Investor Diversity and Liquidity in The Secondary Loan Market

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Received: 23 August 2020 / Revised: 7 January 2022 / Accepted: 30 January 2022 / Published online: 7 April 2022
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Abstract
We find strong evidence that investor diversity is beneficial to loan liquidity: More diverse syndicates, as measured by the number of investor-types or the concentration of loan shares by investor-type, hold loans that have lower quoted bid-ask spreads in the secondary market. These results are robust, and do not appear to be driven by investors’ borrower/loan selection. Further, they are not driven by the presence of any particular type of investors. Our findings are consistent with Goldstein and Yang (J Financ 70:1723–1765 2015) insight that there is a strategic complementarity between different groups in trading on their information and producing information.

Keywords Loan syndicate · Investor diversity · Loan market liquidity · Loan bid-ask spreads · Informed investors

JEL Classification G14 · G21 · G22 · G23

1 Introduction

The literature on the liquidity effects of securities’ ownership structure has focused almost entirely on the role of informed investors in the stock and the bond markets.1 In this paper, we consider the secondary loan market and capitalize on our knowledge about the portfolio of loan owners to investigate the importance of investor diversity for loan liquidity.

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1 For example, Chiang and Venkatesh (1988), Sarin et al. (2000) and Dennis and Weston (2001) study the impact of informed investors on stocks’ bid-ask spreads while Kedia and Zhou (2009) investigate whether informed investors affect bond liquidity.

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Goldstein and Yang (2015) predict that when uncertainty about security prices is multidimensional and different types of investors specialize in acquiring information about each dimension of the uncertainty, aggressive trading on the information produced by one type of investors would reduce the uncertainty faced by the other types of investors, thereby encouraging them to trade more and produce more information. In other words, there is a strategic complementarity between different investor groups in trading on their information and producing information. We aim to empirically test this hypothesis in the context of the secondary loan market.

The secondary loan market provides a good setting to examine the impact of investor diversity on liquidity because, besides banks, a variety of nonbank institutional investors actively trade in this market. In the last three decades, the secondary loan market evolved from an inactive market, where its dominant investors, banks, traded on occasion, to an active market with a large and diversified presence of nonbank institutional investors including CLOs, loan mutual funds, hedge funds, pension funds, insurance companies, finance companies, brokers, and private equity firms (Bord and Santos 2012). According to the Loan Syndication Trading Association (LSTA), the U.S. secondary loan market trading volume increased from $8 billion in 1991 to $743 billion in 2019, representing a compound annual growth rate of 28.5%. Several studies, including Massoud et al. (2009), Ivashina and Sun (2011) and Bushman et al. (2011), have documented that nonbank institutional investors use private information obtained from participating in syndicated loans to trade in other markets. It is likely that they also use that information to trade in the secondary loan market.

Gurley and Shaw (1955) highlights the important role of nonbank financial institutions in the economic development and points out that these institutions compete among themselves and with banks, in funding firms’ external capital needs and that each type of them provides distinctive financial services. Competition incentivizes different types of financial institutions to develop a unique business model and a distinctive competence by specializing in a particular market segment and/or financial product. One example of institutional specialization is documented in Carey et al. (1998), which shows that finance companies complement banks in corporate lending through funding riskier borrowers. Another example are the hedge funds which appear to be capable of obtaining/generating private information about the firms they invest in (e.g., Massoud et al. 2009; Agarwal et al. 2013; Jiao et al. 2016). It is also well established that different types of financial institutions follow different investment strategies and styles. For example, Fung and Hsieh (1997) show that, different from mutual funds, hedge funds use highly dynamic investment strategies. Assuming that financial institutions take advantage of their specialized knowledge to produce information about borrowing firms, then institutional diversity within a loan syndicate could proxy for information diversity. Further, if information diversity engenders strategic complementarities in trading and information acquisition as predicted by Goldstein and Yang (2015), then loans owned by more diverse types of investors should be more liquid.

Up to now, data limitations precluded researchers from investigating issues related to the ownership structure of loans. The secondary loan market pricing data jointly provided

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2 Relatedly, Gopal and Schnabl (2021) documents that the upsurge of small business lending by finance companies and FinTech lenders made up for the decrease in bank lending after the 2008 financial crisis.

3 Investor diversity may matter for other reasons. For example, Hong and Page (2004) show that diverse problem-solving teams outperform homogeneous teams because they benefit from different backgrounds, ideas, and experiences of their members. Levine et al. (2014) find that, in a diverse market, traders are more likely to scrutinize the other traders’ behavior instead of placing greater confidence in the actions of the other traders and mimicking them, leading to more accurate pricing.
by LSTA and LPC (the Thomson Reuters Loan Pricing Corporation) does not report information on trading volume or buyers’ and sellers’ identity for confidentiality reasons. LPC DealScan, the other main data source on the syndicated loan market, reports information on the identity of loans’ owners, but only at the time of the loan origination and, even then, the information it reports on investors’ loan shares is very sparse.  

The Shared National Credit (SNC) program allows us to overcome these limitations. The program, which was established in 1977, covers syndicated loans of $20 million or more that are held by three or more supervised institutions. The SNC program is useful to investigate issues related to loans’ ownership because it collects information, both at the time of the loan origination and at the end of each calendar year, on the identity of all loan investors and on their loan shares. We draw on the SNC data and the growing presence of nonbank institutions among loan investors to investigate to what extent diversity among investor types plays a role on the loan liquidity in the secondary market.

We focus on the diversity of types of investors as defined by their business model (i.e. banks, insurance companies, CLOs, hedge funds, mutual funds, pension funds, etc.) because the specialization of each type of institutions arguably allows them to produce unique information. We consider two proxies for investor diversity – the number of different types of loan investors and the Herfindahl-Hirschman index of the investor-types’ loan shares. These two measures capture different but related aspects of investor diversity. They are both driven by differences in investors’ specialization, with the second one accounting for the loan shares that each type of investors owns. We measure loan liquidity by its bid-ask spread, a widely used measure of liquidity in financial markets.

Our results reveal that investor diversity is an important determinant of loan bid-ask spreads. Specifically, our baseline loan bid-ask spread regressions show that more diverse syndicates, as measured by the number of investor-types or the concentration of loan shares by investor-type, hold loans that have lower quoted bid-ask spreads in the secondary market. A one-standard deviation increase in the number of investor types is associated with a decrease of 12 bps in the loan bid-ask spread (representing a 8.7% decrease in the sample mean bid-ask spread). A one-standard deviation decrease in the concentration of investor types’ loan shares is associated with a decrease of 4 bps in the loan bid-ask spread (representing a 2.9% decrease in the sample mean bid-ask spread). These results support the insight that information diversity among investors, as driven by (or at least partially driven by) their distinct business models, is beneficial to loan liquidity.

