Lender Coordination and Loan Renegotiation*

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Abstract

This paper employs an unsupervised machine learning technique to develop a novel measure, "clique," representing groups with maximal interconnections among lenders in the syndicated loan market. Drawing upon network theory, the clique measure captures the informational role of networks that facilitate cooperation. We show that loan renegotiation increases in syndicates with a higher proportion of clique lenders, i.e., participant lenders from the same clique as the lead lender. Results remain robust when controlling for bilateral relationships between participant and lead lenders, lead-lender centrality, and borrower-year fixed effects, as well as through a reduced-form estimation involving a plausibly exogenous shock to the proportion of clique lenders. Loan performance improves with a higher proportion of clique lenders. However, the presence of clique lenders can be costly for borrowers with high proprietary costs. Overall, our study highlights the crucial role of lender clique in facilitating lender coordination by acting as an ex-ante mechanism.

Keywords: Syndicated loans; Renegotiation; Incomplete contracting; Network structure

JEL Classifications: G21; G30; M41

1 Introduction

Incomplete contract theory, pioneered by Grossman and Hart (1986) and subsequently extended to various corporate finance areas, underscores the critical role played by renegotiation.[1] The general idea is that loan contracts are inherently incomplete and renegotiation serves as a mechanism for reallocating control rights across different states (e.g., Garleanu and Zwiebel, 2009). Consistent with this argument, recent research shows renegotiation is prevalent in syndicated loan markets (e.g., Roberts, 2015; Nikolaev, 2018).[2] However, a typical syndicated loan involves multiple lenders, and loan provision amendments often require a majority consensus. This introduces coordination challenges, as reaching an agreement through renegotiation among a diverse group of lenders with different interests can be complex (e.g., Roberts and Sufi, 2009; Caskey, Huang and Saavedra, 2024).[3] This study focuses on an ex-ante mechanism that can reduce coordination costs, thereby facilitating renegotiation and potentially leading to Pareto-improving outcomes.

The ex-ante mechanism we focus on is a network structure known as a 'clique,' defined as a group of individuals interconnected by the maximum number of bilateral relationships possible within a social network ("maximal interconnections").[4] In other words, each member in this network structure has a direct relationship with *every other* member (see Figure 1(a)). Prior studies in social networks (e.g., Ali and Miller, 2013) highlight that social networks with unconnected bilateral partnerships (see Figure 1(b)). face challenges when enforcing cooperation. While players are informed about their own partnerships, they lack direct access to information regarding the interactions between their partners and others. This limitation

[1] Refer to Bolton and Scharfstein (1996) and Bolton and Freixas (2000; 2006) for financial contracts; Aghion and Bolton (1992) and Maskin and Tirole (1999) for capital structure; and Diamond and Rajan (2000; 2001; 2005) for banking.

[2] Roberts (2015) shows that each loan experiences an average of 3.5 renegotiations over its stated maturity at origination of 51 months. Nikolaev (2018) corroborates these findings with similar patterns observed in a more extensive sample of renegotiations.

[3] Roberts and Sufi (2009) show that the mean and median numbers of lenders are 8.6 and 6, respectively, for loans experiencing renegotiation.

[4] The term "maximal" indicates that no other members can be added to the clique without diminishing its interconnectedness.

makes it challenging for players to reward or penalize their partners based on their behaviors in other relationships. As a result, the unconnected bilateral partnerships can undermine the enforcement of cooperation among players. In contrast, in a clique network, every member is directly connected to each other, allowing them to know their partners' behaviors in other relationships and leverage these interconnections to influence and incentivize cooperative behavior (Karlan et al., 2009; Ali and Miller, 2013). Thus, by playing an informational role, clique structure improves coordination and decision-making within the group via rewards and punishments in other relationships. Note that clique structure contrasts with networks centered around one player, examined in prior studies (e.g., Ivashina, 2009). For example, in Figure 1(a), if Player A misbehaved in the interaction with Player B, Players C through G can be informed by direct connections with Player B, while in Figure 1(b), they might not be informed, as they are unconnected non-central players.

In the context of the syndicated loan market, lead lenders play a dominant role in monitoring borrowers (Ball, Bushman and Vasvari, 2008). Therefore, we argue that having more lenders from the same clique as the lead lender ("clique lenders") can mitigate lead lenders' incentives for shirking and improve the incentive of every clique member in the lending syndicate to cooperate. For example, in Figures 1(c) and 1(d), lead lender A and participant lenders B, C, and D jointly fund a syndicated loan. If all four lenders are members of the same clique (Figure 1(c)), lead lender A is more likely to monitor the loan diligently. This is because any shirking behavior by A can be disseminated throughout the entire clique, and lenders E, F, and G, who are also members of the clique, can punish A for her misbehavior. This potential punishment incentivizes A to fulfill her monitoring responsibilities. As a response, lenders B, C, and D maintain cooperative behavior. In contrast, if the four lenders belong to the non-clique structure (Figure 1(d)), lead lender A can reduce monitoring effort, because E, F, and G, being unconnected with B, C, or D, cannot impose penalties. Consequently, we expect a higher level of cooperation from participant lenders B, C, and D under the clique structure compared to the non-clique structure. Based

on the above argument, we predict that the likelihood and intensity of renegotiation increase with the percentage of clique lenders in a loan. Furthermore, if a higher percentage of clique lenders facilitates more Pareto-improving renegotiations and motivates lead lenders to diligently monitor borrowers, we expect the loan to perform better.

To identify clique lender structures, we follow prior studies (e.g., Blondel et al., 2008; Crane, Koch and Michenaud, 2019) and employ the Louvain algorithm, an unsupervised machine learning technique, to detect patterns in the relationships between lenders in DealScan. For each year, the algorithm identifies cliques wherein each lender pair is connected. We consider two lenders to be connected in a given year if they have shared at least one syndicated loan annually for the preceding three consecutive years. This empirical measure is motivated by network theory, which suggests that repeated social interactions provide a strategic foundation to form a clique (e.g., Raub and Weesie, 1990; Ali and Miller, 2013).

We investigate the likelihood and intensity of renegotiation, and ultimately the loan performance, to analyze how clique lenders reduce coordination costs in a syndicated loan. Following Nikolaev (2018), we collect the data on renegotiations from SEC filings, supplemented by facility amendments in DealScan. To measure the role of clique lenders in each syndicate, we calculate the percentage of participant lenders from the same clique as the lead lender at the loan initiation year, *Clique_Lender%* . Our final sample consists of 23,983 facilities, corresponding to 16,861 unique loan packages and 3,116 unique borrowers, from 1995 to 2017.[5] On average, we find that 38% of lenders in a given loan belong to the same clique as the lead lender. This percentage is significantly higher than 3% that would be expected if participant lenders were randomly selected from the credit market. The substantial difference suggests that the choice of clique lenders is likely driven by strategic considerations.

We begin our analysis by examining whether the likelihood and frequency of renegotiation increase with *Clique_Lender%* . Consistent with our hypothesis, we find a higher likelihood and frequency of renegotiations for syndicates with a higher *Clique_Lender%* . In

[5]The sample ends in 2017, which is determined by the availability of DealScan-Compustat Link provided by Chava and Roberts (2008).

economic terms, a one-standard-deviation increase in *Clique_Lender%* is associated with a higher likelihood of renegotiations, accounting for approximately 3.1% to 6.1% of the unconditional mean (i.e., 55 percentage points). To examine the incremental effect of clique lenders beyond simple bilateral ties, we follow Ivashina (2009) and create two controls based on the percentage of participant lenders having bilateral relationships with the lead arranger. We find that our results are robust after including both controls. Thus, the impact of clique lenders in a syndicate cannot be solely due to lenders' standalone bilateral relationships. Collectively, our findings are consistent with the notion that syndicating loans with clique members has lower coordination costs.

One potential endogeneity issue arises when unobservable lender characteristics, which influence the choice of members in a syndicate and thereby determine *Clique_Lender%* , covary with the likelihood and intensity of renegotiation. To alleviate this concern, we follow Irani et al. (2021) and use the U.S. implementation of Basel III in 2012 Q2 as a negative shock that unexpectedly raised the capital requirement for commercial banks.[6] Gopalan, Nanda and Yerramilli (2011) point out banks experiencing negative shocks tend to collaborate more with lenders they have previously worked with.[7] Based on their argument, we conjecture that the shock increases members' propensity for collaboration among cliques that have a higher percentage of commercial banks, as they are more likely to be directly affected by the shock. Consistent with this prediction, we find that after the shock, lead lenders from cliques with more commercial banks are significantly more likely to syndicate loans with their clique members. This empirically validates our maintained assumption that Basel III introduces an exogenous variation to *Clique_Lender%* .

Building on the above evidence, we employ a research design that resembles a difference-in-difference analysis. We find a higher positive association between the ratio of commercial

[6]Following Irani et al. (2021), we examine the Basel III proposal rather than its official 2014 implementation, as their study suggests that banks started adjusting their regulatory capital in anticipation of the regulation.

[7]The rationale is that previous lending relationships reduce information asymmetry between the lead and participant lenders and improve the lead lender's incentive to monitor borrowers, which in turn results in better loan performance and improves regulatory capital.

banks in a lead lender's clique and both the likelihood and frequency of renegotiations in the post-period, suggesting a plausibly exogenous increase in *Clique_Lender%* leads to more renegotiations. Note that our results are insensitive to the inclusion of lender fixed effects, which further alleviates the concern that unobservable time-varying lender characteristics drive our main results.

Next, we conduct three cross-sectional tests to further bolster our inferences. In the first two tests, we examine variations in borrower uncertainty and the experience of lead lenders, both of which amplify the importance of renegotiation due to contract incompleteness. First, building upon prior research (Grossman and Hart 1986; Roberts 2015), we expect our main results to be more pronounced for borrowers with higher uncertainty. Consistent with this prediction, we find that for borrowers with high uncertainty, i.e., when the volatility of the borrower's operating cash flows increases by 1%, *Clique_Lender%* increases the renegotiation likelihood by an additional 13%, accounting for 23.6% of the unconditional mean (i.e., 55 percentage points).

Second, we investigate how lead-lender experience affects our main results. Inexperienced lead lenders are more likely to draft initial contracts that may not comprehensively capture the borrower's credit risk, making renegotiation a crucial tool for addressing such initial inadequacies. As such, we expect our main results to be stronger for loans led by inexperienced lead lenders. Indeed, we find that *Clique_Lender%* increases the renegotiation likelihood by an additional 12% when lead lenders are less experienced, accounting for 21.8% of the unconditional mean (i.e., 55 percentage points).

Third, as prior studies suggest coordination costs increase with the number of lenders (e.g., Bergman and Callen, 1991; Brunner and Krahnen, 2008), we examine whether the results are stronger when a lending syndicate involves a larger number of lenders. We find that *Clique_Lender%* increases renegotiation likelihood by an additional 5% for syndicates with a larger group of lenders, accounting for 9.1% of the unconditional mean (i.e., 55 percentage points). The result is consistent with the view that the clique lender structure yields greater

benefits when coordination costs would otherwise be high. Overall, our cross-sectional evidence reinforces that more clique lenders in a lending syndicate facilitate coordination and are pivotal for the occurrence of renegotiation to achieve Pareto-improving outcomes.

The next question we address is whether the presence of clique lenders ultimately enhances loan performance. Loans with a higher proportion of clique lenders tend to perform better for two reasons. First, a greater percentage of clique lenders reduces coordination costs and boosts the likelihood of renegotiation, which often leads to Pareto-efficient outcomes. Second, having more clique lenders in a syndicated loan reduces the likelihood of the lead lender shirking, thereby improving overall loan performance. By measuring loan performance based on changes in borrowers' credit ratings before loan maturity, we find that a one-standard-deviation increase in *Clique_Lender%* reduces the probability of loan default by 13.3% of the unconditional mean (i.e., 7 percentage points), and lowers the probability of falling below investment grade by 6.7% of the unconditional mean (i.e., 15 percentage points). These findings suggest that the clique network structure plays an important role in reducing coordination costs and enhancing loan outcomes.

While our evidence suggests that interconnections among lenders improve loan performance, potentially benefiting borrowers, a question remains: are there any associated costs? We seek to answer this question by exploring the potential costs from the borrowers' perspective. Prior studies suggest borrowers bear proprietary costs when lending institutions disseminate borrowers' private information (e.g., Carrizosa and Ryan, 2017; Griffin, Hong and Ryou, 2022). Since a larger clique size facilitates the wider dissemination of borrowers' private information, we expect that borrowers with high proprietary costs are less likely to borrow from lead lenders with a large clique size. Consistent with this prediction, we find that the size of the lead-lender clique decreases by approximately 12%, when the borrower has high proprietary costs. This finding thus highlights one downside of lending cliques — information exchange can facilitate the dissemination of borrowers' private information, increasing borrowers' proprietary costs.

