Modeling the role of networks in loan syndicate markets*

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Abstract

We analyze a stylized loan-auction model where competing banks internalize the trade-off between gaining lead status and attracting participation in large syndicated loans. We show that successful syndicate leaders can sustain low lending rates by earning higher fee income and reducing syndication risk. Consistent with our model whereby networks affect bidding outcomes, we find that well-connected lenders form larger syndicates, use fewer co-arrangers, and offer lower rates. To address endogenous firm-bank matching, we exploit exogenous credit relationship transfers around bank mergers. Our findings help explain why the syndicated loan market remains competitive despite the rise in bank consolidations.

The key to success in this business is being close to the market. [...] being in touch with banks on a weekly, if not daily, basis. We started with [...] approximately 90 banks [...] that might be interested in this deal. This kind of analysis illustrates our closeness to the market and our confidence in the deal. — (Esty, 2001)

Loan syndication is a multilateral market-making process whereby a bank makes a loan to a borrower jointly with several lenders. In this process, banks first submit bids to become lead arrangers, and then the winning bidder is tasked with assembling a syndicate of lenders. Thus, bidders first compete effectively by offering lower interest rates, but not so low as to dissuade other banks from joining the syndicate. This study shows that proven, well-connected lenders are most successful in navigating this process. Specifically, proven, well-connected banks with access to a large network of potential syndicate members are more successful at mitigating syndication risk. As a result, these banks can bid aggressively for the lead mandate, yet maintain the lion's share of the underwriting fees by employing fewer co-arrangers.

To illustrate this process, we develop a stylized loan-auction model to formalize the impact of cross-lender relationships on syndication and loan pricing strategies. In the model, existing connections reduce the cost of assembling syndicates and raise deal value, giving connected lenders the incentive to offer lower rates. The model predicts that well-connected syndicate leaders can leverage their connections to assemble larger, more dispersed syndicates and offer lower rates. In this light, the model predicts that lead arrangers benefit from dispersed syndication structures in two ways. First, by including more syndicate participants, lead arrangers reduce their risk exposure by retaining a smaller share of the loan. Second, by limiting the number of co-arrangers, they increase fee income by retaining a greater portion of the fees (which are shared with co-arrangers). Our model recognizes that this syndicate strategy increases the risk of undersubscription. We posit that network connections mitigate this risk and give proven, well-connected lenders the incentive to offer lower rates when bidding for the lead arranger mandate.

Our model assumes that arrangers do not exploit their network connections to collude with potential competitors for the lucrative lead arranger role, as some regulators fear.[1] Specifically, lenders may impose higher rates by submitting loan bids jointly or refusing to co-syndicate with banks that undercut the collusive price (Hatfield et al., 2020). Distinguishing our model from this alternative collusive equilibrium is an empirical question with significant implications. We test the predictions of our model using a large set of syndicated loans in the U.S. and find that proven, well-connected lead arrangers offer lower loan rates by 5-15 basis points on average. In addition, well-connected arrangers establish more dispersed syndication structures with more junior participants and fewer co-arrangers. The evidence is consistent with our model of the loan syndication process within a network framework.

Our empirical results overcome two main challenges that make it difficult to assess whether syndication networks improve or worsen contract terms for borrowers: measurement and identification. First, to measure connectedness, we calculate network centrality for each bank based on previous syndication relationships. These measures reflect lenders' past leadership and participation in the syndicated loan market. Second, well-connected lenders may endogenously match with high credit-quality firms, which borrow at low rates. To address this selection problem, we exploit the transfer of a firm's credit relationship from a non-connected to a well-connected lender after bank mergers. This identification strategy is in line with the Strahan (2008) argument that the ideal test involves exogenous changes to relationship lending after bank mergers.

In our setting, treatment comes from credit relationships that transfer from low to high out-degree centrality lenders following a bank merger. Firms borrowing from a highly connected bank both before and after a bank merger serve as control firms because they experience no significant *change* in out-degree centrality. Moreover, by examining loan terms offered to the same borrower both pre- and post-merger, we mitigate the concern that

[1] See "Roundtable on competition, concentration and stability in the banking sector" (https://bit.ly/3srvuCs), or "EU loan syndication on competition and its impact in credit markets" (https://bit.ly/3LujWXV).

lower spreads simply reflect the fact that firms with high credit quality borrow from well-connected lenders. Motivated by economic theory suggesting that lending relationships are sticky (Sharpe, 1990; Rajan, 1992), we track bank-firm links around bank mergers, which mitigates a host of selection problems.

While bank mergers help rule out selection concerns, mergers often reflect complementarities and synergies that may also affect lending terms. To address this concern, we examine the changes in loan prices in the cross-section of firms that borrow from the same well-connected lender after a merger but differ in their bank's pre-merger centrality. These borrowers are thus subject to similar synergistic gains. In addition, since mergers increase bank size, which may affect lending efficiency and borrowing costs, we directly control for bank size in our empirical work. We note, however, that while mergers increase bank size, not all mergers result in big changes to centrality.[2]

We build on prior research to ascertain the channel that drives our results. First, we find that transferring to a highly central bank after a merger reduces the days the loans remain in syndication and the loan shares underwriters retain, mitigating risk. To offer more competitive loan spreads in the bidding stage, successful lead underwriters attract sufficient demand from other banks in the syndication stage. Bank connections mitigate several problems when bidding for the mandate with lower rates: reduced deal revenues, extended underwriting periods, and increased risk of retaining larger loan shares. These results are consistent with the findings of prior studies that associate lead arrangers' demand discovery function with faster syndication (Ivashina and Sun, 2011) and lower loan retention shares (Bruche et al., 2020).

Second, our analysis indicates that improved loan terms do not stem from a superior ability to screen or monitor borrowers. Using a variety of post-origination firm- and loan-performance metrics, such as firm value, firm profitability, and debt contract violations, we

[2]For instance, the 2004 merger between two proven, highly central banks (Bank of America and Fleet-Boston) significantly increased the bank's size but did not materially change centrality. The pre- and post-merger *difference* in loan rates within highly central banks serve as the counterfactual.

fail to find evidence that firms in the portfolio of proven, highly central banks outperform those in the portfolio of other banks. Naturally, network centrality metrics are correlated with lender attributes such as size, reputation, and capitalization. Our tests account for these attributes by leveraging variation in network centrality from large, reputable, and well-capitalized international banks that are not as connected as their U.S.-based competitors.

Third, we find no evidence that improved loan terms result from informational advantages or market power in the syndicated loan market. While networks may generally facilitate information sharing, we do not find that lenders with high syndicate participation (measured, e.g., by in-degree, closeness, or betweenness centrality) offer better loan terms. Likewise, we do not find that bank size or proxies for bank dominance (such as market share, eigenvector, and closeness centrality) are associated with improved lending terms. Out-degree centrality, that is the bank's proven, highly central position, is the determining factor driving our results. In fact, our results are consistent with the ability of the lead arranger to learn about investor demand (Bruche et al., 2020) and use syndicate structures that reduce their risk exposure while retaining larger portions of the syndication fees (Esty, 2001).

Our study provides an intuitive link between lender relationships, reputation, and syndicate structures and adds to the mounting evidence of the importance of networks in capital markets. Ross (2010) suggests that lender market shares proxy for reputation and signal superior screening and monitoring abilities. Reputation may also have the opposite effect on monitoring if reputable lenders retain smaller loan shares as in Sufi (2007) and Lin et al. (2012). Our findings complement these studies and posit that the effects of reputation materialize through lenders' network position and their ability to attract participation in future deals. For example, reputational damage inhibits future syndicate building and forces underwriters to retain larger loan shares (Gopalan et al., 2011).

Our study suggests that reputation matters and affects underwriting structures because proven, highly central banks can better connect with investors to build syndicates more effectively. Moreover, our network-based metric captures the benefits of reputation (commonly more vaguely proxied by size or another isolated bank characteristic) and is quantitatively and economically more relevant for empirical work in markets where cross-lender interactions matter. In addition, our evidence provides an intuitive explanation of the observed market structure, whereby a few well-connected lenders dominate the market.

