increasing quotes.

More importantly, even after controlling for fund flows as a measure of liquidity demand, we find that loan market returns negatively affect current changes in spreads. If the LL100 loses 1% (or about one return standard deviation) of its value within a week, the average bid-ask spread is raised by 1.4% (or 39% of the standard deviation in week-to-week spread changes). Thus, consistent with the theoretical predictions in the collateral-based models in Gârleanu and Pedersen (2007) and Brunnermeier and Pedersen (2009), by influencing the collateral value of dealer inventories, and, hence, the dealer's funding constraints, loan price-induced wealth changes affect market liquidity. However, the funding cost or collateral value paradigm relating market price movements to liquidity has an even more subtle implication: negative market returns should decrease liquidity much more than positive returns increase liquidity because it is exactly in down markets where liquidity providers are likely to hit their wealth or financing constraints. We test this asymmetric response of liquidity to market moves in column (2) of Table 3 where we replace the LL100 return and its absolute value by separate variables for up and down market movements. The results are revealing and in line with asymmetric effects on liquidity: while average spreads rise by 2.5% if the market drops 1% in a given week, they only fall by 0.3% if the market goes up 1%. This asymmetric response is also statistically significant at the 1% level.

In columns (3) and (4) of Table 3, we implement predictive versions of the previous regressions where we lag all independent variables by one week. To account for serial correlation in weekly liquidity changes, we include the lagged dependent variable on the right-hand side of the regression. In line with previous results from the stock market (e.g., Chordia et al., 2002; Hameed et al., 2010; Nagel, 2012), we find that liquidity is highly predictable by changes in market trading volumes, loan fund net outflows, past market returns, and by changes in the financial markets turmoil state variable (VIX). The asymmetric response of spreads to up and down markets also obtains in the forecasting regression, although at an economically weaker degree and statistically insignificant level. Also noteworthy is the high adjusted R^2 in both the contemporaneous (about 47%) and the predictive regressions (about 30%). This compares favorably to numbers reported in the stock market literature and provides further confidence that our capital constraints motived variables capture an important share of the weekly variation in market-wide dealer spreads. In sum, Table 3 presents strong evidence in line with the funding or capital constraints paradigm of market liquidity. Market liquidity drops after negative loan index price returns and during times of enhanced financial market stress because the aggregate collateral of loan dealers falls and inventory financing constraints become more binding, making it difficult to provide liquidity exactly at times when investors need it most. Liquidity demand by fire sellers cannot fully explain this asymmetric effect of market returns on liquidity, emphasizing the separate role of liquidity supply in market declines.

4.1.2. Robustness

In this subsection, we investigate the robustness of our previous results on the collateral paradigm of liquidity supply across three dimensions: time, market segment, and region. That is, we rely on weekly time series of aggregate liquidity indices provided by LCD to 1) study a much longer period, 2) focus on the top 10 (or 15) traded facilities only, and 3) extend the analysis to the European loan market. All indices are constructed by first averaging quoted bid-ask spreads across index constituents and then aggregating the resulting series to a weekly frequency. In particular, LCD reports average dealer bid and ask quotes for all 15 (U.S.), respectively ten (Europe) constituents in their U.S. and European "flow-name composites". These composites are a regularly updated sampling of facilities widely traded in the respective secondary markets, per LCD's discussion with dealers and investors in the market. In addition, LCD also provides a broad European index covering all facilities quoted by Markit.

Table IA1 in the Internet Appendix reports descriptive information for levels and week-to-week changes of the four liquidity indices (including our baseline U.S. index from Subsection 4.1.1 in Panel A). Fig. 1 depicts the evolution of the index levels, together with the LL100 (Panels A and B) and the ELLI (Panels C and D) price index levels.[12] By construction, the liquid segments (i.e., the flow names) in both regions show much lower transaction cost levels and volatilities than the corresponding overall markets. More importantly, trading in the U.S. market is generally cheaper and investors are exposed to less liquidity risk compared to the European market. For example, the median quoted bid-ask spread across the top 10 widely traded European facilities is 64 bps but just 43 bps for the top 15 U.S. facilities. In addition, average and median spread levels are 10%–15% tighter in the U.S. market and the spread volatility is 30% smaller.

Panels B to D in Fig. 1 also reveal the effect of the COVID-19 related market turmoil on liquidity. Over the period from February to March 2020, average quoted bid-ask spreads increased by 527.8% (from 44.3 bps to 233.8 bps) for the 15 U.S. flow names, by 476.5% (from 53.3 bps to 254.0 bps) for the ten European flow names, and by 212.5% (from 129.3 bps to 274.8 bps) for the broad European market. In April 2020, bid-ask spreads started to fall again for the flow names, to 187.2 bps (U.S.) and 224.0

[12] To capture price movements in the European loan market, we employ the price return of the S&P European Leveraged Loan Index (ELLI), which is the European pendant to the U.S.-based S&P/LSTA LLI.

Table 4

Robustness of time series regressions. This table reports the results of OLS time series regressions of contemporaneous changes in the market-average quoted bid-ask spread of three LCD liquidity composites. The U.S. flow names and the E.U. flow names consist of 15 resp. ten facilities which are widely traded in the secondary market. The E.U. broad index represents the general European secondary market. The dependent variable is the week-to-week change in the respective composite, measured in basis points. The explanatory variables are the weekly changes (in basis points) in: the VIX (ΔVIX), and the TED spread (ΔTED). *Market Return* is the price return of the market index, i.e., the LL100 for the U.S. and the ELLI for the E.U. composites (in basis points), and (*Market Return*) is the proxy for loan market volatility. Net fund inflows resp. outflows in $ million are represented by max[0, *Net Flow*] resp. min[0, *Net Flow*]. In columns (2), (4) and (6), the market return and its volatility proxy are replaced by the positive market return (max $\left[0, \textit{Market Return}\right]$) and the negative market return (min $\left[0, \textit{Market Return}\right]$). Newey-West standard errors are reported in parentheses, the number of lags is automatically selected according to Newey and West (1994). $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	U.S. flow names (05/30/2002 – 07/02/2020)		E.U. flow names (01/08/2004 – 07/02/2020)		E.U. broad index (12/30/2004 – 07/02/2020)	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−82.443*	−82.443*	−90.966**	−90.966**	−46.005**	−46.005**
	(46.921)	(47.939)	(36.090)	(36.090)	(20.156)	(20.313)
max[0, *Net Flow*]	0.075	0.075	0.034	0.034	−0.001	−0.001
	(0.063)	(0.063)	(0.034)	(0.034)	(0.014)	(0.014)
min[0, *Net Flow*]	−0.242**	−0.242**	−0.193**	−0.193**	−0.076**	−0.076**
	(0.110)	(0.112)	(0.096)	(0.096)	(0.039)	(0.039)
Market Return	−2.705***		−4.246***		−1.996***	
	(0.993)		(0.948)		(0.338)	
max[0, *Market Return*]		−0.286		−2.698***		−0.572*
		(0.891)		(0.987)		(0.330)
min[0, *Market Return*]		−5.123***		−5.793***		−3.420***
		(1.835)		(1.519)		(0.625)
|*Market Return*|	2.419**		1.548*		1.424***	
	(1.063)		(0.861)		(0.369)	
ΔVIX	0.386***	0.386***	0.217***	0.217***	0.017	0.017
	(0.096)	(0.095)	(0.056)	(0.056)	(0.014)	(0.014)
ΔTED	0.078	0.078	0.051**	0.051**	0.040***	0.040***
	(0.078)	(0.077)	(0.025)	(0.025)	(0.011)	(0.011)
Observations	943	943	859	859	808	808
Adjusted R^2	0.167	0.167	0.368	0.368	0.423	0.423

bps (Europe), respectively, but further increased by about 100 bps (to 371.6 bps) for the broad European market.