If different types of investors develop unique information about the firms they invest in, then we would expect the effect of investor diversity on loan liquidity to be more prevalent among informationally opaque borrowers. Indeed, taking a closer look at borrowers’ information opacity, identified based on whether the borrower has a credit rating or a bond that trades in the secondary market, we find that investors’ diversity brings a higher liquidity benefit for loans of more informationally opaque borrowers. In addition, we conduct a series of robustness tests to address the endogeneity concerns that our baseline results could be driven by investors’ borrowers/loan selections. Specifically, we show that our results

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4 For example, information on the lead bank share is missing for more than half of DealScan credits and information on the shares of syndicate participants is even more sparse.

5 See, for example, Demsetz (1968), Tinic (1972), Stoll (1978 and 1989), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985), Easley and O’Hara (1987).
continue to hold when we restrict our sample to an homogeneous set of loans; when we include loan fixed effects; and when we control for borrower-year fixed effects.

Lastly but importantly, we show that the effect of investors’ diversity is not driven by the presence of any particular type of investors, consistent with the idea that the joint presence of distinct investor types fosters trading and loan liquidity. Our results show that the coefficient estimates on our two information diversity variables remain statistically significant with a consistent sign when we account for the relative importance of each type of investors owning the loan through controlling for either the number of investors in each investor type or the loan shares held by each investor type. These results are consistent with the central theme of Goldstein and Yang’s model (2015) that the joint presence of diverse investor types (i.e. information diversity) matters for loan liquidity.

Our paper empirically tests the trading complementarity hypothesis and provides new insights into the role of securities’ ownership on their liquidity. The impact of stocks'/bonds’ ownership structure on their liquidity has been extensively examined, but this research has almost exclusively focused on the liquidity effects of the presence of informed investors. Researchers have not yet considered other aspects of securities’ ownership effect on their liquidity, possibly because the complete information on stocks’ or bonds’ ultimate owners is not readily available. In contrast, our information on the dynamic changes of the entire loan ownership structures provide us a unique opportunity to expand this literature by investigating the liquidity effects from a new perspective – the effect of investors’ information diversity as driven by their distinctive business models and specializations.

Our paper also adds to the literature on loan liquidity in the secondary loan market. This literature has focused on issues other than the impact of the ownership structure on the loan liquidity. For example, Bhasin and Carey (1999) and Wittenberg-Moerman (2008) investigate how different loan-specific features affect the loan liquidity while Gupta et al. (2008), Nigro and Santos (2009), and Kamstra et al. (2014) investigate the interplay between liquidity in the secondary loan market and interest rates in the primary market.

The remainder of the paper is organized as follows. Section 2 presents our methodology, our data sources, and characterizes our sample. Section 3 presents our baseline results of the impact of investor diversity on loan liquidity. Section 4 presents the results of our robustness tests. Section 5 concludes the paper with some final remarks.

2 Methodology, data and sample characterizations

We begin in this section with a presentation of the methodology we use to investigate whether investor diversity impacts the loan liquidity in the secondary market. This is followed by a presentation of our data sources and a characterization of our sample.

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6Copeland and Galai (1983) and Glosten and Milgrom (1985) suggest that the presence of informed traders imposes adverse selection costs on other traders, leading to a reduction in liquidity. Admati and Pfleiderer (1988) and Holden and Subrahmanyam (1992), in contrast, show that when multiple informed investors of a security compete with each other, the speed of the price discovery increases, leading to higher liquidity. Manconi and Massa (2009) and Han and Zhou (2014) empirically study the role of informed investors on bond liquidity, a number of other papers examine the impact of informed investors on stock liquidity (e.g. Chiang and Venkatesh 1988; Sarin et al. 2000; Dennis and Weston 2001; Easley and O’Hara 1987; Glosten and Harris 1988; Lee et al. 1993; Kavajecz 1999; Liu 2013; Blume and Keim 2012).
2.1 Methodology

Our methodology builds on the following model of loans’ bid-ask spreads:

\[
BID - ASK_{l,b,t} = \alpha DIVERSITY_{l,b,t-1} + \beta SYNDICATE_{l,b,t-1} + \gamma LOAN_{l,b,t-1} + \lambda BORROWER_{l,b,t-1} + Time_t + \epsilon_{l,b}. \tag{1}
\]

\(BID - ASK\) is the mean bid-ask spread on borrower \(b\)'s loan \(l\) over the year \(t\). We measure this spread over the year because our information on loan investors is as of the year end. This is our measure of loan liquidity.\(^7\)

The key variable of interest in Eq. 1 is \(DIVERSITY\). This variable attempts to capture the diversity of types of investors that own the loan. We expect diverse syndicates to contribute to loan liquidity. Investor diversity indicates differences in investors’ business model and specialization, which allow them to generate different information on the value of the loan and thus trigger trading. Further, if as we conjectured in the introduction information diversity engenders strategic complementarities in trading and information acquisition among investors, then we would expect investor diversity to be associated with higher loan liquidity.

We use two different, but complementary measures of loan investor diversity. The first measure is the number of different types of investors, \(TYPES\), such as banks, CLOs, finance companies, loan mutual funds, hedge funds and pension funds, brokers, and insurance companies. The second measure is the Herfindahl-Hirschman index of the sum of the squared loan shares that each lender type owns, \(HHI\). While the first measure focuses on the types of investors without accounting for their loan investments, the second measure gauges the degree of concentration of investor-type shares. If investor diversity matters, then we should find that loans held by more investor types and loans held by less concentrated syndicates in terms of investor-type shares to have a lower average bid-ask spread in the secondary market.

We attempt to identify the impact of investor diversity on loan liquidity controlling for a set of variables suggested by the literature on securities’ liquidity, which we discuss next. We start by discussing our syndicate-specific controls, \(SYNDICATE\). We control for the share of the loan the arranger retains, \(ARRANGERSH\), for two reasons. First, the size of arranger’s exposure to the loan will likely influence its incentives to gather borrower-specific information, and available theories suggest that the presence of informed investors can affect securities’ liquidity. Copeland and Galai (1983) and Glosten and Milgrom (1985), for example, show that the presence of information-motivated traders imposes adverse selection costs on dealers and other non-information motivated traders, driving up securities’ bid-ask spreads and lowering their liquidity. Admati and Pfleiderer (1988) and Holden and Subrahmanyam (1992), in contrast, show that when multiple informed investors compete with each other, and especially when there is a large uninformed investor base, the speed of the price discovery increases, lowering securities’ bid-ask spreads and increasing their liquidity. Second, sometimes the arranger of the loan also acts as a dealer for the loan.

\(^7\)Theories of the bid-ask spread posit that the quoted spread accounts for three forms of transaction costs faced by dealers (order processing costs, inventory costs, and information costs) which vary inversely with the liquidity of security. It is believed that the size of the order flow and frequent trading activities reduce the fixed costs of trading (Demsetz 1968). Similarly, the ease with which a dealer can either acquire a security or dispose of it will lower its inventory costs. See Tinic (1972), Stoll (1978 and 1989), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985) and Easley and O’Hara (1987) for theories of bid-ask spreads.
Therefore, the arranger will need to retain a portion of the loan to act as market maker in which case it will also affect loan liquidity in the secondary market.