Finally, we conduct five additional analyses to shed further light on the role of lending cliques in loan renegotiation and the robustness of our findings. First, we examine renegotiation timeliness by conducting the Cox hazard ratio analysis. We find that the first renegotiation occurs earlier when the loan has higher *Clique_Lender%* , suggesting that having a greater representation of lenders from the same clique improves coordination and thus facilitates quicker responsiveness to changing circumstances. Second, we attempt to rule out the possibility that our findings are due to our variable of interest, *Clique_Lender%* , capturing the centrality of lead lenders. Following Peña-Romera (2019), we construct three alternative measures for the centrality of a lead lender. We show that our main findings are robust to including any of these measures. Third, we replace our main independent variable *Clique_Lender%* with an alternative measure, *Clique_Lender_Share*, which takes into account each individual lender's credit contribution. It is defined as the percentage of the loan amount contributed by clique lenders, following Caskey, Huang and Saavedra (2024). Our main results are robust to this alternative measure. Fourth, the main results continue to hold when we include the interaction of borrower and facility-start year fixed effects, which eliminates the possibility that certain time-varying borrower characteristics can drive our main results. Fifth, we restrict the sample to the largest facility within a package, to address the concern that the serial correlation of multiple facilities within a loan package drives our findings. Our main results are robust to this subsample.

The primary contribution of this study is the development of a novel AI-based measure that captures the clique structure among lenders in syndicated loan markets. This measure is distinct from others, such as the measure of standalone bilateral relationships between one participant lender and one lead lender (Ivashina, 2009), or the centrality of a lead lender (e.g., Peña-Romera, 2019). All these measures are rooted in theory — suggesting that socially connected groups have social incentives and generate the greatest cooperation (Coleman, 1988; Glaeser, Laibson and Sacerdote, 2002). However, our measure is unique as it captures a network structure deemed superior for incentivizing cooperation, as suggested

by Ali and Miller (2013). We find empirical evidence that supports their theory: specifically, clique lenders contribute uniquely and incrementally to loan renegotiation and improve loan performance. Our findings align with previous economic and finance studies (e.g., Bagwell and Staiger, 1996; Maggi, 1999; Crane, Koch and Michenaud, 2019), demonstrating the superiority of cliques in enhancing coordination in various contexts. Although it is beyond the scope of this study, our measure opens avenues for further research to investigate the importance of lender coordination in debt contract design, and the formation and evolution of clique structures.

Incomplete contracting theory (Aghion and Bolton 1992; Hart and Moore 1994; 1998; and Bolton and Scharfstein 1990; 1996) highlights the important role of renegotiation in improving contracting efficiency and extant empirical research shows that private debt renegotiation occurs frequently (Roberts and Sufi, 2009; Roberts, 2015; Nikolaev, 2018). Given that renegotiation is costly and requires coordination among lenders, a growing body of research is exploring the mechanisms that facilitate effective renegotiation. Some potential mechanisms that have been studied include formal contractual clauses, such as participating lenders waiving the rights to borrowers' private information (Amiraslani et al., 2023) and the voting rules to amend loan contracts (Caskey, Huang and Saavedra, 2024), as well as informal social networks with central lenders (e.g., Peña-Romera, 2019). By contributing to this growing field, our research enhances the understanding of how renegotiation can be effectively facilitated.

2 Literature review and hypothesis development

Renegotiation is viewed as an action taken by parties involved in a contract when an ex-post surplus under the revised terms of the contract exists (Roberts and Sufi, 2009). Renegotiation would be unnecessary in a frictionless world, where the initial contract is complete. However, in the real world, it is almost impossible for borrowers and lenders to nail down any possibly onerous or restrictive terms in the initial contract. Frictions

arising from bounded rationality, transaction costs, and non-verifiability of information can result in incomplete contracts (Hart, 1995). Such contractual incompleteness gives rise to the opportunities of Pareto-improving renegotiation, when new information arrives and/or outside options change (e.g., Bolton, 1990; Roberts, 2015). Therefore, renegotiation is an important mechanism for dynamically completing contracts and resolving inefficient ex-post outcomes.

However, renegotiations for syndicated loans can be costly due to the involvement of multiple lenders. After a loan origination, each lender retains the authority to vote on any changes to the governing agreement during the life of the loan. As Taylor and Sansone (2006) explain, the basic rule of voting in a credit agreement is that the "majority" or "required" lenders must approve any modification, waiver, or supplement to any provision of the credit agreement. "Majority" or "required" typically means lenders together holding more than 50 percent of the aggregate credit exposure. Changes to crucial loan terms such as interest rate, amortization, and the amount of commitment commonly require unanimous consent of any affected syndicated members. Therefore, consensus is important or even necessary under certain circumstances in the renegotiation process. The presence of multiple lenders and their heterogeneous incentives can make consensus costly and difficult to achieve. With an increase in the number of lenders in a syndicate, decision-making takes a longer time, which increases opportunity costs (e.g., options foregone) and reduces the probability of workout success (Brunner and Krahnen, 2008).

Network theory suggests that the clique structure enjoys a unique advantage over other community structures in enforcing cooperation (e.g., Karlan et al., 2009; Ali and Miller, 2013). A clique is a network structure where all members are connected, leading to maximal interconnections. To illustrate its advantage, we use the example in Ali and Miller (2013). Consider the incentives when Player A cooperates with Player B in a specific network where A also interacts with Players C, D, E, F, and G. The question Player A faces is whether she can exploit her partners before they punish her for shirking. Player A's strategic decision

to cooperate or shirk depends on how efficiently the network's layout enables information about her behavior to reach her other partners. The clique structure, characterized by maximal interconnections, can propagate A's shirking information to all clique members faster than any other network structure, thereby allowing for more effective deterrence of A's non-cooperative behaviors. In contrast, in traditional network structures with one central player, as illustrated with Player A in Figure 1(b), each player directly connected to Player A (Players B, C, D, E, F, and G) only knows what happens within their own relationship with A. They can hardly know how A behaves with the other players in the network. Consequently, if A shirks with B, Players C, D, E, F, and G lack direct access to this information, making it difficult for them to reward or punish A for her actions, potentially tempting A to exploit B.

Building upon the theoretical insights on the informational advantages of the clique structure in enforcing cooperation, we hypothesize that cliques, informally formed by maximal interconnections among lenders, can reduce coordination costs, thereby improving contract efficiency and leading to better loan outcomes. In the context of syndicated loans, lead lenders play a pivotal role in monitoring the borrower throughout the life of the loan. The presence of more participant lenders from the same clique as the lead lender (clique lenders) is expected to heighten the lead lender's monitoring incentives, given that any information on their shirking behaviors can be transmitted and thus punished throughout the entire clique. Turning to participant lenders from the same clique, the clique structure can incentivize them to maintain collective action, reducing the likelihood of deviations. Therefore, we expect a reduction in coordination costs when more participant lenders are part of the same clique as the lead lender. The reduced coordination costs can be manifested in the renegotiation process, encouraging clique lenders to vote together with the lead arranger, and facilitating the achievement of consensus during loan renegotiations. Consequently, we predict an increase in the likelihood and intensity of renegotiation, when the percentage of clique lenders is higher. This leads to our first hypothesis:

H1: The proportion of clique lenders is positively associated with the likelihood and the frequency of renegotiations.

If the interconnections among clique members lead to more Pareto-improving renegotiation and encourage lead lenders to engage in effective monitoring, loans with a higher percentage of clique lenders are likely to perform better. This prediction leads to our second hypothesis:

H2: The percentage of clique lenders is positively associated with loan performance.

3 Clique construction

This section discusses how we empirically capture lending cliques. A clique is defined as a community of individuals, such as lending institutions, where every two entities are directly linked, forming a highly connected and decentralized system.

We take two steps to empirically identify cliques formed in the syndicated loan market in a given year t. First, we construct an adjacency matrix for lenders in year t based on our definition of pairwise connections. We define a pair of lenders as connected in year t if they co-fund at least one syndicated loan every year in the past three consecutive years, following (Ivashina, 2009). This empirical construction is motivated by prior studies that suggest repeated interactions play a crucial role in enforcing cooperative strategies within a network (e.g., Raub and Weesie, 1990; Ali and Miller, 2013). After defining the connection between each pair of lenders, we construct an $N_t \times N_t$ adjacency matrix of lender-to-lender relationships for all lenders in the market for each given year, where N_t represents the total number of lenders in year t. The off-diagonal elements of the matrix take a value of one if the corresponding pair of lenders is identified as connected and zero otherwise. The diagonal entries of the adjacency matrix are set to zero by default in network analysis. Note that the dimension N_t of the adjacency matrix corresponds to the total number of lenders in year t and thus could be ultra-high dimensional.

In the second step, we apply a community-detection algorithm to identify cliques in

year t, based on the adjacency matrix constructed in the first step. A variety of community-detection algorithms have been developed over the past decades, enabling us to approximately solve the clique-detection problem.[8] Our study adopts the widely used Louvain algorithm based on a well-established degree-corrected stochastic block model (e.g., Blondel et al., 2008; Karrer and Newman, 2011; Chen, Li and Xu, 2018; Crane, Koch and Michenaud, 2019). This is an unsupervised machine learning tool commonly utilized to extract meaningful patterns from big data (Segal et al., 2005; Abbe, 2017; Li et al., 2020). The Louvain algorithm assigns each lender to one specific clique in year t. The algorithm determines the clique assignments by maximizing the corresponding modularity, which is measured as the density of connections within the cliques relative to connections outside the cliques. Meanwhile, the degree-corrected stochastic block model ensures that individuals within the same clique exhibit similar connectivity patterns. This approach aims to achieve a decentralized structure within each clique.[9]

These two steps are repeated for each year in our sample. The number of cliques and the size of each clique are completely determined by the data. Figure 2 illustrates an example of the cliques constructed with our data in a randomly selected year. Notably, in a given year, a lender can only be a part of at most one clique. Additionally, it is possible for certain lenders not to belong to any clique at all.

4 Sample and data

4.1 Sample

We collect data on syndicated loans from DealScan, which provides extensive loan details such as start and end dates, loan amount, lender composition, and pricing and non-

[8] Perfect clique detection remains a significant challenge in network analysis due to the computational difficulty and would be infeasible given the size and complexity of the considered network of lenders' coordination. Therefore, empirical results obtained from all community-detection algorithms are approximations.

[9] A special case arises when a lender is connected to two cliques in an identical manner. For example, a lender may be fully connected to all lenders in both Clique A and Clique B. In this scenario, the algorithm assigns the lender to the clique whose members have similar relationships with the rest of the lenders in the market (i.e., those that are neither in Clique A nor Clique B) as the lender of interest.

pricing terms. We only include loans with at least one lead and one participant lender. We exclude sole-lender loans, as we are interested in investigating the coordination among lenders in a syndicated loan. To identify the lead lender, we follow Ivashina (2009) and classify a lender titled administrative agent as the lead lender. If the administrative agent is missing in a syndicate, we classify the agent, arranger, bookrunner, lead arranger, lead bank, or lead manager as the lead lender. To identify clique lender structures, we start with syndicated loans from 1992 onwards, as data before that is of low quality. Our final sample starts in 1995 because we require each lender's syndicate records from the previous three years to identify the clique membership of a lender in each syndicated loan. The sample ends in 2017 due to the availability of the DealScan-Compustat Link provided by Chava and Roberts (2008).

Next, we collect facility-level renegotiation data from two sources: (1) SEC EDGAR filings, following Nikolaev (2018), and (2) DealScan amendments. To identify when a facility experienced amendments, we first search for keywords related to amendments or renegotiations in forms 8-K, 10-K and 10-Q of a borrowing firm. Though our main analysis focuses on syndicates, we collect renegotiation data for both syndicated and sole-lender loans in DealScan to ensure data accuracy. This step allows us to compare our data with those in Nikolaev (2018), and we find that they are indeed comparable. Specifically, when combining the two types of loans, we find 57,532 renegotiations for 16,983 facilities between 1995 and 2017. On average, each facility experiences about three renegotiations, which aligns with the average number in Nikolaev (2018), where it is approximately 3.06 (=12,451/40,558). To ensure completeness, we further supplement the renegotiation data with facility amendments in DealScan. We find 15,216 more renegotiations for 7,401 facilities in addition to the ones identified in the SEC filings.

We note that we do not take a stance on whether borrowers or lenders initiate the renegotiation process. This neutrality recognizes that renegotiation can potentially lead to Pareto efficiency improvements for both parties involved. Although this argument implies

that renegotiations are beneficial for lenders, the presence of information asymmetry and varying preferences among lenders within a syndicate can still impede or delay the renegotiation process. These factors contribute to the prominence of clique lenders, which is the focus of our study.