Turning to our tests on the supply and demand effects on equilibrium market liquidity, in columns (1) and (2) of Table 4 we replicate the regressions of the corresponding columns in Table 3, but now use the liquidity index based on the U.S. flow-name composite as the dependent variable.[13] Restricting the analysis to the top 15 facilities in terms of liquidity enables us to investigate whether the collateral or funding constraints view of liquidity supply applies more broadly or whether the asymmetric response of liquidity to market returns is just driven by some infrequently traded facilities. A priori, one might suspect that liquidity-constrained dealers restrict their market making activities more for relatively illiquid facilities, and thus partially insulate liquid facilities from changing market conditions. There might even be some kind of a flight-to-liquidity at work, favoring the liquid segment of the market during downturns. Furthermore, since the weekly composite is available from the last week of May 2002 to the first week of July 2020 (944 weeks in total, or twice the size of the series in Table 3), our time series regressions now capture a wider range of market dynamics, including the recent COVID-19 related market turmoil. This should further increase the generalizability and robustness of our results.

Importantly, the asymmetric response of liquidity to market movements survives in the longer series and among the liquid facilities: the average spreads rise by 5.1% if the market drops 1% in a given week, yet they only fall by 0.3% if the market goes up 1%. This difference in coefficients is again statistically significant at the 1% level. In line with previous results on the importance of a liquidity demand channel, bid-ask spreads of the top 15 facilities increase by 2.1% if retail accounts face outflows of one standard deviation ($871.8 million). Inflows, in turn, do not move liquidity. Interestingly, VIX changes become economically more important: a one standard deviation (12.2%) increase in this market turmoil proxy raises spreads by 4.7% (or 0.27 standard deviations).

We next examine the liquidity dynamics of the top 10 traded facilities in the European market. These regressions encompass the period from the first week of January 2004 to the first week of July 2020 (860 weeks in total). The results in columns (3) and (4) of Table 4 generally agree with the ones for the U.S. market. For example, spreads increase by 5.8% if the market falls 1%, and drop by 2.7% if the market moves up 1%, a statistically significant difference. Retail outflows of one standard deviation ($914.0 million) raise spreads by 1.8% (or 0.19 standard deviations). Overall, the columns (1) to (4) present a consistent picture: during phases of severe market turmoil, even previously liquid facilities suffer significant increases in transaction costs. Hence, our results offer no evidence for a flight-to-liquidity *within* the loan asset class in times of stress.

[13] Since we do not have information on the aggregate market trading volume for the full length of the U.S. flow-name composite series, we drop the change in aggregate trading volume from the regression.

Finally, columns (5) and (6) of Table 4 present results for the broad European liquidity index that contains all quoted facilities and covers the period from the last week of 2004 to the first week of July 2020 (809 weeks in total). Results are in line with those found previously. For example, the asymmetric liquidity response to market returns is significant at the 1% level, and while VIX changes lose statistical and economic significance, changes in the TED spread become significantly positive at the 1% level. In addition, the explanatory power of the regression is also quite high, with an adjusted R^2 of 42%.

In sum, the results in Table 4 confirm that the findings in Table 3 are not specific to a particular period, extend to the European loan market, and even to a limited set of widely traded and liquid facilities. Hence, both tables offer rich evidence in favor of the funding constraints and a collateral value view of liquidity supply, after controlling for the liquidity demand of retail accounts.

4.2. Cross-sectional determinants of liquidity

4.2.1. Univariate sorts

Classic market microstructure theories suggest two main paradigms that determine cross-sectional variation of transaction costs in any market: the inventory holding costs and the adverse selection paradigm. The former predicts that liquidity is influenced by inventory concerns caused by an imbalance between buyer- and seller-initiated trades (e.g., Demsetz et al., 1968; Stoll, 1978; Ho and Stoll, 1981) and the latter states that in the presence of information asymmetry between buyers and sellers, liquidity suppliers face the risk of trading against better informed counterparties (e.g., Glosten and Milgrom, 1985; Kyle, 1985). These two paradigms serve as the theoretical underpinning for our selection of facility and trade characteristics likely to affect transaction costs.

4.2.1.1. Return volatility. Our first candidate characteristic is return volatility. Increased price fluctuations might cause a decrease in liquidity due to increased inventory risk and/or a heightened level of information asymmetry. We measure realized return volatilities of a facility using 60 days of midquote returns from $t-61$ to $t-1$, where t is the trading day, requiring at least 20 daily returns.

In Panel A of Table 5, we sort trades into quintiles according to the corresponding facility volatility. Quintile Q1 contains the 20% of trades in low volatility facilities and Q5 the trades in the riskiest facilities. As can be seen, the quintile sort generates a high Q5 versus Q1 spread in volatilities, amounting to 57.5 bps in the mean and 40.9 bps in the median, much of which is due to the high daily return fluctuations of 62.5 bps (mean) and 45.2 bps (median) for Q5 facilities. In line with the theoretical predictions of both paradigms, columns (3) and (4) of Table 5 show that mean and median transaction costs monotonically increase from the lowest to the highest quintile. The mean (median) quintile spread in *EHS* is 42.3 bps (27.4 bps), strongly significant at lower than the 1% level. These findings are also consistent with Stoll's (2000) result that stock return variance is a highly significant cross-sectional determinant of both quoted and effective spreads in public equity markets.

4.2.1.2. Facility excess return. Next, we consider a facility's past 20 days excess return ($ExR_{i;t-21,t-1}$). We calculate idiosyncratic returns based on midquote changes in excess of contemporaneous LL100 price returns. On the one hand, extreme past idiosyncratic price changes might be the result of price pressure caused by non-informational demand for immediacy in facilities with low liquidity. However, the price pressure caused by noise traders is not lasting as trading is unrelated to information. Liquidity suppliers anticipate the deviation of the transaction price from the fundamental value and absorb the demand for liquidity to exploit the noise trading-induced profit opportunity which reverts the prices. Hence, persistent negative or positive returns over an extended period of 20 days might rather signal the presence of private information that is slowly incorporated into quotes, generating permanent midquote changes. Either way, extreme past returns should be associated with less current liquidity or higher transaction costs.[14] Moreover, past returns might trigger asymmetric effects on liquidity, as argued by Cheng et al. (2017). In particular, past extreme price declines ("losers") can induce exits by (de facto) liquidity providers due to portfolio or risk management constraints, reputational concerns, or funding restrictions (higher haircuts or margin requirements). If true, this argument implies that extreme losers should face even higher trading costs than extreme winners.

Both predictions show up in the data (see Panel B of Table 5). Extreme past losers in Q1 and extreme winners in Q5 suffer a mean *EHS* of 67.7 bps and 52.9 bps, respectively, significantly higher than the 37.8 bps found for neutral Q3 facilities. In addition, the mean (median) *EHS* spread between Q1 losers and Q5 winners is 14.7 bps (10.4 bps), verifying that extreme losers are indeed more expensive to trade than extreme winners.

4.2.1.3. Quoted half-spread. Next, we sort trades according to the quoted half-spread (*QHS*). The results in Panel C show that mean quoted and effective half-spreads are very close to each other across all quintiles, as the differences are just between 5 and 10 bps.[15] This provides further confidence for our time series analysis and suggests that the use of average indicative quoted bid-ask spreads to capture the dynamics of market liquidity is unlikely to lead to false conclusions. However, while mean and median quoted spreads are similar within each quintile (Q5 appears to be an exception), a large gap exists in the

[14] Alternatively, momentum trading strategies can foster a positive relation between past returns and illiquidity. If extreme past returns attract momentum traders (buying winners and selling losers), the existing order imbalances of dealers might even be more strained, causing spreads to be raised.

[15] The fact that for each quintile mean *EHS* is greater than mean *QHS*, suggests that for some trades, past midquotes lag current day fundamental values. However, effective spreads do not appear to be systematically inflated because median *EHS* is less than median *QHS*.