We control for the number of top loan dealers, DEALERS, that are among the loan investors. We opt for controlling for this variable because we expect the number of dealers with a stake in the loan to be more informative than the often used number of dealer quotes in LSTA/LPC database (Wittenberg-Moerman 2008; Nigro and Santos 2009). However, in the robustness tests we investigate what happens when we control instead for QUOTES, the daily average number of dealer quotes a loan received over the past year. In another test, we control for TRADING, the total number of trading days with price changes (i.e., today’s quote price minus yesterday’s quote price is not equal to zero) over the past year.

Next, we discuss our set of loan-specific controls, LOAN. We restrict our analysis to term loans. Nonbank lenders rarely appear in the syndicates of credit lines (Bord and Santos 2012), consistent with Holmstrom and Tirole (1997) and Kashyap et al. (2002) insight that banks are better positioned than non-bank lenders to provide liquidity to corporations. Also, only a small number of credit lines trade in the secondary loan market. Following Stoll’s (1978) and Ho and Stoll (1981) insight that dealers’ inventory costs are higher for riskier securities, and Bhasin and Carey (1999) and Wittenberg-Moerman (2008) evidence that riskier loans have higher bid-ask spreads, we control for the risk of the loan as determined by its arranger’s loan rating. Banks rate loans by assigning a portion of the loan into five categories: pass, PASS, special mention, SPECIALMENTION, substandard, SUBSTANDARD, doubtful, DOUBTFULL, and loss, LOSS. We complement these ratings with a set of dummy variables to account for the credit rating of the borrower.

Additionally, we distinguish term loans of type A, TL OAN A, from those of type B, TL OAN B, and those of type C, TL OAN C, since these loans have different features and target different investors. For example, term loans A typically amortize evenly over 5 to 7 years. These loans are normally syndicated to banks along with revolving credits as part of a deal. Term loans B and C include second-lien loans and covenant-lite loans. They came into broad usage during the mid-1990s as nonbank institutional loan investor base grew. They usually involve a large bullet payment in the last year, allowing borrowers to defer repayment of a large portion of the loan. In the robustness tests, we further control for the lagged average price of the loan as quoted by dealers, PRICE, and the volatility of the loan price, PRICEVOL. While riskier loans will carry lower price and will also likely have more volatile prices, these variables may also be driven by the liquidity of the loan. It is for this reason that we only use them in our robustness tests.

We control for the size of the loan, LAMOUNT, the log of the loan amount. Larger loans are likely to attract more investors, and “safer” borrowers usually take out larger loans. Demsetz (1968) argues that the size of the order flow reduces dealers’ fixed costs of trading, and Wittenberg-Moerman (2008) finds that larger loans have lower bid-ask spreads. Further, we control for the number of years left until the loan reaches its maturity, MATLEFT, because liquidity likely decreases with the age of the loan. In the robustness tests, we allow for potential nonlinear effects of the loan age by including a dummy variable to isolate the first two years of the loan, AT ORIGINATION, and a dummy variable to isolate the last two years before maturity, AT MATURED Y. Loans are likely to be most liquid in the early

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8While we are able to identify the presence of major dealers among the loan investors, we are unable to determine whether each one of them acts as a market maker for most of our loans.
years after origination, and their liquidity likely declines significantly as they approach the maturity date. For example, the bond literature documents that the age of a bond is inversely related to its liquidity. Sarig and Warga (1989) point out that bonds tend to be traded less and less over time as they are absorbed in the investors’ inactive buy-and-hold portfolios.

Lastly, we use a set of dummy variables to account for the purpose of a loan as different investors may specialize on loans taken out for different purposes. We distinguish loans for working capital, $\text{WORKCAP}$, mergers and acquisitions, $\text{M}\&\text{A}$, recapitalization, $\text{RECAP}$, capital expenditures, $\text{CAPEXP}$, project finance, $\text{PROJFIN}$, and debt repayment, $\text{DEBPREPAY}$.

Our next set of controls accounts for borrower-specific factors, $\text{BORROWER}$. As we mentioned above, we use a set of dummy variables to account for the credit rating of the borrower. In contrast to our bank loan ratings, which cover all loans in our sample, only a subset of borrowers has a credit rating. However, firm credit ratings may still be informative because they are more granular than bank loan ratings. In addition, we use a set of dummy variables to account for the borrower’s main sector of activity as defined by 1-digit SIC code because investors may have preferences for different sectors of activities. We do not control for other borrower-specific variables because this would force us to rely on publicly listed borrowers and would reduce our sample significantly. As we will argue below, the absence of these controls is not critical for our attempt to investigate the impact of investor diversity on liquidity.

Finally, we include year fixed effects to absorb time heterogeneity at the yearly level, which is the frequency of our loan ownership data. The robust standard errors are all clustered at the borrower level in our regressions.

2.1.1 Accounting for loan ownership endogeneity

A potential concern with the methodology described so far is that it does not account for the endogeneity of investors’ investment decisions. For example, it is possible that the liquidity effect of investor diversity does not derive from the presence of different investor types, but is instead a result of investors’ borrower/loan selection decisions.

To reduce concerns with this problem, we carry out a set of robustness tests. In one test, we restrict the sample to a subset of homogeneous loans. In another test, we include loan fixed effects. Yet in a third test, we take advantage of the borrowers in our sample with multiple outstanding loans trading in the secondary market at the same time, and estimate our model with borrower-year fixed effects. To the extent that investors’ selection decisions are driven by borrower-specific factors, this test will account for those factors. That test will also alleviate any concerns with omitted borrower specific controls in our regressions.

2.1.2 Identifying the effect of loan ownership diversity

Another potential concern with our methodology is whether it identifies the effect of investor diversity. Even though we use two different measures of investor diversity, one may wonder whether a particular type of investors alone could drive our findings. To address this concern, we reestimate our model controlling for the share of the loan held by each investor type or the number of individual investors in each investor type. If a particular investor type were to drive our findings, then adding these controls should capture that effect and make our measures of investor diversity insignificant.
2.2 Data sources

The main data sources for this paper are the Mark-to-Market Loan Pricing Service jointly offered by the Loan Syndication Trading Association (LSTA) and Thomson Reuters Loan Pricing Corporation (LPC), and the Shared National Credit (SNC) Program run by the Federal Deposit Insurance Corporation, the Federal Reserve Board, and the Office of the Comptroller of the Currency.

Under an LSTA license, the LPC started to facilitate the daily mark-to-market process between loan dealers and investors through the creation of the LSTA/LPC Mark-to-Market Pricing Service in June of 1998. The LPC/LSTA data provides information on the loan identifier (i.e., LIN number), bid and ask prices, and the number of dealers (i.e., the number of quotes) for each loan that is available to be traded on the market on a daily basis. The bid/ask prices are the average prices reported to the LPC by all the trading desks at institutions that make the market for the loan. Loan prices are quoted as a percentage of par. We use LSTA/LPC data to identify loans that trade in the secondary market and to get the daily bid and ask prices as well as the number of dealers offering quotes on each loan.