Last, we merge in borrower characteristics for all syndicated loans in our sample, using the Compustat annual database via the DealScan-Compustat Link provided by Chava and Roberts (2008). This step reduces our sample size to 3,116 unique borrowing firms, 4,228 unique lenders, and 23,983 facilities from 1995 to 2017. We note that the sample sizes can vary across analyses due to data availability. For all continuous variables, we winsorize them at the 1st and 99th percentiles.

4.2 Descriptive statistics

Table 1 presents the summary statistics of the main variables used in our main analysis. The unit of observation is at the facility level. With the focus on syndicated loans, our sample consists of borrowing firms and loans that are relatively large. The average (median) firm in the sample owns \$8,396 (\$1,559) million in assets, has an average (median) asset growth of 22% (7%), and an average (median) leverage of 29% (26%). These firms are larger than the ones in Nikolaev (2018), which includes both sole lender and syndicated loans, with an average (median) firm size of \$2,560 (\$251) million. This difference possibly explains why our sample has a higher mean and median for both the likelihood and intensity of renegotiation than those in Nikolaev (2018). Specifically, around 55% of facilities experienced at least one renegotiation in our sample, with a median of four and a mean of nine renegotiations per facility.

Figure 3 presents the time-series characteristics of cliques. As discussed in Section 3, a lender can be a part of only one clique per year, or they may not belong to any clique at all. In Figure 3(a), the blue line represents the total number of lenders in the syndicated loan market for each year, while the red line shows the number of lenders belonging to

a clique. Four observations are worth noting. First, we find that the fraction of lenders in cliques has increased over time, suggesting greater collaboration in the form of cliques among lending institutions. Second, there is a rise in the total number of lenders in the earlier sample period, consistent with deregulations in the banking industry at that time, which allows both commercial and non-commercial banks easier access to the syndicated loan market (Jiang, Li and Shao, 2010). Moreover, we observe a significant decrease in the number of lenders starting in 2007, coinciding with the onset of the financial crisis. Finally, the sharp decline in the number of lenders in 2017 is due to data availability issues, as the DealScan and Compustat mapping does not provide complete coverage of loans originated in that year.

In Figure 3(b), the blue line depicts the number of syndicates originated each year throughout our entire sample period, while the red line represents the number of syndicates with at least one participant lender belonging to the same clique as the lead lender. We label this type of participant lenders as clique lenders. We find that the proportion of syndicates that have at least one clique lender has grown over time, suggesting an increasing tendency for lenders to form syndicates with lenders from the same clique. As with Figure 3(a), the sharp decline in 2017 is due to data availability issues. Taken together, Figure 3 suggests an increasing trend of lenders collaborating with each other, and forming syndicates with fellow clique members.

Figure 4 further explores the characteristics of clique membership within a syndicated loan. The x-axis shows the number of participant lenders in a syndicate. The left y-axis displays the number of clique lenders, with the red line representing their average count for a given number of participant lenders in a syndicate. The right y-axis indicates the frequency of syndicates with a given number of participant lenders, illustrated by the blue bars. We observe a decreasing frequency of syndicates as the number of participant lenders increases, consistent with previous studies suggesting that coordination costs rise with the total number of lenders in a syndicated loan (e.g., Bergman and Callen, 1991; Brunner

and Krahnen, 2008). More interestingly, we find that the number of clique lenders exhibits a linear relation with the total number of participant lenders in a syndicate, which may suggest the strategic selection of participant lenders.

To shed further light on the strategic formation of lending syndicates by including clique lenders, we create a placebo measure for our main independent variable of interest, *Clique_Lender%* , which measures the percentage of participant lenders that are from the same clique as the lead lender. The placebo measure is defined as the percentage of participant lenders that would be from the same clique as the lead lender if participants were randomly selected from the entire loan market. For each facility, we randomly select a set of participant lenders, matching the actual number of participants, and calculate the placebo *Clique_Lender%* measure. The placebo measure has a mean of 0.03 and a median of 0.03, both economically and statistically lower than the actual *Clique_Lender%* mean of 0.38 and median of 0.33. This evidence suggests that lending syndicates involving clique lenders are not formed randomly but rather reflect a strategic preference for clique lenders.

5 Empirical analysis

5.1 Clique lenders and renegotiation

We begin our analysis by examining how the likelihood and frequency of renegotiations are associated with the percentage of participant lenders in the same clique as the lead lender. We estimate the following regression model using our main sample:

$$\begin{aligned} Renegotiation_{i,j,t} = {} & b_1 * Clique_Lender\%_i + b_2 * One_to_One_{i,t-3\,to\,t-1} + \\ & b_3 * Rev_One_to_one_{i,t-3\,to\,t-1} + \boldsymbol{b'} * Borrower_Char_{j,t-1} + \\ & \boldsymbol{c'} * Facility_Char_{i,t} + Industry\,FE + Start\,Year\,FE, \end{aligned} \tag{1}$$

where i represents a facility originated in year t to the borrowing firm j. The dependent variable *Renegotiation* is measured in two ways: (1) *Reneg_Dummy*, an indicator variable

taking the value of one if facility i experiences at least one renegotiation, and zero otherwise; and (2) *Ln_Reneg_Count*, the natural logarithm of one plus the total number of renegotiations facility i experiences. The main independent variable of interest is *Clique_Lender%*$_i$, the percentage of participant lenders in facility i that are clique lenders. For example, if a syndicate has five participants and one of them is a clique lender, the value of *Clique_Lender%* is 0.2. Cliques are identified in year t-1, based on bilateral relationships observed from t-3 to t-1. For facilities with multiple lead lenders, we take an average across all lead lenders within a facility.

Turning to the control variables, we first include two proxies to capture the bilateral relationships between each pair of lead and participant lenders, following Ivashina (2009). The first proxy, *One_to_One*, is the percentage of participant lenders in facility i who also participated in other syndicated loans arranged by facility i's lead lender in the past three years. The second proxy, *Rev_One_to_One*, is the percentage of participant lenders that arranged syndicated loans in the past three years, in which the lead lender of facility i was a participant (i.e., lead and participant lenders switched roles). For facilities with multiple lead lenders, we average over all lead lenders within a facility. As shown in Figure 1(b), these one-to-one connections around a lead lender can form a core-periphery network structure, with the lead lender in a central position. Thus, higher values of *One_to_One* and *Rev_One_to_One* can also capture the percentage of participant lenders that are from a network where the lead lender holds a central position.

Furthermore, we control for facility characteristics and time-varying borrower characteristics. Control variables for facility characteristics include *Log(Amount)*, *Log(Maturity)*, *Revolver*, and *Inst_Tranche*. *Revolver* indicates whether a facility is a revolving loan, which poses higher risks for lenders compared to term loans, as revolving loan borrowers can continually borrow and repay funds (e.g., Asquith, Beatty and Weber, 2005; Berlin, Nini and Yu, 2020). *Inst_Tranche* indicates whether a facility belongs to Term B through Term K, representing institutional term loans participated by nonbanks. These facilities are intended for

re-sale to nonbank institutional investors. In such transactions, the lead lenders relinquish their control rights (e.g., Taylor and Sansone, 2006; Nini, 2008), which consequently weakens the incentives for renegotiation. For borrower characteristics, we include *Log(Total_Assets)*, *ROA*, *MTB*, *R&D_Dummy*, *Asset_Growth*, and *Asset_Intensity*, following Roberts and Sufi (2009) and Nikolaev (2018). All borrower characteristics are measured in the most recent fiscal year-end before the facility starts. Lastly, we include facility start-year fixed effects and industry fixed effects based on two-digit SIC codes. Standard errors are clustered at the package level. Detailed definitions of variables are in Appendix A.1.

Table 2 presents the results estimated from Equation (1). Column (1) presents the empirical results without any fixed effects, while column (2) includes the fixed effects specified above. In both specifications, the main independent variable, *Clique_Lender%*, has a positive and statistically significant coefficient. In economic terms, a one-standard-deviation increase of 0.35 in *Clique_Lender%* (see Table 1) is associated with a 1.22% to 2.38% higher likelihood of renegotiations, depending on model specifications. This accounts for approximately 3.1% to 6.1% of the unconditional mean (i.e., 55 percentage points). In columns (3) and (4), we replace the likelihood measure, *Reneg_Dummy*, with the frequency measure, *Ln_Reneg_Count*, and the results remain consistent. A one-standard-deviation increase of 0.35 in *Clique_Lender%* leads to an increase in *Ln_Reneg_Count* by 3.1% to 6.4%, depending on model specifications. This accounts for approximately 2.2% to 4.5% of the unconditional mean of 1.41.

Turning to the coefficients on control variables, we find that the two proxies for bilateral relationships between each pair of lead and participant lenders do not show positive associations with the occurrence of renegotiation. There are two potential explanations. First, the two proxies are highly correlated with each other (approximately 0.5). Second, for more than half of the facilities in our sample, all participant lenders have bilateral relationships with the lead lender (see Table 1). Therefore, there is limited variation in this variable. For facility characteristics, we find loan maturity to be positively associated with

the likelihood and intensity of renegotiations, consistent with the findings in Roberts and Sufi (2009). For borrower characteristics, we code *R&D_Dummy* following Nikolaev (2018) and find consistent results. That is, *R&D_Dummy* exhibits a statistically significant negative relation with the likelihood and intensity of renegotiation. This finding implies that borrowers with R&D investment opportunities are less likely to structure debt contracts in ways that trigger frequent renegotiations because of shareholder-creditor conflicts over investment decisions.

Collectively, our results support the argument that a higher proportion of clique lenders within a syndicate reduces coordination costs during loan renegotiations. Notably, the results remain robust when controlling for one-to-one connections between each pair of participant and lead lenders, indicating that the interconnections among lenders provide incremental explanatory power beyond the standalone bilateral relationships identified in prior studies.

5.2 Endogeneity concern

One potential endogeneity concern is that our main results may be driven by unobservable time-varying lender characteristics, as the lead lender can choose the syndicate structure. To mitigate this concern, we explore the Basel III regulation proposed in 2012. This regulation allows us to explore plausibly exogenous variations in same-clique lenders forming syndicates together, which is captured by our main independent variable in Equation (1), *Clique_Lender%*. On June 7, 2012, U.S. federal banking agencies announced the proposed adjustments to the types of capital counted in Tier 1 capital and risk-weights on numerous real estate exposures. These adjustments resulted in increased capital requirements for commercial banks in the U.S. (Berrospide and Edge, 2016).[10] Irani et al. (2021) investigate how banks react to the regulation proposal and find that commercial banks indeed increase their regulatory capital by a great amount in a short time period right after the proposed adjustments were announced. Their evidence suggests this proposed regulation

[10] www.federalreserve.gov/newsevents/pressreleases/bcreg20120607a.htm

change is a negative shock to commercial banks. Prior studies find that, when facing negative shocks, banks are more likely to syndicate loans with lenders with whom they have established previous relationships (Gopalan, Nanda and Yerramilli, 2011). The reasoning behind this is that repeated interactions increase the lead lender's incentive to monitor borrowers, which, in turn, improves loan performance. Building upon these findings, we conjecture that commercial banks (CBs) are more likely to form syndicates with clique members after the regulation change in an effort to enhance regulatory capital. Therefore, we expect that members in a clique with a higher percentage of CBs are more likely to collaborate with each other in the post-period. In other words, facilities set up by lead lenders in cliques with a higher percentage of CBs are more likely to include participant lenders from the same clique, i.e., higher *Clique_Lender%*. To test this prediction, we focus on a short window around the regulation change, specifically two years before and after 2012, as Irani et al. (2021) find that CBs react to the proposal shortly after its announcement. We then estimate the following regression model:

$$\begin{aligned} Clique_Lender\%_i = {} & b_1 * CB\%_i * Post2012_t + b_2 * CB\%_i + b_3 * Post2012_t \\ & + b_4 * One_to_One_{i,t-3\,to\,t-1} + b_5 * Rev_One_to_One_{i,t-3\,to\,t-1} \\ & + \boldsymbol{b'} * Borrower_Char_{j,t-1} + \boldsymbol{c'} * Facility_Char_{i,t} \\ & + Industry\,FE + Start\,Year\,FE. \end{aligned} \tag{2}$$

The unit of observation is at the facility level. For each facility i, *CB%* represents the percentage of commercial banks within the clique that the lead lender belongs to. Commercial banks are identified by the classification of financial institutions in DealScan following Jiang, Li and Shao (2010). *Post2012* is an indicator variable that takes the value of one for years after 2012, and zero otherwise. We exclude facilities initiated in 2012 for this analysis to eliminate any potential anticipation impacts right before the proposal announcement.

