Dispersion across CLOs on Marking Corporate Loans

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Keywords: CLO, Disagreement, Fair value, Loan liquidity, Securitization

***JEL* classification**: D82, G12, G14, G23

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Abstract

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1. Introduction

The abrupt failures of the Silicon Valley Bank and the Signature Bank have given rise to a heated debate about the different accounting impacts of holding-to-maturity and marking-to-market practices on the balance sheet of a financial institution when it values a debt asset.[1] What is common about the two big bank runs is the enormous realized losses when the banks sell the debt assets that are marked to market in the secondary market. To the extent that regulators provide little guidance on the marking policies, understanding how financial institutions mark and trade debt assets is extraordinarily important for risk management in the finance industry and corporate financing in the capital markets.

The literature so far has focused on how fund managers exploit the marking policy ambiguity and manipulate asset valuations to smooth fund performances (Cici, Gibson, and Merrick (2011)) or to comply with covenant tests (Loumioti and Vasvari (2018)). However, to value an asset, a fund manager also needs to acquire information about the fundamentals of the asset. How much information a manager knows about an asset determines the manager's marking accuracy and portfolio management efficiency given that the manager can improve fund performance by trading on the information. In this paper, I explore a novel dataset that has granular information about how different CLO managers holding a same loan mark different values for the loan. And different from the existing literature, I examine whether CLOs' dispersion on loan valuation contains private, diverse information and how the information (if any) is incorporated into the secondary loan market.[2]

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[1] See recent articles on Wall Street Journal, e.g., https://www.wsj.com/articles/as-interest-rates-rose-banks-did-a-balance-sheet-switcheroo-8e71336f?mod=hp_lead_pos2 and https://www.wsj.com/articles/declines-in-loan-values-are-widespread-among-banks-c3ee622f?mod=hp_lead_pos2.

[2] The secondary loan market has experienced a significant growth in the past two decades. According to the Loan Syndications and Trading Association (LSTA), the par dollar amount of loans tracked by the

The development of loan securitizations in the last two decades has changed the lender base in the corporate loan market. According to S&P Global Market Intelligence, about 70% of the new institutional loans are purchased by CLOs in 2018. It is not uncommon that a loan is held by dozens of CLOs. As an obligation to the CLO investors, a CLO manager needs to prepare monthly reports and mark each loan in its portfolio to market. The manager could use the pricing service from third party agents such as Markit, aggregate quotes from at least three different dealers, or estimate by herself. Moreover, because CLO managers retain part of the gains (e.g., 20%) from the improved performance of their loan portfolios, they are incentivized to engage in information production (DeMarzo (2005)). The diverse information sources and CLOs' own information production can lead to CLOs' different estimations about the value of a loan.

When investors possess diverse information, trading becomes strategic because every investor has some advantage over others in that she possesses unique information that is not known by others (e.g., Admati and Pfeiderer (1988), Holden and Subrahmanyam (1992), He and Wang (1995), Foster and Viswanathan (1996), Back, Cao, and Willard (2000), and Goldstein and Yang (2015)). An aggressive strategy enables an investor to profit before others but releases the private information too quickly. A conservative strategy, on the contrary, maximizes trading profits but might miss the opportunity to trade if other informed investors trade faster.

To provide a conceptual framework for the analysis, consider a market where there are informed investors, liquidity investors, and a dealer. Investors submit orders to the

S&P/LSTA Leveraged Loan Index has totaled more than $1 trillion by the end of 2018. The rapid growth can be largely attributed to the development of the collateralized loan obligations (CLOs) that securitize more than 70% of the institutional term loans (ITLs) that are actively traded on the secondary market.

dealer, and the dealer sets prices to clear the market. Each informed investor receives a signal about the value of a loan. One part of the signal is known by other informed investors (common information).[3] The other part is private (private information). It is private information that results in investor disagreement. Ex ante, neither common nor private information is known by liquidity investors or the dealer.

The common information leads to competition among informed investors because everyone wants to trade before others. This reveals the common information to the public very quickly and increases market depth. Liquidity investors are benefited because of the reduced Kyle's lambda (Admati and Pfeiderer (1988), Holden and Subrahmanyam (1992), and Back, Cao, and Willard (2000)). I denote this argument as the *competition hypothesis*.

Competition has no impact on revealing the diverse, private information to the public (Hellwig (1980)). The diversely informed investors still maintain monopoly power. To maximize trading profits, the investors have incentives to make smaller but more frequent transactions so that their private information is revealed to the market slowly (Kyle (1985)). The dealer becomes more uncertain about the private signals contained in the order flow because the orders submitted by informed investors are all small and indistinguishable. This gives rise to an adverse selection concern for the dealer and discourages liquidity investors to trade (Admati and Pfeiderer (1988) and Back, Cao, and Willard (2000)). I denote this scenario as the *adverse selection hypothesis*.

The *competition* and the *adverse selection hypotheses* have opposite predictions about the impact of investor disagreement on asset liquidity. To distinguish them, I exploit

[3] For example, different CLOs could use a same pricing service (e.g., Markit) to value a loan.

a novel dataset from Creditflux that contains CLOs' different estimations about the value of a same loan in a same month and their real transactions for the loan. I construct a panel sample of 102,527 loan-month observations for 7,378 unique corporate loans that are rated above Caa (exclusive) from December 2008 to October 2018.[4] I define CLO disagreement (*CLODIS*) for a loan as the standard deviation of loan values reported by all CLOs with reported holdings in the loan and illiquidity (*LOANILLIQ*) as the absolute return divided by the dollar trading amount as in Amihud (2002).

I find that a one standard deviation increase of *CLODIS* leads to an increase of 11% of the standard deviation of *LOANILLIQ* or a 35 basis points (bp) increase of the impact of a $1 million purchase order on loan price. The impact is not completely driven by trading volume because I also find that a one standard deviation increase of *CLODIS* is associated with a 41 bp increase of the absolute value of loan return.[5]

The positive impact of *CLODIS* on *LOANILLIQ* is consistent with the *adverse selection hypothesis*. But it could be also due to non-information related explanations because diverse information may not be the only reason that leads to investor disagreement. For example, Cici, Gibson, and Merrick (2011) find that the different fair values marked by publicly traded bond mutual funds for an identical corporate bond are driven by fund managers' opportunistic return-smoothing behaviors. Note that CLO managers may have incentives to manipulate the fair values of default loans or loans rated below Caa (inclusive) because they are valued at the fair values when calculating covenant tests (Loumioti and

[4] The beginning of the sample is the result of the 2008-09 financial crisis – the crisis shrank the CLO market and many collaterals in CLOs' portfolios prior to the crisis were high-yield bonds and structured products. The sample ends in October 2018 because of data availability.

[5] Lou and Shu (2017) find that the impact of the Amihud illiquidity measure on stock return is not attributable to the price impact but driven completely by the trading volume.

Vasvari (2018) and Cordell, Roberts, and Schwert (2022)). But the managers have no incentive to manipulate the fair values for loans rated above Caa (exclusive) because they are valued at par when calculating covenant tests no matter what fair values the managers provide. I exclude default loans or loans rated below Caa (inclusive) from the sample, so the CLO disagreement measure is not due to CLO managers' performance manipulation.

The literature has also documented another three mechanisms that can generate investor disagreement: limited attention, agreement to disagree, and private information (e.g., Hong and Stein (2007)). Because public firms attract more attention from investors than private firms and investors are less likely to have different priors about the value of transparent firms than that of opaque firms, public and transparent firms should be negatively associated with CLO disagreement if the disagreement is due to limited attention or agreement to disagree.

Moreover, private information production is a tradeoff between marginal costs and marginal profits. Public and transparent firms have lower marginal production costs and probably lower marginal profits than private and opaque firms. If the latter is true, public and transparent firms should be negatively related with CLO disagreement. However, I find that public firms, larger firms, and firms with more analyst coverages are associated with higher CLO disagreement. These findings suggest that public and transparent firms have lower marginal information production costs and that the disagreement is a result of private information rather than limited attention or agreement to disagree.

I also find that the impact of CLO disagreement on loan illiquidity is weaker for loans issued by public or larger firms. Because public firms are required to disclose financial information and larger firms typically have longer operating records, the results suggest that the *competition* effect becomes stronger when CLOs have more common information about the value of a loan. However, the *adverse selection* effect still plays a more important role.

CLOs are expected to sell and buy loans if they fail covenant tests. Expected transactions by informed CLOs will exacerbate the adverse selection concern for dealers in the secondary market. I find that the impact of CLO disagreement on loan illiquidity is stronger when more CLOs in a loan failed covenant tests in the previous month. The results provide further supports to the *adverse selection hypothesis*.

Furthermore, CLO disagreement increases trading frequency and decreases trading amount per transaction. And the impact of CLO disagreement on loan illiquidity decays gradually, with a still economically large and statistically significant effect after twelve months. These results suggest that diversely informed CLOs trade strategically to reveal their private information slowly to the market.

CLOs acquire credit ratings from rating agencies for the loans in their portfolios. Ratings for a same loan could be different if CLOs hire different rating agencies. I find that, although rating discrepancy does not independently affect loan illiquidity, it attenuates the impact of CLO disagreement on loan illiquidity. I also find that the impact of CLO disagreement on loan illiquidity is stronger when stock analyst disagreement is higher. These findings imply that, relative to the diverse information from CLOs, the information produced by rating agencies is partly substitute whereas that produced by stock market analysts is complement.

Loans are traded over the counter. What if a dealer also has information about a traded loan? I find that the information possessed by potential dealers (banks in a loan syndicate), measured by their lending relationships with a borrower in the past five years, can mitigate the impact of CLO disagreement on loan illiquidity. That is, dealers' own information reduces the monopoly power of diversely informed CLOs and alleviates the adverse selection concern.