To our knowledge, this paper is the first to provide a theoretical model of syndication in credit markets that incorporates network connections and empirically demonstrates that these connections are significant determinants of lenders' syndication and pricing strategies. Our model and evidence are thus consistent with several stylized facts among practitioners. Namely, proven, well-connected arrangers garner participation interest, which in turn affects how they structure the syndicate and how much they profit from the deal. These results can further explain why banks actively seek to establish relationships with other market participants (even if their compensation is small) because connections allow them to compete more effectively for future, more profitable lead underwriter opportunities (Ljungqvist et al., 2008). The evidence also supports recent theoretical work that models the importance of connections in raising capital for large investments that require the participation of multiple members (Akerlof and Holden, 2016, 2019).

Lastly, our study contributes to the burgeoning literature on how networks shape agents' behavior in economics and finance (Jackson, 2014). Hochberg et al. (2007), for instance, find that venture capital (VC) networks improve fund performance, and Bajo et al. (2016) show that highly central underwriters improve initial public offering (IPO) characteristics. Rossi et al. (2018) show that more central managers earn higher risk-adjusted returns, and Houston et al. (2018) find that connections through lenders' boards facilitate information flows. Our evidence from the syndicated loan market, characterized by repeated, relationship-driven transactions with unique information frictions (Sharpe, 1990; Boot, 2000) and agency problems related to monitoring (Diamond, 1991; Park, 2000), adds to our understanding of how networks influence financial markets.

1. A model of lender networks and syndicate structures

We develop a stylized model that incorporates syndicate structures in the bidding strategies for the lead arranger mandate. The model's assumptions are based on common practices in the syndicated loan market, namely that a bank is reluctant to finance a large loan deal on its own and requires the participation of several syndicate members who join either as junior participants or senior co-arrangers. We model this behavior by assuming that lenders are risk averse and senior co-arrangers require higher compensation for joining the syndicate. We first analyze the participant's and the lead arranger's problem, and then use backward induction to arrive at the equilibrium bidding strategy between competing arrangers as a function of their network size.

1.1. The participant's problem

We first analyze the problem that prospective banks face when they participate in a loan syndicate. The bank's portfolio consists of a risk-free asset and a risky loan. The risk-free asset offers a gross return $R_f > 1$. The risky loan earns a return R and is paid in full with probability $0 < \alpha < 1$, and defaults with probability $1 - \alpha$. To rule out degenerate cases, we let $\alpha R > R_f$, suggesting that a risk-averse lender will require an expected return from participating in the deal that exceeds the risk-free rate. For ease of exposition, we assume that the recovery rate in the event of default is zero, even though a nonzero recovery rate does not alter any of the conclusions from the model. The horizon for the loan is one period, and the bank has log utility. The bank has initial funds W and lends $0 \leq q \leq W$. The participant solves the following problem:

$$\max_{q} \; E[\log((W-q)R_f + q\,R\,1_{\{repaid\}})], \tag{1}$$

$$s.t. \; E[\log((W-q)R_f + q\,R\,1_{\{repaid\}})] \geq \log(WR_f),$$

where $E[\log((W-q)R_f + q\,R\,1_{\{repaid\}})] = \alpha\,\log[(W-q)R_f + Rq] + (1-\alpha)\log[(W-q)R_f]$. Solving the first order condition, we get the optimal quantity:

$$q^* = \frac{\alpha R - R_f}{R - R_f} W. \tag{2}$$

The optimal amount that a syndicate participant contributes to the loan deal is positive ($q^* > 0$) under the assumption that $\alpha R > R_f$.

1.2. The lead arranger's problem

Next, we analyze the lead arranger's problem. The lead arranger needs to form a syndicate to reduce its exposure to a single loan and free up capital for additional loans. Therefore, the arranger faces the additional challenge of finding and coordinating a syndicate of lenders that jointly fund the loan amount. We change the notation slightly and consider the quantity that a prospective syndicate member (indexed by subscript i) is willing to supply at a rate R. We denote this quantity by $q_i(R)$. The arranger's task is to determine the optimal number of syndicate members to satisfy the client's demand Q. The lead arranger incurs costs associated with participating syndicate members that could arise from coordination costs and search frictions. We model these costs linearly, noting that there are two types of syndicate members: (a) junior participants, who provide fewer services and receive smaller compensation in fees, and (b) senior co-arrangers, who are more involved in the loan underwriting process and thus receive a larger fraction of the fees. As a result, each additional bank added as a junior participant involves a fixed cost of c, and each bank added as a co-manager involves a larger cost of C (i.e., $C > c > 0$).

The arranger's problem is to pick n participating banks and m co-arrangers in the syndicate. We denote the set of investors that can join a lender's syndicate as junior participants by N, and the set of investors that can join as co-arrangers by M. The arranger that wins the lead underwriter mandate in the bidding stage charges an interest rate of R, and collects $C \times Q$ in underwriting fees. The lead arranger must supply enough credit (q_0) based on the rate R that offsets potential shortcomings from the rest of the syndicate members: $q_0(R) = Q - \sum_{i \leq n} q_i(R) - \sum_{j \leq m} q_j(R)$. Therefore, the utility $U(\cdot)$ that the arranger seeks to maximize is:

$$\begin{aligned} U(n, m; R) \quad &= \quad \alpha \log\Big(W_0 R_f + C\,Q - c\sum_{i\leq n} q_i(R) - C\sum_{j\leq m} q_j(R) + q_0(R - R_f)\Big) \\ &\quad + (1-\alpha)\log\Big(W_0 R_f + C\,Q - c\sum_{i\leq n} q_i(R) - C\sum_{j\leq m} q_j(R) - q_0 R_f\Big). \end{aligned} \tag{3}$$

Lastly, the lead arranger observes a signal about the quality of the borrower that they are obligated to share with other syndicate members.[3] Instead of discrete banks, we assume that there is a continuum of identical junior banks and a continuum of identical co-arrangers. Thus, upon observing signal θ about the quality of the borrower, the lead arranger can determine the probability of default (i.e., $\alpha = \alpha(\theta)$) and, consequently, the supply curve of each lender. We further assume that all lenders are ex ante identical. Fixing R, we use the result in equation (2) from the previous section to get the quantity supplied by each syndicate member: $q^*(R, \alpha) = \frac{\alpha R - R_f}{R - R_f} W$.

The arranger chooses n and m that maximize its expected utility U that, after dropping the argument R and α from the q^* expression to simplify the notation, leads to:

$$\begin{aligned} U(n, m; R, \alpha) \quad &= \quad \alpha \log\Big(W\,R_f + (C + R - R_f)(Q - m\,q^*) - (c + R - R_f)n\,q^*\Big) \\ &\quad + (1-\alpha)\log\Big(W\,R_f + (C - R_f)(Q - m\,q^*) - (c - R_f)n\,q^*\Big). \end{aligned}$$

LEMMA 1: An arranger would exhaust junior participants before inviting co-arrangers into the syndicate.

PROOF: See Online Appendix, Section A.1.

[3] Syndicate members indirectly participate in the equilibrium so they have the same information set as the lead arranger.

Lemma 1 implies that syndication with more participants and fewer co-arrangers increases the lead arranger's utility from the deal. As a result, the lead arranger's problem can be solved using a two-step process. First, the arranger chooses the number of junior participants $\tilde{n}$, such that: $\tilde{n} = arg\max_n U(n, 0; R))$. Second, suppose the arranger is connected to a sufficiently large number of investors willing to join the syndicate as junior participants (N) to underwrite the loan amount Q fully. In that case, the arranger does not include co-arrangers and thus $m^* = 0$. If the number of willing investors is insufficient to underwrite the full amount, the arranger uses N as junior participants and chooses m^* co-arrangers by solving $\max_m U(N, m; R, \alpha)$.