Column (1) of Table 3 presents the results estimated from Equation (2). We find

the interaction term, *CB% * Post2012*, loads with a positive coefficient that is statistically significant at the 10% level. This result is consistent with our prediction – lead lenders from cliques with a higher percentage of CBs are more likely to form syndicates with clique members in the post-period. More importantly, this evidence lends empirical support to our underlying assumption that the Basel III proposal can generate exogenous variation in *Clique_Lender%*, allowing us to re-examine the main hypothesis.

Relying on the results in column (1), we then conduct an analysis that resembles the differences-in-differences research design to exploit the plausibly exogenous variation in *Clique_Lender%* and test its impact on loan renegotiations. Specifically, we estimate the following regression model:

$$\begin{aligned} Regenegotiation_{i,j,t} = {} & b_1 * CB\%_i * Post2012_t + b_2 * CB\%_i + b_3 * Post2012_t \\ & + b_4 * One_to_One_{i,t-3tot-1} + b_5 * Rev_One_to_One_{i,t-3\,to\,t-1} \\ & + \boldsymbol{b'} * Borrower_Char_{j,t-1} + \boldsymbol{c'} * Facility_Char_{i,t} \\ & + Industry\,FE + Start\,Year\,FE. \end{aligned} \tag{3}$$

Columns (2) and (3) of Table 3 present the results estimated from Equation (3). In both columns, we find that the interaction term, *CB% * Post2012*, loads with positive coefficients that are statistically significant at the 5% level. The coefficient on *Post2012* is subsumed by year fixed effects. Furthermore, the variable *CB%* has an insignificant coefficient, alleviating the concern that our results are driven by any trend in the pre-period. In addition, in columns (4) to (6), we find that the results are robust to including lender fixed effects.

Collectively, these findings alleviate the concerns about our main results being driven by unobservable lender characteristics and provide further support for our main hypothesis. That is, the likelihood and frequency of renegotiations both increase when lead lenders form syndicates with a higher percentage of clique lenders, suggesting that the clique lender structure reduces coordination costs in syndicated loans.

5.3 Cross-sectional analyses

Next, we conduct cross-sectional analyses to investigate whether the heightened likelihood and frequency of renegotiations indeed reflect lower coordination costs due to a higher proportion of clique lenders in a syndicated loan. Specifically, we explore whether the main results vary across (1) the uncertainty of borrowers' future performance, (2) the experience of the lead lenders, and (3) the number of lenders in syndicated loans.

5.3.1 Uncertainty of a borrower's future performance

Prior research (Grossman and Hart, 1986; Roberts, 2015) suggests that uncertainty is the source of debt contract incompleteness, and renegotiation plays an important role in restoring equilibrium. Increased uncertainty in a borrower's future performance can complicate the prediction of their ability to fulfill loan payments, leading to a higher demand for ex-post renegotiation. Moreover, borrower uncertainty can exacerbate the information disadvantage faced by participant lenders, resulting in higher coordination costs (Sufi, 2007; Ivashina, 2009). Therefore, we expect the positive relationship between renegotiation and the percentage of clique lenders in a syndicated loan to be more pronounced when a borrower has greater uncertainty. To capture a borrower's uncertainty, we create the variable *CFO_Volatility*, defined as the volatility of a borrower's cash flow from operations, measured over a five-year window preceding the loan initiation, following Nikolaev (2018). To address potential outlier concerns, we convert this variable into a percentile rank. In the regression analysis, we interact *CFO_Volatility* with all our independent variables and fixed effects in Equation (1). The sample size for this analysis is smaller than that in Table 2 due to the availability of five-year operation cash flow data.

Columns (1) and (2) of Table 4 present the results for the likelihood and frequency of renegotiations, respectively. In both columns, the main interaction term of interest, *Clique_Lender%* * *CFO_Volatility*, has positive and statistically significant coefficients. In terms of the economic magnitude, when the volatility of the borrower's operating cash flows

increases by 1%, *Clique_Lender%* increases the likelihood of renegotiation by an additional 13%, which accounts for 23.6% of the unconditional mean (i.e., 55 percentage points). These results highlight that lender cliques play a crucial role in facilitating the renegotiation process, particularly in circumstances characterized by heightened borrower uncertainty, which can lead to greater debt efficiency.

5.3.2 Experiences of lead lenders

Our second cross-sectional analysis investigates how the benefits of having clique members form syndicates together vary with the experience of lead lenders in arranging syndicates. The track record of lead lenders can serve as an important signal of their quality. Therefore, the role of a clique in reducing information asymmetry is expected to be more valuable when the lead lender is less experienced. As such, we expect our results to be stronger for syndicated loans arranged by inexperienced lead lenders. To test our prediction, we first create a dummy variable *Inexp_Lead_Lender* that identifies lead lenders with three years or less of experience in acting as lead lenders in the syndicated loan market. We then interact *Inexp_Lead_Lender* with all independent variables and fixed effects in Equation (1), and estimate the model.

Columns (1) and (2) of Table 5 present the results for the likelihood and frequency of renegotiations, respectively. In both columns, the main interaction term of interest, *Clique_Lender%* * *Inexp_Lead_Lender*, loads with positive coefficients statistically significant at the 1% level. In economic terms, for less experienced lead lenders, *Clique_Lender%* increases the likelihood of renegotiation by an additional 12%, which accounts for 21.8% of the unconditional mean (i.e., 55 percentage points). Our findings of stronger results for syndicated loans arranged by inexperienced lead lenders support the notion that lender cliques can help less experienced lead lenders navigate the challenges in arranging syndicated loans by reducing coordination costs.

5.3.3 Number of lenders in syndicated loans

Both prior theoretical and empirical studies suggest a positive correlation between coordination costs and the number of lenders in a syndicate. This is because a larger number of lenders increases the heterogeneity of interests among them. This heterogeneity, in turn, lengthens the coordination time for decision-making and reduces the probability of workout success (e.g., Bergman and Callen, 1991; Brunner and Krahnen, 2008). Drawing from this literature, we conjecture that the benefits of having clique members in a syndicate are more pronounced when the syndicated loan involves a larger number of lenders. To test this prediction, we first create a dummy variable *Large_Group_Lenders*, which indicates whether the number of lenders in a given syndicate exceeds the sample median value of seven. We then interact *Large_Group_Lenders* with all independent variables and fixed effects in Equation (1).

Columns (1) and (2) of Table 6 present the results for the likelihood and frequency of renegotiations, respectively. We find that the main interaction term of interest, *Clique_Lender%* * *Large_Group_Lenders*, has a positive coefficient that is statistically significant at the 10% level. In economic terms, when the number of lenders is above the sample median, *Clique_Lender%* increases the likelihood of renegotiation by an additional 5%, which accounts for 9.1% of the unconditional mean (i.e., 55 percentage points). This finding supports our argument that having clique members is more beneficial when coordination costs are likely to be high, underscoring the value of interconnected relationships in the syndicated loan market. Overall, our cross-sectional evidence reinforces the main findings, confirming that more clique lenders in a lending syndicate facilitate coordination and are pivotal for the occurrence of renegotiation to achieve Pareto-improvement outcomes.

5.4 Clique lenders and loan performance

Our results so far have supported our first hypothesis that interconnected relationships within a lending syndicate can facilitate the renegotiation process. The next question is

whether enhanced coordination can further improve loan outcomes. As posited in our second hypothesis, we expect that the enhanced coordination can lead to renegotiations that benefit both the lenders and borrowers, manifested by improved loan outcomes. Furthermore, involving more clique members in syndicated loans would motivate lead lenders to exercising greater diligence in monitoring borrowers throughout the loan's duration, which can also contribute to improved loan outcomes. To empirically test the prediction, we create two dependent variables: (1) *DG_to_Default*, defined as a dummy variable indicating whether the borrowing firm has ever been downgraded to a default rating of "D" or "SD" during the duration of the facility, following Cornaggia, Krishnan and Wang (2017); and (2) *Below_Investment_Grade*, measured as an indicator variable that is equal to one if the borrower firm's credit rating falls below investment grade before loan maturity, and zero otherwise, following Caskey, Huang and Saavedra (2024). We obtain credit ratings from S&P and drop those observations with missing data. This step leads to a significant decrease in the sample size. We then replace the dependent variable in Equation (1) with our two loan performance measures and re-estimate the regression model.

Table 7 presents the results. In column (1), we find that loans with a higher proportion of clique lenders have a lower likelihood of default during the loan's lifespan. Economically, a one-standard-deviation increase in clique lender percentage reduces default probability by 0.93%, which accounts for 13.3% of the unconditional mean (i.e., 7 percentage points). In column (2), we investigate the likelihood of a borrower's credit rating falling below investment grade before loan maturity. A one-standard-deviation increase in *Clique_Lender%* reduces this likelihood by 1.0%, which accounts for 6.7% of the unconditional mean (i.e., 15 percentage points).

To ensure that our results are not driven by ex-ante operating performance of the borrowing firm, we control for ROA in the most recent fiscal period end immediately before the loan origination. We find ROA has a statistically significant negative relation with the likelihood of being downgraded to a default rating. This finding is consistent with the view

that firms with better operating performance have lower default risk. More importantly, our results on loan performance are not affected by controlling for the ex-ante borrower operating performance.

Taken together, our findings from testing the two hypotheses suggest that the clique lender structure plays a crucial role in lowering coordination costs, enabling renegotiation and consequently improving loan performance.

5.5 Additional analyses and robustness check

In this section, we conduct additional analyses to provide further support for our main findings. In Section 5.5.1, we examine how the time to first renegotiation is associated with the participation of clique members. In Section 5.5.2, we test to see if our main findings are robust while controlling for different measures of the centrality of a lead lender. In Section 5.5.3, we examine whether our main results are robust to different research designs, including (1) using an alternative of our main independent variable–the percentage of loan amounts contributed by clique lenders, (2) controlling for borrower-year fixed effects, and (3) restricting our sample to the largest facility in each package.

5.5.1 Time to the first renegotiation

To corroborate the results in Table 2, we investigate how the time to the first renegotiation is associated with the percentage of clique lenders in a facility. We anticipate that syndicated loans with a higher percentage of clique members will not only reduce coordination costs but also motivate the lead lender to put more effort into post-origination monitoring. Therefore, a facility with a higher percentage of clique lenders is likely to experience the first renegotiation sooner after its origination. To empirically test this prediction,

we follow Nikolaev (2018) to employ a proportional hazard duration model (Cox, 1972):

$$\begin{aligned} h(t) = h_0(t) \exp(&b_1 * Clique_Lender\%_{i,t-1} + b_2 * One_to_One_{i,t-3\,to\,t-1} \\ &+ b_3 * Rev_One_to_One_{i,t-3\,to\,t-1} + \boldsymbol{b'} * Borrower_Char_{j,t-1} \\ &+ \boldsymbol{c'} * Facility_Char_{i,t} + Industry\,FE + Start\,Year\,FE, \end{aligned} \tag{4}$$

where $h_0(t)$ is a non-parametric baseline hazard function and t is the time to the first renegotiation in months. We include the same set of control variables and fixed effects as those in Equation (1). A higher hazard rate implies a shorter time leading to the first renegotiation.

Table 8 presents the results. To facilitate interpretation, we present the marginal effects, which are inversely related to the duration of time leading up to the first renegotiation. The main independent variable of interest, *Clique_Lender%*, loads with a positive and statistically significant coefficient. This result indicates that the percentage of clique lenders exhibit a positive association with the renegotiation hazard rate, which translates into a shorter time to the first renegotiation. This evidence is in line with our main results, suggesting that coordination costs decrease with the presence of more clique lenders in a syndicate.

5.5.2 Does the percentage of clique lenders merely capture the centrality of a lead lender?

In this subsection, we perform additional analysis to examine whether clique membership differs from lead lender centrality, an aspect of network structure studied by Peña-Romera (2019). Conceptually, a network with a central player, known as a core-peripheral network, features a central player connected to non-central players who are not interconnected among themselves. This structure can impose challenges in aligning the interests of all members due to the lack of interconnections (e.g., Hojman and Szeidl, 2008). Although

a lead lender in a central position is likely to have an information advantage (Peña-Romera, 2019), the dissemination of information to all members is not guaranteed. For example, as in Figure 1(b), if Player A behaves poorly in the interaction with Player B, the information might not be shared with Players C through G. In contrast, the clique structure disciplines all players and promotes coordination by enabling information sharing among all members, so that any deviation from collective actions can result in losing future cooperation opportunities within the clique. Therefore, the centrality of a lead lender is not expected to impact coordination through the same mechanism as lender cliques. Empirically, we test whether our findings are robust to controlling for the centrality of the lead lender.