To address the potential reverse causality and omitted variable biases, I create an instrumental variable (IV) *TrusteeCLORel* to predict the CLO disagreement and run a two stage least square (2SLS) regression. *TrusteeCLORel* equals the average relationship between CLO managers in a loan and their trustee banks. A trustee bank provides custodial services to many different CLO manager. It helps a CLO manager prepare monthly trustee reports and legal documents and distribute them to CLO investors. A trustee bank therefore becomes an information hub in the credit market. A CLO manager is more likely to access information that is not known by other loan investors if it has a stronger relationship with a trustee bank. When different CLO managers in a loan choose different trustee banks, this would lead to a higher disagreement about the value of the loan. Indeed, the first stage regressions show that the IV is positively related with CLO disagreement. The second stage regression results show that the instrumented CLO disagreement still has a positive and significant impact on loan illiquidity, suggesting that the results are robust after addressing potential endogeneity issues.

The existing literature on CLOs and the secondary loan market focuses on CLO fund performance (Loumioti and Vasvari (2019)), the probability of defaults and downgrades between securitized and non-securitized loans (Bord and Santos (2011) and

Benmelech, Dlugosz, and Ivashina (2012)), and how a dealer's capital affects the quoted bid and ask spreads of traded loans (Berger, Zhang, and Zhao (2020)). Yet, none of them sheds light on the information structure in the secondary loan market. My paper suggests that CLOs produce unique information about corporate loans and provides the first empirical evidence on how CLOs' diverse, private information affects their strategic trading and loan liquidity.

The paper is also related to a large literature that attempts to measure investor disagreement. Some papers use indirect proxies such as trading volume and return volatility (e.g., Berkman, Dimitrov, Jain, Koch, and Tice (2009) and Chang, Hsiao, Ljungqvist, and Tseng (2022)) or the dispersion of analysts' forecasts on earnings per share (EPS) (e.g., Diether, Malloy, and Scherbina (2002)). In a recent study, Carlin, Longstaff, and Matoba (2014) use the Bloomberg survey data on dealers' prepayment speed forecasts for a generic mortgage-backed security (MBS) to measure investor disagreement. Their measure has no cross-sectional variations and dealers are different from investors.

Different from all these studies, the CLO disagreement measure in my paper directly measures opinions from loan investors and captures both time-series and cross-sectional variations. A similar work is from Cici, Gibson, and Merrick (2011) that measures investor dispersion by the different fair values marked by mutual fund managers for an identical corporate bond. But their dispersion measure mainly captures managers' return-smoothing behaviors, which is different from the disagreement measure in my paper that captures the private information known by different CLO managers. In this regard, my paper also contributes to the literature on the marking-to-market practice and suggests that investors produce information when they mark assets to market. Liquidity investors should take this information disadvantage into account when they manage their portfolios.

This paper also complements the theoretical studies on the complementarity or substitutability of investors' information (e.g., Admati and Pfleiderer (1987), Paul (1993), Lee (2010), and Goldstein and Yang (2015)). Information possessed by financial institutions in a same market (CLOs, rating agencies, and potential dealers) are substitutable while that produced by financial institutions from a different market (stock analysts) are complementary.

The reminder of the paper is structured as follows. Section 2 discusses the institutional background. Section 3 introduces the CLO-i database and describes sample selection. Section 4 examines the relation between CLO disagreement and loan liquidity. Section 5 explores the information structure of the loan market and its impact on CLO disagreement and loan liquidity. Section 6 shows robustness and addresses the potential endogeneity issues. Section 7 concludes the paper.

2. Institutional Background

2.1. Information Structure of the Syndicated Loan Market

A syndicated loan is not recognized as a security under the Securities and Exchange Commission (SEC) regulations. As a result, public disclosure requirements are minimal, especially for private firms. Even for public firms, a loan issuer does not need to disclose as much information as it does in stock or bond offerings. A large portion of the information in the loan market remains unknown to the public.

CLOs have dramatically changed the landscape of the corporate loan market. Different from traditional loan investors that usually buy and hold loans until maturity, CLOs frequently trade loans on the secondary market.[6] The monthly trading volume of securitized loans in the U.S. reported by CLOs increased from $2 billion in December 2008 to $31 billion in October 2018. Loan transactions are typically completed by a dealer in an over-the-counter market.

In addition to active trading, another unique role played by CLOs in the loan market is that CLOs issue securities backed by syndicated loans. By securitizing a loan, a CLO becomes an important bridge of information. On one hand, it invests in a (private) loan and gains access to the publicly unavailable information about the loan. On the other hand, it has an obligation to disclose information such as holdings, loan value, and transactions on a regular basis because it issues asset-backed securities such as triple-A rated bonds. Many CLOs invest in a same loan, so CLO disagreement on the loan value is directly observable.[7] The above unique nature of CLOs makes the syndicated loan market arguably the best laboratory to study market information structure and secondary trading.

2.2. Estimations of Loan Value in the Monthly Reports of CLOs

After the month in which a CLO fund closes, the manager of the fund needs to compile a trustee report in every month before the fund matures. In a month when there

[6] A typical CLO has a four-year reinvestment period during which the manager can trade loans if the CLO meets collateral quality and subordination level requirements. After all the necessary payments to the government and the noteholders, the manager usually receives 20% of the remaining amounts as a management incentive fee. This incentive fee encourages the manager to trade loans to boost performance.
[7] In my sample, the average number of CLO funds (managers) is 33 (11). A CLO manager may own multiple funds at the same time.

are cash flow distributions, the manager needs to prepare a payment report which contains information on payments to all investors in the CLO fund in addition to the information that is included in a trustee report. In these monthly reports, a CLO manager needs to provide price estimations (in percentages over par) for each loan in its portfolio. The purpose for managers to value loans in their portfolios includes marking portfolios to market, managing risk, and supporting trading decisions.

Because trading in the secondary loan market is sporadic, sometimes there are no market transaction prices to be used as reference points. Typically, a CLO manager uses the following rules to determine loan value. 1) The manager obtains the bid price determined by an approved independent pricing service such as the Loan Pricing Corporation, LoanX Inc., or Markit Group Limited. 2) If 1) is not available, the manager uses the arithmetic average of bid-side quotations obtained from three independent dealers. 3) If neither 1) nor 2) is available, the manager determines the loan value by exercising reasonable commercial judgment. 4) If none of the above are available, the value is set at zero until any of the above becomes available. Note that for non-zero evaluations, the CLO manager does not disclose which one it uses.[8]

Different CLO managers often provide different prices for the same loan in the same month. The difference could result from CLO managers' different information sources (indirect information production). For example, some CLO managers may get price estimations from pricing service companies, and some others may seek bids from secondary market dealers. The difference could also result from CLO managers' own analyses on the value of the loan (direct information production). In this study, I will

[8] These institutional details are from CLO offering prospectuses in the Creditflux database.

abstract away the reasons behind this difference. After all, a CLO manager's private information can come from both indirect and direct information productions.

It has been documented that bond mutual fund managers could manipulate marked bond prices to inflate their performances (Cici, Gibson, and Merrick (2011)). However, this is not the case for CLO managers. Inflating price estimations cannot increase CLO fund returns because CLO managers will only get paid (except for the fixed senior management fee) if the collateralization tests are passed. Therefore, the managers would manipulate the price estimations only if doing so can improve their collateralization test results. Loumioti and Vasvari (2019) find that for default and Caa-rated loans, CLO managers have incentives to manipulate the price estimations to pass the monthly covenant tests. However, for non-default and non-Caa loans that are the focus of this paper, they are valued at par when computing covenant tests. The managers have no incentive to manipulate the price estimations for these loans.

3. Data and Sample Description

3.1. CLO-i Data, Sample Selection, and Variable Construction

The sample is from Creditflux CLO-i database. Creditflux is a leading media company that provides specialist news, research analyses, and data on global financial markets, with a focus on CLOs in the US and Europe. The CLO-i database contains comprehensive data on loan collaterals, CLO bond tranches, collateralization test results, and equity tranche payments. Creditflux retrieves information from payment reports and monthly trustee reports distributed by CLO managers.

Most of the papers in the literature use dispersion of analyst forecasts on EPS – the standard deviation divided by the absolute mean – to measure investor disagreement (e.g., Diether, Malloy, and Scherbina (2002), Johnson (2004), and Sadka and Scherbina (2007)). As suggested by Cen, Wei, and Yang (2017), the numerator in this measure captures the disagreement. And the denominator, which is simply a scalar to make this variable cross-sectionally comparable, might capture investors' underreaction to information. Because loan evaluations are measured as percentages over par, normalization is not needed. Therefore, to focus on the investor disagreement, I measure CLO disagreement on loan value as the standard deviation across the price estimations:

$$CLODIS = \sqrt{\frac{\sum_{j=1}^{n_{i,t}}\left(Price_{i,j,t} - MPrice_{i,t}\right)^2}{n_{i,t}}} * 100$$

Where $n_{i,t}$ is the number of CLO managers in month t in loan i, $Price_{i,j,t}$ is the price reported by CLO manager j in month t for loan i, and $MPrice_{i,t}$ is the average price across CLO managers in month t for loan i.[9]

I start from 21,804,352 loan-CLO fund-month level observations in the CLO-i database. I exclude bonds, equities, credit default swaps (CDS), loans that are not syndicated in the U.S., loans that are not denominated in USD, and loans with no issuer names, maturity dates, or issue types. This step reduces the number of observations to 16,300,847. I exclude loans with reported values that are missing, negative, or zero, which reduces the sample size to 5,013,406. I also exclude 66,004 observations for defaulted loans and 487,182 observations for loans that are rated below Caa (inclusive) because CLO

[9] The results are robust if CLO disagreement is measured as the standard deviation across price estimations divided by the mean.

managers may manipulate the prices of these loans to pass the over-collateralization tests (Loumioti and Vasvari (2019)).[10] This step reduces the sample to 4,460,220, which consists of 20,813 unique loans held by 1,555 CLO funds or 160 unique CLO managers. Because CLO funds owned by the same manager typically provide same or very close prices for the same loans in their monthly reports, I aggregate the fund level data into manager level and calculate the weighted average price for these loans. The manager-level sample has 1,485,894 observations. Finally, defining CLO disagreement downgrades the sample from loan-CLO manager-month level to loan-month level, which includes 124,055 observations.