Let us formulate the first step of the problem, i.e. $\max_n U(n, 0; R, \alpha)$. The first order condition $\frac{\partial U(.)}{\partial n} = 0$ yields:

$$\tilde{n}q^* = \frac{c + \alpha R - R_f}{c + R - R_f}\frac{R_f}{c - R_f}W + \Big[\frac{C - R_f}{c - R_f}\frac{c + \alpha R - R_f}{c + R - R_f} + (1 - \alpha)\frac{R}{c + R - R_f}\Big]Q. \quad (4)$$

Note that if the loan is small enough there is no syndication. Therefore for the remainder of the analysis, we will assume that Q is sufficiently large.

If $\tilde{n} > N$, then $n^* = N$ and $m^* > 0$. The problem then becomes:

$$\max_m \ \alpha \log\Big(WR_f + (C + R - R_f)(Q - m\,q^*) - (c + R - R_f)Nq^*\Big)$$
$$+ (1 - \alpha)\log\Big(WR_f + (C - R_f)(Q - m\,q^*) - (c - R_f)N\,q^*\Big).$$

The solution to the FOC is:

$$m^*q^* = Q + \frac{C + \alpha R - R_f}{C + R - R_f}\frac{R_f}{C - R_f}W$$
$$- \Big[\frac{c - R_f}{C - R_f}\frac{C + \alpha R - R_f}{C + R - R_f} + (1 - \alpha)\frac{R}{C + R - R_f}\Big]N\,q^*. \quad (5)$$

For the remainder of the paper, we assume that both N and Q are sufficiently large. Given a large enough Q, then $n^* = N$ and m^* is given by expression (5). An alternative representation of the solution considers the quantity q_0 provided by the lead arranger. If Q is large enough (i.e. $\tilde{n} > N$), then the problem can be expressed as:

$$\max_{q_0} U(q_0) = \alpha \log[WR_f + (C + R - R_f)q_0 + (C - c)Nq^*] \\ + (1-\alpha)\log[WR_f + (C - R_f)q_0 + (C - c)Nq^*].$$

The solution to the problem is given by:

$$q_0^* = \frac{C + \alpha R - R_f}{C + R - R_f} \frac{1}{R_f - C}\Big[W\,R_f + (C - c)N\,q^*\Big].$$

Substituting q_0^* in the expression for expected utility, we get:

$$U(q_0^*) = \alpha \log(\alpha) + (1-\alpha)\log(1-\alpha) + \log(R) - (1-\alpha)\log(C + R - R_f) \\ + \log\Big(WR_f + (C - c)N\,q^*\Big) - \alpha \log(R_f - C).$$

We can also define the excess expected utility from underwriting the loan at a promised rate of R and repayment probability of α:

$$V(R, \alpha) = U(q_0^*) - \log(W\,R_f).$$

The following lemma characterizes the derivatives of the value function $V(R, \alpha; N, Q)$ with respect to its arguments.

LEMMA 2: Given a large enough N (and by extension Q to guarantee $\tilde{n} > N$), the derivatives $\frac{\partial V(.)}{\partial R} > 0$, $\frac{\partial^2 V(.)}{\partial R \partial \alpha} < 0$ and $\frac{\partial^2 V(.)}{\partial \alpha \partial N} > 0$.

PROOF: See Online Appendix, Section A.2.

1.3. Two competing lead arrangers

We start with the assumption that a borrower sets a first-price auction and approaches two arrangers to submit bids for a large loan. The two arrangers have connections to potentially different sets of banks. Without loss of generality, we let the size of the network of the first arranger $N_1 > N_2$, and we denote arrangers by the subscripts 1 and 2. We further assume that M_1 and M_2 are sufficiently large.

Upon examining the borrower's financial statements, each arranger estimates the supply function $q^*(\cdot)$ that prospective members will insist on. We model this process as observing signals θ_1 and θ_2 for arrangers 1 and 2, respectively. We assume that the borrower quality signals θ_i inform the probability of loan repayment $\alpha(\theta_i, \theta_j) : [\underline{\theta}, \bar{\theta}]^2 \to (0, 1)$. We also assume that this mapping is continuous and strictly increasing in both θ_1 and θ_2.

Note that each arranger chooses interest rate R to maximize the product of the probability of winning the bidding auction and the expected utility subject to their participation constraint: $\max_R Prob(win) \times V_i(R, \alpha; Q)$, s.t: $V_i(R, \alpha; Q) \geq 0$. First, we prove that the game has a Nash equilibrium. Second, we show that the arranger with the largest network provides the best rate on average.

We first start by defining regular strategies. By regular strategies, we refer to a mapping $R_i(\theta_i) : [\underline{\theta}, \bar{\theta}] \to [\underline{R}, \bar{R}]$ that is Lipschitz continuous and strictly decreasing over the support of the function where the bank bids.

We appeal to the first-bid sealed auction setting of Lizzeri and Persico (2000). We assume that the joint distribution $f(\theta_1, \theta_2) : [\underline{\theta}, \bar{\theta}]^2 \to [0, \infty)$ satisfies conditions A1 ($f \in C^1$ and $f(\theta_1, \theta_2) > 0$) and A2 ($\theta_1$ and θ_2 are affiliated). We further assume that the borrower sets a reservation rate $\bar{R}$, above which they will not borrow. Furthermore, assume that for a poor quality firm, i.e. θ_i sufficiently low ($\theta_i < \theta^*$), $V_i(R, \alpha(\theta_i, \theta_j)) < 0$, $\forall R < \bar{R}$. This assumption is satisfied if the signal θ_i indicates a low enough probability of repayment. In our setting, if there exists $\theta^*, \alpha(\theta^*, \bar{\theta}) = (R_f - C)/\bar{R}$, then all banks will not lend at rates below $\bar{R}$, and assumption A3 is satisfied.

THEOREM 1: There exists a unique pure strategy equilibrium.

PROOF: See Online Appendix, Section A.3.

THEOREM 2: Assuming that the signals (θ_1, θ_2) that the two arrangers observe are identically distributed and that the repayment probability is symmetric in θ_i, θ_j (i.e., $\alpha(\theta_i, \theta_j) = \alpha(\theta_j, \theta_i)$, $\forall \theta_i, \theta_j$), then arranger 1 offers a lower rate than arranger 2 given the same signal $R_1(\theta) \leq R_2(\theta)$, or equivalently the inverse rate $p_1(\theta) \geq p_2(\theta)$, $\forall \theta \in (\underline{\theta}, \bar{\theta}]$.

PROOF: See Online Appendix, Section A.4.

The equilibrium in the model is consistent with a non-monopolistic market structure. Lenders with varying network sizes have a non-zero probability of winning the lead mandate because they receive different signals about the quality of the borrower (θ). Figure 1 uses a stylized representation of the bid distributions to illustrate this intuition for two lenders with different network centralities. The overlap in the density functions indicates that the low centrality bank has a positive probability of winning the bid. In other words, conditional on observing the same signal, the high-centrality lender offers a lower rate $R(\theta)$. However, a low centrality lender will win the lead mandate if its borrower quality signal (θ) is sufficiently higher than that observed by the high centrality lender.

To summarize, the model predicts that more connected lenders $(N_1 > N_2)$ form larger syndicates that involve more junior participants and fewer co-arrangers. These larger syndicates allow the lead arranger to retain a smaller share of the loan in its own portfolio. Retaining a smaller fraction reduces the risk exposure of the lead arranger, while having fewer co-arrangers allows the lead underwriter to claim a larger share of the fees. Therefore, proven, well-connected lenders receive higher compensation at lower risk.

2. Data and summary statistics

We collect data for all syndicated loans in the U.S. between 1994 and 2019 from the Loan Pricing Corporation's (LPC) Dealscan database. Dealscan contains detailed loan contract information, such as the loan spread and underwriting fees, loan maturity, loan amount, and financial covenants. While the final terms of the loan contract may differ from the preliminary terms that prospective lenders offer when they bid for lead arranger status, they still proxy for the most competitive offer that the borrower received overall (Esty, 2001).