To empirically differentiate lender cliques from the centrality of a lead lender, we include two controls for the bilateral relationships, i.e., *One_to_One* and *Rev_One_to_One*, in all our main analyses. As discussed in Section 5.1, these two variables capture the percentage of participant lenders from the network in which the lead lender has a central role. Our main results show that the impact of lender cliques is not substituted by these two controls for one-to-one connections. In this subsection, we create three additional measures to capture the centrality of lead lenders, following Peña-Romera (2019). The first measure is *Degree*, which captures the number of connections each lender has. The second measure is *Betweenness*, which captures the number of times that the lender lies on the shortest path between two other lenders. The third measure is *Eigenvector*, which captures the influence of a lender in a network and is calculated based on the relative importance of other lenders that the focal lender is connected with.

We test to see if our results on renegotiation are robust to adding these three measures of centrality. Table 9 presents the results. To make sure the measures are comparable, we convert the three centrality measures and *Clique_Lender%* to percentile ranks. We consistently find a positive coefficient on *Clique_Lender%* that is significant at the 1% level, when each of the three measures for centrality is added to the regression analysis, respectively. Moreover, including the proxies for centrality does not reduce the magnitude of coefficients

on *Clique_Lender%*. These results, along with our main findings, indicate that the impact of lender cliques on reducing coordination costs cannot be absorbed by the centrality of lead lenders.

5.5.3 Additional robustness analyses

We conduct a series of additional robustness analyses to provide further support for our main results in Table 2. First, we create an alternative measure for our main independent variable. While our primary measure for *Clique_Lender%* is the number of same-clique participant lenders relative to the total number of participant lenders in a loan, in this analysis, we explore the percentage of loan amount contributed by lenders following Caskey, Huang and Saavedra (2024). Specifically, we replace *Clique_Lender%* in Equation (1) with *Clique_Lender_Shares*, measured as the percentage of loan amount contributed by clique lenders. Columns (1) and (2) of Table 10 present the results. We find that *Clique_Lender_Shares* has a statistically significant positive relation with both the likelihood and frequency of renegotiations. In addition, this analysis includes the control variable, *Threshold*, which is measured as the minimum percentage of loan amount required for loan amendment. *Threshold* has a statistically significant negative relation with the likelihood and frequency of renegotiations, consistent with the view that higher amendment thresholds lead to higher coordination costs in renegotiations. We note that the sample sizes for these two tests are much smaller than that of our main analysis due to data availability issues when we require a facility to have data on renegotiations, shares contributed by lenders, and the amendment threshold. Overall, the evidence suggests that our main findings are robust to the alternative measure for our main independent variable.

Second, to eliminate the possibility that certain time-varying borrower characteristics serve as correlated omitted variables that drive our main results, we include the interaction of borrower and facility start year fixed effects in Equation (1) and re-estimate the regression model. The sample for this analysis is smaller than that for our main analysis since we

drop singletons for all regression analyses. Borrower-year pairs with only one observation in the sample are eliminated. Columns (3) and (4) of Table 11 present the results. All control variables for borrower characteristics listed in Equation (1) are dropped, as they are subsumed by the borrower-year fixed effects. We find that the main independent variable of interest, *Clique_Lender%*, still has a statistically significant positive relation with the likelihood and number of renegotiations after adding borrower-year fixed effects. These findings suggest that our main results cannot be fully driven by any time-varying borrower characteristics.

Third, we only retain the facility with the largest loan amount within each package in our analysis and re-estimate Equation (1). Since our main sample is at the facility level, doing so helps us address the concern that loan deals with multiple facilities drive our findings. Columns (5) and (6) of Table 11 present the results. Our results on both the likelihood and frequency of renegotiations are robust when we only focus on the largest facility from each package.

In addition, we also extend our sample to year 2020 by assuming that the borrower id-gvkey pairs identified in the DealScan-Compustat link table provided by Chava and Roberts (2008) remain consistent post-2017. We note that borrowers who enter the private loan market after the year 2017 are not included in this analysis, as we are unable to link them to Compustat. In an untabulated analysis, we find that our main results on the likelihood and frequency of renegotiations continue to hold when the sample is extended to year 2020.

5.6 Cost of clique lender structures

So far, our empirical analysis shows that the presence of more clique lenders is associated with a higher likelihood and intensity of renegotiation, and better loan performance. Our findings have revealed the benefits of having clique lenders in a syndicate, and have demonstrated that the results are robust to different specifications. In this subsection, we explore the costs of having clique lenders. The improved information sharing among lenders

can raise concerns about the dissemination of borrower proprietary information. When selecting which group of lenders to borrow from, firms face a trade-off between securing better financing terms and protecting their proprietary information (e.g., Boone, Floros and Johnson, 2016; Griffin, Hong and Ryou, 2022). We hypothesize that borrowing from a lead lender belonging to a larger clique involves costs associated with a higher likelihood of disseminating proprietary information. Thus, we expect a negative relation between the size of the lead lender's clique and the proprietary cost of the borrower. To test this conjecture, we estimate the following regression model:

$$Log(Clique_Size + 1)_{i,j,t} = b_1 * Proprietary\ Cost_{i,t-1} + \boldsymbol{b'} * Borrower_Char_{j,t-1} + \boldsymbol{c'} * Facility_Char_{i,t} + Industry\,FE_j + Start\,Year\,FE_t. \quad (5)$$

To capture the borrower's proprietary costs, we use the following measures. *R&D_Cont* is the percentage of R&D expenditure relative to total assets (Boone, Floros and Johnson, 2016). *Redaction_dummy* is a dummy variable that indicates whether a firm has redacted material information from its financial statements (Chen, Tian and Yu, 2022). *Asset_Intensity*, calculated as the ratio of net property, plant, and equipment to total assets, is an inverse measure of proprietary information (Wyatt, 2005). We also create a comprehensive measure of proprietary information costs, *High_Proprietary*, a dummy variable indicating whether a firm has positive R&D expenditures, redacts information in its financial statements, and has asset intensity below the sample median.

Table 12 presents the results estimated from Equation (5). We find that the size of the clique to which the lead lender belongs is negatively correlated with *R&D_Cont* and *Redaction_Dummy*, and positively correlated with *Asset_Intensity*. In addition, it is negatively correlated with our comprehensive measure, *High_Proprietary*. The findings are statistically significant at conventional levels and are consistent with the view that borrowers take into account proprietary costs when seeking debt financing.

5.7 Clique formation

Our study takes clique formation as given and uses an unsupervised machine learning algorithm to identify cliques. We acknowledge that clique formation is unlikely to be random and can be influenced by underlying economic factors such as social ties among loan officers Bushman et al. (2021) and geographical proximity Dass and Massa (2011). However, since our investigation focuses specifically on the choice of clique lenders in a syndicate, we consider the topic of clique formation to be beyond the scope of our study. Note that we utilize an instrumental variable approach, in which we explicitly consider the choice of clique lenders as an endogenous variable. We show that our results are robust to this approach.

6 Conclusion

Building upon network theory, this study develops a novel AI-based measure to capture the maximal interconnections among lenders (cliques) in the syndicated loan market. We hypothesize that clique lending structures can facilitate information sharing, serving as a coordination mechanism for cooperation among clique members in a syndicate, and result in more frequent loan renegotiations and better loan outcomes.

Empirically, we employ the Louvain algorithm, an unsupervised machine learning technique, to identify cliques. We find that, in a syndicated loan, a higher percentage of clique lenders, i.e., participant lenders from the same clique as the lead lender, is positively associated with the likelihood and frequency of renegotiation and leads to more timely first-time renegotiation. The results are robust to controlling for the bilateral relationships between the lead and participant lenders, and the centrality of the lead arranger in the entire loan market. Furthermore, the results continue to hold when we exploit a plausible exogenous variation in the presence of clique lenders in a syndicate. Our findings are also robust when we include borrower-year fixed effects, and restrict our sample to the largest facility in each package.

In the cross-section, we find that the benefits of clique lender structures are amplified when the value of ex-post renegotiation is high or the coordination costs are heightened. Our results concentrate on syndicated loans with more lenders involved, borrowers with more uncertain future performance, and inexperienced lead arrangers. Lastly, we find that the presence of more clique lenders improves loan outcomes.

In addition to the benefits of clique lender structures, we also explore the associated costs. We demonstrate that borrowers with greater proprietary costs are less likely to engage with syndicates arranged by lead lenders from large cliques. The findings suggest that borrowers trade off the benefits of raising funds from clique members against the cost of the potential increase in proprietary costs due to information sharing within cliques.

Overall, our study helps to understand the seemingly puzzling phenomenon that syndicated loans, which typically involve multiple lenders with heterogeneous interests, are frequently renegotiated. Our findings highlight that clique lending structures, in which each lender is connected with all other lenders in a repeated relationship, can improve lender coordination and significantly reduce renegotiation costs in the syndicated loan market. As a result, contracting efficiency rises. Importantly, the value is incremental to the bilateral relationships studied in prior studies (e.g., Ivashina, 2009; Caskey, Huang and Saavedra, 2024).

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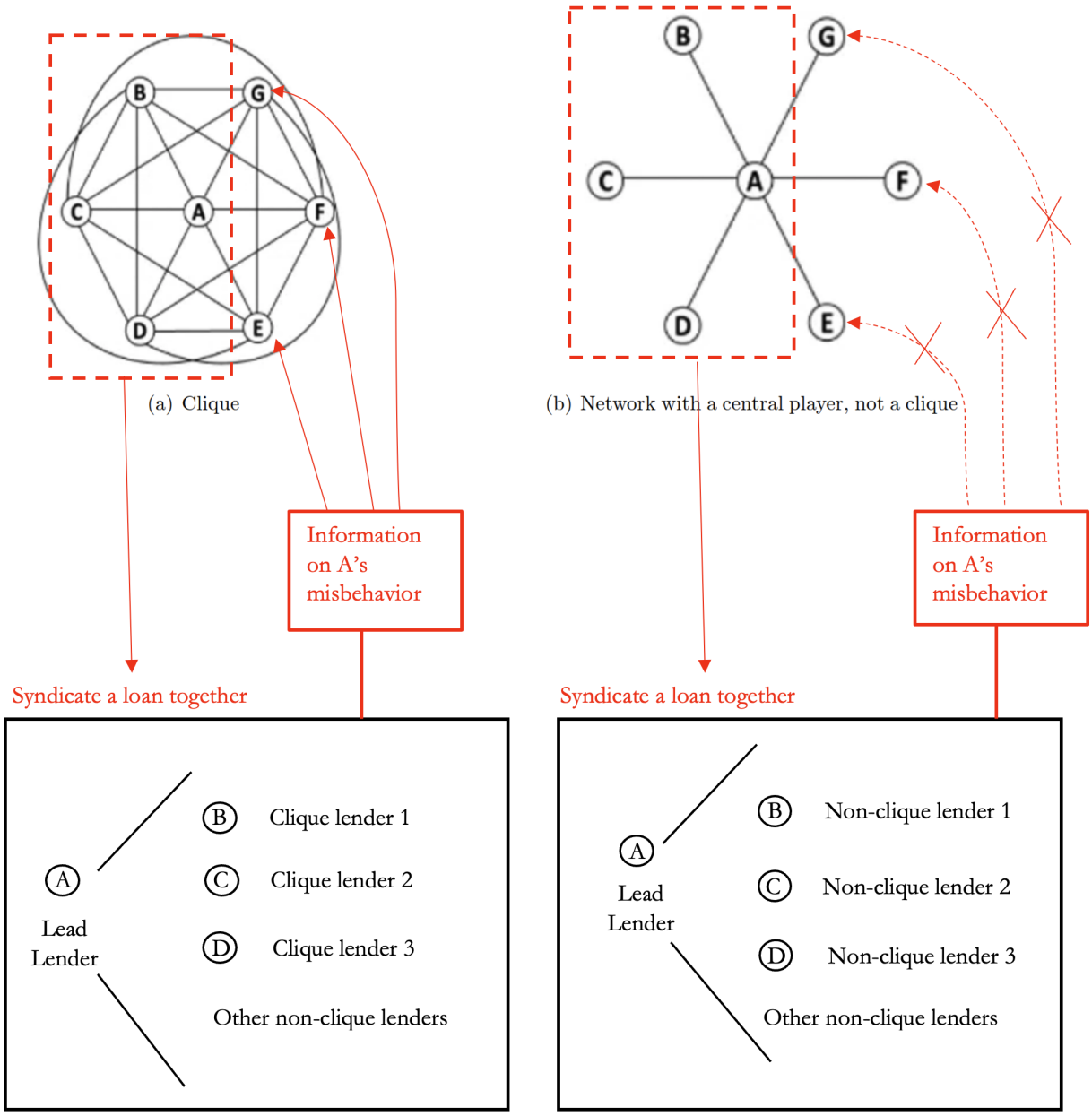
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Figure 1 Network Structure