Table 5
Univariate sorts of facility and trade characteristics. This table provides descriptive information on various facility and trade characteristics together with the corresponding liquidity measures. In every panel, trades are assigned to the quintiles Q1 to Q5 according to the respective sorting variable, i.e., the facility and trade characteristics. Transaction costs, price impacts, the facility's past volatility and past excess return, and the quoted half-spread are measured in basis points. The number of dealers is the raw number of market makers providing quotes for the respective facility. The facility's time on the market is measured in days, the facility's size and past cumulative trading volume are denoted in $ million. Relative trade size is measured as the percentage of the transaction's par amount scaled by the facility's notional amount. The inverse price is denoted as inverse percent of par. The average LL100 bid price is denoted in percent of par.

Quintile	Sorting variable		*EHS*		*TPI*		*PPI*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Panel A: Past 60 days facility midquote volatility								
Q1	5.019	4.304	36.167	19.500	21.806	13.750	14.281	5.000
Q2	8.901	7.296	35.058	20.850	18.596	14.150	16.426	7.850
Q3	12.562	10.562	40.552	23.750	21.033	13.750	19.400	9.500
Q4	19.284	16.831	48.937	25.650	18.908	15.050	29.925	12.500
Q5	62.506	45.157	78.454	46.850	8.795	15.350	69.548	31.250
Panel B: Past 20 days facility excess return								
Q1	−223.547	−107.763	67.652	37.500	12.913	16.650	54.693	16.350
Q2	−16.911	−15.334	40.340	22.500	17.564	14.250	22.659	7.850
Q3	20.343	14.361	37.823	21.400	19.409	14.100	18.328	7.600
Q4	56.265	49.260	39.920	22.450	19.406	13.000	20.486	9.350
Q5	190.933	125.298	52.942	27.100	19.566	14.200	33.252	12.500
Panel C: Quoted half-spread								
Q1	22.176	21.900	27.710	14.600	10.701	7.500	16.976	8.450
Q2	28.761	26.750	33.283	19.600	15.400	12.000	17.843	8.350
Q3	35.171	33.350	40.212	25.000	20.584	15.650	19.605	8.350
Q4	44.831	43.750	52.187	33.300	21.179	21.350	30.895	10.000
Q5	77.960	67.850	87.972	56.200	24.242	26.550	63.530	22.900
Panel D: Number of active dealers in a specific facility								
Q1	1.774	2.000	58.044	33.350	28.645	24.500	29.207	8.350
Q2	3.455	3.000	49.020	28.250	22.215	17.700	26.756	8.350
Q3	4.874	5.000	43.491	24.250	16.609	13.400	26.825	10.000
Q4	6.946	7.000	42.078	21.400	10.116	9.350	31.950	11.100
Q5	10.297	10.000	37.542	17.700	7.241	7.650	30.310	10.750
Panel E: Facility's time on the market								
Q1	68.410	52.000	43.140	24.900	24.837	15.900	18.279	8.300
Q2	256.867	225.000	47.328	25.000	16.849	14.350	30.313	10.700
Q3	476.508	440.000	47.309	25.000	12.831	12.500	34.408	12.450
Q4	740.348	658.000	48.266	25.000	15.307	12.625	32.897	11.150
Q5	1,165.515	1,062.000	50.217	25.850	21.218	15.750	28.918	8.350
Panel F: Facility size								
Q1	213.759	220.000	62.944	37.500	35.136	25.000	27.612	6.250
Q2	444.488	433.860	51.060	29.150	19.434	17.500	31.605	9.900
Q3	730.820	710.000	42.352	25.000	16.230	12.500	26.065	10.950
Q4	1,255.873	1,250.490	41.895	21.400	11.164	10.200	30.707	11.600
Q5	2,841.041	2,200.000	36.830	18.050	7.201	6.850	29.608	11.650
Panel G: Past 60 days accumulated trading volume								
Q1	0.345	0.000	60.666	33.350	32.653	24.400	27.746	7.500
Q2	2.909	2.756	47.541	25.500	15.624	15.000	31.874	10.000
Q3	6.191	5.976	43.619	25.000	16.468	13.000	27.133	10.000
Q4	11.566	11.283	41.608	22.500	13.233	12.450	28.374	10.000
Q5	28.496	24.782	41.347	20.150	11.366	8.850	29.985	12.500
Panel H: Relative trade size								
Q1	0.015	0.013	43.967	23.450	5.958	8.100	38.008	14.600
Q2	0.048	0.045	42.867	23.450	12.115	11.250	30.715	12.500
Q3	0.099	0.095	44.100	24.500	15.074	13.000	28.960	9.650
Q4	0.200	0.190	47.101	25.000	21.701	16.050	25.366	8.400
Q5	0.801	0.501	57.582	31.250	34.883	23.450	22.487	6.250

(*continued on next page*)

Table 5 *(continued)*

Quintile	Sorting variable		*EHS*		*TPI*		*PPI*	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Panel I: Inverse trade price								
Q1	0.00994	0.00995	28.169	16.700	16.699	12.000	11.448	6.300
Q2	0.01001	0.01000	28.610	18.300	13.862	11.450	14.726	7.500
Q3	0.01008	0.01005	40.549	25.000	22.200	18.750	18.230	8.150
Q4	0.01020	0.01014	55.684	33.850	26.851	21.850	28.658	12.500
Q5	0.01285	0.01072	88.191	50.500	12.409	20.850	75.644	33.725
Panel J: Average LL100 market bid quote								
Q1	90.177	90.395	60.792	33.250	18.209	16.250	42.466	16.250
Q2	94.039	94.117	46.079	25.000	18.485	13.000	27.522	12.500
Q3	95.942	95.983	45.487	25.000	16.927	12.500	28.490	10.400
Q4	97.060	97.001	42.925	25.000	14.801	13.400	28.088	8.850
Q5	98.420	98.394	40.664	22.200	22.475	15.150	18.060	6.200

corresponding mean and median *EHS* values. This implies that the cross-sectional distribution of trading costs is more positively skewed than the distribution of quoted spreads, highlighting the need to look at actual prices in order to understand the cross-sectional determinants of loan market liquidity. Some extreme actual price deviations from the pre-trade benchmark (the $t-1$ midquote) are not captured by quoted spreads.

4.2.1.4. Number of dealers. We next use the number of dealers active in a facility as the sorting variable. We call this variable *NumDealers*. Intuitively, a higher number of dealers supplying liquidity in a facility increases the competition for order flow, thereby reducing dealer rents and ultimately customer trading costs. Similarly, high dealer coverage can make inventory risk sharing between dealers more efficient, eventually leading to an active interdealer market that minimizes inventory holding durations and costs. These arguments imply that *NumDealers* should be negatively associated with trading costs, a prediction we find supported by the data in Panel D. The Q1 versus Q5 spread in average *EHS* is 20.5 bps, and the spread in medians is 15.7 bps, both significant at the 1% level. Also noteworthy is the large cross-sectional variation in dealer coverage: Q5 facilities are served by about ten dealers, compared to just two for Q1 facilities.

4.2.1.5. Facility's time on the market. A prominent result in the corporate bond literature is the negative correlation between bond age and liquidity. This finding is usually attributed to a gradual settlement of most bonds into portfolios of buy-and-hold investors like insurance companies (Warga, 1992; Alexander et al., 2000). We apply this prediction to the loan market by defining the variable $Time-on-Market$ (*ToM*) that measures the difference (in days) between the trade day and the start of secondary market trading in a facility. We approximate the establishment of a secondary market by the first day for which quotes are available from Markit. Panel E shows that the Q1 versus Q5 *EHS* spread is in the predicted direction but the size (7.1 bps in the mean, and 1.0 bps in the median) is economically small.