Since LSTA/LPC data does not contain information on loan investors, we use the SNC database to identify the portfolio of investors for each loan. The SNC program gathers confidential information on syndicated loans that exceed $20 million and are held by three or more federally supervised institutions at the end of the year. The program reports the identity of the borrower, the type of credit (e.g., term loan, credit line), its purpose (e.g., working capital, mergers and acquisitions), the outstanding amount, the origination and maturity dates, and the internal bank rating. In addition, the program reports information on the lead arranger and syndicate participants, including the share of the credit that they hold. We use this information to identify the portfolio of loan investors for each loan and track how this portfolio changes during the life of the loan.

We complement the SNC data with information from Moody’s Structured Finance Default Risk Service Database, the Intex Agency CDO deal library, and Standard and Poor’s Capital IQ. We use Moody’s and Intex’s databases to identify CLOs among the syndicate participants reported in the SNC program, and the Capital IQ database to identify private equity firms, hedge funds, and mutual funds among the syndicate participants. We also use Capital IQ database to gather credit rating information on borrowers with trading loans.

2.3 Sample characterization

To build our sample, we start out with all term loans with market data in the LSTA/LPC database over the 1998-2014 time period. We leave out credit lines because they are dominated by banks and only a reduced number of them trade in the secondary market. Next, we merge these loans with data from the SNC program to get information on their characteristics, their investors, and investors’ loan shares in each year. This leaves us with a sample of 3,044 loans from 1,805 corporations for a total of 6,084 loan-year observations. 751 of the corporations in our sample have at least two loans throughout the sample period. This set of firms, in particular the 497 of them which have more than one loan trading at a given year, is useful for our investigation — they allow us to isolate the effect of investors’ loan ownership on loan liquidity from the effect of investors’ (firm) investment selection. These 497 firms account for 1,201 of our 3,044 loans and 2,334 of the 6,084 loan-year observations.

9Before 1998, there was no mark-to-market service available to the loan buyers (Marsh 2017).
Figure 1 plots the loan bid-ask spread against our two measures of investor diversity. In line with our expectation, this figure suggests that investor diversity improves loan liquidity. Loans with more types of investors and loans with a lower investor-type concentration have on average lower bid-ask spreads.

Table 1 characterizes our sample by comparing the 3,482 loan-year observations for loans with a number of investor types below the sample median of 6 (i.e. low investor type group) with the 2,602 loan-year observations for loans that have a number of investor types above the median (i.e., high investor type group). Panel A compares our loans for the secondary market variables we use in our study while panel B compares them according to their syndicate structure. Panels C and D, in turn, compare our loans according to their characteristics and borrower-specific factors, respectively.

The result of the mean difference test on the bid-ask spread is in line with Fig. 1, namely, loans held by a more diverse set of investors are more liquid. As we can see from Panel A, the average bid-ask spread for loans in the low investor type group is 1.63%. In contrast, the average bid-ask spread for loans in the high investor type group is 1.13%, significantly lower than that for loans in the low investor type group (with a $t$ statistic of -13.46). In line with this insight, we see that the former loans receive fewer quotes from dealers (i.e., an average of 1.91 per day vs. an average of 3.96 per day for loans in the high investor type).

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10 We have performed a similar comparison to that reported in Table 1, but this time using investor concentration – our second measure of investor diversity, $HHI$ – and found, consistent with Fig. 1, that loans with less concentrated syndicates have a lower average bid-ask spread. Results available upon request.
Table 1  Summary statistics. This table presents summary statistics for the total sample, comparing term loans with investor types below vs. above sample median. See Appendix for the definitions of all variables.

| Variables            | Number of investor types above median? | Diff | t-stat |
|----------------------|----------------------------------------|------|--------|
|                      | No           | Yes             |      |        |
| **Panel A: Market-related variables** |
| BID – ASK            | 1.634        | 1.132           | -.502 | -13.46*** |
| PRICE                | 92.673       | 94.439          | 1.766 | 5.02***  |
| PRICEVOL             | 2.515        | 2.890           | .375  | 3.35***  |
| QUOTES               | 1.908        | 3.962           | 2.054 | 38.73***  |
| TRADING              | 19.979       | 70.166          | -50.187 | 40.25***  |
| **Panel B: Syndicate-related variables** |
| ARRANGERSH           | .085         | .021            | -.064 | -23.80***  |
| DEALERS              | 5.135        | 8.890           | 3.755 | 33.56***  |
| TYPES                | 3.471        | 8.989           | 5.518 | 119.87***  |
| HHI                  | .390         | .273            | -.116 | -31.64***  |
| BANKS                | 9.362        | 14.435          | 5.073 | 19.54***  |
| INSURANCE            | .485         | 6.136           | 5.652 | 45.51***  |
| FINANCE              | 1.139        | 3.339           | 2.199 | 29.28***  |
| BROKERS              | .297         | 1.828           | 1.530 | 42.12***  |
| PEFIRMS              | .190         | 1.209           | 1.019 | 44.63***  |
| FUNDS                | 4.166        | 42.752          | 38.586 | 48.75***  |
| CLOS                 | 8.303        | 60.904          | 52.601 | 50.05***  |
| **Panel C: Loan-specific variables** |
| LAMOUNT              | 11.684       | 12.739          | 1.055 | 41.42***  |
| MATLEFT              | 4.014        | 4.663           | .648  | 15.27***  |
| ATMATURITY           | .184         | .087            | -.097 | -10.80***  |
| ATORIGINATION        | .433         | .483            | .050  | 3.84***  |
| PASS                 | .730         | .692            | -.039 | -3.29***  |
| SPECIALMENTION       | .097         | .120            | .024  | 2.94***  |
| SUBSTAND             | .129         | .162            | .033  | 3.68***  |
| DOUBFUL              | .029         | .017            | -.012 | 3.25***  |
| LOSS                 | .016         | .010            | -.006 | -2.48**  |
| WORKCAP              | .018         | .027            | .008  | 2.14**  |
| M&A                  | .028         | .075            | .047  | 8.54***  |
| RECAP                | .005         | .017            | .012  | 4.55***  |
| CAPEXP               | .002         | .001            | -.001 | -1.04  |
| PROJFIN              | .004         | .002            | -.003 | -1.92*  |
| DEBPREPAY            | .020         | .073            | .054  | 10.30  |
| TLOANA               | .613         | .434            | -.180 | -14.12***  |
| TLOANB               | .062         | .147            | .085  | 11.07***  |
| TLOANC               | .005         | .013            | .008  | 3.46***  |
Looking at the other mean difference test results reported in Table 1, we get a mixed picture. For example, we find that loans with more investor types are larger \textit{LAMOUNT}, and have more years left before their maturity date, \textit{MATLEFT}, two attributes believed to help with the liquidity in the secondary market. We also find that these loans appear to be safer according to their price in the secondary market, \textit{PRICE}, (i.e., loans in the high investor type group have a higher average price of 94.44\% compared with 92.67\% for those in the low investor type group). However, loans with more investor types appear to be riskier according to bank ratings (e.g., a smaller percentage of such loans have the safest bank rating, \textit{PASS}) or the borrower’s credit rating (i.e., a larger percentage of such loans have a non-investment grade rating below BBB).