I estimate the average price impact in a month using the real transaction data in the spirit of Amihud (2002),

$$LOANILLIQ_{i,t} = \frac{1}{N_{i,t}} * \sum_{k=1}^{N_{i,t}} \frac{1}{Q_{i,k}} \frac{\left|P_{i,k} - P_{i,k-1}\right|}{P_{i,k-1}} * 100$$

where $N_{i,t}$ is the number of returns in month t of loan i, $P_{i,k}$ is the average trading price on day k of loan i, and $Q_{i,k}$ is the dollar trading amount in millions on day k of loan i. The illiquidity measure is available for 107,341 observations.[11] I exclude DIP, revolver, letter of credit, term loan A, and other loans and focus on ITLs. This reduces the sample to 102,930 observations. After removing 403 observations with missing values in the regressors, the final sample includes 102,527 observations for 7,378 unique loans.

[10] The results are robust if I include these loans. Please see Specification (6) in Table 11.

[11] Following the bond literature (e.g., Bessembinder, Kahle, Maxwell, and Xu (2008) and Bao, O'Hara, and Zhou (2018)), I exclude transactions with amount less than or equal to $100,000 to avoid the noises that these small transactions introduce into prices. Nevertheless, including these small trades yields robust results.

3.2. Overview of CLO Disagreement and Loan Illiquidity

Figure 1 shows the variations of *CLODIS* and *LOANILLIQ* across time and ratings. Panel A shows the time-series variations for the sample period from December 2008 to October 2018. The high level of *CLODIS* in 2008 and 2009 is due to the profound uncertainty caused by the financial crisis. The spike around August 2011 is likely due to the credit downgrade of U.S. sovereign debt from AAA to AA+ by Standard & Poor's. The peak in the end of 2015 is probably caused by the credit downgrading by Fitch in the third quarter of 2015 in the U.S. energy industry.

LOANILLIQ decreased dramatically after the financial crisis. Except for two slight bumps in January 2010 and August 2011, it kept declining until May 2014. It increased steadily from June 2014 to December 2015 then decreased towards the end.

In Panel B, I plot *CLODIS* and *LOANILLIQ* together by different rating categories. About 60% of the loans are rated B1 and B2. Almost all loans are non-investment grade. Both *CLODIS* and *LOANILLIQ* increase monotonically when loan rating decreases.

3.3. Summary Statistics

Table 1 shows the summary statistics. The average value of *CLODIS* is 0.66. To put this number into perspective, consider a loan with two CLO investors. The value 0.66 would correspond to one CLO investor pricing the loan at 99.34 and the other pricing the loan at 100.66. The average value of *PriceDispersion* is 0.67. And the average difference between the highest and the lowest prices is 1.84.

The average *LOANILLIQ* is 1.28 and the median value is 0.34.[12] The average monthly trading amount is $1.18 million. To benchmark the numbers, the average value of *LOANILLIQ* means that a sell order with an average amount of $1.18 million will decrease the price from 100.00 to 98.49 (100-1.28 *1.18). As a comparison to the bond market, in Bao, O'Hara, and Zhou (2018), a $1 million sell order will reduce the price from 100.00 to 98.40. On average, there are approximately 2.86 days ((1-87%) *22) with transactions in a trading month. The mean and median value of the number of transactions in a month is 8.40 and 3.00, respectively. These numbers suggest that loans are traded as sporadically as corporate bonds. As reported by Goldstein and Hotchkiss (2020), for corporate bonds, the average monthly non-zero trading days is 3.40, and the mean and median value of monthly trades is 20.00 and 3.10, respectively.

An average loan has about 59 months to maturity (the difference between the maturity date and the report date). The average CLO holding amount is $68.68 million. 50.60% of the observations are for term loans and 44.40% of the observations are for term loan B (TLB).[13] For public firms, the average total assets is $8,569 million. The mean value of leverage and Tobin's Q is 0.63 and 1.89, respectively. On average, about 6 analysts cover a borrower's stock and the standard deviation of analysts' forecasts on EPS is 0.26.

4. CLO Disagreement and Loan Illiquidity

[12] The distribution of *LOANILLIQ* is skewed right. The baseline regression results are robust if I use *Log (1+LOANILLIQ)* as the dependent variable.

[13] Many loans are classified as term loans in Creditflux. I cannot determine whether these loans are TLB, term loan C (TLC), or second lien, etc, so I create a dummy variable for term loans to account for the potential different impact of term loans on loan illiquidity.

4.1. Baseline Results

I investigate how CLO disagreement affects loan illiquidity by estimating the following model:

$$LOANILLIQ_{ijt} = \alpha + \beta CLODIS_{ijt} + \gamma Controls_{ijt} + Rating\ FEs + YearQuarter\ FEs + Firm\ FEs + \epsilon_{ijt}, \quad (1)$$

where i, j, t indicates loan, loan rating, and CLO report month, respectively. To account for cross-sectional correlations within the same report month, I cluster standard errors at the report month level.[14] The dependent variable, *LOANILLIQ*, is the absolute return divided by the trading amount. It is averaged within a month. The independent variable of interest is *CLODIS*, which is the standard deviation of the prices provided by the CLO investors in a loan.

Controls consists of a set of confounding factors that would affect loan liquidity. Investors are more uncertain about the value of a loan with a longer maturity than a similar loan with a shorter maturity, which makes the former loan more difficult to trade. *Log (TotalCLOHoldings)* is correlated with the outstanding amount of a loan and would affect the transaction amount per each deal.[15] To control for CLO investors' specific interests in TLB (Nadauld and Weisbach (2012)), I include five loan type dummies in the regressions. Loans labeled as term loan D (TLD) are the base group, so the indicator variable for these

[14] For example, the Federal Reserve System might announce an interest rate change in a month. The CLO reports issued in that or the following month will incorporate such market-level variations into the pricing of securitized loans, which increases the cross-sectional correlation on loan values. Results are similar if I cluster the standard errors at firm level.

[15] Another proxy for the outstanding amount of a loan is the offering amount. It is not available in the CLO-i dataset and does not account for amortizations, so I use total CLO holdings in the main analyses. The results are robust if I use offering amounts for a very small sample matched between CLO-i and DealScan.

loans is omitted in the regressions. Funding conditions affect a dealer's inventory costs and asset liquidity (Brunnermeier and Pedersen (2009)). I use *VIX* (the Volatility Index from the Chicago Board Options Exchange (CBOE)) and *TEDSpread* (the difference between the 3-month London Interbank Offer Rate (LIBOR) and the 3-month Treasury rate) to control for the funding conditions of financial institutions (Brunnermeier, Nagel, and Pedersen (2008)). Because loans are traded infrequently and information may still flow in days without any transactions for a loan, I include the monthly return of the S&P/LSTA U.S. Leveraged Loan 100 Index. Illiquidity and credit risk are positively correlated (e.g., Ericsson and Renault (2006), Chen, Lesmond, and Wei (2007), and Bao, Pan, and Wang (2011)), so I include loan rating fixed effects to account for the potential impact of credit risk on loan illiquidity. I also include borrower and CLO report quarter fixed effects.

The OLS regression results are reported in Table 2. From Columns (1) to (7), I gradually include control variables and use different fixed effects to alleviate the concern that the potential correlations between *CLODIS* and other control variables might bias the estimation toward finding favorable results and to understand the main variations that drive the results. In Column (7), the coefficient estimate on *CLODIS* is 0.26 and is statistically significant at the 1% level. Economically, a one standard deviation increase of *CLODIS* is associated with 0.35 increase in *LOANILLIQ*, which represents 11% of the standard deviation of *LOANILLIQ* or a 35 bp increase of the impact of a $1 million purchase order on loan price.

For the control variables, loans with longer maturities are associated with greater illiquidity, consistent with the findings in the bond market (Amihud and Mendelson (1991), Chen, Lesmond, and Wei (2007), and Bao, Pan, and Wang (2011)). Total CLO holding amount is negatively related with loan illiquidity, suggesting that smaller loans or loans with lower CLO demands are less liquid in the secondary market. Relative to TLD, second lien and TLC are more liquid while term loans and TLB tend to be less liquid. The coefficient on *VIX* is positive, suggesting that tighter funding constraints increase loan illiquidity (Bao, O'Hara, and Zhou (2018)).

4.2. CLO Disagreement: Opacity, Agreement to Disagree, or Diverse Information?

After the establishment of a strong impact of CLO disagreement on loan illiquidity, it is important to pinpoint what drives CLO disagreement. The disagreement among CLOs in a loan may not necessarily result from CLOs' diverse information. It might be because little information is available about the loan or investors pay little attention to the borrower. Also, CLOs are more likely to have different priors or agree to disagree about the credit risks of opaque loans than transparent loans. Therefore, if CLO disagreement is due to the opacity of a loan, limited attention, or disagreement to agree, there should be a negative (positive) correlation between loan transparency (opacity) and CLO disagreement.

To that end, I construct three proxies to measure a firm's transparency and regress CLO disagreement on each of them. Precisely, I run the following regression model:

$$CLODIS_{ijt} = \alpha + \beta Transparency_{ijt} + \gamma Controls_{ijt} + Rating\ FEs + YearQuarter\ FEs + Firm\ FEs + \epsilon_{ijt}, \quad (2)$$

where i, j, t indicates loan, loan rating, and CLO report month, respectively. *Transparency* is measured by *PublicDum* that equals one if a firm can be matched with Compustat, *Log (NumAnalyst)* that is the natural logarithm value of the number of analysts covering a firm's stock, and *Log (TotalAsset)* that is the natural logarithm value of the total assets. *Controls* consists of the same variables as in Equation (1). The OLS regression results are reported in Table 3.

The coefficient estimates on *PublicDum*, *Log (NumAnalyst)*, and *Log (TotalAsset)* are all positive. This suggests that everything else equal, more transparent (opaque) firms are associated with higher (lower) CLO disagreement. These results are opposite to the argument that CLO disagreement is driven by the opacity of a borrower or different priors of CLOs. Because public firms receive more attention from investors than private firms, the positive correlation between *PublicDum* and *CLODIS* also suggest that the CLO disagreement is not due to limited attention (Hong and Stein (2007)). Because all loans are private, the opacity of borrowers should be irrelevant to the marginal value of a piece of private information. If anything, the marginal cost of information production is lower for a transparent borrower than for an opaque borrower. Therefore, the results are consistent with the notion that the CLO disagreement is a result of CLOs' information production.