4.2.1.6. Facility size. Next, we sort trades into quintiles according to the nominal amount of the traded facility (see Panel F). Facilities can become quite large, culminating into an average of $2.8 billion (median: $2.2 billion) in Q5, compared to less than $0.25 billion in Q1. Trading in larger facilities might be less costly due to more market participants either demanding or supplying liquidity, or less asymmetric information issues. In line with this prediction, we find that *EHS* decreases from an average of 62.9 bps in Q1 to 36.8 bps in Q5. The corresponding drop in median spreads is of similar magnitude (19.5 bps), and again statistically significant at 1%.

4.2.1.7. Past trading volume. Market microstructure models in Demsetz et al. (1968), Stoll (1978), and Ho and Stoll (1981) suggest that high trading volumes reduce inventory risk per trade and thus should result in smaller effective spreads. Similarly, higher transaction demand should lead to more profits and competition among dealers, and hence cheaper provision of liquidity services. Stoll (2000) finds that quoted and effective spread measures decrease in a stock's daily dollar trading volume. To test this prediction, we sort trades according to the facility's past 60 days accumulated trading volume executed by CLOs in our sample. Because we are restricted to CLO trades with trade day information available, our trading volume measure (*Past Volume*60) is a rather noisy proxy for the actual trading volume handled in a given facility. This might bias us against finding any relation between past volume and transaction cost. However, Panel G reveals a significant (at 1%) *EHS* spread of 19.3 bps (60.7 minus 41.4 bps) between low (Q1) and high volume (Q5) facilities. The spread in medians is 13.2 bps. We find similar results if we measure past volume over the preceding 30 or 90 days.

4.2.1.8. Relative trade size. Well-known models of market making suggest that large trades should cost more either because informed traders prefer to make large trades to fully exploit their information advantage (as in Easley and O'Hara, 1987), or if large trades occur predominantly in volatile assets and market makers are risk-averse (as in Grossman and Miller, 1988). However, informed traders may act strategically, break up large trades, and spread them over time to reduce price impact and transaction costs (as in Kyle, 1985). Moreover, if trade processing costs are substantial, transaction costs could decline when the size of the trade increases. In sum, the theoretical relation between trade size and transaction costs is ambiguous, which motivates our empirical investigation of this relation in Panel H. We sort trades according to relative trade size (i.e., the par amount traded, scaled by the notional amount of the traded facility). The mean trade size is about 1.5 bps of the facility par in Q1 and about 80 bps in Q5. We find transaction cost to be lowest (on average, 43–47 bps) for small and medium trade sizes in quintiles Q1-Q4, and higher (on average, 57.6 bps) for the extreme quintile Q5.

Table IA2 in the Internet Appendix provides further detail on the trade size quintiles. It reveals that Q1 trades have very low par amounts (mean: $0.27 million) and are directed into large facilities (mean size: $2.0 billion) with heavy trading interest (mean *Past Volume*90: $21.1 million). These trades might be costly due to a high level of fixed order processing costs, as well as more informed trading due to the breakup of informed orders. In contrast, Q5 trades are large (mean par amount: $2.2 million), and channeled into small facilities (mean size: $403.3 million) with less trading interest (mean *Past Volume*90: $7.0 million). Hence, small inventory turnover rates and inventory overload might cause these trades to be relatively expensive.

4.2.1.9. Inverse trade price. In Panel I, we look at the relationship between liquidity and trade price (more precisely, the inverse of the price). Distressed facilities (priced below 90) are natural candidates associated with significant adverse selection risks. Therefore, effective spreads for distressed facilities should reflect such increased probability of informed trading. Sorting trades according to the inverse of trade price reveals that Q1 trades occur at a mean and median price of 100 and Q5 trades are heavily discounted at an average price of 76.9 (median: 90.9). This price difference translates into a pronounced spread in trading costs. The mean *EHS* increases monotonically from 28.2 bps (median: 16.7 bps) to 88.2 bps (median: 50.5 bps). These results are generally consistent with Stoll's (2000) finding that stock liquidity is increasing in stock price.

4.2.1.10. Average market bid quote. Finally, in Panel J we relate loan investor sentiment to liquidity. We proxy for investor sentiment by the average bid price across all facilities in the LL100 index. Low bid prices might act as a loan market "turmoil" state variable, signaling less confidence in the overall asset class, higher aggregate default rates, and ultimately less trading interest, liquidity, and higher spreads. This prediction shows up in the data. When average bids are low at about 90, effective spreads on average are 20.1 bps higher compared to a hot market with average bids at 98.4.

4.2.2. Multivariate results

Table 6 presents the results of multivariate OLS regressions of transaction costs on the various facility and trade characteristics. We double-cluster standard errors at the facility and month level. Separate variables for positive and negative past idiosyncratic midquote returns are included in the regression for column (1). The coefficient estimates are frequently statistically significant and generally support the findings from the previous univariate sorts in Table 5. For example, a one standard deviation (42.1 bps) increase in *Volatility* raises the average spread by 3.3 bps, and for every 10 bps more *QHS*, the *EHS* jumps by 8.5 bps.[16] If idiosyncratic midquote returns fall by one standard deviation (305.5 bps) during the past 20 days, current spreads are 3.4 bps higher, and if average market bids drop by one standard deviation (3.0%), spreads move up by 6.3 bps. Moreover, one additional dealer reduces average spreads by 0.6 bps.

While the quadratic term on relative trade size is negative and significant in the columns (1) and (2) of Table 6, it loses its significance when facility fixed effects are included. In addition, the economic effect of trade size squared is small, with an implied inflection point at a rather extreme relative size of 71.7%, suggesting that for almost all trades, costs are linearly increasing in size.[17] To further verify that the essential significant trade size relationship is linear, we sort trades into relative trade size deciles. In Figure IA1 in the Internet Appendix, we plot the mean *EHS* against mean trade size for each decile. The plot reveals an upward-sloping transaction cost function, which is almost exactly linear (the R^2 is 94%).

In line with the univariate sorts in Table 5, the marginal effect of *Facility Size* is negative (trades in larger facilities are conditionally cheaper), but economically weak (the one standard deviation effect is just 0.5 bps) and statistically not significant. We highlight one difference compared to the univariate sorts: *ToM* exhibits a negative conditional correlation with trading costs (trades in older facilities are cheaper – by 2.2 bps for a standard deviation increase in log(*ToM*)).[18]

In the regression for column (2), we replace the past return variables by separate dummies for the five return quintiles in Panel B of Table 5. For example, the dummy *Extreme Loser* indicates Q1 trades, the dummy *Loser* Q2 trades, and so on. The base category is Q3 trades. Compared to this benchmark, *Extreme Losers* trade at 12.1 bps higher, and *Extreme Winners* cost 5.3 bps more to trade.

To account for unobserved, time-invariant facility-level heterogeneity like transfer restrictions imposed by the private equity (PE) sponsor of the borrower, we expand the previous specifications by including facility fixed effects in addition to month fixed

[16] If a (not too small) share of loan market investors is exposed to significant search frictions, a scenario studied in random search models a la Duffie et al. (2005, 2007) and others, we would not expect a one-to-one relation to exist between quoted and effective spreads. The reason is that our quoted spreads are averages across all dealers making a market in a given facility. Holding fixed any other frictions (e.g., inventory concerns or asymmetric information), high search cost investors will on average trade at the average quoted spreads, whereas low cost investors benefit from their ability to identify the dealer with the best quotes. Similar predictions emerge in the presence of other frictions, like dealer-customer relationships or variation in customer bargaining power.

[17] Because quadratic $ax^2 + bx + c$ turns over at $x = -b/2a$, the inflection point is $-3.726/(2 \cdot (-0.026)) = 71.7\%$.

[18] Pairwise correlations are likely responsible for this difference. See Table IA3 in the Internet Appendix for the pairwise correlation matrix. log(*ToM*) shows stronger correlations with *Volatility* (13%) and *QHS* (21%).