In terms of the syndicate structure, we see from Panel B that loans involving more investor types have a lower average loan share held by the arranger, but have more top dealers holding a stake of the loan. Not surprisingly, these loans involve more investors in each investor type including banks, insurance companies, finance companies, brokers, private equities, funds and CLOS. The average number of funds and the average number of CLOs for loans in the high investor type group (42.75 and 60.90, respectively) is strikingly higher than the corresponding numbers for loans in the low investor type group (4.17 and 8.30, respectively).

In the next section, we investigate whether the diversity of loan investors affects loan liquidity, controlling for our sets of syndicate-, loan- and borrower-specific factors. We also attempt to account for investors’ loan investment selection.

### 3 Investor diversity and loan liquidity

Table 2 reports the first set of results of our investigation on the liquidity impact of investor diversity. It shows the results from the estimation of our model of loan bid-ask spreads (See Eq. 1). The two key variables of interest are our proxies for investor information diversity:
| Variables          | 1            | 2            |
|--------------------|--------------|--------------|
| TYPES              | -0.037***    |              |
|                    | (-6.44)      |              |
| HHI                |              | 0.252**      |
|                    |              | (2.09)       |
| Syndicate controls |              |              |
| ARRANGERSH         | -0.455***    | -0.279**     |
|                    | (-3.40)      | (-2.04)      |
| DEALERS            | -0.022***    | -0.028***    |
|                    | (-5.78)      | (-6.98)      |
| Borrower controls  |              |              |
| AAA-A              | 0.516        | 0.526        |
|                    | (0.60)       | (0.59)       |
| BBB                | -0.245***    | -0.188***    |
|                    | (-4.35)      | (-3.27)      |
| BB+                | -0.086       | -0.039       |
|                    | (-1.05)      | (-0.48)      |
| BB                 | -0.166***    | -0.153***    |
|                    | (-4.01)      | (-3.68)      |
| BB-                | -0.204***    | -0.208***    |
|                    | (-5.49)      | (-5.59)      |
| B+                 | -0.131**     | -0.139***    |
|                    | (-2.47)      | (-2.64)      |
| B                  | -0.032       | -0.045       |
|                    | (-0.41)      | (-0.57)      |
| B-                 | -0.238*      | -0.237*      |
|                    | (-1.91)      | (-1.88)      |
| CCC-D              | 0.150        | 0.143        |
|                    | (0.48)       | (0.45)       |
| Loan controls      |              |              |
| LAMOUNT            | -0.158***    | -0.185***    |
|                    | (-7.37)      | (-8.92)      |
| MATLEFT            | -0.011       | -0.022**     |
|                    | (-1.05)      | (-2.08)      |
| PASS               | -2.911***    | -2.906***    |
|                    | (-14.82)     | (-14.77)     |
| SPECIALMENTION     | -2.461***    | -2.468***    |
|                    | (-12.23)     | (-12.25)     |
| SUBSTANDARD        | -1.765***    | -1.774***    |
|                    | (-8.51)      | (-8.54)      |
Table 2 (continued)

| Variables   | 1          | 2          |
|-------------|------------|------------|
| WORKCAP     | -0.028     | -0.024     |
|             | (-0.37)    | (-0.31)    |
| M&A         | 0.031      | 0.002      |
|             | (0.47)     | (0.02)     |
| RECAP       | 0.118      | 0.083      |
|             | (1.14)     | (0.80)     |
| PROJFINANCE | 0.533**    | 0.604**    |
|             | (1.97)     | (2.24)     |
| CAPEXP      | -0.089     | -0.018     |
|             | (-0.96)    | (-0.20)    |
| DEBTREPAY   | -0.055     | -0.095     |
|             | (-0.92)    | (-1.60)    |
| TRLOANA     | 0.186***   | 0.190***   |
|             | (4.39)     | (4.48)     |
| TRLOANB     | -0.051     | -0.069     |
|             | (-1.18)    | (-1.60)    |
| TRLOANC     | -0.292**   | -0.325**   |
|             | (-2.16)    | (-2.46)    |
| constant    | 5.840***   | 6.018***   |
|             | (15.82)    | (16.39)    |
| Observations| 6084       | 6084       |
| R-squared   | 0.461      | 0.458      |

This table reports results for all credits in our sample. The dependent variable is BID-ASK SPREAD: Average bid-ask spread over the year. All of the models include year dummy variables and dummy variables for the borrower’s sector of activity as defined by SIC one-digit code. See Appendix in the paper for the definitions of all controls included in the models. Models are estimated with robust standard errors, clustered by borrower. We report t statistics in parentheses.

*** denotes 1% significance level; ** denotes 5% significance level; * denotes 10% significance level

Types, the number of different types of loan investors in the syndicate (banks, insurance companies, finance companies, brokers, CLOs, hedge funds, pension funds, among others), and HHI, the HHI of investor-types’ loan shares, respectively.

Both TYPES and HHI suggest that an increase in the diversity of investors in the syndicate is associated with a decline in the loan’s bid-ask spread. A one-standard deviation increase in the number of investor types is associated with a decrease of 12 bps in the loan bid-ask spread (model 1). A one-standard deviation decrease in the concentration of investor-types’ loan shares is associated with a decrease of 4 bps in the loan bid-ask spread (model 2).

Looking at the control variables, we see that ARRANGERSH is negative and statistically significant, indicating that the larger the arranger’s loan share the more liquid the loan is. Given that the arranger is arguably the best informed loan investor, this result appears to run counter the idea that the presence of an informed investor adversely affects liquidity.
However, this relationship seems to be driven by those instances in which the lead arranger retains a share of the loan in order to act as a dealer for the loan.\footnote{In a separate analysis, indeed we find that the negative relationship between bid-ask spreads and the loan share of lead arranger is driven by the arranger’s role as a dealer for the loan. When the arranger does not play this role, that relationship becomes positive, consistent with the idea that the presence of an informed investor adversely affects market liquidity. These findings are only suggestive because we have information on whether the arranger acts as a dealer for only 22% of our loan-year observations. Also, whether an arranger acts as a dealer is endogenous.}

Turning our attention to the remaining controls, we see that loans that have a larger number of the top dealers among their investors, \textit{DEALERS}, have lower bid-ask spreads. Larger loans, \textit{LAMOUNT}, and loans with more years to maturity, \textit{MATLEFT}, tend to have a lower average bid-ask spread. Safer loans also have on average lower bid-ask spreads. In particular, the results on banks’ loan ratings show that both \textit{PASS}, \textit{SPECIALMENTION}, and \textit{SUBSTANDARD}, are negative and statistically significant, indicating that safer loans carry a lower bid-ask spread relative to the riskiest loans (omitted group that receives a \textit{DOUBTFULL} or \textit{LOSS} rating). The same insight is present in the borrowing firm’s credit ratings, though not as strikingly.

With regards to the purpose of the loan, the only one which appears to differentiate loans is project finance: loans for this purpose have on average a significantly higher bid-ask spread. Lastly, contrary to expectations, term loans A do not have lower spreads than term loans B or C, even though they tend to be safer, possibly because fewer types of investors (e.g. banks and insurance companies) tend to own these loans.