4.3. Alternative Measures of CLO Disagreement and Loan Illiquidity

I use two alternative illiquidity measures. First, I extract quoted bid and ask prices from Thompson Reuters and the Loan Syndications and Trading Association (LSTA) and define *QuoteSpread* as the spread between the average bid and ask prices.[16] Second, I calculate an estimated bid and ask spread using daily high and low trading prices as in

[16] Since 1999, Thompson Reuters Loan Pricing Corporation and the LSTA have jointly formed the first secondary mark-to-market service to provide daily bid and ask quotes for widely traded syndicated loans.

Corwin and Schultz (2012).[17] Corwin and Schultz (2012) suggest that the ratio of high-to-low prices for a day reflects both the fundamental volatility of the stock and its bid-ask spread given that daily high (low) prices are almost always buyer (seller) - initiated trades. Because the component of the high-to-low price ratio that is due to volatility increases proportionately with the length of the trading interval and the component due to bid-ask spreads does not, a stock's bid-ask spread is a function of the high-to-low price ratio for a single 2-day period and the high-to-low ratios for 2 consecutive single days. Precisely, I calculate *EstSpread* using the following formula:

$$EstSpread = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}$$

where $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$. $\beta = \sum_{j=0}^{1}\left[\ln\left(\frac{H_{t+j}^{O}}{L_{t+j}^{O}}\right)\right]^2$ and $\gamma = \left[\ln\left(\frac{H_{t,t+1}^{O}}{L_{t,t+1}^{O}}\right)\right]^2$. H_{t+j}^{O} (L_{t+j}^{O}) is the observed high (low) price on day $t + j$. $H_{t,t+1}^{O}$ ($L_{t,t+1}^{O}$) is the observed high (low) price over the two-day period. The *EstSpread* could be negative when γ is too high. Following Corwin and Schultz (2012), I set negative value of *EstSpread* to be zero.

In Table 4, the dependent variable in Columns (1) and (2) is *EstSpread* and *QuoteSpread*, respectively. The coefficient estimates on *CLODIS* are both positive and are statistically significant at the 1% level, suggesting that measuring loan illiquidity by the estimated or quoted bid and ask spread does not change the baseline results.

I also define another two CLO disagreement measures, *PriceSTDMean* and *PriceRange*. The former is the standard deviation divided by the mean of CLO investors'

[17] Schestag, Schuster, and Uhrig-Homburg (2016) find that the estimated bid and ask spread proposed by Corwin and Schultz (2012) is one of the best illiquidity measures for low-frequently traded assets.

valuations on the same loan, and the latter is the highest minus the lowest loan valuations. The results in Columns (3) and (4) show that both *PriceSTDMean* and *PriceRange* are positive and are statistically significant at the 1% level, suggesting that the results are robust with alternative disagreement measures.

4.4. CLO Disagreement and Loan Illiquidity: Common vs Private Information

The positive impact of CLO disagreement on loan illiquidity as documented in Table 2 is consistent with the conjecture that the presence of investors with diverse, private information increases the transaction costs due to adverse selection. I shed further light on this conjecture by investigating how the impact of CLO disagreement on loan illiquidity varies with the amount of common information known to all CLOs. Because more common information leads to a stronger competition effect, I expect the impact of CLO disagreement on loan illiquidity to be weaker if there are more common information.

I create two variables to measure CLOs' common information. *PublicDum* is a dummy variable that equals one if a borrower can be matched with Compustat and zero otherwise. *Log (TotalAssets)* is the natural logarithm value of the total assets of a borrower. Public firms are required to disclose information. And larger firms typically have longer operating records than smaller ones. The OLS regression results are reported in Table 5.

The coefficient estimates on *CLODIS*PublicDum* and *CLODIS*Log (TotalAssets)* are both negative and are statistically significant at the 1% level. These findings suggest that the impact of CLO disagreement on loan illiquidity is attenuated when CLO investors have more common information. They are consistent with the argument that CLOs compete trading on common information while maintain monopolistic power on private information.

4.5. Expected Informative Trading of CLOs

Although many theoretical papers suggest that trading by informed investors impairs market liquidity, empirical studies provide mixed evidence (e.g., Cornell and Sirri (1992), Lee, Mucklow and Ready (1993), Bettis, Cole and Lemmon (2000), and Cao, Field, and Hanka (2004)). In this section, I examine how expected trading by informed CLO investors affects the impact of CLO disagreement on loan illiquidity.

Trading is more likely to take place if a CLO fails covenant tests or it is near the test threshold. Like covenants in bond and loan contracts, covenant tests in CLOs are used to help CLO bond investors to monitor the quality of the assets. For example, the weighted average spread (WAS) test requires a CLO to keep the WAS above a certain level. If the WAS is below the required level in a month, the CLO manager needs to trade in the secondary market to increase the WAS. Other frequently used covenant tests include the weighted average rating factor (WARF) tests, the tranche A overcollateralization (OC) tests, and the tranche A interest coverage (IC) tests.[18]

I proxy the likelihood of CLOs' informed trading by two variables that are related to the covenant tests. *FailFundRatio* is the number of CLOs that have failed any of the covenant tests divided by the total number of CLOs in a loan. *CovTestDist* is the weighted

[18] Tranche A OC test ratio is the principal balance of tranche A securities divided by the total principal balance of the collaterals. Tranche A IC test ratio is the interest payment of tranche A securities divided by the total interest payments from the collaterals. There are also OC tests for other CLO tranches.

average distance between the current WAS test result and the failure threshold for a loan.[19] The weight is a CLO's holding divided by the total CLO holding amount in a loan. Table 6 shows the OLS regression results.

In Column (1), the coefficient estimate on the interaction term *CLODIS*FailFundRatio* is 0.25 and is statistically significant at the 1% level, suggesting that *CLODIS* has a stronger impact on *LOANILLIQ* when more CLOs in a loan failed covenant tests in the previous month. The coefficient estimate on *CLODIS*CovTestDist* is -0.50 and is statistically significant at 1% level, suggesting that the impact of *CLODIS* on *LOANILLIQ* is more pronounced in loans where CLOs' test results are closer to the failure thresholds. These findings suggest that expected informative trading by CLO investors worsens the adverse selection concern for dealers and increases transaction costs.

4.6. CLO Disagreement and Strategic Trading

4.6.1. CLO Disagreement, Trading Frequency, and Trading Amount

The *adverse selection* hypothesis also suggests that diversely informed investors will trade more frequently with a smaller amount in each transaction. In this section, I test this implication and examine how CLO disagreement affects trading frequency and trading amount. The OLS regression results are presented in Table 7.

The results in Columns (1) and (2) show that CLO disagreement is negatively associated with the portion of zero trading days in a month and positively associated with

[19] I choose WAS test to calculate the test difference because WAS is the most frequent covenant test in the sample.

the number of trades in a month. The coefficient estimates are statistically significant at 1% level and are economically important. For example, a one standard deviation increase of the *CLODIS* is associated with a decrease that is 2% of the standard deviation of the *ZeroTradeDayPortion*. In Columns (3) and (4), CLO disagreement is negatively correlated with the trading amount and the portion of large trades that are greater or equal to $1 million. The coefficient estimates are also statistically and economically significant. For example, a one standard deviation increase of the *CLODIS* is associated with a decrease of $25,968 (3% of the standard deviation of *TradeAmt*) in the trading amount per transaction. These results provide further supports to the *adverse selection* hypothesis.

4.6.2. The Persistence of the Impact of CLO Disagreement on Loan Illiquidity

The strategic trading (i.e., trading more frequently but with a smaller amount each time) of diversely informed CLOs should lead to slow revelation of CLOs' private information. In this section, I extend the illiquidity measure to longer periods to investigate how fast the private information is incorporated into loan prices.

Table 8 reports the OLS regression results. The dependent variables are the mean value of *LOANILLIQ* in the next 3, 6, 9, 12 months after a CLO report month, respectively. The coefficient estimates are all positive and are statistically significant at the 1% level. More importantly, the magnitudes reduce gradually as I extend the calculation window of the illiquidity variable. For example, the coefficient estimates on *CLODIS* from Columns (1) to (4) decline monotonically from 0.24 to 0.16. The impact of *CLODIS* on *LOANILLIQ* after twelve months still represents 62% of the impact in the first month.

These findings suggest that when investors have diverse and private information about the value of an asset, the secondary market incorporates their private information slowly due to investors' strategic trading behaviors. The results also suggest that the disagreement among CLO investors does not result from their irrational believes (e.g., over or under confidence) because uninformative shocks are transitory.

5. Information Structure of the Loan Market, CLO Disagreement, and Loan Illiquidity

5.1. Information from Rating Agency

In the monthly CLO reports, each loan is rated by at least one of the three biggest rating agencies: Moody's, Standard & Poor's, and Fitch. It is not uncommon that different CLOs in the same loan acquire ratings from different agencies and that the rating agencies assign different ratings to that loan. In this section, I run a horse race regression between CLO disagreement and disagreement among rating agencies and investigate whether rating agencies hold similar or different information as CLO investors.

The OLS regression results are reported in Table 9 Columns (1) to (4). In Columns (1) and (3), I add *RatingSTD* and *DiffRate* into the regressions, respectively. *RatingSTD* is the standard deviation of the ratings across different CLO reports for a loan. *DiffRate* is a dummy variable that equals one if at least two CLO reports have different ratings for the same loan and zero otherwise. In both regressions, the coefficient estimates on *CLODIS* are almost identical to that in the baseline regressions, suggesting that controlling for rating disagreement does not change the impact of *CLODIS* on *LOANILLIQ*.[20] Besides, in

[20] The negative sign on *RatingSTD* is likely due to the positive correlation between *RatingSTD* and *CLODIS*.

Columns (2) and (4), both interaction terms are negative and are statistically significant at the 1% level, suggesting that rating discrepancy attenuates the positive impact of *CLODIS* on *LOANILLIQ*. In other words, the diverse information from CLOs and the information produced by rating agencies are partly substitutes.

5.2. CLO Disagreement and Stock Analyst Disagreement

Different from a bond or a stock, a loan is not a registered security. The information in a loan contract does not need to be released to the public. Moreover, a loan contract has a put option feature. Holding a loan is different from holding a stock and does not gain from the growth opportunities of the borrower. With these fundamental differences, loan investors may acquire materially different information than equity investors (Ivashina and Sun (2011), Goldstein and Yang (2015), and Addoum and Murfin (2019)). In this section, I examine how the information obtained by stock analysts in a firm affects the impact of CLO disagreement on the firm's loan illiquidity.