Table 6

Regressions of transaction costs on facility and trade characteristics. This table reports the results of OLS panel regressions of transaction costs on various facility and trade characteristics. The past facility excess return *ExR* is separated into the positive (negative) past facility excess return max[0, *ExR*] (min[0, *ExR*]) which is zero if the return is negative (positive). In columns (2), (4), and (6), the past return variables are replaced by separate dummies for the five return quintiles in Panel B of Table 5, where the dummy *Extreme Loser* indicates Q1 trades, *Loser* are the Q2 trades, *Winner* are the Q4 trades and *Extreme Winner* are the Q5 trades. The base category are the Q3 trades. All other variables are defined as in Table 5. The models for columns (1) and (2) include month fixed effects, the models for columns (3) to (6) additionally include facility fixed effects. Standard errors, reported in parentheses, are double-clustered by facility and month. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Volatility	0.078∗∗∗	0.104∗∗∗	0.056	0.083∗∗∗	0.050	0.077∗∗∗
	(0.026)	(0.023)	(0.036)	(0.026)	(0.035)	(0.025)
max[0, *ExR*]	0.003		−0.002		−0.001	
	(0.003)		(0.002)		(0.002)	
min[0, *ExR*]	−0.011∗∗		−0.012∗∗		−0.012∗∗	
	(0.005)		(0.005)		(0.005)	
Extreme Loser		12.062∗∗∗		7.179∗∗∗		6.854∗∗∗
		(1.559)		(1.238)		(1.260)
Loser		0.854		−0.014		−0.115
		(0.836)		(0.943)		(0.945)
Extreme Winner		5.316∗∗∗		1.225		1.162
		(1.457)		(1.308)		(1.308)
Winner		1.133		0.428		0.443
		(0.990)		(0.777)		(0.777)
QHS	0.845∗∗∗	0.804∗∗∗	0.610∗∗∗	0.602∗∗∗	0.492∗∗∗	0.491∗∗∗
	(0.031)	(0.032)	(0.046)	(0.046)	(0.064)	(0.065)
NumDealers	−0.576∗∗∗	−0.480∗∗∗	−1.074∗∗∗	−0.971∗∗∗	−2.570∗∗∗	−2.404∗∗∗
	(0.167)	(0.165)	(0.271)	(0.267)	(0.500)	(0.497)
log(*ToM*)	−2.270∗∗∗	−2.469∗∗∗	−3.605∗∗∗	−3.729∗∗∗	−3.734∗∗∗	−3.849∗∗∗
	(0.464)	(0.449)	(0.983)	(0.980)	(0.966)	(0.964)
log(*Facility Size*)	−0.511	−0.799				
	(0.710)	(0.697)				
log(*Past Volume*60)	−0.512	−0.782∗	−1.624∗∗∗	−1.693∗∗∗	−1.601∗∗∗	−1.670∗∗∗
	(0.473)	(0.469)	(0.443)	(0.453)	(0.439)	(0.450)
Relative Trade Size	3.726∗∗∗	3.833∗∗∗	2.542∗∗	2.588∗∗	2.558∗∗	2.600∗∗
	(1.017)	(1.056)	(1.200)	(1.208)	(1.200)	(1.207)
Relative Trade Size^2	−0.026∗∗∗	−0.028∗∗∗	−0.016∗	−0.016∗	−0.016∗	−0.016∗
	(0.010)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)
Inverse Price	0.006	0.007	0.139∗∗	0.161∗∗	0.131∗∗	0.152∗∗
	(0.069)	(0.078)	(0.061)	(0.066)	(0.057)	(0.062)
Average Market Bid	−2.118	−2.388∗	−3.900∗∗∗	−4.024∗∗∗	−3.569∗∗	−3.686∗∗
	(1.327)	(1.416)	(1.452)	(1.551)	(1.460)	(1.560)
QHS × *NumDealers*					0.038∗∗∗	0.037∗∗∗
					(0.012)	(0.012)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	No	No	Yes	Yes	Yes	Yes
Observations	141,958	141,958	141,958	141,958	141,958	141,958
Adjusted R^2	0.187	0.190	0.304	0.305	0.305	0.306

effects and present the results in columns (3) and (4).[19] Not surprisingly, *Volatility* loses significance, both statistically and economically, in line with the view that risk is more like a persistent characteristic of a facility than a time-varying feature. In contrast, the negative association between past trading volume and effective spreads now becomes significant at the 1% level. Furthermore, the R^2 moves up by about 11% (from 19% to 30%), indicating the importance of controlling for unobserved facility characteristics.

Columns (5) and (6) reveal that the conditional correlation between average quoted spreads and average effective spreads increases with dealer coverage (i.e., the interaction effect between *QHS* and *NumDealers* is positive and significant). Hence, the information content of average indicative bid-ask spreads for actual transaction costs increases if more dealers contribute to the average. This finding is intuitively appealing and provides further support for our decision to exclude facilities served by only one dealer (*NumDealers* = 1) from the construction of the market liquidity index in Subsection 4.1.1.

[19] Some loan package language contains large “blacklists” (with up to 500 names) that specify sets of potential investors (like vulture funds or rival PE firms) prohibited from investing into facilities of the package. See “*The Blacklist That Rules Wall Street's Loan Market*” by Nabila Ahmed and Kristen Haunss (Bloomberg News, December 18, 2014). Furthermore, the transfer of facility shares (by assignment) requires the consent of the borrower (or the borrower's PE sponsor). These “soft” or hard to quantify features can seriously limit the transferability of facilities, ultimately lowering their liquidity.

4.3. Sources of illiquidity

The previous analysis reveals that several facility and trade characteristics motivated by classic paradigms of market making (inventory concerns and adverse selection) explain a sizeable fraction of cross-sectional variation in trading costs. Although informative, the results so far do not speak to the relative importance of these two major costs of providing liquidity. In general, understanding the relative importance of the key sources of illiquidity is important for policy-making and market design. For instance, if adverse selection costs are the main factor, improvements in disclosure and greater parity between traders should be considered. As outlined in Subsection 2.3, however, due to the special informational nature of the lender-borrower relationship and the categorization of loans as non-securities, by necessity and design a high level of informed trading is inherently linked to the secondary loan market.

In this section, we estimate the contributions of adverse selection costs and inventory holding costs (combined with order processing costs and dealer rents) to facility illiquidity and price (midquote) movements. To achieve this goal, we rely on a key insight of the market microstructure literature: trades by investors possessing superior information exert lasting pressure (a "permanent impact") on prices, to the detriment of liquidity suppliers. In contrast, temporary imbalances in asset demand and supply absorbed into the inventories of dealers produce price impacts that disappear shortly after the completion of the trade when liquidity suppliers react to these profitable price deviations from fundamentals (a short-term price reversal). Following this insight, we can decompose the effective spread (the total price impact) into two parts: a permanent price impact (*PPI*) and a temporary price impact (*TPI*). Formally:

$$\begin{aligned} EHS_{it} &= \quad TPI_{it} + \quad PPI_{it} \\ Q_{it}(P_{it} - M_{it-1}) &= Q_{it}(P_{it} - M_{it+\Delta}) + Q_{it}(M_{it+\Delta} - M_{it-1}), \end{aligned} \tag{2}$$

where Q, P, and M are defined as for equation (1). Hence, the permanent price impact is measured from a pre-trade benchmark price to a post-trade benchmark price. Here, we again follow the literature and use midquotes as benchmarks. The interval Δ should be sufficiently long to ensure that prices have had time enough to incorporate the information conveyed by the trade. In general, an appropriate choice of the interval is difficult to make; the standard choice is 5 min in developed stock markets. However, information on trades takes more time to be disseminated in opaque markets like the loan market, suggesting a relatively high value for Δ. We set Δ to 10 days in our main analyses and provide some robustness for $\Delta = 20$ days.

We found previously that trading costs are increasing in relative trade size. This relation gives loan traders an incentive to break-up a large order into several smaller ones spread out over time, thereby potentially generating autocorrelated order flow.[20] If customer buys (sells) are more likely followed by further customer buys (sells), measuring permanent and temporary price impacts of trades by using midquotes after a relatively long time frame is likely misleading. To address this concern, we also show results on *PPI* and *TPI* calculated for the shortest time window possible ($\Delta = 1$ day) in the Internet Appendix (Table IA4).