### 3.1 Loan ownership, market liquidity and borrower opacity

As we discussed in the introduction, one of the premises for investor diversity to influence liquidity is the existence of information frictions among investors. As such, we should expect the liquidity effects of diversity to be more pronounced among loans of more informationally opaque borrowers. To investigate this hypothesis, we start by classifying our borrowers according to their informational opacity. We assume that borrowers with a credit rating, \textit{RATING}, are less informationally opaque because there is more information available about them. As an alternative definition, we assume that borrowers with a bond trading in the secondary bond market, \textit{BOND}, are less informationally opaque by virtue of the information released in that market. Next, we compare the liquidity effect of loan investors’ diversity across borrowers depending on their informational opacity.

The results of this exercise are reported in Table 3. Panel A reports the results when we use \textit{RATING} to classify borrowers as to whether they are informationally opaque, while panel B reports the results when we use \textit{BOND} to classify our borrowers. Both panels yield similar results. First, loans of less informationally opaque borrowers are more liquid. The estimated coefficient on \textit{RATING} is negative, though statistically significant only in model 1, while that on \textit{BOND}, is negative and statistically significant in all models. Second, consistent with our priors, we find strong evidence that investor diversity is more important for the liquidity of loans of more informationally opaque borrowers. This holds true for both proxies of diversity when we use \textit{RATIND} to distinguish borrowers according to their level of informational opacity. Specifically, the coefficient estimate on the interaction term between \textit{RATING} and \textit{TYPES} is positive and statistically significant at the 1% level while that on the interaction between \textit{RATING} and \textit{HHI} is negative and statistically significant at the 5% level. It is also true when we rely on \textit{BOND} to distinguish...
Table 3  Borrower opacity, loan investor ownership and liquidity

| Variables                  | 1           | 2           |
|---------------------------|-------------|-------------|
| **Panel A: Borrowers with and without a credit rating** |             |             |
| RATING                    | -0.429***   | -0.009      |
|                           | (-7.05)     | (-0.13)     |
| TYPES                     | -0.051***   |             |
|                           | (-7.21)     |             |
| HHI                       | 0.346**     |             |
|                           | (2.37)      |             |
| RATINGxTYPES             | 0.047***    |             |
|                           | (5.81)      |             |
| RATINGxHHI                |             | -0.383**    |
|                           |             | (-2.24)     |
| constant                  | 5.835***    | 5.976***    |
|                           | (15.95)     | (16.31)     |
| Observations              | 6084        | 6084        |
| R-squared                 | 0.462       | 0.458       |
| **Panel B: Borrowers with and without a trading bond** |             |             |
| BOND                      | -0.394***   | -0.209**    |
|                           | (-4.46)     | (-2.15)     |
| TYPES                     | -0.039***   |             |
|                           | (-6.53)     |             |
| HHI                       | 0.243*      |             |
|                           | (1.91)      |             |
| BONDxTYPES                | 0.025**     |             |
|                           | (2.22)      |             |
| BONDxHHI                  |             | -0.039      |
|                           |             | (-0.15)     |
| constant                  | 5.870***    | 6.030***    |
|                           | (16.02)     | (16.48)     |
| Observations              | 6084        | 6084        |
| R-squared                 | 0.461       | 0.458       |

The dependent variable is BID-ASK SPREAD: Average bid-ask spread over the year. RATING and BOND are dummy variables if the borrower has a credit rating or a bond trading in the secondary market, respectively. Included in the models are all of the variables used in the models reported in Table 2. See Appendix in the paper for the definitions of all controls included in the models. Models are estimated with robust standard errors, clustered by borrower. We report t statistics in parentheses.

borrowers’ level of information opacity, although in this case the interaction of this variable with HHI is not statistically significant.

In sum, the findings from our pooled regression analysis so far are unambiguously consistent with the insight that investor diversity is beneficial to loan liquidity. Syndicates with a larger number of investor types, as well as less concentrated syndicates in terms of investor-types’ loan shares are both associated with more liquid loans. Further, consistent with our
expectations, these effects are more pronounced for more informationally opaque borrowers. In the next section, we take a closer look at the robustness of our findings and attempt to address concerns with investors’ borrower-investment selection.

4 Robustness tests

We begin this section of robustness tests by investigating potential concerns with investors’ borrower-investment selection. After that, we look into whether our findings on investor diversity could derive from the presence of any single type of investors. We conclude the section with a brief summary of robustness tests that we have investigated to account for additional controls that may impact loan liquidity.

4.1 Accounting for investors’ borrower-investment selection

Since investors’ decision on whether to invest in a particular loan is endogenous, one may wonder to what extent these decisions drive our findings. In this subsection, we present the results of several tests we considered to address this concern. In the first test, we investigate what happens when we restrict our sample to an homogeneous subset of loans. Next, we investigate what happens when we include arranger fixed effects, loan fixed effects, and borrower-year fixed effects, respectively.

4.1.1 Restricting the sample to homogeneous loans

One simple way to ascertain the importance of investor-borrower selection is to focus the analysis on a subset of homogeneous loans. To that end, we reestimate our model of loan bid-ask spreads on the subset of term loans A. We choose to conduct the tests on term loans A primarily because they account for about half of our sample. In addition, focusing on term loans B (and higher), to some extent, biases against diversity because banks, insurance companies and finance companies are less likely to invest in these loans.

The results of this exercise are reported in columns (1) and (2) of Table 4. A quick comparison of these results with our baseline results derived on the entire sample (Table 2) shows that restricting the sample to term loans A has only marginal effects on the magnitude and the statistical significance of our proxies for investor diversity: TYPES and HHI. The estimated coefficient on TYPES remains negative and statistically significant at the 1% level with a marginally increased magnitude (i.e., -0.039 for term loans A compared with -0.037 for the full sample). Similarly, the estimated coefficient on HHI remains positive and statistically significant at the 5% level with a larger magnitude (i.e., 0.420 for term loans A compared with 0.252 for the full sample).

We also try to address the concern of reverse causality by putting our measures of investor diversity on the left hand side and the lagged loan bid-ask spreads on the right hand side with the same set of control variables. We find that the lagged loan liquidity does not explain the number of investor types in the syndicate, TYPES, while it does explain the concentration in the loan syndicate, HHI, but in a way inconsistent with reverse causality. These tests, however, suffer from an important limitation – they rely on annual data.

Nonetheless, we also run the tests on term loans B and get equally strong results when we proxy diversity by the number of investor types but weaker results when we do it by the HHI of investor types’ loan shares.
### Table 4  Liquidity effects of ownership structure: Accounting for selection

| Variables | Term loans A only | Arranger FE | Loan FE | Borrower-year FE |
|-----------|------------------|-------------|---------|------------------|
| TYPES     | -0.039***        | -0.043***   | -0.032**| -0.024**         |
| HHI       | 0.420**          | 0.325**     | 0.304   | 0.299***         |
| constant  | 5.465***         | 5.307***    | 2.276*  | 3.086***         |
| Observations | 3265       | 3265        | 6084    | 6084             |
| R-squared | 0.505            | 0.503       | 0.497   | 0.980            |

The dependent variable is BID-ASK SPREAD: Average bid-ask spread over the year. Included in the models are all of the variables used in the models reported in Table 2. See Appendix in the paper for the definitions of all controls included in the models. Models are estimated with robust standard errors, clustered by borrower. We report t statistics in parentheses.