The OLS regression results are reported in Table 9 Columns (5) and (6). The coefficient estimates on *EPSSTD* are not statistically significant. The interaction term, *CLODIS* EPSSTD*, is positive and is statistically significant at 1% level. The results suggest that loan investors and stock analysts specialize in different types of information production. They hold different and complementary information.

5.3. Dealer's Private Information over the Course of a Lending Relationship

When dealers also know a loan, the adverse selection due to CLO investors' diverse, private information becomes a lesser concern. Therefore, I conjecture that the impact of CLO disagreement on loan illiquidity is weaker if dealers in the secondary loan market know more about a loan.

Because most of the primary market lenders reported in DealScan are banks and typically will become dealers in the secondary loan market, I measure dealers' private information by the lending relationship between the syndicate lenders of a loan and the borrower (Bharath, Dahiya, Saunders, and Srinivasan (2011), Ivashina and Kovner (2011), and Zhang, Zhang, and Zhao (2023)).[21] Particularly, I define three different but related variables. *RelationDum* is a dummy variable that equals one if any of the syndicate lenders have lent to the borrower in the past five years before the current loan and zero otherwise. *RelationNum* (*RelationAmt*) is the number (amount) of loans from a lender divided by the total number (amount) of loans issued by the borrower in the past five years. The greatest value is chosen when there are multiple lenders in a loan syndicate.

The OLS regression results are reported in Table 10. The interaction terms between *CLODIS* and the three relationship variables are all negative and are statistically significant at the 5% or 1% levels. This means that the information known by potential dealers reduces the monopolistic power of diversely informed CLO investors, which reduces the adverse selection problems in the secondary loan market.

[21] Due to tax reasons, CLOs rarely purchase syndicated loans from the primary market. Instead, they get their loan shares via primary assignments in which the lead arranger of a loan will hold the loan on its book for some short period after the loan closes and then sell it to these CLOs at a pre-determined price (S&P (2006)).

6. Robustness Test Results and the Endogeneity Issues

6.1. Robustness Tests

I execute a rich set of tests to diagnose the robustness of the baseline findings. Table 11 reports the OLS regression results. In Column (1), I cluster the standard errors at firm level rather than CLO report month level. In Column (2), I exclude 609 observations that are during the financial crisis period (from July 2007 to April 2009). The results are similar as in the baseline regressions. The results are also similar if I add the lead lender fixed effects in Column (3) to further account for dealers' inventory costs or funding constraints.

Lou and Shu (2017) find that the pricing of the Amihud illiquidity measure is not attributable to the return-to-volume ratio that is constructed to capture price impact but is driven by the trading volume component. I follow Lou and Shu (2017) and construct a return component of the Amihud illiquidity measure as the monthly average absolute loan returns. The coefficient estimate on *CLODIS* in Column (4) suggests that a one standard deviation increase of *CLODIS* increases the absolute loan return by 41 bp. That is, the impact of *CLODIS* on *LOANILLIQ* is driven by the change of both the volume and return.

In Columns (5) and (6), I add trades smaller than $100,000 and loans of which the prices are subject to potential CLO manipulations into the sample, respectively. The results are robust.

Another potential concern of the baseline results is the omitted firm characteristics.[22] Although I have included firm fixed effects to account for the impact of time-invariant firm characteristics on loan illiquidity, it is still possible that time-varying

[22] Approximately 70% of the loans in the sample are borrowed by private firms that do not have financial information in Compustat, so I do not control for firm characteristics in the baseline regressions.

firm-level variables may drive the results. In Column (7), I control for firm-year fixed effects. The coefficient estimate on *CLODIS* is still positive and is statistically significant at the 1% level. Column (8) adds *Log (TotalAssets)*, *Leverage*, and *TobinQ* in the regression and produces robust results.

6.2. Addressing the Endogeneity Issues and Identifying the Information Channel

The reverse causality may not be a critical concern for the paper. Even if a market is illiquid, it can still be informationally efficient (Kyle (1985)). Also, a CLO manager's access to pricing services companies does not depend on the illiquidity of a loan. Moreover, the disagreement here is mainly driven by CLOs' private signals. When a market is illiquid, investor monitoring becomes difficult. CLOs' incentive to produce private information is reduced, which leads to a lower CLO disagreement (e.g., Holmstrom and Tirole (1993)). This predicts a negative correlation between illiquidity and CLO disagreement, which is opposite to the findings in this paper.

For the omitted variable bias, recall that the results are robust when loan fixed effects and year-month fixed effects are controlled for in Table 2 Column (6). The results are also robust when a two-way firm and year fixed effects and when additional firm characteristics are included in Table 11 Columns (7) and (8), respectively.

Nevertheless, to address the potential endogeneity issues, I create an instrumental variable (IV), *TrusteeCLORel* that equals the average relationship between CLO managers and trustee banks in a loan, to predict the CLO disagreement and run a two stage least square (2SLS) regression. A trustee bank provides custodial services to many different

CLO managers. It helps a CLO manager compile monthly trustee reports and distributes them to CLO investors. A trustee bank therefore becomes an information hub in the credit market. A stronger relationship between a CLO manager and a trustee bank could more likely give the manager access to some information that is not known by other loan investors. When different CLO managers in a loan choose different trustee banks, this would lead to a higher disagreement about the value of the loan. The first stage regression results in Table 12 Column (1) suggest that the IV is positively related with CLO disagreement and is statistically significant at 1% level. That is, the IV satisfies the relevance condition.

The exclusion condition is also arguably satisfied. First, a CLO manager chooses a trustee bank before it constructs the loan portfolio in the warehouse period. Second, a trustee bank does not make transaction decisions for nor give trading advice to a CLO manager. Therefore, the selection between a CLO manager and a trustee bank does not play an important role in the empirical analysis. The IV then affects loan illiquidity only through its correlation with CLO disagreement that results from CLOs' access to different information hubs. The diagnostic statistics reported at the bottom of Column (1) in Table 12 reject the null hypotheses that the IV is weak or the model is under-identified.

We then use the IV to run a 2SLS regression. The second stage results are in Columns (2) to (4). In Column (2) where we use the full sample, the coefficient estimate on the predicted CLO disagreement is 0.458 and is statistically significant at 10% level. It is only slightly greater than 0.258 in the OLS regression. In Columns (3) and (4), we split the sample by the trustee concentration that is the sum of squared ratio of the number of CLO managers that use a same trustee bank divided by the total number of CLO managers in a loan. The IV impact should be stronger when there are more information hubs in a loan. This is what I find in Columns (3) and (4). That is, the baseline findings are robust after addressing the potential endogeneity issues.

7. Conclusions

In this paper, I exploit a new dataset that contains granular information on CLOs' diverse opinions on loan value and real transaction information for a large sample of securitized loans. I study how CLO disagreement affects loan illiquidity and how the impact varies with the information structure of the secondary loan market.

I find that the dispersion across CLOs on marking corporate loans is driven by CLOs' diverse information, not performance manipulation, borrower opacity, agreement to disagree, or limited attention. Diversely informed CLOs trade strategically by increasing trading frequency and reducing trading amount per transaction, which increases loan illiquidity and leads to slow revelation of CLOs private information to the market.

CLOs' strategic trading increases dealers' uncertainty about the private signals in the secondary market and gives rise to an adverse selection concern. When dealers also possess information about the traded loan, this adverse selection concern is alleviated.

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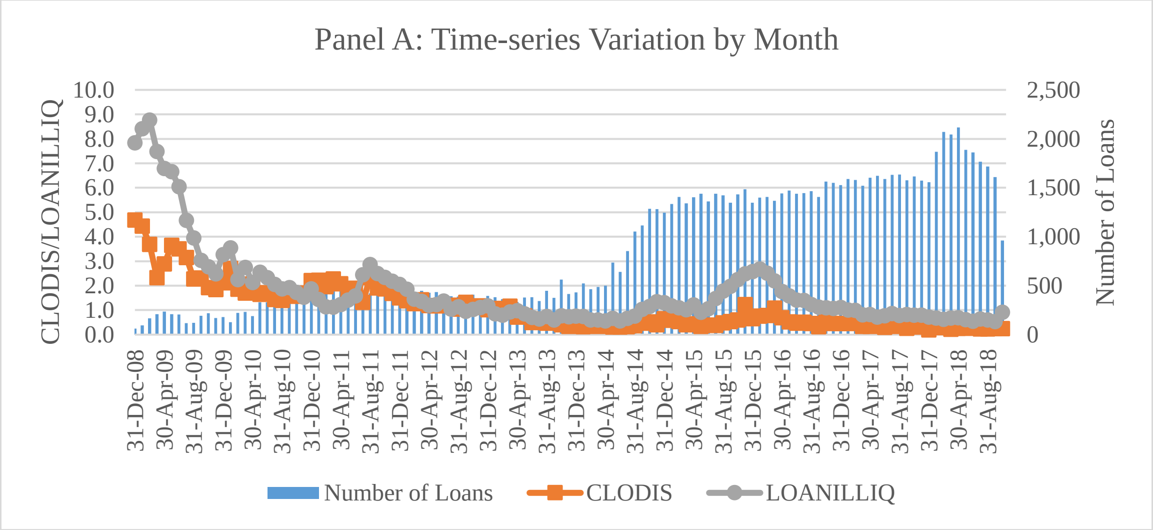
Figure 1. Variations of CLO Disagreement and Loan Illiquidity

This figure shows variations of *CLODIS* and *LOANILLIQ* across time and ratings. The sample is from December 2008 to October 2018. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. *LOANILLIQ* equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. Panels A and B show the variations by month and ratings, respectively.