The temporary price impact *TPI* (also called the realized spread) is measured from the trade price to a post-trade benchmark price. It can be seen as a measure of the profit earned by the liquidity supplier on the trade at time t if he is willing and able to unwind his position at the midquote at $t + \Delta$. Consequently, effective spreads are likely to overestimate liquidity suppliers' gains (and therefore liquidity demanders' trading costs) if after a trade prices move in the direction of the trade, i.e., investors have advance information (*PPI* is positive).

To start, we estimate the relative contributions of liquidity provision costs (*TPI*) and adverse selection costs (*PPI*) for the univariate sorts in Table 5. Columns (5) to (8) in this table report mean and median values of *TPI* and *PPI* for the corresponding quintile buckets (Δ is set to 10 days here). In line with intuition and predictions from models of dealer competition and market making, pronounced returns from liquidity provision are achievable by executing relatively large trades (Q5 median *TPI*: 23.5 bps) at low trade prices (Q5: 20.9 bps) in facilities with high *QHS* (Q5: 26.6 bps), low dealer coverage (Q1: 24.5 bps), small par amounts (Q1: 25.0 bps), and low past trading interest (Q1: 24.4 bps).

As explained above, due to the absence of mandatory pre-trade information disclosure rules and the missing governance function of securities laws, we would expect a relatively high level of informed trading in the loan market. Recall that informed trading manifests itself in a positive correlation between the change in the midquote following a trade and the trade's direction. High values for *PPI* reflect such a positive correlation.[21] We find a sizeable degree of informed trading in facilities with high risk (Q5 median *PPI*: 31.3 bps), extreme past returns (Q1: 16.4 bps, Q5: 12.5 bps), high *QHS* (Q5: 22.9 bps), low trade prices (Q5: 33.7 bps), in smaller sized trades (Q1: 14.6 bps), and when average market valuations are low (Q1: 16.3 bps).

Table 7 presents the multivariate version of the univariate results in Table 5. The specifications are the same as in the trading cost regressions of Table 6 (columns without facility fixed effects). However, the dependent variables are now either *TPI* or *PPI* (for Δ equal to 10 or 20 days).[22] The results in columns (1) and (3) broadly confirm the univariate findings for *TPI*: gains from liquidity provision are negatively associated with facility risk, extreme winners and losers, dealer coverage, *ToM*, *Facility Size*,

[20] We thank an anonymous referee for raising this point.

[21] For instance, a median *PPI* of 31.3 bps for the highest quintile of *Volatility* implies that for a typical buyer- (seller-) initiated trade in a high-risk facility, the midquote moves up (down) by 31.3 bps from the day before the trade to 10 days after the trade.

[22] Note that by construction and for corresponding specifications, the sum of a given variable's *TPI* and *PPI* regression coefficients equals this variable's coefficient in the trading cost regression of Table 6. For instance, the marginal effect of *Volatility* on *EHS* in column (1) of Table 6 is 0.078, which is decomposed in Table 7 into a marginal effect on liquidity provision costs of −0.090 and an effect of 0.167 on adverse selection cost.

Table 7

Regressions of temporary and permanent price impact on facility and trade characteristics. This table reports the results of OLS panel regressions of the temporary and permanent price impact on several facility and trade characteristics. Regression results are reported for the intervals $\Delta = 10, 20$. The model specifications are the same as in the transaction costs regressions of Table 6 (models without facility fixed effects). Standard errors, reported in parentheses, are double-clustered by facility and month. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Δ = 10				Δ = 20			
	TPI	*PPI*	*TPI*	*PPI*	*TPI*	*PPI*	*TPI*	*PPI*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility	−0.090	0.167∗∗	−0.109∗∗	0.213∗∗∗	−0.140∗	0.204∗∗∗	−0.157∗∗∗	0.263∗∗∗
	(0.062)	(0.069)	(0.045)	(0.057)	(0.076)	(0.079)	(0.042)	(0.051)
max[0, *ExR*]	0.003	−0.0001			−0.001	0.013		
	(0.004)	(0.006)			(0.010)	(0.011)		
min[0, *ExR*]	0.012	−0.023∗			0.008	−0.022		
	(0.014)	(0.013)			(0.020)	(0.019)		
Extreme Loser			−8.632∗∗	20.720∗∗∗			−8.883∗	21.036∗∗∗
			(3.530)	(3.682)			(5.279)	(5.091)
Loser			−1.800	2.675∗			−3.632∗∗	4.532∗∗
			(1.364)	(1.455)			(1.763)	(1.861)
Extreme Winner			−3.485∗	8.819∗∗∗			−2.586	7.949∗∗∗
			(1.779)	(1.915)			(2.597)	(2.828)
Winner			−1.773	2.975∗∗			−1.398	2.585
			(1.101)	(1.179)			(1.901)	(1.956)
QHS	0.247∗∗∗	0.598∗∗∗	0.265∗∗∗	0.539∗∗∗	0.105	0.738∗∗∗	0.130	0.671∗∗∗
	(0.061)	(0.065)	(0.060)	(0.062)	(0.083)	(0.087)	(0.080)	(0.082)
NumDealers	−1.354∗∗∗	0.794∗∗	−1.419∗∗∗	0.955∗∗	−1.560∗∗∗	0.989∗∗	−1.620∗∗∗	1.159∗∗
	(0.333)	(0.376)	(0.340)	(0.379)	(0.445)	(0.493)	(0.460)	(0.509)
log(*ToM*)	−2.819∗∗∗	0.532	−2.657∗∗∗	0.168	−2.799∗∗∗	0.508	−2.705∗∗∗	0.247
	(0.838)	(0.867)	(0.831)	(0.839)	(0.969)	(1.026)	(0.966)	(1.014)
log(*Facility Size*)	−3.515∗∗∗	2.967∗∗	−3.382∗∗∗	2.548∗∗	−3.324∗∗	2.811∗∗	−3.126∗∗	2.302∗
	(1.218)	(1.292)	(1.189)	(1.229)	(1.342)	(1.367)	(1.321)	(1.305)
log(*Past Volume*60)	−0.767	0.343	−0.619	−0.077	1.610	−2.041∗	1.760	−2.489∗∗
	(1.011)	(0.942)	(0.995)	(0.931)	(1.294)	(1.230)	(1.290)	(1.259)
Relative Trade Size	9.661∗∗∗	−5.993∗∗∗	9.636∗∗∗	−5.861∗∗∗	11.099∗∗∗	−7.351∗∗∗	11.010∗∗∗	−7.126∗∗∗
	(1.867)	(1.376)	(1.840)	(1.305)	(2.052)	(1.684)	(2.016)	(1.605)
Relative Trade Size^2	−0.078∗∗∗	0.052∗∗∗	−0.077∗∗∗	0.050∗∗∗	−0.088∗∗∗	0.062∗∗∗	−0.087∗∗∗	0.059∗∗∗
	(0.019)	(0.013)	(0.019)	(0.012)	(0.021)	(0.016)	(0.021)	(0.015)
Inverse Price	0.338	−0.340	0.336	−0.337	0.342	−0.340	0.342	−0.349
	(0.289)	(0.249)	(0.277)	(0.225)	(0.284)	(0.238)	(0.277)	(0.228)
Average Market Bid	−11.371∗	9.175∗	−11.284∗	8.822	−10.310∗	8.372	−9.672	7.230
	(5.817)	(5.428)	(5.994)	(5.583)	(6.198)	(5.844)	(6.327)	(5.924)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Facility FE	No	No	No	No	No	No	No	No
Observations	141,575	141,575	141,575	141,575	141,083	141,083	141,083	141,083
Adjusted R^2	0.024	0.042	0.024	0.045	0.015	0.030	0.015	0.031

and past trading interest (not significant). *TPI* is positively related to quoted spreads and scaled trade size (inflection point at 61.9%). For instance, one additional dealer reduces the average compensation for liquidity provision by about 1.4 bps, and a 10 bps higher *QHS* increases dealer profits by on average 2.5 bps. The one standard deviation effects of *Volatility*, log(*ToM*), and *Facility Size* are 3.8 bps, 2.7 bps, and 3.4 bps, respectively. Noteworthy, the effect of *Average Market Bid* turns negative, statistically significant (at 10%), and economically large (about 33.9 bps for a one standard deviation change). Hence, liquidity provision is more profitable in times of market stress, a finding in line with our previous results and intuition.