*** denotes 1% significance level; ** denotes 5% significance level; * denotes 10% significance level.

### 4.1.2 Controlling for arranger fixed effects

One could also wonder whether our results derive from arrangers’ potential preference for loans with different liquidity together with their potential role in selecting investors for their syndicates. In this case, the association between the number of investor types (or the concentration of investor types’ holdings) with loan liquidity could derive from arrangers’ selection. A simple way to address this concern is to include arranger fixed effects. The results of this investigation are reported in columns (3) and (4) of Table 4. Adding arranger fixed effects only slightly changes the coefficient estimates on our two measures of investor diversity without affecting their statistical significance.

### 4.1.3 Controlling for loan fixed effects

A better way to investigate the importance of investor-borrower selection is to estimate our model of loan bid-ask spreads with loan fixed effects. In this case the identification of the liquidity impact of investor diversity is driven by changes in investor diversity within each loan that occur over the life of the loan. The results of this investigation are reported in columns (5) and (6) of Table 4. Our two proxies for investor diversity retain their expected signs although only TYPES retains its statistically significance.

### 4.1.4 Controlling for borrower-year fixed effects

Arguably, an even more stringent test to address the issue of investor-borrower selection is to consider borrower-year fixed effects. In this case, the liquidity effect of loan ownership is derived by comparing multiple loans from the same borrower that are traded at the same time. We are able to carry out the borrower-year fixed effect test because 497 of the 1,805 borrowers in our sample have multiple loans trading at the same time. These borrowers account for 2,334 of the 6,804 loan-year observations in our sample.
The results of this test are reported in columns (7) and (8) of Table 4. Our proxies for investor diversity retain their expected signs and their statistical significance. Among the outstanding loans of a given borrower, those that have a larger number of investor types, $\text{TYPES}$, have lower bid-ask spreads. Similarly, among the outstanding loans of a given borrower, those held by less concentrated syndicates, $\text{HHI}$, have lower bid-ask spreads. These findings provide strong supporting evidence that investor diversity plays a role in the liquidity of loans that are traded in the secondary market.

### 4.2 Accounting for types of investors

In addition to the concern about the issue of investor-borrower selection, one may wonder whether our findings are driven by a single type of investors in which case these investors rather than investor diversity would explain loan liquidity. For example, it is believed that institutional investors i.e. banks, insurance companies, and finance companies, follow a buy-and-hold strategy while asset managers, i.e., mutual funds, pension funds, hedge funds, and CLOs, are active traders.\(^\text{14}\) Could it be that the presence of any of these active traders drive our findings? Alternatively, diversity may matter because of a joint presence of distinct types of investors. According to Goldstein and Yang (2015), investor diversity (i.e., a joint presence of distinct types of investors) can lead to an increase in liquidity if there are strategic complementarities in trading and information acquisition among different types of investors.

To disentangle these two alternative explanations, we begin by expanding our baseline model which we reported in Table 2 to control for the share of the loan held by each investor type. The results of this exercise are reported in columns 1 and 2 of Table 5. Adding the new controls does not affect either the size or the statistical significance of our two proxies for investors diversity, $\text{TYPES}$ and $\text{HHI}$.\(^\text{14}\)

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\(^{14}\)For example, Peristiani and Santos (2019) document that CLOs are active traders in the secondary loan market.
In columns 3 and 4 of Table 5, we go a step further and control for the number of individual investors in each investor type. Doing so only marginally reduces the magnitude of the coefficient estimates on \( \text{TYPES} \) and \( \text{HHI} \) as well as the statistical significance of the latter. Importantly, we continue to find that loans with more investors types as well as loans held with less concentrated investor type ownership have on average a lower bid-ask spread. Given that these findings account for the relative importance of the various types of investors owning the loan, they add important support to our key finding in this paper that diversity among investors, i.e. the joint presence of different types of investors, improves loan liquidity in the secondary market.

4.3 Additional robustness tests

In this subsection, we report the results of robustness tests we carry out to account for a set of additional controls that may impact loan liquidity.

4.3.1 Controlling for the credit’s age

The results we presented thus far account for the number of years left until the credit will mature, \( \text{MATLEFT} \). Available evidence for both treasury bonds and corporate bonds shows that on-the-run bonds (i.e., the most recently issued bonds) are generally more liquid than off-the-run bonds (e.g., Amihud and Mendelson 1991; Houweling et al. 2005). If this difference applies to the loan market, our control for the maturity left of the loan may not capture it since it is linear. To address this possibility, we expand our controls to include two dummy variables: \( \text{ATORIGINATION} \), which takes the value one if the loan is in the first two years of its life and \( \text{ATMATURITY} \), which takes the value one if the loan has less than two years until it reaches its maturity.

The results of this investigation depict a picture similar to that existing in the bond market – new loans are relatively more liquid. \( \text{ATORIGINATION} \) is negative and statistically significant in all of our models. Liquidity seems to decline in the last two years of the loan’s life but by an amount that is not statistically different from zero. More importantly, adding the new controls does not affect the two proxies we use for loan investor diversity: \( \text{TYPES} \), and \( \text{HHI} \).

4.3.2 Controlling for market pricing

It is well established that credit risk is a key driver of market liquidity (Bhasin and Carey 1999; Wittenberg-Moerman 2008). Our results confirm this finding. In our initial analysis, we account for the risk of the loan by controlling for the bank’s loan rating and the borrower’s credit rating. In addition, we distinguish whether term loans are of types A, B or C given that differences in amortization schedules affect the risk of the loan. Notwithstanding our use of these controls, one may still worry about the potential impact of credit risk on our findings. For example, while all of the loans in our sample have a bank rating, not all borrowers have a credit rating from a rating agency.

To further reduce concerns with the importance of credit risk, we expand our controls to account for the price of the loan in the secondary market, as determined by the average price quoted by the dealers that make the market for that loan, \( \text{PRICE} \). In addition, we control for the volatility of the loan’s price, as measured by the standard deviation of the
quoted prices, $PRICEVOL$. Consistent with expectations, the results show that riskier loans have higher bid-ask spreads. However, adding the new controls does not affect our key findings on the liquidity impact of investor diversity.

### 4.3.3 Controlling for dealer quotes

All of the results we reported so far account for the number of top loan dealers that are present in the loan syndicate as investors. As noted in the methodology section, we opt for controlling for this variable because we believe it is more informative than the often used number of quotes provided in the LSTA/LPC database. Under this assertion, the larger the number of top dealers in the syndicate the more liquid the loan will likely be. Indeed, as we saw from Table 2, the number of major dealers in the loan syndicate is strongly negatively related to the loan’s bid-ask spread.

A potential concern with this control is that not all top dealers may make the market for the loans they invest in. To reduce concerns with our decision to control for top dealers, we expand our set of controls to account for the daily average number of quotes the loan receives throughout the year, $QUOTES$. The new control variable, $QUOTES$, comes out negative and significant, suggesting that loans with more quotes are more liquid, in line with existing studies of loan market (Wittenberg-Moerman 2008; Nigro and Santos 2009). Again, adding this control does not affect our finding on the liquidity effect of investor diversity.