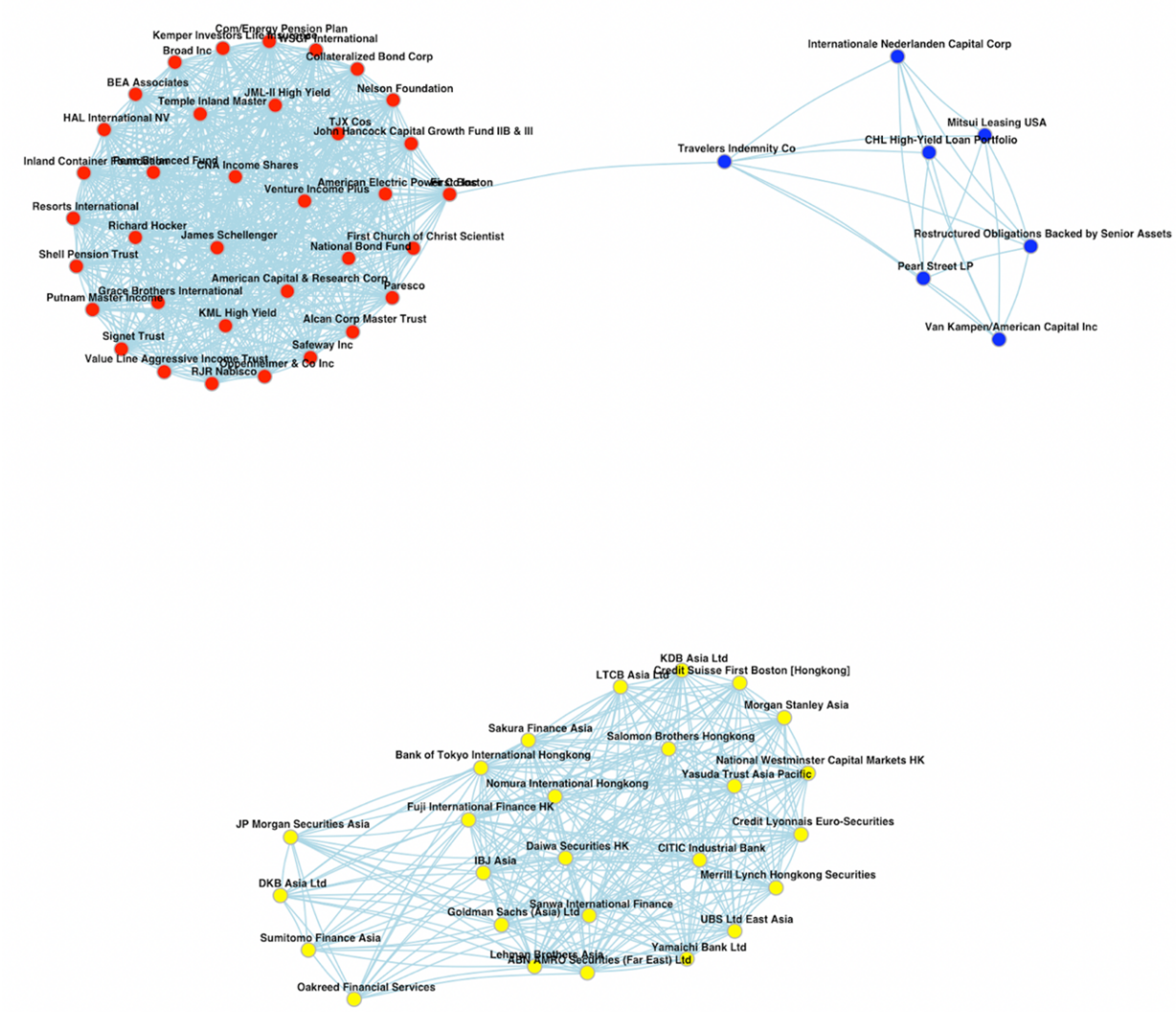


(c) A syndicated loan example involving clique lenders

(d) A syndicated loan example involving no clique lenders

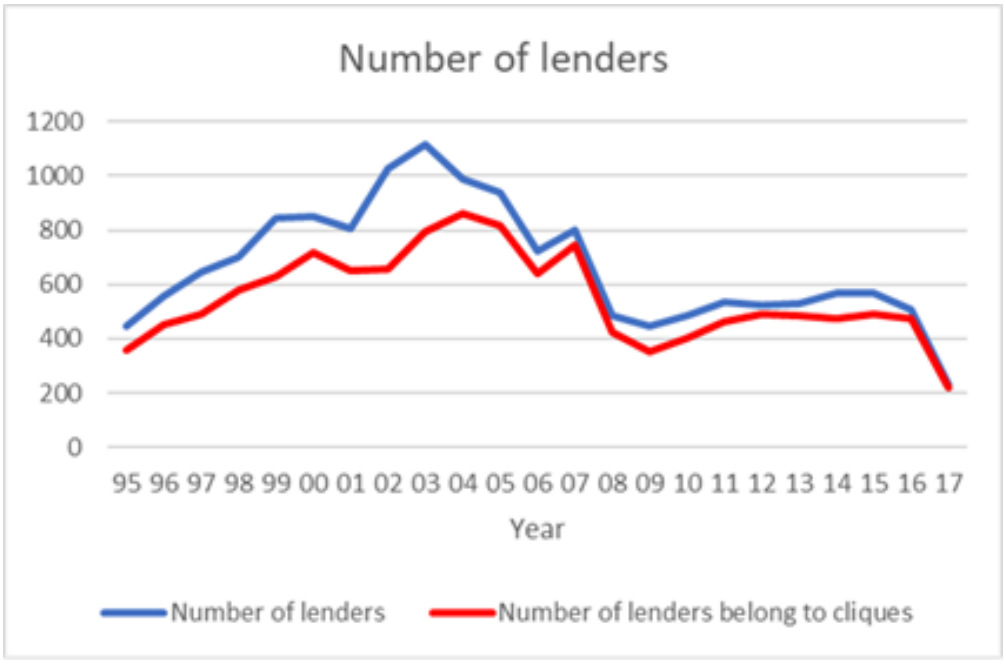
Notes. Figure 1(a) illustrates the structure of a clique, defined as a network wherein every pair of players, such as lending institutions, is interconnected. Figure 1(b) presents a non-clique network. Figure 1(c) presents a syndicated loan example involving clique lenders. Figure 1(d) shows an example of a syndicated loan with no clique lenders.

Figure 2 Examples of Lender Cliques

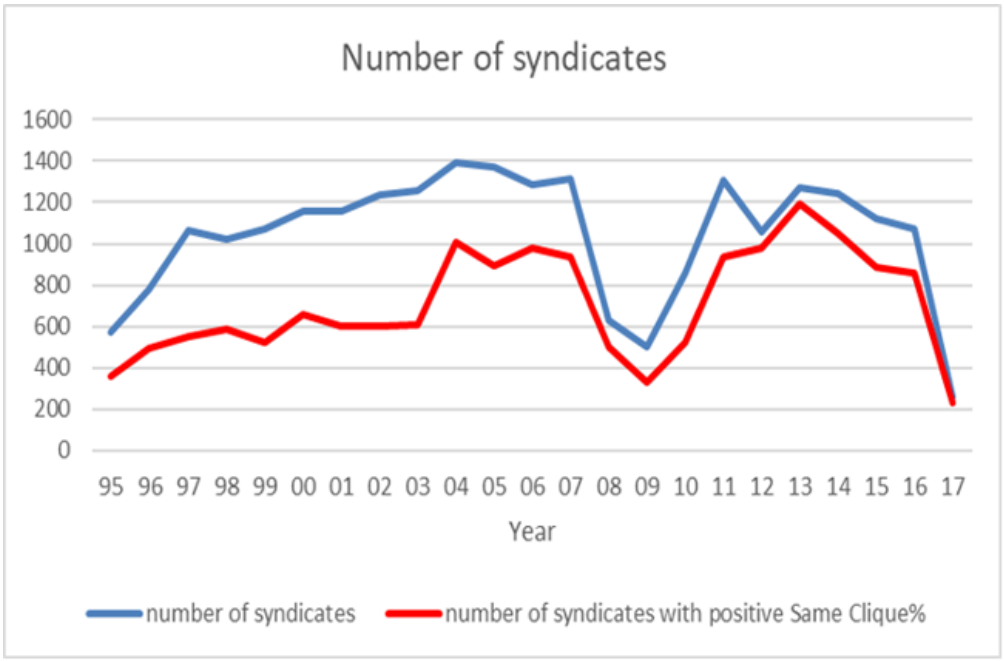


Notes. This figure presents three examples of lender cliques constructed using syndicated loan data.

Figure 3 Time-series Characteristics of Cliques



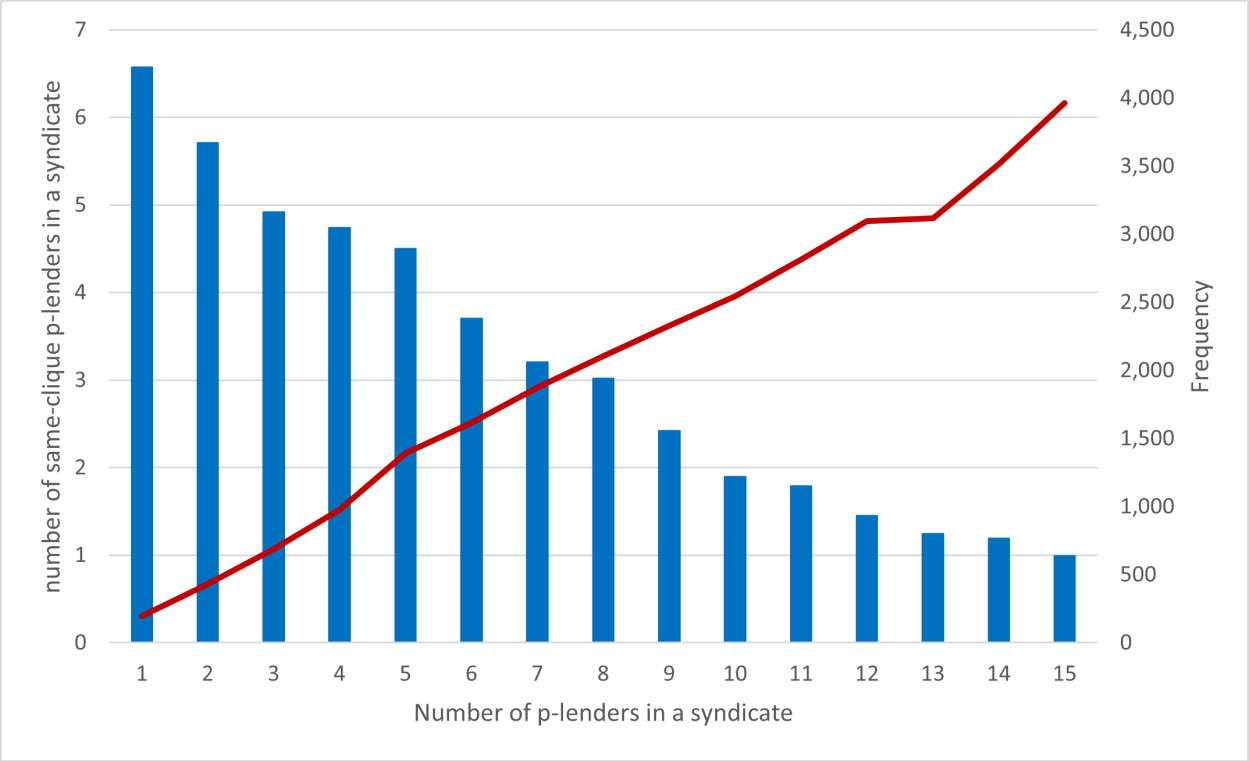
(a) Number of lenders belong to cliques in the syndicated market



(b) Number of syndicates with at least one clique lender

Notes. Figure 3(a) illustrates the annual trend in the number of lenders in the syndicate market. The blue line represents the total number of lenders. The red line focuses on the total number of lenders that belong to a clique. Figure 3(b) illustrates the annual trend in the number of syndicates initiated. The blue line represents the total number of syndicates initiated during the year. The red line focuses on the total number of syndicates with at least one participant lender that belongs to a clique.

Figure 4 Clique Membership within a Syndicated Loan



Notes. This figure presents the number of participant lenders from the same clique as the lead lender within a syndicate and the frequency for the syndicates with a specific number of lenders. The x-axis represents the number of participant lenders in a syndicate. The left y-axis shows the average number of clique lenders in a syndicate, indicated by the red line. The right y-axis depicts the frequency of syndicates with a particular number of participant lenders, represented by the blue bars.