From Dealscan, we combine regional bank branches and subsidiaries operating with different branch names under a common parent company.[4] To identify a lender as the lead arranger, we follow Bharath et al. (2011).We hand-match each lender in our sample with Compustat NA Bank, Compustat Global, and Bankscope to obtain information on each lender's assets, bank equity, and bank deposits (for depository institutions). We observe these variables with annual frequency, allowing us to partial out the effect of time-varying bank characteristics on loan contract terms. Our bank sample consists of 968 lenders (213 with non-missing characteristics).

For each loan in our sample, we collect accounting information about the borrower from Compustat's quarterly fundamentals file using the matching link by Chava and Roberts (2008). We collect information on firm size (assets), profitability (ROA), market-to-book ratio, S&P credit ratings, Altman's Z-score, and book leverage. We winsorize all variables at the top and bottom percentile of their distribution. Finally, we drop observations with missing firm and loan characteristics and exclude financial companies. Our final sample consists of 5,164 firms (borrowers) and 45,717 unique loan facilities.

We use standard measures from network analysis to calculate a variety of metrics characterizing bank positions in the syndicated loan market. For every lender, we calculate six different measures of network centrality: degree, out-degree, in-degree, eigenvector, betweenness, and closeness centrality. We describe these measures here and provide a detailed definition of each measure in the Variables definitions Table. Degree centrality counts the number of ties a bank has with other banks in the network. We compute the normalized

[4]For example, Dealscan often reports the name of regional branches using separate lenders (e.g., Bank of America New Mexico). In addition, banks in Dealscan appear active in lending even after their acquired date. For instance, Bank of Tokyo-Mitsubishi UFJ acquired Union Bank in 2008, yet Union Bank appears as a syndicated loan participant even after 2008. To classify banks accurately, we replace the names of these lenders with the name of the parent and treat them as one lender.

degree of centrality by counting the number of different lenders that each bank has co-syndicated with during the past four quarters and then dividing this number by the total number of lenders in that period.[5] This process makes network centrality measures comparable over time, taking into account changes in the network size as lenders enter, exit, or combine via mergers and acquisitions.

Degree centrality presents a simplified view of syndicate relations. Typically, one lender leads the syndicate with multiple other investors (e.g., banks or institutional investors) joining as syndicate participants, so we distinguish between deal participation and deal arranging. To differentiate lead arrangers from syndicate members, we model directed networks and distinguish between deal participation and deal arranging using a lender's in-degree and out-degree centrality, respectively. The difference between deal arranging (out-degree) and deal participation (in-degree) is important in our empirical analysis. Out-degree centrality is high when a bank leads syndicates with many participants and thus captures a bank's ability to attract investors in its deals. Conversely, high in-degree centrality represents bank participation as an investor in many syndicates and thus captures a bank's ability to develop relations or experience in the market (Corwin and Schultz, 2005; Ljungqvist et al., 2008).

We construct additional measures of network centrality based on higher-order connections among banks. *Eigenvector centrality* is similar to degree centrality but assigns larger values to banks that are connected to investors who are also well connected, and therefore measures the influence of a bank in the network. We also construct *Betweenness centrality* to capture a bank's ability to bridge to investors who are otherwise not connected through the syndicated loan market. Lastly, we calculate *Closeness centrality*, a measure similar to eigenvector centrality, constructed based on banks' overall proximity to other investors—the sum of the inverse of the shortest paths between a bank and other lenders in the network.

[5] For instance, assume four active banks in the syndicated loan market A–D form co-syndication relationships with each other when they join a syndicated loan. In this setting, each of the four banks has three potential co-syndicate partners, so the maximum number of co-syndication relationships equals three ($C_{max} = 3$). If bank A connects with bank B in one loan and with bank C in another loan, then its degree centrality is 2 ($c_i = 2$), and its normalized degree centrality is 2/3 or 0.67 ($= \frac{c_i}{C_{max}}$).

Importantly, syndicated loan networks are dynamic and change over time, so we update our network measures on a rolling four-quarter window. Figure 2 illustrates the time-series average of the centrality measures based on co-syndication relationships and shows that all three measures have increased since 1994. Notably, deal arranging (out-degree centrality) increases after the 2007 financial crisis, likely driven by the consolidation of large lenders in the industry.

Naturally, lenders' network centrality measures are closely related to lender attributes such as size, market share, or lending specialization in a specific industry. As lenders increase market share, they also expand their network of relationships with other market participants. The concurrent increase in lenders' market share and dependence on their co-syndication relationships suggests that traditional measures of market concentration conflate whether and how these attributes affect loan prices.

Specifically, a larger market share affects loan prices by (a) having an anti-competitive effect and raising the prospect of collusion (Hatfield et al., 2020), (b) proxying for lenders' reputation and a signal for a higher quality of products and services (Fang, 2005; Ross, 2010), and (c) affecting lenders' incentive to soften competition to mitigate the negative externalities of aggressive product market behavior (Saidi and Streitz, 2021). This study proposes an additional—non-mutually exclusive—channel through which market shares affect loan prices. Our model internalizes the value of connections in banks' utility and shows that lenders have the incentive to offer lower rates and still gain from a deal by altering the seniority of the participants in their syndicate structures.

Lender network centrality measures are not perfectly correlated with size. Figure 3 illustrates this point and plots the connections of dominant lenders. Note that large lenders, such as Santander, Societe General, and Sumitomo Mitsui, are less connected than smaller institutions like Morgan Stanley. In addition, the top 3 syndicated lenders—JPMorgan Chase, Bank of America Merrill Lynch, and Wells Fargo—with a combined market share of 30%—are smaller than Mitsubishi UFJ, HSBC, and BNP Paribas. Deutsche Bank, Credit

Suisse, and Goldman Sachs consistently rank among the top 10 lenders in global syndicated loan league tables, but do not rank among the top 10 banks by assets.

Firms that access the syndicated loan market are typically large, almost by definition, because syndicated loans are also large. The median firm in our sample has $3.1 billion in assets, considerably larger than the median Compustat firm (approximately $205 million). Approximately 62% of the loans are credit lines, and 35% are term loans. Syndicated loans are commonly secured with collateral, and their average maturity is 53 months, much shorter than bonds that are usually subordinated to bank debt. The dollar value of syndicated loans is also large: the average loan amount in our sample is $720 million. Banks have the incentive to syndicate these loans to reduce their risk exposure and improve their liquidity position. As a result, the average syndicate contains 7.25 participants and 3.1 arrangers. Underwriting fees are not trivial. Loan fees are, on average (median), equal to 50% (30%) of loan spreads and contribute significantly to borrowers' total cost of borrowing (Berg et al., 2016).

We find that across the sample period, the average lender has a market share of approximately 8.2%, but the distribution is positively skewed (Panel B of Table 1). The top three lead arrangers cumulatively provide approximately 30% of the total amount of syndicated loans. However, lenders tend to specialize in specific industries, such that the median lender provides 5.1% of all loans in a given (SIC-3) industry. In Table 1, we see that the average bank is connected to 13.5% of the other banks in the network (average degree centrality). The average in-degree centrality is 12.03%, so the typical bank partners at least once with 12 out of 100 other banks in a given year. Out-degree centrality, or deal-making, is lower (at 4.43%), so the average bank arranges deals with approximately four other banks active in lending the prior year.[6]

[6]The average centrality measures are higher when we limit the sample that includes only banks that have merged (or have been acquired) at some point in the sample. We also consolidate subsidiaries at the parent-bank level.

3. Lender networks, syndicate structures, and loan prices

Our model illustrates that a greater number of connections to prospective investors reduces the cost of assembling a syndicate and maximizes the share of the loan's fees for the lead underwriter for a given interest rate. Therefore, connected lenders gain more value from underwriting a loan while sustaining lower rates on their loans. In this section, we test this hypothesis empirically. We start the analysis by examining the relation between lender centrality and loan spreads using the following regression model:

$$Y_{i,t,b} = \alpha_i + \alpha_t + \beta_1 C_{b,t} + \beta_2 X_{i,t} + \gamma \text{Lender Centrality}_{b,t} + \epsilon_{i,b,t}, \tag{6}$$

where i represents a firm that receives a loan from bank b in year t. Therefore, the unit of analysis is at the firm-loan observation.[7] The outcome variable Y is equal to the natural logarithm of the loan's spread, net of fees. *Lender centrality* is the past 4-quarter average of a lender's centrality. The regression controls for other bank characteristics $C_{b,t}$: the natural log of *Bank assets*, the *Bank capitalization, Market share,* and *Industry specialization*. We also control for firm- and loan-related characteristics $X_{i,t}$: the natural log of *Firm assets*, *Market-to-Book* ratio, *Book leverage* ratio, *Tangibility*, and *ROA*. We define the construction of all variables in the Variables Definitions Table.