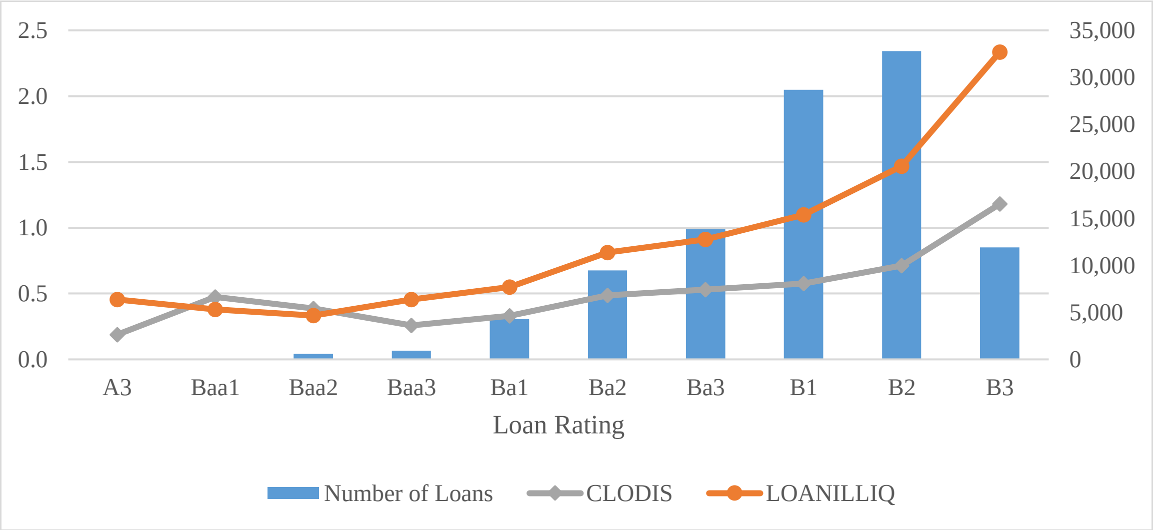


Table 1. Summary Statistics

This table shows the summary statistics for the sample in this paper. All the continuous variables are winsorized at the 1st and 99th percentiles. The number of observations varies due to missing values. Please see Appendix A for variable definitions.

	N	Mean	STD	P25	Median	P75
CLODIS	102,527	0.661	1.333	0.144	0.241	0.507
PriceSTDMean	102,527	0.719	1.537	0.144	0.242	0.521
PriceRange (% of Par)	102,527	1.841	3.593	0.417	0.719	1.491
LOANILLIQ	102,527	1.275	3.126	0.129	0.342	0.938
EstSpread	30,698	0.151	0.675	0.000	0.000	0.000
QuoteSpread	60,911	0.785	0.582	0.477	0.602	0.873
Turnover (%)	93,298	25.890	57.860	3.554	8.669	21.770
ZeroTradeDayPortion (%)	102,527	86.820	11.280	81.820	90.910	95.450
NumTrade	102,527	8.394	13.730	1.000	3.000	9.000
Log (NumTrade)	102,527	1.369	1.161	0.000	1.099	2.197
TradeAmt ($Thousand)	102,527	1,175.000	797.600	601.400	1,000.000	1,500.000
Log (TradeAmt)	102,527	6.847	0.692	6.399	6.908	7.313
LargeTradePortion (%)	102,527	45.587	38.259	0.000	41.667	83.333
MonthtoMature	102,527	59.100	18.070	46.630	60.900	74.070
Log (1+MonthtoMature)	102,527	4.038	0.366	3.864	4.126	4.318
TotalCLOHolding ($Million)	102,527	68.630	91.140	14.560	34.650	82.720
Log (TotalCLOHolding)	102,527	3.554	1.191	2.678	3.545	4.415
SecondLienDum	102,527	0.025	0.155	0.000	0.000	0.000
TermLoanDum	102,527	0.506	0.500	0.000	1.000	1.000
TermLoanBDum	102,527	0.444	0.497	0.000	0.000	1.000
TermLoanCDum	102,527	0.020	0.141	0.000	0.000	0.000
TermLoanDDum	102,527	0.004	0.065	0.000	0.000	0.000
VIX	102,527	15.930	5.014	12.550	14.340	18.060
TEDSpread (%)	102,527	0.323	0.115	0.226	0.294	0.398
LoanIndexReturn (%)	102,527	0.396	0.960	-0.057	0.338	0.721
PublicDum	102,527	0.317	0.465	0.000	0.000	1.000
RatingSTD	102,527	0.315	0.357	0.000	0.288	0.516
DiffRate	102,527	0.536	0.499	0.000	1.000	1.000
RelationDum (Decimal)	77,431	0.800	0.400	1.000	1.000	1.000
RelationNum (Decimal)	77,431	0.641	0.388	0.333	0.750	1.000
RelationAmt (Decimal)	77,431	0.672	0.393	0.395	0.868	1.000
TrusteeRel (Decimal)	102,527	0.696	0.191	0.556	0.667	0.833
ArrangerRel (Decimal)	102,527	0.421	0.134	0.333	0.400	0.500
FailFundRatio (Decimal)	102,527	0.548	0.301	0.289	0.500	0.833
CovTestDist (Decimal)	102,527	0.195	0.187	0.046	0.142	0.264
TotalAsset ($Million)	31,466	8,569.000	12,022.000	1,651.000	3,895.000	9,189.000
Log (TotalAsset)	31,466	8.302	1.245	7.409	8.268	9.126
Leverage	30,215	0.629	0.366	0.406	0.563	0.752
TobinQ	24,643	1.891	1.208	1.192	1.561	2.154
EPSSTD	16,269	0.262	0.554	0.039	0.099	0.250
NumAnalyst	20,257	6.280	5.993	2.000	4.000	9.000
Log (NumAnalyst)	20,257	1.403	0.962	0.693	1.386	2.197

Table 2. CLO Disagreement and Loan Illiquidity

This table shows the OLS regression results of the impact of CLO disagreement on loan illiquidity. The dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. The dependent variable is measured in month t. Time-varying independent variables are calculated in month $t-1$. Term loan D in loan types is the base group and is omitted in the regressions. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CLODIS	0.251***	0.263***	0.258***	0.384***	0.257***	0.215***	0.258***
	(8.273)	(8.852)	(8.629)	(9.886)	(8.418)	(6.011)	(8.584)
Log (1+MonthtoMature)		0.190***	0.160***	-0.024	0.159***	1.486***	0.160***
		(5.770)	(4.996)	(-0.710)	(4.907)	(6.884)	(4.970)
Log (TotalCLOHolding)		-0.218***	-0.178***	-0.272***	-0.182***	-0.074***	-0.179***
		(-13.819)	(-13.146)	(-14.944)	(-13.082)	(-4.486)	(-13.178)
SecondLienDum			0.772***	0.416***	0.760***		0.772***
			(5.354)	(3.136)	(5.251)		(5.351)
TermLoanDum			-0.117	-0.080	-0.122		-0.116
			(-0.884)	(-0.803)	(-0.920)		(-0.875)
TermLoanBDum			-0.127	-0.131	-0.130		-0.125
			(-0.971)	(-1.356)	(-0.995)		(-0.961)
TermLoanCDum			0.831***	0.777***	0.826***		0.831***
			(5.351)	(4.808)	(5.326)		(5.350)
VIX				0.018***			0.018***
				(3.331)			(2.834)
TEDSpread				0.331			0.246
				(1.459)			(1.046)
LoanIndexReturn				0.012			0.012
				(0.558)			(0.517)
Constant	6.110***	5.501***	5.715***	4.512***	5.737***	-1.200	4.927***
	(30.596)	(27.171)	(22.168)	(11.328)	(21.628)	(-0.929)	(15.808)
Observations	102,527	102,527	102,527	101,438	102,527	102,527	102,527
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	No	No	Yes
Industry FE	No	No	No	Yes	No	No	No
Loan FE	No	No	No	No	No	Yes	No
Year-Month FE	No	No	No	No	Yes	Yes	No
Adjusted R-Squared	0.289	0.292	0.295	0.154	0.296	0.373	0.295

Table 3. Opacity, Agreement to Disagree, or Diverse Private Information

This table shows the OLS regression results about the factors that affect CLO disagreement. The dependent variable is *CLODIS*, the standard deviation of CLO investors' valuations on a loan and multiplied by 100. The dependent variables are measured in month t. Time-varying independent variables are calculated in month $t-1$ or from the latest annual reports for public firms. *PublicDum* is a dummy variable that equals one if the issuer can be matched with Compustat and zero otherwise. *Log (NumAnalyst)* is the natural logarithm value of the number of analysts covering a firm's stock. *Log (TotalAsset)* is the natural logarithm value of the total assets. Term loan D in loan types is the base group and is omitted in the regressions. The number of observations varies because of missing values. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	CLODIS		
	(1)	(2)	(3)
PublicDum	0.035***		
	(3.599)		
Log (NumAnalyst)		0.005	
		(0.601)	
Log (TotalAssets)			0.030
			(1.013)
Log (1+MonthtoMature)	-0.487***	-0.354***	-0.559***
	(-8.002)	(-5.517)	(-7.193)
Log (TotalCLOHolding)	0.069***	0.044***	0.055***
	(7.375)	(3.154)	(4.340)
SecondLienDum	0.488***	-0.229	-0.024
	(4.120)	(-1.567)	(-0.222)
TermLoanDum	0.053	0.155*	0.234***
	(0.619)	(1.766)	(4.134)
TermLoanBDum	0.058	0.167*	0.251***
	(0.669)	(1.836)	(4.152)
TermLoanCDum	0.287***	0.054	0.264***
	(3.477)	(0.611)	(4.390)
VIX	-0.004	-0.003	-0.002
	(-0.626)	(-0.391)	(-0.187)
TEDSpread	-0.157	0.059	-0.199
	(-0.518)	(0.130)	(-0.480)
LoanIndexReturn	0.020	0.046**	0.034*
	(1.045)	(2.189)	(1.711)
Constant	10.861***	4.168***	10.881***
	(32.969)	(5.553)	(18.649)
Observations	91,119	18,306	28,211
Rating FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Adjusted R-Squared	0.229	0.400	0.405