Table 1 Summary Statistics

	N	Mean	SD	Q1	Median	Q3
Outcome variables:						
Reneg_Dummy	23,983	0.55	0.50	0	1	1
Reneg_Count	23,983	9.54	15.06	0	4	12
Ln_Reneg_Count	23,983	1.413	1.425	0.000	1.609	2.565
DG_to_Default	9,332	0.07	0.26	0.00	0.00	0.00
Below_Investment_Grade	9,332	0.15	0.36	0.00	0.00	0.00
Time_to_First_Reneg (in month)	23,983	30.47	25.61	9.87	18.63	59.83
Independent variables:						
Clique_Lender%	23,983	0.38	0.35	0	0.33	0.67
Total_Assets ($Million)	23,983	8,396	37,945	505	1,559	5,088
ROA	23,983	0.03	0.08	0.01	0.04	0.07
Leverage	23,983	0.29	0.21	0.13	0.26	0.41
MTB	23,983	1.33	0.90	0.78	1.09	1.61
R&D_Dummy	23,983	0.31	0.46	0	0	1
Asset_Growth	23,983	1.22	0.53	0.99	1.07	1.23
Asset_Intensity	23,983	0.31	0.25	0.10	0.24	0.49
Amount ($Million)	23,983	460	667	100	215	500
Maturity (in month)	23,983	49.54	22.67	36	60	60
Revolver	23,983	0.58	0.49	0	1	1
Inst_Tranche	23,983	0.10	0.31	0	0	0
One_to_One	23,983	0.84	0.27	0.80	1	1
Rev_One_to_One	23,983	0.64	0.31	0.48	0.70	0.92
CB%	4,598	0.76	0.21	0.67	0.80	0.89
Cross-sectional cuts:						
CFO_Volatility	17,549	0.505	0.289	0.250	0.500	0.750
Inexp_Lead_Lender	23,983	0.525	0.499	0.000	1.000	1.000
Large_Group_Lenders	23,979	0.546	0.498	0.000	1.000	1.000

Notes. This table reports the summary statistics of variables in our analyses. See the detailed definitions of all variables in Appendix A.1.

Table 2 Clique Lenders and Loan Renegotiation

	(1)	(2)	(3)	(4)
	DV=Reneg_Dummy		*DV=Ln_Reneg_Count*	
	(1)	(2)	(3)	(4)
Clique_Lender%	**0.0681*****	**0.0349****	**0.1817*****	**0.0874****
	(5.54)	(2.50)	(5.22)	(2.23)
Log(Total_Assets)	-0.0403***	-0.0479***	-0.1338***	-0.1431***
	(-10.51)	(-11.85)	(-12.73)	(-12.89)
ROA	-0.2361***	-0.2077***	-0.7500***	-0.7387***
	(-4.12)	(-3.55)	(-4.55)	(-4.44)
Leverage	-0.0571***	-0.0289	-0.1225*	-0.0361
	(-2.60)	(-1.26)	(-1.91)	(-0.54)
MTB	-0.0023	-0.0033	-0.0266*	-0.0194
	(-0.44)	(-0.63)	(-1.82)	(-1.31)
R&D_Dummy	-0.0286***	-0.0192	-0.0969***	-0.1119***
	(-3.03)	(-1.47)	(-3.65)	(-2.97)
Asset_Growth	0.0062	0.0187**	0.0671***	0.0793***
	(0.76)	(2.24)	(2.61)	(3.05)
Asset_Intensity	-0.0167	0.0318	0.0710	0.1618**
	(-0.99)	(1.25)	(1.46)	(2.12)
Log(Amount)	0.0257***	0.0272***	0.0819***	0.0850***
	(5.61)	(6.01)	(6.55)	(6.93)
Log(Maturity)	0.1043***	0.1140***	0.5704***	0.6070***
	(16.76)	(17.53)	(35.64)	(35.52)
Revolver	0.0508***	0.0435***	0.0890***	0.0755***
	(7.04)	(6.15)	(4.45)	(3.87)
Inst_Tranche	0.0398***	0.0230*	0.1754***	0.1352***
	(3.18)	(1.85)	(4.61)	(3.60)
One_to_One	-0.0113	-0.0199	-0.0666	-0.0741
	(-0.61)	(-1.08)	(-1.23)	(-1.38)
Rev_One_to_One	-0.0892***	-0.0722***	-0.2549***	-0.2138***
	(-5.49)	(-4.48)	(-5.51)	(-4.64)
Constant	Yes	No	Yes	No
Facility start year FE	No	Yes	No	Yes
Industry FE	No	Yes	No	Yes
R-squared	0.050	0.081	0.114	0.146
Observations	23,983	23,983	23,983	23,983

Notes. This table presents results on the association between renegotiation and percentage of clique lenders within a syndicate. Columns (1) and (2) present the results using an indicator of renegotiation as the dependent variable. Columns (3) and (4) present the results with the natural logarithm of one plus the number of renegotiations as the dependent variable. We control for the characteristics of borrowing firms and loans. For columns (2) and (4), we include facility start year and borrowing firm industry fixed effects. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 3 Addressing the Endogeneity Concern: Basel III, Clique Lenders, and Loan Renegotiation

	(1) *Clique_Lender%*	(2) *Reneg_Dummy*	(3) *Ln_Reneg_Count*	(4) *Clique_Lender%*	(5) *Reneg_Dummy*	(6) *Ln_Reneg_Count*
CB%	-0.110**	-0.0123	-0.0932	0.0331	-0.0323	-0.205
	(-2.434)	(-0.243)	(-0.641)	(0.747)	(-0.486)	(-1.067)
CB%*Post2012	**0.663*** **	**0.262** **	**0.810** **	**0.454*** **	**0.471** **	**1.349*** **
	(6.921)	(2.066)	(2.538)	(6.010)	(2.574)	(3.315)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,598	4,598	4,598	4,502	4,502	4,502
R-squared	0.305	0.078	0.128	0.475	0.120	0.168
Sample period	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014	2010-2014
Facility Start Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Lead-lender F.E.	No	No	No	Yes	Yes	Yes

Notes. This table presents results that use the Basel III proposal as a plausible exogenous shock to the percentage of clique lenders within a syndicated loan. Columns (1) through (3) include facility start year and firm industry fixed effects, while columns (4) through (6) incorporate an additional set of fixed effects: the lead-lender fixed effects. Columns (1) and (4) provide validation evidence that the Basel III proposal impacts *Clique_Lender%* . Columns (2) and (3), along with columns (5) and (6), present the impacts on renegotiation. The same set of controls as in Table 2 are included. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 4 Cross-sectional Analysis: Borrower Uncertainty

	(1) *DV=Reneg_Dummy*	(2) *DV=Ln_Reneg_Count*
Clique_Lender%	-0.0142	-0.0351
	(-0.390)	(-0.367)
Clique_Lender% *CFO_Volatility	**0.130****	**0.317***
	(2.093)	(1.919)
Controls*CFO_Volatility included	Yes	Yes
Controls included	Yes	Yes
Observations	17,549	17,549
R-squared	0.493	0.547
Facility start Year FE*CFO_Volatility	Yes	Yes
Industry FE*CFO Volatility	Yes	Yes

Notes. This table presents how borrower uncertainty affects the positive association between the percentage of clique lenders and renegotiations. The variable *CFO_Volatility* measures the volatility of a borrower's operating cash flows over the five years leading up to loan initiation. This variable is converted into percentile ranks to minimize the impact of outliers. We include the same set of controls as in Table 2. We interact *CFO_Volatility* with all control variables, facility start year, and industry fixed effects. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 5 Cross-sectional Analysis: Inexperienced Lead Lenders

	(1) *DV=Reneg_Dummy*	(2) *DV=Ln_Reneg_Count*
Clique_Lender%	0.00383	0.0312
	(0.222)	(0.640)
Clique_Lender% *Inexp_Lead_Lender	**0.121*** **	**0.244*** **
	(4.190)	(3.014)
Controls* Inexp_Lead_Lender	Yes	Yes
Controls included	Yes	Yes
Observations	23,983	23,983
R-squared	0.093	0.156
Facility Start Year F.E.* Inexp_Lead_Lender	Yes	Yes
Industry F.E.* Inexp_Lead_Lender	Yes	Yes

Notes. This table presents how the positive association between the percentage of clique lenders and renegotiation changes with lead-lender experience. The indicator variable *Inexp_Lead_Lender* takes the value of one for lead lenders with three years or less of experience in the role, and zero otherwise. For facilities with multiple lead lenders, the variable equals one if at least one lead lender is inexperienced. We include the same set of controls as in Table 2. We interact *Inexp_Lead_Lender* with all control variables, facility start year fixed effects, and industry fixed effects. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). *T*-statistics are presented beneath the coefficient estimates in parentheses.

Table 6 Cross-sectional Analysis: Number of Lenders in a Syndicated Loan

	(1) *DV=Reneg_Dummy*	(2) *DV=Ln_Reneg_Count*
Clique_Lender%	0.00433	0.0291
	(0.250)	(0.591)
Clique_Lender% *Large_Group_Lenders	**0.0494***	**0.0762**
	(1.758)	(0.970)
Controls* Large_Group_Lenders	Yes	Yes
Controls included	Yes	Yes
Observations	23,983	23,983
R-squared	0.104	0.167
Facility Start Year FE* Large_Group_Lenders	Yes	Yes
Industry F.E.* Large_Group_Lenders	Yes	Yes

Notes. This table presents how the positive association between the percentage of clique lenders and renegotiation changes with the number of lenders in a facility. The indicator variable *Large_Group_Lenders* is set to one for facilities when the number of lenders in the syndicate is above the sample median, and zero otherwise. We include the same set of controls as listed in Table 2. We interact *Large_Group_Lenders* with all control variables, facility start year fixed effects, and industry fixed effects. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 7 Clique Lenders and Loan Performance

	DV=DG_to_Default (1)	*DV=Below_Investment_Grade* (2)
	(1)	(2)
Clique_Lender%	**-0.0266****	**-0.0299***
	(-2.20)	**(-1.75)**
Log(Total_Assets)	-0.0012	-0.0195***
	(-0.42)	(-4.94)
ROA	-0.4475***	-0.8163***
	(-6.22)	(-9.03)
Leverage	0.1106***	0.0997***
	(4.54)	(3.35)
MTB	-0.0135***	-0.0348***
	(-2.72)	(-5.17)
R&D_Dummy	0.0079	-0.0099
	(0.66)	(-0.61)
Asset_Growth	0.0129*	0.0210**
	(1.76)	(2.25)
Asset_Intensity	0.0839***	0.1356***
	(3.49)	(4.18)
Log(Amount)	0.0048*	0.0011
	(1.67)	(0.27)
Log(Maturity)	0.0298***	0.0517***
	(4.75)	(6.49)
Revolver	-0.0046	-0.0158**
	(-0.76)	(-2.04)
Inst_Tranche	-0.0114	0.0103
	(-1.10)	(0.78)
One_to_One	-0.0487***	-0.0539**
	(-2.82)	(-2.34)
Rev_One_to_One	0.0051	0.0078
	(0.35)	(0.38)
Facility start year FE	Yes	Yes
Industry FE	Yes	Yes
R-squared	0.138	0.165
Observations	9,332	9,332

Notes. This table presents results on the association between loan performance and the percentage of clique lenders within a syndicate. In column (1), the outcome variable *DG_to_Default* is an indicator that equals one if the borrower's rating is downgraded to default before the facility matures, and zero otherwise. In column (2), the outcome variable *Below_Investment_Grade* is an indicator that equals one if the borrower's rating falls below the investment grade, and zero otherwise. We control for characteristics of borrowing firms and loans. Facility start year and firm industry fixed effects are included for all tests. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). *T*-statistics are presented beneath the coefficient estimates in parentheses.