Figure 4 presents the relations between each measure of lender centrality and the loan's cost of debt. We group lenders into 20 bins based on their network centrality measures and plot the average residual (i.e., after controlling for firm, bank, and loan characteristics) of the loan spread for each centrality group using regression (6). The figure illustrates that lead arrangers' centrality is negatively associated with firms' cost of borrowing.

Table 2 presents results from regressions of loan spreads on network centrality measures after controlling for other lender characteristics, including their market share and industry specialization (or concentration). As shown, a change in lenders' centrality (degree, in-

[7]For instance, one observation in our sample appears as follows: Williams-Sonoma (the firm), receiving a \$300 million line of credit (the loan) from Bank of America (the bank) as a lead arranger.

degree, out-degree, eigenvector, closeness, and betweenness) from the median to the 90th percentile is associated, on average, with a 5% (or 5–10 basis points) reduction in the offered loan spread. The decrease in the cost of debt is moderate and economically higher for lenders with high out-degree centrality. This finding is consistent with a bank's ability to attract investors in the second stage of the syndication process playing a vital role in their loan pricing strategy. This effect appears over and above the effects of market share, industry specialization, and prior relationship status with the borrower and further indicates that common bank attributes are linked to bank network connections and affect borrowers' cost of capital through the same network channel. The results are consistent with the view that well-connected lenders offer lower yields without altering the total underwriting fees.

Our model shows that banks may forego higher interest rate revenues to earn higher fees associated with winning the lead arranger mandate. We hypothesize that loan syndication networks improve lenders' ability to market their deals and achieve a better risk-return trade-off by altering syndicate structures. Specifically, lenders connected to more investors may be able to underwrite loans with more junior participants and fewer senior co-underwriters. With fewer co-arrangers, underwriters retain a greater portion of the fees (while keeping overall fees fixed), and with more junior syndicate participants, they retain smaller fractions of the loan. This deal structure reduces syndication risk and frees up capital for additional investments.

In Table 3, we show that well-connected lenders construct more dispersed syndicates. Specifically, *Syndicate concentration*, measured by the loan's Herfindahl Hirschman Index (HHI), is negatively associated with lender network centrality measures, most likely driven by the increase in junior participants in the syndicate. Figure 5 corroborates this view by illustrating the diverging patterns in the number of senior versus junior participants in loan deals. Loans originated by well-connected lenders have (a) a larger number of junior participants and (b) fewer senior co-arrangers. These results obtain even after we account for firm, bank, and loan controls (including firm, bank, and loan size) and a host of firm, loan type, loan-purpose (e.g., acquisition, LBO, corp. purposes, etc.), rating, and year-quarter fixed effects.

Figure 6 presents regression estimates of the effect of lender centrality on the number of participants and arrangers (top panel), as well as on lead lender's allocation and total fee income (bottom panel). More central lead arrangers construct deals with more participants but fewer co-arrangers, reducing their allocation and freeing up capital. With fewer co-lead arrangers, lead lenders also increase the share of fees they retain.[8]

4. Evidence from Bank Mergers

To address endogeneity concerns from self-selection and omitted variables in the results presented above, we exploit shocks to firm-bank relationships induced by bank mergers. We focus on firms that borrow both pre- and post-merger from banks acquired or involved in mergers from 1994 to 2015. To this end, we identify all mergers in the sample period using SDC Platinum to track mergers between lenders, and search their individual histories to confirm the effective date of the merger.[9]

Our identifying assumption is that variation in the network centrality of a firm's underwriter is generated by a merger and is unrelated to unobservable firm characteristics, market synergies, and firm-bank matching. Importantly, the variation in lending relationships arising from mergers is plausibly exogenous to the characteristics of borrowing firms. This assumption relies on the notion that bank relationships are valuable for most corporate borrowers (Strahan, 2008). Further, our empirical design accounts for a host of borrower and lender characteristics as well as firm fixed effects to minimize omitted variable bias in

[8] We tabulate the estimates of the regression from Figure 6 in Tables B.1, B.2, B.3, and B.4 in the Online Appendix, respectively.

[9] Dealscan does not provide identifiers for lenders at the parent level, so we hand-match lenders from Dealscan with SDC Platinum. We use a more limited sample for these tests because our hand-collected merger sample ends in 2015.

the following regression model:

$$
\begin{aligned}
\text{Loan Spread}_{i,b,t} = {} & \alpha_i + \alpha_t + \beta_1 X_{i,t} + \beta_2 C_{b,t} \\
& + \gamma_1 \text{Post Merger}_{b,t} + \gamma_2 \Delta.\text{Lender centrality high}_{i,b,t} \\
& + \gamma_3 \text{Post Merger}_{b,t} \times \Delta.\text{Lender Centrality high}_{i,b,t} + \epsilon_{i,t,b}.
\end{aligned} \tag{7}
$$

In regression (7), subscript i is for the firm that receives a loan, t is for the year-quarter, and b is for the bank. Similar to model (6), we include time-varying controls ($X_{i,t}$) and bank controls ($C_{i,t}$). Modeling the transfer of lending relationships after bank mergers is at the crux of our identification strategy. Δ.*Lender centrality high* is an indicator variable that equals one if the firm extends a relationship with a lender whose network centrality changes from the bottom or middle tercile to the top tercile and varies at the firm-bank-quarter level (i, b, t).[10]

This distinction is particularly important for our identification strategy. As we illustrate in Figure 7, two different firms, *1* and *2*, may borrow from the same high-centrality post-merger lender (b) in the same quarter but can vary in terms of Δ.*Lender centrality high* if firm *1* transfers from a high-centrality bank and thus serves as a control, and firm *2* transfers from a low-centrality bank and thus we consider as treated. In our sample, approximately 30% of firm loans are in the treatment group since the merger resulted in a change in the centrality of the relationship lender. Before the merger, these firms maintained a relationship with a low-centrality bank, and the merger resulted in a combined bank with high centrality. Conversely, 70% of firm loans comprise our control sample as the centrality of their relationship bank remains unchanged — the centrality either remains high (54%) or low (16%).

Table 4 presents the results with this identification approach. We find that borrowers who shift from a low-centrality relationship lender to a high-centrality bank after the merger do not experience a statistically significant change in their cost of borrowing unless the merger

[10] We impose the restriction that treated firms must have had at least one loan with one of the merging banks as a lead lender not more than five years before the merger and borrow again within five years after the merger.

involves a highly out-degree central lender. In column (3), we find that firms that extend a relationship with a highly out-degree lender after a merger receive, on average, a 4.3%–7.8% reduction in their cost of borrowing (or 10–15 basis points).

The findings in Table 4 emphasize the value of networks for banks' underwriting functions. After addressing selection in firm-bank choice, we show that only out-degree centrality is associated with lower spreads. Only proven, well-connected banks facilitate capital formation with a greater ability to estimate market demand for a syndicated loan. Importantly, we find no association between spreads and other highly correlated centrality measures, such as in-degree, eigenvector, closeness, and betweenness. Together, these findings indicate that indirect connections are not important, either because banks do not share secondhand information or because (unobservable) confounding factors attenuate their effect.