Columns (2) and (4) in Table 7 present results for a trade's information content (its permanent price impact). Small trades in large and risky facilities with extreme past idiosyncratic returns, higher dealer coverage, and wider quoted spreads are generally more informed (higher *PPI*). For instance, future midquotes of extreme losers and extreme winners move on average 20.7 bps and 8.8 bps, respectively, more in the direction of the trade initiator than trades in facilities with mild past midquote changes. A context for evaluating these results on *PPI* can be found in related equity market research. Partially in line with our findings, Stoll (2000) reports that informational friction measures in the stock market generally increase with a stock's return variance and trading imbalance and decrease with stock price and daily trading volume.

Columns (5) to (8) of Table 7 report identical specifications but for a quote adjustment horizon of $\Delta = 20$. As can be seen, our findings remain qualitatively unchanged; however, some variables lose statistical significance. In addition, Table IA4 in the Internet Appendix shows *PPI* and *TPI* regressions for $\Delta = 1$ to address the concern that autocorrelated order flow potentially distorts the previous findings. Almost all coefficients keep their sign and statistical significance (but with sometimes reduced economic significance), further highlighting the fact that the determinants of price impacts are not particularly sensitive to the choice of Δ.

Unsurprisingly, trading in leveraged loans is costly: the mean (median) *EHS* is 47.6 (25.0) bps (see Table 2). While it might be tempting to conclude that this high cost provides on average attractive profit opportunities for liquidity suppliers, this is not actually the case. A long-lasting pressure on prices exerted by trades of investors with advance information reduces the gains liquidity providers can pocket. Assuming they are able to unwind their position at the midquote 10 days after the trade day, liquidity suppliers realize just about one-third of the effective spread (mean *TPI*: 17.5 bps; see Table 2). Despite these seemingly low average gains,[23] we identify trade and facility characteristics that appear to be more profitable to approach from the viewpoint of liquidity providers (e.g., large trades in small, low-risk facilities with limited inter-dealer competition).

4.4. Pricing of liquidity

Starting with the seminal paper by Amihud and Mendelson (1986), many theoretical models predict that asset prices compensate investors for trading costs (i.e., the liquidity level) and systematic variation in liquidity (i.e., liquidity risk) through higher expected returns. Equivalently, if less liquid asset are traded at lower prices for the same future cash flows, they should offer higher yields. We test this theoretical prediction in this section by investigating whether the liquidity level is priced in the secondary leveraged loan market, that is, whether our liquidity proxies (*EHS* and *QHS*) can explain cross-sectional variation in loan yield spread levels.

Examining the association between liquidity and loan yield spreads is challenging due to the likely endogeneity of liquidity. In particular, regardless of how we measure liquidity, any such proxy could also be informative about the credit quality of a loan, and thus affect yield spreads via the credit risk channel. For example, low-quality borrowers may face stronger asymmetric information issues and therefore more severe adverse selection problems that could lead in turn to higher illiquidity. This would make it difficult to interpret the coefficient on a liquidity proxy purely in terms of transaction costs.

Hence, any serious attempt to study the pricing of liquidity must successfully disentangle liquidity and credit risk. Previous studies that focus on the corporate bond market (e.g., Chen et al., 2007; Dick-Nielsen et al., 2012; Friewald et al., 2012) try to achieve this through a set of credit risk-related controls like ratings, accounting ratios, stock price variables, and even CDS spreads. Obviously, all of these controls have their own shortcomings in terms of update frequency, informativeness, actuality, and availability, raising serious doubts that this approach indeed solves the endogeneity issue. In this paper, we apply a non-parametric approach instead, which is inspired by Dick-Nielsen et al. (2012). That is, rather than find enough controls that capture all dimensions of credit risk, arguably not a promising road to go, we try to “dummy out” credit risk. More precisely, the fact that for a large number of borrowers two or more facilities trade simultaneously on the secondary market at varying spreads and transaction costs enables us to include borrower × month fixed effects into a regression of spreads on liquidity. That way, any possible endogeneity bias due to omitted credit risk variables should be eliminated and the regression coefficient on a liquidity proxy can be estimated consistently.

Because loans pay a floating interest rate (fixed margin plus variable base rate[24]) and future coupons are not fixed in advance, a classical yield spread measure as for bonds cannot be computed for loans. We follow Beyhaghi and Ehsani (2017) and general market practice and calculate a spread-to-maturity (*STM*) by solving the following:

$$Trade\ Price = \sum_{i=t}^{T} \frac{Repayment_i}{(1+STM)^i} + \sum_{j=t'}^{T'} \frac{Margin_j}{(1+STM)^j}, \tag{3}$$

for *STM*. Here, i is the ratio of remaining days to a principal repayment to 360 and j is the ratio of remaining days to a margin payment to 360.[25] *STM* can be interpreted as the loans' yield if all future base rates are equal to zero.

To implement our within-borrower regression approach to dummy out credit risk, we construct a data set of secondary market *STM*s and transaction costs at the facility × month level. That is, for each trade in facility i of borrower j in month t, we compute the corresponding *STM* and a liquidity proxy (either the *EHS* or the *QHS*). We aggregate these numbers at the monthly frequency by calculating equal and trade size (par) weighted averages. For the subset of borrowers with at least two traded facilities in a given month, we estimate the flowing regression equation:

$$STM_{ijt} = \beta_0 + \beta_1 Liquidity_{ijt} + FE_{jt} + Controls_{ijt} + \varepsilon_{ijt}. \tag{4}$$

Importantly, the borrower × month fixed effects FE_{jt} control non-parametrically for all observed and unobserved time-varying characteristics that affect a borrower's default risk. Hence, the regression exploits only within-borrower variation in spreads and trading costs among facilities traded at the same time to identify β_1. That way, β_1 should capture just the pricing of liquidity but not the compensation for borrower default risk. To mitigate concerns that default risk operates not only at the borrower but also at the facility level (e.g., due to differences in seniority that translate into differences in liquidity), we restrict our sample to first-lien institutional term loans and include the $Time - to - Maturity$ and the initial spread over the base rate (*Margin*) as additional controls. Both variables are mechanically related to *STM* and might likewise influence liquidity.

Column (1) in Table 8 shows the results from a benchmark specification with equal weighted averages of trade-level variables and *EHS* as liquidity proxy. Standard errors are double-clustered by borrower and month. The regression is estimated on 11,665 facility × months observations, spread across 4,720 borrower × months clusters, with an average of 2.5 facilities per cluster.

[23] A $5 million trade offers gross proceeds of just $8,700, from which order processing costs, funding costs, etc. have to be subtracted.
[24] For 75.3% of our sample facilities, the base rate is LIBOR, and EURIBOR for the remaining 24.7%.
[25] Some functionality was adapted and modified from the R package *jrvFinance* (Varma, 2019) to compute *STM*.