Table 8 Additional Analysis: Time to the First Renegotiation

	Hazard ratio reported below *DV=Time_to_First_Reneg*
	(1)
Clique_Lender%	**1.1084*****
	(2.65)
Log(Total_Assets)	0.8671***
	(-12.55)
ROA	0.4659***
	(-4.64)
Leverage	0.9359
	(-1.04)
MTB	0.9971
	(-0.19)
R&D_Dummy	0.9111**
	(-2.55)
Asset_Growth	1.0836***
	(3.30)
Asset_Intensity	1.1152
	(1.51)
Log(Amount)	1.0729***
	(5.48)
Log(Maturity)	0.7908***
	(-10.38)
Revolver	1.1355***
	(6.17)
Inst_Tranche	1.1168***
	(3.11)
One_to_One	0.9232
	(-1.57)
Rev_One_to_One	0.8087***
	(-4.82)
Observations	23,983
Std Error Clustered	Package
Facility Start Year F.E.	Yes
Industry F.E.	Yes

Notes. This table presents results on the association between the timing of the first renegotiation and the percentage of clique lenders. The outcome variable, *Time_to_First_Reneg*, measures the number of months from loan initiation to the first renegotiation. The hazard rates from the Cox analysis are listed. We control for the characteristics of borrowing firms and loans. We include facility start year and firm industry fixed effects. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 9 Additional Analysis: Controlling for Lead-lender Centrality

	DV=Reneg_Dummy			*DV=Ln_Reneg_Count*		
	(1)	(2)	(3)	(4)	(5)	(6)
Clique_Lender%	**0.0540*** **	**0.0562*** **	**0.0531*** **	**0.143*** **	**0.149*** **	**0.139*** **
	(4.196)	(4.380)	(4.134)	(3.968)	(4.168)	(3.886)
Proxies for lead-lender centrality:						
Degree	0.0336**			0.128***		
	(2.092)			(2.828)		
Betweenness		0.0226			0.0954**	
		(1.413)			(2.120)	
Eigenvector			0.0395**			0.149***
			(2.512)			(3.354)
Controls included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,983	23,983	23,983	23,983	23,983	23,983
R-squared	0.082	0.082	0.082	0.147	0.147	0.147
Facility Start Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the results of the association between renegotiation and the percentage of clique lenders while controlling for lead-lender centrality. The same set of controls and fixed effects included in Table 2 are also used. We transform *Clique_Lender%* and the three proxies for lead-lender centrality into percentile ranks to facilitate coefficient comparisons. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). *T*-statistics are presented beneath the coefficient estimates in parentheses.

Table 10 Alternative Measure: Shares Contributed by Clique Lenders

	(1) *DV=Reneg_Dummy*	(2) *DV=Ln_Reneg_Count*
Clique_Lender_Shares	**0.0706****	**0.152***
	(2.187)	(1.708)
Threshold	-0.00159	-0.00442
	(-1.536)	(-1.540)
Log(Amount)	-0.00839	-0.0140
	(-0.967)	(-0.603)
Log(Maturity)	0.116***	0.716***
	(9.267)	(22.11)
Revolver	-0.000878	-0.0505
	(-0.0604)	(-1.263)
Inst_Tranche	-0.0162	0.107
	(-0.401)	(0.816)
Log(Total_Assets)	-0.0287***	-0.105***
	(-3.733)	(-5.076)
ROA	-0.329***	-1.193***
	(-3.142)	(-3.967)
Leverage	-0.0531	-0.0499
	(-1.225)	(-0.409)
MTB	0.00808	0.00254
	(0.886)	(0.102)
R&D_Dummy	-0.00671	-0.0949
	(-0.285)	(-1.420)
Asset_Growth	0.0113	0.0838**
	(0.764)	(1.978)
Asset_Intensity	-0.00221	0.0898
	(-0.0461)	(0.667)
One_to_One	-0.0532*	-0.135
	(-1.699)	(-1.489)
Rev_One_to_One	0.0401	0.117
	(1.359)	(1.374)
Constant	1.065***	1.642***
	(6.284)	(3.669)
Observations	6,105	6,105
R-squared	0.099	0.193
Facility Start Year F.E.	Yes	Yes
Industry F.E.	Yes	Yes

Notes. This table presents results re-estimated from our main model, replacing the main independent variable *Clique_Lender%* with *Clique_Lender_Share*, defined as the percentage of shares contributed by clique lenders. We include the same set of controls and fixed effects as in Table 2. In addition, we control the loan amendment threshold, following Caskey, Huang and Saavedra (2024). Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 11 Additional Robustness Analysis

	Whole sample; Including Borrower*Facility Start Year F.E.		Largest facility for each package	
	Reneg_Dummy	*Ln_Reneg_Dummy*	*Reneg_Dummy*	*Ln_Reneg_Dummy*
	(1)	(2)	(3)	(4)
Clique_Lender%	**0.0767****	**0.227*****	**0.0483*****	**0.119*****
	(2.401)	(2.670)	(3.753)	(3.470)
Log(Amount)	0.0169***	0.0455***	0.0490***	0.157***
	(4.388)	(4.484)	(9.513)	(11.43)
Log(Maturity)	0.0901***	0.529***	0.0916***	0.507***
	(10.19)	(22.50)	(13.39)	(29.61)
Revolver	0.0354***	0.109***	0.112***	0.246***
	(6.369)	(7.265)	(11.34)	(9.107)
Inst_Tranche	-0.00882	0.0521*	0.0584***	0.213***
	(-0.873)	(1.892)	(3.503)	(4.251)
One_to_One	0.0613	0.196*	-0.0418**	-0.138***
	(1.572)	(1.832)	(-2.426)	(-2.871)
Rev_One_to_One	-0.116***	-0.319***	-0.0761***	-0.187***
	(-3.613)	(-3.589)	(-4.996)	(-4.546)
Log(Total_Assets)			-0.0571***	-0.178***
			(-14.38)	(-16.73)
ROA			-0.271***	-0.892***
			(-5.067)	(-6.076)
Leverage			-0.0559***	-0.0804
			(-2.599)	(-1.336)
MTB			-0.000615	-0.0186
			(-0.126)	(-1.448)
R&D_Dummy			-0.0201*	-0.0918***
			(-1.656)	(-2.781)
Asset_Growth			0.0155**	0.0642***
			(2.050)	(2.873)
Asset_Intensity			0.0260	0.162**
			(1.103)	(2.469)
Constant	-0.120	-1.482***	0.439***	0.163
	(-1.490)	(-6.978)	(5.766)	(0.818)
Observations	15,429	15,429	16,734	16,734
R-squared	0.801	0.838	0.096	0.155
Borrower *Facility Start-year F.E.	Yes	Yes	No	No
Facility Start Year F.E.	No	No	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes

Notes. This table presents the results of two sets of robustness analyses. Columns (1) and (2) present the re-estimated results from the main regression model after including borrower-facility start year fixed effects. Thus, the borrower characteristics are subsumed. Columns (3) and (4) present the results re-estimated from the main regression model for the sample of the largest facilities in each package. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

Table 12 Downside of the Cliques: Borrower's Proprietary Costs

	DV=Log(Clique_Size+1)			
	(1)	(2)	(3)	(4)
R&D_Cont	**-23.88***			
	(-1.947)			
Redaction_Dummy		**-0.0428***		
		(-1.941)		
Asset_Intensity			**0.109***	
			(1.662)	
High_Proprietary				**-0.120*****
				(-2.669)
Log(Total_Assets)	0.0219**	0.0281***	0.0283***	0.0285***
	(2.413)	(3.173)	(3.194)	(3.227)
ROA	0.0196	0.0142	0.039	0.0126
	(0.112)	(0.0806)	(0.222)	(0.0717)
Leverage	-0.0949	-0.0784	-0.0935	-0.0845
	(-1.484)	(-1.230)	(-1.449)	(-1.326)
MTB	0.016	0.0145	0.0141	0.0161
	(1.091)	(0.982)	(0.954)	(1.093)
Asset_Growth	-0.0243	-0.0222	-0.0202	-0.0205
	(-1.147)	(-1.051)	(-0.955)	(-0.970)
Log(Amount)	0.0255**	0.0284***	0.0271***	0.0281***
	(2.468)	(2.745)	(2.617)	(2.717)
Log(Maturity)	0.0291*	0.0291*	0.0297*	0.0289
	(1.651)	(1.651)	(1.683)	(1.636)
Revolver	-0.00186	-0.00122	-0.00249	-0.00144
	(-0.101)	(-0.0658)	(-0.135)	(-0.0778)
Inst_Tranche	-0.00691	-0.00782	-0.0059	-0.00811
	(-0.231)	(-0.261)	(-0.198)	(-0.271)
Constant	4.004***	3.818***	3.786***	3.805***
	(19.03)	(18.61)	(18.33)	(18.55)
Observations	28,307	28,307	28,307	28,307
R-squared	0.144	0.144	0.144	0.144
Facility Start Year F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	No

Notes. This table presents the results of whether borrowers with high proprietary costs are concerned about information dissemination within a clique. We regress the natural logarithm of one plus the size of a clique on four proxies for borrowers' proprietary costs. The same set of controls as in Table 2 are included. Standard errors are clustered by package. Appendix A.1 contains detailed variable definitions. *, **, and *** represent the statistical significance at the 10%, 5%, and 1% level, respectively (two-tailed). T-statistics are presented beneath the coefficient estimates in parentheses.

A Appendix

A.1 Variable Definitions

Variable	Definition
Outcome variables (listed in alphabetical order):	
Below_Investment_Grade	An indicator that equals one if the borrower's rating falls below the investment grade, and zero otherwise.
Clique_Size	The number of lenders in a clique.
DG_to_Default	A dummy variable that equals one if the borrowing firm's rating falls into the default grades (D or SD) before the loan matures, and zero otherwise.
Reneg_Count	The number of renegotiations that a facility experiences before maturity.
Reneg_Dummy	A dummy variable that equals one if a facility experiences one or more renegotiations before maturity, and zero otherwise.
Time_to_First_Reneg	The number of months between the facility start date and the date of the first renegotiation.
Main independent variable:	
Clique_Lender%	The number of participant lenders that are in the same clique as the lead lender, scaled by the total number of participant lenders in a syndicate. For facilities with multiple lead lenders, the value is calculated as the average across all lead lenders.
Other independent variables (listed in alphabetical order):	
Asset_Growth	Current period total assets divided by the total assets of the previous year.
Asset_Intensity	The ratio of net property, plant, and equipment to total assets.
Betweenness	A centrality measure that is calculated based on how often the lender is on the shortest path between two other lenders in the market. This variable is transformed into percentile ranks in the regression analysis.
CB%	The number of lenders that are classified as commercial bank in the clique, scaled by the total number of lenders in the clique.
CFO_Volatility	The volatility of operating cash flows, calculated as the difference between the highest and lowest operating cash flows divided by the midpoint, over a five-year period. This variable is transformed into percentile ranks in the regression analysis.

Clique_Lender_Shares	The percentage of loan shares contributed by participant lenders from the same clique as the lead lender.
Degree	A centrality measure calculated as the number of lenders the lead lender is connected with. This variable is transformed into percentile ranks in the regression analysis.
Eigenvector	A centrality measure calculated as relative scores for all lenders in the market, measuring how well a lender is connected to other central lenders. This variable is constructed following Pena Romera (2019), and is transformed into percentile ranks in the regression analysis.
High_Proprietary	A dummy variable that equals one if a firm has an R&D expenditure greater than zero, redacts information in its annual report, and has asset intensity below the sample median; otherwise, it equals zero.
Inexp_Lead_Lender	A dummy variable that equals one if the lead lender has three years or less of experience. For facilities with multiple lead lenders, it equals one if any lead lender is identified as inexperienced.
Inst_Tranche	An indicator variable that equals one if the classification of facility belongs to type B to type K, representing institutional term loans participated by nonbanks.
Large_Group_Lenders	A dummy variable that equals one if the number of lenders in the facility is above the sample median, and zero otherwise.
Leverage	The ratio of long-term debt to total assets.
Maturity (in months)	Stated maturity of the facility.
MTB	The market value of equity plus the value of total liabilities divided by the book value of total assets.
One_to_One	The number of participant lenders that have one-to-one connections with the lead lender, scaled by the total number of participant lenders in the syndicated loan. One-to-one connection means that the lead (participant) lender acted as the lead (participant) lender in the previous facilities. For facilities with multiple lead lenders, the value is calculated as the average across all the lead lenders.
R&D_Cont	The ratio of R&D expense to total assets.
R&D_Dummy	An indicator variable that equals one when the R&D expense is positive, and zero when it is zero or missing. Note that a missing R&D expense indicates that the amount is not material and therefore is not separately disclosed.
Redaction_Dummy	A dummy variable that equals one if the firm redacts information in its annual report, and zero otherwise.
Revolver	An indicator variable that equals one if the facility is a revolving loan, and zero otherwise.

Rev_One_to_One	The number of participant lenders that have reversed one-to-one connections with the lead lender, scaled by the total number of participant lenders in the syndicate. A reversed one-to-one connection means that the participant (lead) lender acted as the lead (participant) lender in previous facilities. For facilities with multiple lead lenders, the value is calculated as the average across all lead lenders.
ROA	Earnings before extraordinary items divided by total assets.
Threshold	The percentage of the deal commitment that lenders must hold in order to approve any modifications to the current deal.
Total_Assets ($Million)	Total assets of the borrowing firm.