5. Channels

5.1. Networks and market demand

Lenders' relationships with market participants play a critical role in arrangers' loan syndication and pricing strategy. After banks win the lead mandate, they start receiving bids from investors who want to participate in the syndicate. The initial interest rate may change during the book-building process depending on investor demand for the loan. Therefore, network relationships may allow lenders to underwrite a loan with more competitive terms by reducing the costs associated with attracting investor demand.[11] A lead arranger must also navigate the uncertainty in the syndication process. For instance, loan underwriters rarely make firm commitments or pre-commit to a book-building calendar. In this setting, well-connected lead arrangers can build syndicates more efficiently, mitigating borrower risk.

[11]Previous literature emphasizes the importance of market demand in syndication. Bruche et al. (2020) show that lead arrangers "solve a demand discovery problem" and retain lower loan shares in loan deals with high demand. Ivashina and Sun (2011) show that when market demand for a loan is high, deals become fully subscribed, and the duration of the syndication process (time on the market) is short. Bajo et al. (2016) find that well-connected IPO underwriters attain more favorable deals for their clients in IPO markets by attracting investors' attention to their deals.

A lender that can attract investors more easily during the book-building stage should also be able to complete the underwriting process faster and retain a smaller share of the loan. To test these hypotheses, we first calculate the number of days it takes for lead arrangers to complete the book-running process.[12] On average, lead arrangers take approximately 28 days to bring a deal to the market. We then examine whether post-merger lead lender centrality affects the time it takes to complete the book-running process. We regress the number of days to complete syndication (*Days in Market*) on lead lender (out-degree) centrality and present our estimates in Table 5. As shown, a large increase in post-merger lead lender centrality reduces the time it takes to complete the book-running process by approximately five days—an almost 19% reduction from the sample mean (column (1)).

In addition, if co-syndication relationships allow well-connected banks to attract investor demand, well-connected arrangers should also be able to retain a smaller fraction of the loan Bruche et al. (2020). We find evidence consistent with this hypothesis in Table 5. Specifically, we find that switching from low to high out-degree centrality lender following a bank merger leads to about a 1.1% reduction in the fraction of the loan that lead arrangers own in the deal (column (2)).

We find additional evidence that supports the relationship between bank networks and the market demand channel. Loan syndication is a private, over-the-counter market that involves large investments to borrowers for whom information is often limited and not public. Therefore, the ability to attract investors should be more important for deals that involve borrowers with higher levels of information asymmetry. To test this hypothesis, we segment our sample into firms with high information asymmetry (private or smaller firms) and low information asymmetry (public or larger firms) and examine whether firms with high information asymmetry are more sensitive to changes in prior lead arranger status (out-degree

[12]To estimate high or low demand, Bruche et al. (2020) use data on market "flex," a loan contract clause allowing the lead bank to change spreads based on market demand. Because we do not have data on market flex, we follow Ivashina and Sun (2011) and measure the number of days between the loan launch date (the start of the book-running period before loan terms are finalized) and the loan completion date. We use a smaller sample for this analysis because Dealscan does not always provide loan launch dates.

centrality) after a merger. Table 6 presents results from regressions of loan spreads for each group. The triple interaction of *Post Merger*, Δ.*Out-degree high*, and *Private* allows us to test whether private firms experience a larger reduction in their cost of debt when lead lender centrality increases after a merger. These results confirm that private (column (1)) and small firms (column (2)) experience an 8%–14% reduction (approximately 15–30 basis points) in their cost of debt by borrowing from a highly central bank after it merges with a highly lead-central lender.[13]

5.2. Alternative channels

5.2.1. Synergies

Since the credit quality of any single borrowing firm does not drive the mergers and acquisition activity of the world's largest banks, we rule out the reverse causality problem. However, endogeneity in our setting may arise if bank mergers driven by synergies or possible complementarities also correlate with the cost of capital (Levine et al. (2017)). Controlling for bank size, specialization, and market share may not be able to capture all possible mechanisms (other than centrality) through which mergers affect lending. In this light, we further refine the comparison group to partial out the effect of synergies.

To mitigate the impact of other potential synergistic effects of bank mergers, we limit our sample to mergers between lenders with high and low network centrality. The key feature in this sample is that all firms borrow from a high network centrality lender that just went through a merger. The main difference is that, before the merger, some firms borrowed from the lender with low centrality (treated), and others borrowed from the lender that was already highly central (control). Any post-merger synergies should have a similar impact on the cost of capital for both groups, allowing us to isolate the impact of the *change* in centrality on loan terms.

[13] The indicator variable *Private* is reported from Dealscan and does not vary over time, and for this reason, we drop this variable from the regression.

We first classify mergers into different groups based on the centrality of the merging banks before and after the merger. To isolate the impact of merger synergies so that our treated and control group are comparable, we only include firm-loan pairs that include pre- and post-merger loans straddling a merger between a highly central and a non–highly central bank. As a result, our final sample includes only firms that borrow from banks with high network centrality after the merger, and we identify those firms that switch from a low centrality relationship lender as our treated group. Table 7 presents the results based on the regressions of our refined sample. In column (1), we show that switching from a low-centrality to a high-centrality lender after the merger leads to a lower borrowing cost than firms whose relationship lender was already highly central. These regressions mitigate the impact of unobservable characteristics of highly central banks that correlate with borrowers' cost of debt, and using a bank×quarter fixed effect in column (2) forces our estimates to obtain from the change in centrality *across borrowers* borrowing at the same time from the same bank.[14]

Of course proven, well-connected lenders may also exploit their network position to better extract industry- or borrower-specific knowledge from participating investors. Likewise, these banks may possess superior screening or monitoring abilities. Further, synergies from bank mergers may simply correlate with our findings. We discuss these additional channels below.

5.2.2. Industry- and borrower-specific knowledge

If lead arrangers attain their status by exploiting superior industry- or borrower-specific knowledge, this knowledge would be more valuable when asymmetric information is high (consistent with Table 6). Alternatively, well-connected lenders may exploit their network position to better extract industry- or borrower-specific knowledge from syndicate members. However, during the due diligence process that precedes syndication, lead arrangers possess more soft information about the borrower than prospective investors and it is more likely

[14]Our results are qualitatively similar using industry×year and industry×year-quarter fixed effects.

that syndicate members (as a group) provide information about market demand rather than industry- or borrower-specific information. In fact, we find that in-degree centrality, our primary measure of deal participation, is not associated with lower spreads (see Table 4), contrary to the hypothesis that highly-connected participants reduce spreads.

5.2.3. Screening and monitoring

To examine the possibility that well-connected lenders offer lower spreads to borrowers because of superior screening or monitoring ability, we first examine firms' operating and performance and market value after loan origination. With superior screening abilities, firms in the portfolio of highly central lenders should outperform firms in the portfolio of less central banks. However, when we regress changes in operating performance (ROA) and market-to-book (MB) four and eight quarters after loan origination, and after accounting for selection using changes in firm relationships due to bank mergers, we fail to find a statistically significant difference in changes in firm value and performance after loan origination (see Table 8). In fact, using an event-study type of analysis in Figure 8, we show that there is no significant difference in firm values or performance several quarters before and after the origination of the loan.

With superior screening abilities, we surmise that firms in portfolios of highly central lenders should also be less likely to violate a covenant. While we do not observe loan repayment patterns, we observe whether firms violate loan covenants after origination. Covenant violations occur frequently and indicate that a firm is under some financial stress (Chava and Roberts, 2008; Nini et al., 2012). Again, our results do not support this hypothesis. In column (1) in Table 9, we regress an indicator variable that equals one if the firm violates a covenant within two years after loan origination on bank network centrality. Firms borrowing from high-centrality banks are neither more nor less likely to violate loan covenants.

Lastly, we examine whether well-connected banks spend more resources to monitor borrowers by focusing on the structure of restrictive covenants. Although we do not directly observe lead lender monitoring efforts, we plausibly assume that the number and strictness of covenants are associated with increased monitoring. Monitoring is costly but helps creditors to identify warning signs early and intervene when managers make decisions that diminish the value of debt. Without contractual rights—such as covenants—to intervene, there is no benefit to monitoring in the first place.[15]

In Table 9, we regress the strictness of loan covenants (column (2)) and the number of financial covenants (column (3)) on lender out-degree centrality.[16] Our results suggest that a large increase in out-degree centrality after a merger does not affect the number or the strictness of loan covenants that lenders impose on borrowers. Taken together, our findings are inconsistent with the view that well-connected banks offer lower spreads because of increased screening or monitoring efforts.