Table 4. Alternative Definitions of CLO Disagreement and Loan Illiquidity

This table shows the OLS regression results of the impact of CLO disagreement on loan illiquidity using alternative measures. In Specifications (1) and (2), the dependent variable is the estimated and quoted bid-ask spread, respectively. I estimate bid-ask spread from daily high and low transaction prices following Corwin and Schultz (2012). Please see Appendix A for detailed definition of this variable. The quoted bid-ask spread comes from Thompson Reuters and the LSTA. In Specifications (3) and (4), the dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average price on day j, and Q_j is the trading amount in millions on day j. *PriceSTDMean* is the standard deviation divided by the mean of CLO investors' valuations on a loan and multiplied by 100. *PriceRange* is the difference between the highest and the lowest loan valuations. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. The dependent variables are measured in month t. Time-varying independent variables are calculated in month $t-1$. Term loan D in loan types is the base group and is omitted in the regressions. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	EstSpread	*QuoteSpread*	*LOANILLIQ*	
	(1)	(2)	(3)	(4)
CLODIS	0.020***	0.087***		
	(3.369)	(8.774)		
PriceSTDMean			0.269***	
			(9.443)	
PriceRange				0.090***
				(8.196)
Log (1+MonthtoMature)	-0.071***	-0.014	0.173***	0.148***
	(-4.963)	(-1.403)	(5.286)	(4.572)
Log (TotalCLOHolding)	-0.019***	-0.010***	-0.182***	-0.204***
	(-3.897)	(-4.856)	(-13.125)	(-13.870)
SecondLienDum	0.273***	0.357***	0.755***	0.785***
	(3.508)	(12.962)	(5.207)	(5.427)
TermLoanDum	0.361***	0.002	-0.122	-0.108
	(5.471)	(0.109)	(-0.926)	(-0.814)
TermLoanBDum	0.362***	0.005	-0.134	-0.116
	(5.443)	(0.280)	(-1.023)	(-0.886)
TermLoanCDum	0.233***	0.014	0.820***	0.833***
	(3.452)	(0.737)	(5.302)	(5.345)
VIX	0.001	0.004	0.017***	0.019***
	(0.318)	(1.342)	(2.816)	(2.942)
TEDSpread	0.214*	0.020	0.247	0.241
	(1.755)	(0.229)	(1.062)	(1.007)
LoanIndexReturn	0.013*	-0.027***	0.010	0.013
	(1.729)	(-2.764)	(0.443)	(0.561)
Constant	0.374**	2.497***	4.442***	5.259***
	(2.500)	(15.559)	(13.534)	(17.541)
Observations	30,698	60,911	102,527	102,527
Rating FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.073	0.614	0.298	0.295

Table 5. CLO Disagreement and Loan Illiquidity: Common and Private Information

This table shows the OLS regression results of how ex ante information asymmetry about the issuer of a loan affects the impact of CLO disagreement on loan illiquidity. The dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. Information asymmetry is represented by *PublicDum* and *Log (TotalAssets)* in Specifications (1) and (2), respectively. *PublicDum* is a dummy variable that equals one if the issuer can be matched with Compustat and zero otherwise. *Log (TotalAssets)* is the natural logarithm value of the total assets. *Controls* includes *Log (1+MonthtoMature)*, *Log (TotalCOLHolding)*, *SecondLienDum*, *TermLoanDum*, *TermLoanBDum*, *TermLoanCDum*, *VIX*, *TEDSpread*, *LoanIndexReturn*, and *Constant*. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ	
	(1)	(2)
CLODIS	0.330***	0.687***
	(8.996)	(4.996)
PublicDum	-0.040	
	(-0.716)	
*CLODIS*PublicDum*	-0.174***	
	(-5.334)	
Log (TotalAssets)		-0.014
		(-0.209)
*CLODIS*Log (TotalAssets)*		-0.057***
		(-3.648)
Controls	Yes	Yes
Observations	102,527	28,147
Rating FE	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Adjusted R-Squared	0.296	0.308

Table 6. CLO Disagreement and Loan Illiquidity: Informative Trading

This table shows the OLS regression results of how CLOs' potential trading affects the impact of CLO disagreement on loan illiquidity. The dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. I use *FailFundRatio* and *CovTestDist* to measure the likelihood of CLOs' informed trading. *FailFundRatio* is the number of CLOs that failed covenant tests divided by the number of CLOs in a loan. *CovTestDist* is the weighted average distance between the test result and the failure threshold. The weight is each CLO's holding amount divided by the total CLO holding amount in a loan. *Controls* includes *Log (1+MonthtoMature)*, *Log (TotalCOLHolding)*, *SecondLienDum*, *TermLoanDum*, *TermLoanBDum*, *TermLoanCDum*, *VIX*, *TEDSpread*, *LoanIndexReturn*, and *Constant*. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ	
	(1)	(2)
CLODIS	0.084*	0.392***
	(1.741)	(9.391)
FailFundRatio	-0.189**	
	(-2.240)	
*CLODIS*FailFundRatio*	0.253***	
	(3.092)	
CovTestDist		0.190
		(1.631)
*CLODIS*CovTestDist*		-0.496***
		(-5.579)
Controls	Yes	Yes
Observations	102,527	102,527
Rating FE	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Adjusted R-Squared	0.296	0.296

Table 7. CLO Disagreement and Strategic Trading

This table shows the OLS regression results of the impact of CLO disagreement on trading frequency and trading amount. The dependent variables are *ZeroTradeDayPortion*, *Log (NumTrade)*, and *Turnover*. *ZeroTradeDayPortion* is the number of zero trading days divided by 22. *Log (NumTrade)* is the natural logarithm value of the number of trades. *Log (TradeAmt)* is the natural logarithm value of the trading amount. *LargeTradePortion* is the number of trades greater or equal to $1 million divided by the total number of trades. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. The dependent variables are measured in month t. Time-varying independent variables are calculated in month $t-1$. Term loan D in loan types is the base group and is omitted in the regressions. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	ZeroTradeDayPortion	*Log (NumTrade)*	*Log (TradeAmt)*	*LargeTradePortion*
	(1)	(2)	(3)	(4)
CLODIS	-0.155***	0.013***	-0.017***	-0.802***
	(-4.922)	(3.776)	(-6.818)	(-6.925)
Log (1+MonthtoMature)	0.473**	-0.067***	-0.099***	-3.881***
	(2.446)	(-3.549)	(-9.128)	(-7.968)
Log (TotalCLOHoldings)	-1.703***	0.191***	0.026***	0.035
	(-20.378)	(26.939)	(8.824)	(0.214)
SecondLienDum	-4.197***	0.355***	-0.257***	-12.489***
	(-5.771)	(5.292)	(-5.970)	(-5.107)
TermLoanDum	-9.249***	0.762***	0.044	-3.903*
	(-13.870)	(13.733)	(1.185)	(-1.709)
TermLoanBDum	-8.758***	0.699***	0.056	-2.541
	(-12.923)	(12.612)	(1.510)	(-1.125)
TermLoanCDum	-4.105***	0.237***	-0.254***	-9.650***
	(-6.304)	(4.480)	(-5.577)	(-3.603)
VIX	-0.026	0.000	0.000	-0.103
	(-0.423)	(0.089)	(0.055)	(-0.936)
TEDSpread	-0.243	-0.062	0.011	8.342
	(-0.065)	(-0.182)	(0.099)	(1.415)
LoanIndexReturn	-0.116	0.008	0.001	-0.046
	(-0.919)	(0.798)	(0.241)	(-0.187)
Constant	103.712***	-0.107	7.270***	42.669***
	(28.916)	(-0.387)	(55.303)	(5.989)
Observations	102,527	102,527	102,527	102,527
Rating FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.378	0.282	0.178	0.132

Table 8. The Persistence of the Impact of CLO Disagreement on Loan Illiquidity

This table shows the OLS regression results on the persistent impact of CLO disagreements on loan illiquidity. In Specifications (1), (2), (3), and (4) ((5), (6), (7), and (8)), the dependent variable is the mean value of *LOANILLIQ* from month t to month $t+2$, $t+5$, $t+8$, and $t+11$, respectively. *LOANILLIQ* equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. Time-varying independent variables are calculated in month $t-1$. *Controls* includes *Log (1+MonthtoMature)*, *Log (TotalCOLHolding)*, *SecondLienDum*, *TermLoanDum*, *TermLoanBDum*, *TermLoanCDum*, *VIX*, *TEDSpread*, *LoanIndexReturn*, and *Constant*. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ Mean			
	3 Month (1)	6 Month (2)	9 Month (3)	12 Month (4)
CLODIS	0.242***	0.220***	0.184***	0.160***
	(8.678)	(8.708)	(8.443)	(8.391)
Controls	Yes	Yes	Yes	Yes
Observations	102,527	102,527	102,527	102,527
Rating FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.330	0.384	0.437	0.488

Table 9. CLO Disagreement, Rating Discrepancy, and Stock Analyst Disagreement

This table shows the OLS regression results that compare the impact of CLO disagreement with that of rating discrepancy on loan illiquidity. The dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation divided by the mean of CLO investors' valuations on a loan and multiplied by 100. Rating discrepancy by rating agencies is measured by *RatingSTD*, which is defined as the standard deviation of the loan ratings in the CLO reports. *DiffRate* is a dummy variable that equals one if CLOs report different ratings to a loan and zero otherwise. *EPSSTD* is the standard deviation of stock analysts' forecasts on EPS. The dependent variables are measured in month t. Time-varying independent variables are calculated in month $t-1$. *Controls* includes *Log (1+MonthtoMature)*, *Log (TotalCOLHolding)*, *SecondLienDum*, *TermLoanDum*, *TermLoanBDum*, *TermLoanCDum*, *VIX*, *TEDSpread*, *LoanIndexReturn*, and *Constant*. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ					
	(1)	(2)	(3)	(4)	(5)	(6)
CLODIS	0.258***	0.303***	0.258***	0.299***	0.246***	0.171***
	(8.588)	(9.015)	(8.584)	(8.943)	(6.239)	(4.294)
RatingSTD	-0.036	0.080**				
	(-1.091)	(2.296)				
*CLODIS*RatingSTD*		-0.151***				
		(-4.537)				
DiffRate			0.024	0.087***		
			(1.010)	(3.455)		
*CLODIS*DiffRate*				-0.086***		
				(-3.205)		
EPSSTD					0.047	-0.125
					(0.611)	(-1.641)
*CLODIS*EPSSTD*						0.292***
						(4.618)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,527	102,527	102,527	102,527	14,677	14,677
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.295	0.296	0.295	0.295	0.315	0.321