Table 8
Pricing of liquidity. This table reports the results of OLS panel regressions of the spread-to-maturity on liquidity measures and spread determinants. The dependent variable is the spread-to-maturity. The independent variables are the *EHS*, the *QHS*, the facility's remaining time to maturity denoted in years, and the initial margin (i.e., the credit spread in basis points of a facility over the corresponding reference rate). All variables are computed at the trade-level and subsequently aggregated at the facility × month level. Columns (1) to (6) use equally-weighted and columns (7) to (12) use value-weighted spread-to-maturity and trading costs measures, where weighting is done by the traded par amount. In the regressions for columns (3), (6), (9), and (12), the effective and quoted half-spreads are lagged by one month. Standard errors, reported in parentheses, are double-clustered by borrower and month. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Equally-weighted						Value-weighted					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EHS	0.298***	0.226***					0.299***	0.222***				
	(0.062)	(0.058)					(0.059)	(0.055)				
$EHS(t-1)$			0.160						0.198**			
			(0.101)						(0.080)			
QHS				1.827***	1.853***					1.866***	1.881***	
				(0.605)	(0.557)					(0.589)	(0.546)	
$QHS(t-1)$						1.905**						1.917***
						(0.730)						(0.708)
$Time-to-Maturity$		5.042**	7.054**		5.402**	7.338**		6.339***	8.364***		6.664***	8.693***
		(2.033)	(2.897)		(2.058)	(2.915)		(2.090)	(2.985)		(2.090)	(2.965)
Margin		0.966***	0.961***		0.967***	0.974***		0.965***	0.966***		0.966***	0.980***
		(0.057)	(0.103)		(0.055)	(0.092)		(0.054)	(0.100)		(0.052)	(0.090)
Borrower × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of clusters	4,720	4,720	2,194	4,720	4,720	2,194	4,720	4,720	2,194	4,720	4,720	2,194
Observations	11,665	11,665	5117	11,665	11,665	5,117	11,665	11,665	5,117	11,665	11,665	5,117
Adjusted R^2	0.835	0.906	0.904	0.834	0.906	0.906	0.836	0.909	0.907	0.835	0.909	0.908
Within R^2	0.020	0.442	0.384	0.021	0.444	0.400	0.028	0.459	0.403	0.029	0.463	0.417

Importantly, *EHS* is positively and significantly associated with *STM*, even after controlling for time-varying borrower default risk. The *EHS* measure predicts an incremental 0.30 bps increase in *STM* for a 1 bp increase in liquidity costs. In terms of standard deviations, a one standard deviation increase in *EHS* is compensated for by a 0.09 standard deviations higher *STM*. Thus, while liquidity levels are marginally priced in spreads, most of the spread variation is due to changes in borrower fundamentals. This can also be seen from the high adjusted R^2 (83.1%, unreported) obtained from a regression of *STM* on the fixed effects alone. Hence, within-borrower variation in liquidity is responsible for 0.5% ($= 1 - 0.831/0.835$) of the total explained variation in *STM*. Furthermore, the last row in the table shows that once the borrower × months clusters are accounted for, *EHS* explains about 2% of the remaining variation in *STM*.

We next extend the model by controlling for $Time - to - Maturity$ and *Margin* and present the results in column (2). Both coefficients are significant and have the predicted sign: facilities with an additional year to maturity pay 5.0 bps higher spreads, ceteris paribus, and 100 bps (or about one standard deviation) more margin above the base rate translates into 96.6 bps higher *STM*. Importantly, illiquidity is still significantly priced at 0.23 bps for a 1 bp increase in *EHS*.

While the borrower × month fixed effects adequately address any endogeneity bias resulting from omitted credit risk variables, a remaining concern is potential simultaneity bias due to a two-way causal contemporaneous relation between yield spreads (or credit risk) and liquidity. We tackle this issue by lagging the liquidity proxy by one month. Hence, we ask whether within-borrower variation in last month's trading costs predict this month spread variation of the same facilities. The sample size drops by more than half because we now require facilities to be traded in both months, t and $t-1$. The results in column (3) show that the coefficient on liquidity is still positive but marginally insignificant (t-statistic: 1.6).

Next, we replicate the specifications for the first three columns, but instead of equally-weighted averages, we aggregate trade-level *STM* and trading costs to a monthly frequency by calculating trade size (par) weighted averages. That way, larger trades obtain a greater weight, which potentially increases the informativeness of our monthly trading cost proxy. The results in columns (7) to (9) remain basically unchanged; however, the coefficient on lagged trading costs becomes significant at the 5% level. Therefore, simultaneity bias appears not to be a concern.

Columns (4) to (6) and columns (10) to (12) provide equivalent results for *QHS* as a transaction cost measure. The benchmark model used for column (4) predicts an incremental 1.83 bps increase in *STM* for a 1 bp increase in *QHS*. These numbers are comparable to the 2.29 bps increase in the yield spread for a 1 bp increase in the (full) quoted bid–ask spread reported by Chen et al. (2007) for speculative grade corporate bonds. Furthermore, equally- and par-weighted average monthly quoted spreads yield similar results and again, past liquidity is positively and significantly associated with the current *STM*.

Overall, the results in Table 8 support a central prediction from a wealth of asset pricing theory papers: the liquidity level should be priced in loan yield spread levels. This result holds for both realized and quoted transaction costs, in contemporaneous and predictive regressions, and after we control non-parametrically for borrower credit risk and facility-specific spread determinants ($Time - to - Maturity$ and *Margin*).

5. Conclusion

In this paper, we examine trades in institutional facilities of leveraged loan packages executed by CLOs from July 2010 through December 2015. In total, our trade sample covers over $148 billion in trades. In addition, we collect dealer bid and ask quotes from Markit to construct an aggregate market liquidity index that spans the period from January 2008 through December 2016. While loans are expensive to trade with average effective and quoted half-spreads of 47.6 bps and 41.4 bps, respectively, the temporal and cross-sectional variation in trading costs is large.

In the time series, we find evidence in line with the collateral value or funding constraints paradigm of liquidity supply. In particular, periods of general financial market turmoil and heightened loan market price volatility are associated with less liquidity. The deteriorating funding conditions of dealers are also negatively related to loan market liquidity. Importantly, the response of liquidity to loan market returns is asymmetric: negative market returns decrease liquidity much more than positive returns increase liquidity. Liquidity demand by fire sellers cannot fully explain this asymmetric effect of market returns on liquidity, emphasizing the separate role of liquidity supply in market declines.

Cross-sectionally, our results suggest that when markets are thinner, and when there is likely to be significant asymmetric information, transaction costs are higher. In particular, we find that transaction costs are higher when the loan market is cold (low average bid levels), when facilities have greater price volatility or experienced extreme (negative) midquote changes, when facilities are covered by fewer dealers or faced lower past trading interest with shorter trading histories, and when the relative stake of the facility being transacted is larger. These results are generally supportive of the inventory holding costs and adverse selection paradigms of price formation.

For any private market, the missing governance role of securities laws and the absence of regulatory oversight fosters a trading environment that likely suffers from significant asymmetric information. The resulting adverse selection risks may be even more of a concern in loan markets due to lenders privileged access to borrower private and confidential information. Our evidence supports this view. In particular, about two-thirds of the average effective spread represents adverse selection costs, and only one-third compensates the liquidity provider for inventory holding or order processing costs. Hence, effective spreads overestimate liquidity suppliers' gains, and therefore liquidity demanders' trading costs: average *realized* one-way trade execution costs are on the order of 15 bps, rather than 45 bps.

Our final contribution relates to asset pricing theory and lines up nicely with significant evidence from the corporate bond market: while the majority of secondary market spread-to-maturity variation is driven by credit risk, liquidity levels (or transaction costs) are still marginally priced in the loan market.

While we focus on trading liquidity (i.e., trading costs), a second important dimension of liquidity in the leveraged loan market is settlement liquidity. That is, the number of days between the trade date (the oral agreement of the central trade features – price, amount, facility – between buyer and seller) and the subsequent settlement date (the date on which the trade is physically settled). Settlement times for loans are notoriously long, in some cases lasting several weeks, if not months. Since our knowledge of the factors underlying the meaningful temporal and cross-sectional variation in settlement durations is limited, studies in this area present a promising extension for future research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.finmar.2021.100644.

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