6. Network centrality and building reputation

A well-established result in the literature is that underwriter reputation matters for the securities underwriting process. Dennis and Mullineaux (2000) suggest that lenders care about reputational capital, which improves their ability to syndicate a loan, and hold smaller shares of the borrower in their portfolios (see also Sufi, 2007). However, the definition of reputation captures a broad set of attributes intuitively associated with an agent's visibility and relationships among peers. Therefore, even though it is clear that lender reputation is a valuable asset, the underlying mechanism that drives reputation effects is more associated with their relationships with other investors.

[15] In this sense, Park (2000) suggests that covenants increase the benefits from monitoring and, therefore, the incentive to monitor. Similarly, Rajan and Winton (1995) argue that imposing financial covenants is important because it incentivizes lenders to monitor. Empirical studies find evidence consistent with these theories by showing that active monitoring is more associated with stricter financial covenants (Sufi, 2009; Wang and Xia, 2014).

[16] The measure of covenant strictness is based on the probability that the firm will violate at least one covenant in the next quarter and is derived as in Murfin (2012). We are particularly thankful for Justin Murfin's help in constructing the measure.

We propose that our results regarding proven, well-connected banks are likely related to reputation. Past out-degree centrality is a backward-looking quantitative metric that encapsulates the more qualitative and general aspects of reputation. As we show in Section 1, strong prior connections with other lenders (and likely reputation) directly affect banks' ability to compete for deals and profit from underwriting structures.

To explore how reputations are built in the syndicated lending market, we examine various bank attributes that predict lenders' ability to become highly out-degree central. To estimate how lender attributes affect network formation, the outcome variable must account for the entire set of connections among lenders.[17] To address this challenge, we employ exponential random graph (ERG) models that use as outcomes an entire network realization (as opposed to Logit models that model connections only between two nodes).[18] The ERG approach also allows us to exploit the directed nature of loan syndication networks where banks develop relationships by participating in syndicates or arranging deals. Using ERG models, we estimate how bank characteristics (i.e., market share, size, specialization in the borrowers' industry, or the existing relationships with a borrower) affect their ability to become more connected.

We present the estimation results in Table 10. The estimates represent how bank attributes affect the probability of forming a new connection, either by joining or leading a syndicate. As might be expected, we find that banks' overall market share, industry market share, and assets increase the probability of establishing new connections (Columns (1), (3), and (5)). Only market share is not a significant attribute in connections for junior syndicate members when we estimate separately how each bank attribute affects new connections while acting as a *junior* syndicate member or as a *lead* underwriter (columns (2), (4), (6)).

[17] A simple ordinary least squares (OLS) approach is problematic because if lenders tend to reciprocate their invitations to join in deals, a central assumption of OLS (independent and identical errors) is violated. Further, an OLS approach regressing the number of a lender's connections or the existence of bank connections on bank characteristics would, by definition, limit the dependent variable to only the total number of connections, or the relationship of a pair of lenders, ignoring higher-order connections.

[18] Ahern and Harford (2014) use ERG models to estimate the occurrence of cross-industry mergers in the M&A network. The estimation of the parameters is based on Markov Chain Monte Carlo by drawing random networks from the observed network.

These results further support the view that more dominant, reputable banks become more connected by leading more deals. To interpret the economic magnitudes, consider the coefficient on lender market share in column (2). The log-odds ratio of 0.016 suggests that a lender with a median market share (about 6.3%) has a 1.5% probability of connecting with another lender with a median market share via participating (leading) in a deal. The probability increases to 8.5% if the lender's market share is in the 90th percentile.

Importantly, even after controlling for bank size (Columns (5)-(6)), the overall market and industry shares of deal participants have an economically smaller impact on the probability of making new connections.[19] However, these characteristics for lead arrangers remain large and significant, with bank assets as the strongest predictor of new connections. Overall, these findings complement our main result and show that market share (both general and industry-specific) and bank size—attributes associated with reputation—are significantly important for lead arrangers in building new connections in the syndicated loan market.

7. Discussion

The syndicated loan market is one of the most significant external financing sources for firms—corporate debt issuance exceeds the combined value of corporate bond and equity issues. Unlike private one-to-one loans, syndicated loans require lenders to compete and cooperate in a two-stage underwriting process, whereby banks first compete for the mandate of the lead arranger and then collaborate with other banks to underwrite the loans through a syndicate. Motivated by studies that link the relationships among financial market participants with corporate outcomes, we hypothesize that co-syndication networks affect lenders' syndicate structures and loan prices.

We develop a loan auction model and show that past network connections are associated with syndicates with fewer senior co-arrangers and more junior participants. These structures

[19] Our sample size in columns (5) and (6) is smaller relative to columns (1)-(4) due to limited data on lender assets.

increase loan valuations and accommodate more aggressive bids. Consistent with our model, we find evidence that proven, well-connected lenders (those with high out-degree centrality) offer lower spreads and complete the loan syndication faster. The effect is economically larger for private, unrated, and smaller borrowers, suggesting that syndication networks benefit firms with higher levels of information asymmetry by facilitating connections with multiple investors.

Our tests address endogenous firm-bank matching since we use major bank consolidations as a source of exogenous variation in firm-lender relationships. Our results underline the importance of networks by showing that lender relationships affect syndicate structures, reduce underwriter risk exposure, and allow proven, well-connected lenders, to offer more competitive rates while still retaining a higher portion of fees.

Extensive consolidation in the banking industry has created a small number of well-connected lenders that jointly underwrite and co-syndicate most private, primary-market loans. The increase in lending concentration naturally raises regulatory concerns that a few large banks may coordinate their syndication strategies and collude over loan prices. The evidence in this study, however, illustrates that prior lender network relationships serve as a mechanism to enhance competition which ultimately benefits both borrowers and lenders. Proven, well-connected lenders offer lower rates and complete deals faster.

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Variable definitions

This table provides details for the variables used throughout the paper. Accounting data are from Compustat's quarterly file. Loan information is from Dealscan. Bank information is from Compustat NA Bank, Compustat Global, and Bankscope.

Variable Names	Description
	Firm Characteristics
Assets	Book assets ($ m.)
Book Leverage	Total debt / Book assets
ROA	EBITDA / Book assets
Market-to-Book	(Market equity + Total debt + Preferred stock liquidating value - Deferred taxes and investment tax credits) / Book assets
Altman-Z	3.3×Pre-tax income/assets + 0.999×Sales/assets + 1.4 ×Retained earnings/assets + 1.2 × (Current assets - Current liabilities)/assets +0.6×Mkt equity/Total liabilities
	Loan Characteristics
Loan Spread	The All-in-drawn spread (in basis points) for each dollar borrower draw, excluding fees.
Loan Fees	The total underwriting fees (in basis points).
Amount	The total loan amount of a loan facility ($ m.) in a certain loan package.
Loan Maturity	The number of months between the earliest loan origination date and the latest maturity date in a certain loan package.
Participants #	The total number of participating banks (excluding lead-arrangers) in a certain loan facility.
Arrangers	The total number of banks acting as lead arrangers in a certain loan facility.
Days in market	The total number of days between the loan launch date, which is the start of the book-running period, and the loan completion date.
Lead lender allocation	The share of the loan amount (%) the lead arranger retains at loan origination.
Syndicate concentration	Herfindahl Hirschman Index (HHI) of lenders' loan share retained in a loan syndicate. To calculate the HHI we use the sum of the squared allocations of each lender in the syndicate.
Covenants (#)	Total number of financial covenants in the loan contract.
Cov. Strictness	Indicates the probability that the firm will violate at least one of its covenants in the next quarter, and it is constructed based on Murfin (2012).
Cov. Violation	An indicator variable that equals one if the firm reports in its 10-K or 10-Q filings that it is in violation of a loan covenant.
	Bank characteristics
Lender assets	The total value ($ billion) of lenders' assets.
Market share	The percentage of total loan volume originated by the lender in a given year.
Industry market share	The percentage of total loan volume originated by the lender in a three-digit SIC industry in a given year.
Bank capitalization	Bank equity/Bank assets
Share of rel. lending	The percentage of a lender's loan volume (in a given year) toward firms that have an existing relationship with the lender.
Degree centrality	The percentage of all lenders that a bank has co-syndicated with in a given year, normalized by the total number of banks making loans in that year.