Table 10. Information from CLOs' Counterparties

This table shows the OLS regression results on how primary market lender's private information affects the impact of CLO disagreement on loan illiquidity. The dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. *RelationDum* is a dummy variable that equals one if any of the primary market lenders have lent to the borrower in the past five years and zero otherwise. *RelationNum* (*RelationAmt*) is the number (amount) of loans from a lender divided by the total number (amount) of loans issued by the borrower in the past five years. The greatest value is chosen when there are multiple lenders in a loan syndicate. The dependent variables are measured in month t. Time-varying independent variables are calculated in month $t-1$. *Controls* includes *Log (1+MonthtoMature)*, *Log (TotalCOLHolding)*, *SecondLienDum*, *TermLoanDum*, *TermLoanBDum*, *TermLoanCDum*, *VIX*, *TEDSpread*, *LoanIndexReturn*, and *Constant*. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ		
	(1)	(2)	(3)
CLODIS	0.347***	0.345***	0.349***
	(7.628)	(8.187)	(7.987)
RelationDum	0.088*		
	(1.679)		
*CLODIS*RelationDum*	-0.082**		
	(-2.220)		
RelationNum		0.128***	
		(2.622)	
*CLODIS*RelationNum*		-0.106***	
		(-2.797)	
RelationAmt			0.095*
			(1.949)
*CLODIS*RelationAmt*			-0.107***
			(-2.896)
Controls	Yes	Yes	Yes
Observations	77,600	77,600	77,600
Rating FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Adjusted R-Squared	0.307	0.307	0.307

Table 11. Robustness Tests

This table shows the OLS regression results of the robustness checks. The dependent variable is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. *CLODIS* is the standard deviation of CLO investors' valuations on a loan and multiplied by 100. Specification (1) clusters standard errors by firm rather than report month. In Specification (2), I exclude the financial crisis period from July 2007 to April 2009. Specification (3) adds in lead arranger fixed effects. In Specification (4), the dependent variable is the return component in the *LOANILLIQ*. It is the monthly average of daily absolute returns. Specification (5) adds trades smaller than $100,000 to the sample. Specification (6) adds defaulted loans and loans rated at Caa and below to the sample. Specification (7) controls for firm-year quarter fixed effects. Firm fixed effects and year quarter fixed effects are all omitted. In Specification (8), I control for additional firm characteristics in the regression. *Log (TotalAsset)* is the natural logarithm value of the total assets. *Leverage* is the total debt divided by total assets. *TobinQ* is the market value of equity plus total assets minus book value of equity divided by total assets. *Controls* includes *Log (1+MonthtoMature)*, *Log (TotalCOLHolding)*, *SecondLienDum*, *TermLoanDum*, *TermLoanBDum*, *TermLoanCDum*, *VIX*, *TEDSpread*, *LoanIndexReturn*, and *Constant*. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	LOANILLIQ							
	Cluster Firm (1)	Exclude Crisis (2)	Lead Lender FE (3)	Return Component (4)	Include Samll Trade (5)	Include CCC&Default (6)	Firm-Year FE (7)	Additional Financials (8)
CLODIS	0.258***	0.264***	0.282***	0.305***	0.332***	0.172***	0.155***	0.219***
	(11.132)	(8.711)	(8.365)	(6.655)	(8.368)	(6.739)	(5.467)	(6.779)
Log (TotalAssets)								0.065
								(0.762)
Leverage								0.403***
								(3.134)
TobinQ								-0.117***
								(-2.657)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102,527	101,761	77,584	102,527	103,047	117,503	102,527	22,066
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Lead Arranger FE	No	No	Yes	No	No	No	No	No
Firm-Year FE	No	No	No	No	No	No	Yes	No
Adjusted R-Squared	0.295	0.278	0.310	0.105	0.233	0.345	0.434	0.331

Table 12. Endogeneity Issues and the IV Regressions

This table shows regression results that address endogeneity issues. The dependent variable in Specification (1) is *CLODIS*, the standard deviation of CLOs' valuations on a loan and multiplied by 100. The dependent variable in Specifications (2) to (4) is *LOANILLIQ*, which equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{|P_j - P_{j-1}|}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j. The instrumental variable is *TrusteeCLORel*, the average relationship between CLO managers and trustee banks in a loan. Relationship is the number of times that a CLO manager uses a trustee bank divided by the number of CLO offerings for the CLO manager before a CLO offering (excluded). *PredCLODIS* is the predicted CLO disagreement from the first stage regression. Term loan D in loan types is the base group and is omitted in the regressions. Please see Appendix A for variable definitions. Standard errors are clustered at report month level. T-statistics are reported in the parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	First Stage	Second Stage		
	CLODIS	*Amihud*		
			Low Trustee Concentration	High Trustee Concentration
		Full Sample		
	(1)	(2)	(3)	(4)
TrusteeCLORel	0.367***			
	(4.851)			
PredCLODIS		0.458*	0.806***	0.637
		(1.854)	(2.830)	(1.243)
Log (1+MonthtoMature)	-0.466***	0.252**	0.520***	0.400
	(-8.512)	(1.972)	(3.044)	(1.613)
Log (TotalCLOHoldings)	0.055***	-0.191***	-0.205***	-0.245***
	(5.652)	(-9.055)	(-6.304)	(-5.005)
SecondLienDum	0.328***	0.701***	0.947***	0.313
	(3.449)	(4.119)	(2.720)	(0.737)
TermLoanDum	0.017	-0.121	-0.006	-0.454*
	(0.260)	(-0.925)	(-0.023)	(-1.909)
TermLoanBDum	0.060	-0.137	-0.116	-0.491**
	(0.878)	(-1.056)	(-0.415)	(-2.019)
TermLoanCDum	0.137*	0.805***	0.939***	0.437
	(1.948)	(5.198)	(2.600)	(1.552)
VIX	0.007	0.016**	0.007	0.023***
	(0.938)	(2.555)	(0.722)	(2.874)
TEDSpread	-0.301	0.303	0.823*	0.342
	(-1.393)	(1.316)	(1.947)	(1.596)
LoanIndexReturn	0.039**	0.004	0.012	-0.038
	(2.231)	(0.157)	(0.385)	(-1.086)
Constant	6.207***	2.879*	0.976	15.298**
	(16.799)	(1.959)	(0.656)	(2.228)
Observations	102,527	102,527	37,725	33,963
Rating FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.384			
Underidentification Statistic	23.350			
Weak Instrument Statistic	165.100			

Appendix A. Variable Definitions

Variable	Definition
CLODIS	The standard deviation of the estimated prices given by the CLO investors in a loan.
PriceSTDMean	The standard deviation divided by the mean of the estimated prices given by the CLO investors in a loan and multiplied by 100.
PriceRange	The range of the estimated prices given by the CLO investors in a loan.
LOANILLIQ	An illiquidity measure that equals $\frac{1}{N_t} * \sum_{j=1}^{N_t} \frac{1}{Q_j} \frac{\lvert P_j - P_{j-1} \rvert}{P_{j-1}} * 100$ where N_t is the number of returns in month t, P_j is the average trading price on day j, and Q_j is the dollar trading amount in millions on day j.
EstSpread	Estimated bid and ask spread that equals $\frac{2(e^{\alpha}-1)}{1+e^{\alpha}}$ where $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$, $\beta = \sum_{j=0}^{1} \left[\ln\left(\frac{H_{t+j}^{O}}{L_{t+j}^{O}}\right)\right]^2$, and $\gamma = \left[\ln\left(\frac{H_{t,t+1}^{O}}{L_{t,t+1}^{O}}\right)\right]^2$. H_{t+j}^{O} (L_{t+j}^{O}) is the observed high (low) price on day $t+j$. $H_{t,t+1}^{O}$ ($L_{t,t+1}^{O}$) is the observed high (low) price over the two-day period.
QuoteSpread	Quoted bid and ask spread from Thompson Reuters and the LSTA.
ZeroTradeDayPort (%)	The number of zero trading days in a month divided by 22.
NumTrades	The monthly total number of trades.
TradeAmt ($Thousand)	Monthly total trading amount.
LargeTradePortion (%)	Number of trades greater or equal to $1 million divided by the total number of trades.
Turnover	The monthly trading volume divided by the monthly total CLO holdings.
MonthtoMature	The number of months from the CLO report month to the maturity month.
TotalCLOHoldings ($Million)	The monthly total CLO holdings.
SecondLienDum	A dummy variable indicating whether a loan is second lien or not.
TermLoanDum	A dummy variable indicating whether a loan is term loan or not.
TermLoanBDum	A dummy variable indicating whether a loan is term loan B or not.
TermLoanCDum	A dummy variable indicating whether a loan is term loan C or not.
TermLoanDDum	A dummy variable indicating whether a loan is term loan D or not.
TEDSpread (%)	The difference between the 3-month LIBOR and the 3-month treasury rate.
VIX	Equity volatility index from the Chicago Board Options Exchange.
LoanIndexReturn (%)	The monthly return of the S&P/LSTA U.S. Leveraged Loan 100 Index.
PublicDum	A dummy variable indicating whether a firm can be matched with Compustat.
RatingSTD	The standard deviation of the loan ratings in the CLO reports.
DiffRate	A dummy variable indicating whether CLOs report different ratings to a loan.
RelationDum	A dummy variable indicating whether the primary lenders have lent to the borrower in the past 5 years.
RelationNum/RelationAmt	The number/amount of loans from a lender divided by the total number/amount of loans issued by the borrower in the past 5 years.
TrusteeCLORel	The average relationship between CLO managers and trustee banks in a loan. Relationship is the number of times that a CLO manager uses a trustee bank divided by the number of CLO offerings for the CLO manager before a CLO offering (excluded).
FailFundRatio	The number of CLOs that failed covenant tests divided by the number of CLOs.
CovTestDist	The weighted average distance between the test result and the failure threshold.
Leverage	Book value of debt divided by the book value of total assets.
TobinQ	Market value of equity plus total assets minus book value of equity divided by the book value of total assets.
EPSSTD	Standard deviation of analysts' forecasts on earnings per share.
NumAnalyst	Number of analysts covering a firm's stock.