### 4.3.4 Controlling for the presence of loan resale constraints

Pyles and Mullineax (2008) examines loan resale constraints specified in syndicated loan agreement. They show that these clauses are employed to promote relationship banking and to assist financially-distressed firms. Since these contractual clauses directly put restrictions on loan sales (e.g., borrower or arranger consent is required before some loans can change hands), they may affect the loan liquidity. Therefore, we add a dummy variable indicating the presence of a loan resale constraint clause to our loan bid-ask spread regressions. We do not find significant liquidity effect of the presence of loan resale constraint, probably because the information on the original loan contract terms is only available for a small subset of our sampled loans and these terms do not vary over the life of a loan. However, adding this control does not change our main result on the liquidity impact of investor diversity.

### 5 Final remarks

We find supporting evidence to the insight that diversity among investors is beneficial to loan liquidity in the secondary market. More diverse syndicates, as measured by the number of investor-types or the concentration of loan shares by investor-type, hold loans that have lower quoted bid-ask spreads in the secondary market. These findings are robust and do

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15In another test, we control for $TRA D I N G$, the total number of trading days over the year as proxied by the number of days in which the price of the loan changes. This variable comes out negative and statistically significant, but adding it to our model does not affect our measures of investor diversity.
not seem to be driven by investors’ borrower/loan selection. They also do not appear to be driven by the presence of a particular type of investors because they continue to hold when we account for the relative importance of the various types of investors owning the loan. We argue that investor diversity matters for loan liquidity because different types of investors are likely to generate different information about intrinsic loan value, and trading on one type of information is a complement to trading on another type of information (Goldstein and Yang 2015). These complementarities incentivize more trading, which in turn lead to higher loan liquidity.

Our investigation of loan liquidity suggests some fruitful areas for future research. For example, according to Pennacchi (1988) and Gorton and Pennacchi (1995), if banks anticipate that they will not retain an exposure to the loans they originate, then banks will lose their incentives to screen loan applicants and to monitor borrowers during the life of the loan. However, several studies, including Plosser and Santos (2018), Blickle et al. (2020), and Glaser and Santos (2021), do not find supporting evidence to the thesis that the lead share proxies for the lead bank’s monitoring incentives. Our results show that the lead share plays a part in the liquidity of a loan, depending on whether the lead bank also acts as a dealer for the loan. This finding suggests that lead banks retain a loan share for multiple reasons. Therefore, it would seem worthwhile to deepen our understanding of the drivers of the lead share and in turn, how they influence the lead bank’s monitoring incentives.

Our evidence also raises an interesting question for future research about the potential drivers of investor diversity. Borrower-specific features will likely matter but they are unlikely the solo driver because our finding continues to hold when we account for borrower-year fixed effects. Similarly, loan-specific features will likely matter but they too are unlikely the solo driver because our finding continues to hold when we account for loan fixed effects.

Finally, immediately following the Covid-19 outbreak in the US, as loan prices dropped precipitously, liquidity in the secondary loan market dried up. The average loan bid-ask spread more than tripled during March of 2020. It would seem worthwhile investigating whether the liquidity dry up varied with the ownership structure of the loan and in particular whether it had a lesser impact on loans with more diverse ownership structures.

Appendix

Table 6  Variable names and definitions

| Variable name   | Description                                                                 |
|-----------------|-----------------------------------------------------------------------------|
| Market variables|                                                                             |
| BID – ASK       | Average bid-ask spread computed over the year (Bid-Ask is in percentage).   |
| PRICE           | Average loan price quotes (as a percentage of the face value) by dealers over the year. |
| PRICEVOL        | Standard deviation of the loan prices quoted by dealers over the year.       |
| QUOTES          | Daily average number of quotes from dealers over the year.                  |
| TRADING         | Number of trading days with loan price changes (today’s quote price-yesterday’s quote price) for a loan facility within a year. |
Table 6  (continued)

| Variable name | Description |
|---------------|-------------|
| **Loan investor variables** | |
| TYPES | Number of investor types in the loan syndicate. |
| HHI | HHI of investor types’ loan shares. |
| ARRANGERSH | Share of the loan owned by the arranger(s). |
| DEALERS | Number of top dealers among loan investors. |
| BANKS | Number of banks in the syndicate. |
| INSURANCE | Number of insurance companies in the syndicate. |
| FINANCE | Number of finance companies in the syndicate. |
| BROKERS | Number of brokers in the syndicate. |
| PEFIRMS | Number of private equity firms in the syndicates. |
| FUNDS | Number of hedge, mutual and pension funds in the syndicate. |
| CLOS | Number of CLOs in the syndicate. |
| **Loan variables** | |
| LAMOUNT | Log of the loan amount. |
| MATLEFT | Maturity left in the loan, computed in years. |
| ATMATURITY | Dummy variable equal to one if the loan has less than two years to maturity. |
| ATORIGINATION | Dummy variable equal to one if the loan age is less than two years. |
| PASS | Percentage of the loan rated as PASS by its arranger. |
| SPECIALMENTION | Percentage of the loan rated as SPECIAL MENTION by its arranger. |
| SUBSTAND | Percentage of the loan rated as SUB STANDARD by its arranger. |
| DOUBTFULL | Percentage of the loan rated as DOUBTFULL or LOSS by its arranger. |
| WORKCAP | Dummy variable equal to one if the loan is for working capital. |
| M&A | Dummy variable equal to one if the loan is for M&A. |
| RECAP | Dummy variable equal to one if the loan is for recapitalization. |
| CAPEXP | Dummy variable equal to one if the loan is for capital expenditures. |
| PROJFIN | Dummy variable equal to one if the loan is for a project finance. |
| DEBPREPAY | Dummy variable equal to one if the loan is for debt repayment. |
| TLOANA | Dummy variable equal to one if the loan is a term loan A. |
| TLOANB | Dummy variable equal to one if the loan is a term loan B. |
| TLOANC | Dummy variable equal to one if the loan is a term loan C. |
| **Borrower variables** | |
| AAA − A, ... CCC − D | Dummy variable equal to one if the borrower is rated AAA − A, ... CCC − D, respectively. |

**Acknowledgements**  The authors thank an anonymous referee, the editors, N. Prabhala and Haluk Unal, and Max Bruche, Yeejin Jang, and seminar participants at Cass Business School’s Workshop on Corporate Debt Markets, Federal Reserve Bank of Cleveland, Nankai University School of Finance, Xi’an Jiaotong University School of Economics and Finance, and the 2018 Chicago Financial Institutions Conference for valuable comments. The authors also thank Sooji Kim for outstanding research assistance. Pei Shao gratefully acknowledges financial support for this research from the Social Sciences and Humanities Research Council of Canada. The views stated herein are those of the authors and are not necessarily the views of the Federal Reserve Bank of New York, or the Federal Reserve System.
Declarations

Conflict of Interests  The authors have no competing interests to declare that are relevant to the content of this article.

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