In-degree centrality	The percentage of all lenders that a bank has been invited from as a participant (non-lead) in loan syndications in a given year, normalized by the total number of banks making loans in that year.
Out-degree centrality	The percentage of all lenders that a bank has invited in loan syndications while acting as a lead arranger in a given year, normalized by the total number of banks making loans in that year.
Eigenvector centrality	The weighted sum of the eigenvalue centrality of all investors a bank is connected to, where eigenvalue (λ) comes from the equation: $\lambda x = A'x$, where x is the eigenvector of the transposed adjacency matrix A, and λ is the maximum corresponding eigenvalue of the matrix.
Betweenness centrality	$\sum\limits_{j \neq j' \neq i \neq j} (P_{j-i-j'}/P_{j,j'})$, where $P_{jj'}$ is the total number of shortest paths (i.e., shortest connections among different banks) that can bring bank j and j' together, and $P_{j-i-j'}$ is the number of those shortest paths that pass through bank i. Because our network is directed, to normalize this centrality measure we divide by the maximum betweenness in a network with N lenders (i.e., (N-1)*(N-2))
Closeness centrality	$(N-1)/\sum_{i \neq j} D_{i,j}$ where $D_{i,j}$ is the length of the shortest path between bank i and j, and N is the total number of investors in the networks.

Figure 1: Lender bid functions

This figure illustrates the density function of the interest rate bid $R()$ of two lenders with different levels of network centrality conditional on observing signal θ about the quality of the borrower. High centrality lenders offer lower rates than low centrality lenders on average, but not always, due to the variation in borrower-quality signals.

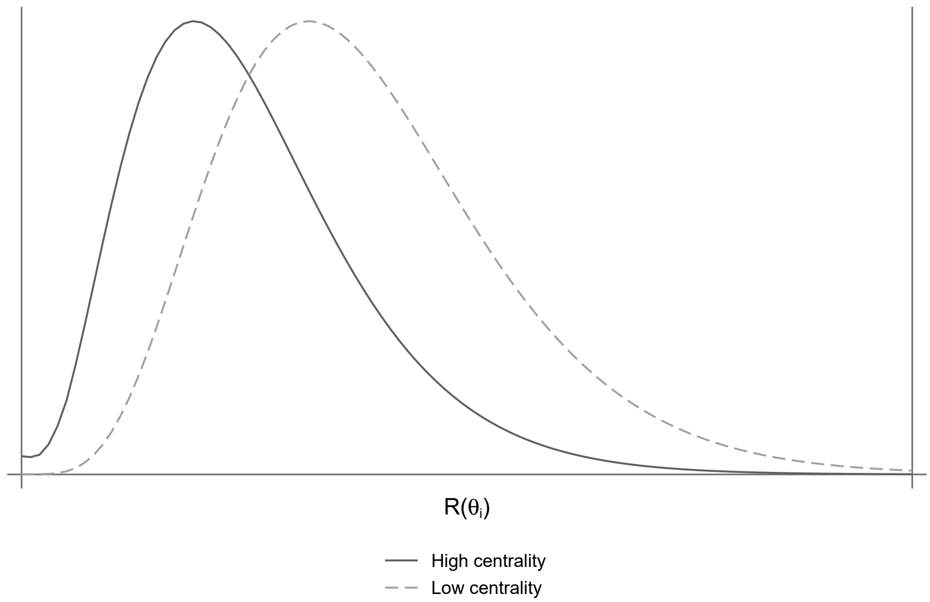


Figure 2: Network centrality measures

This figure shows the average degree, in-degree, out-degree, betweenness, eigenvector, and closeness network centrality measures. We define each centrality measure in the Variable definitions Table.

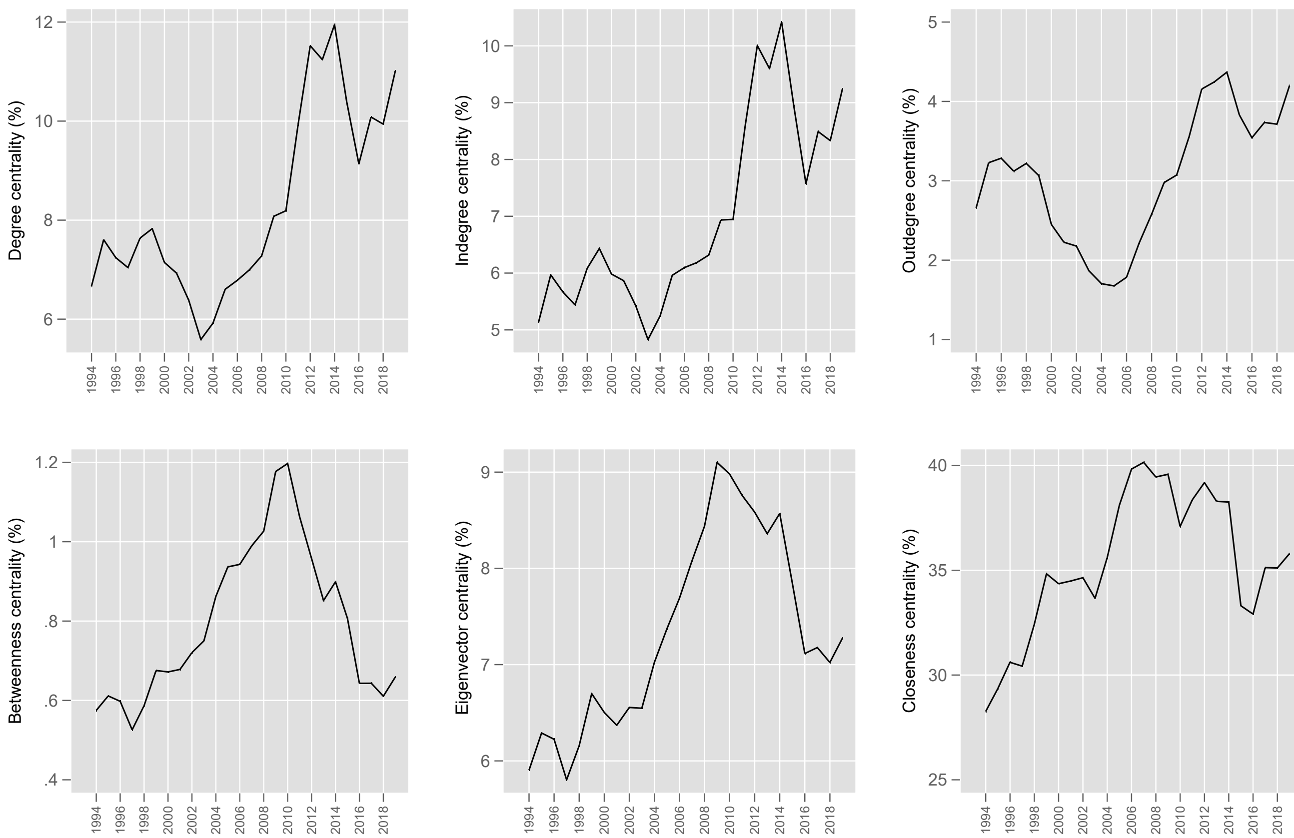


Figure 3: Lender centrality, size, market share, and centrality measures

This figure shows the cross-lender connections of banks that participate in the syndicated loan market in the year 2015. The named nodes on the edge of circle are the top 20 lenders by market share in the US. The size of all nodes is a function of banks' assets. The color of the node represents banks' normalized *Out-degree* centrality. The edges between the pairs of lenders are wider when two banks syndicate more loans with each other in a given year.

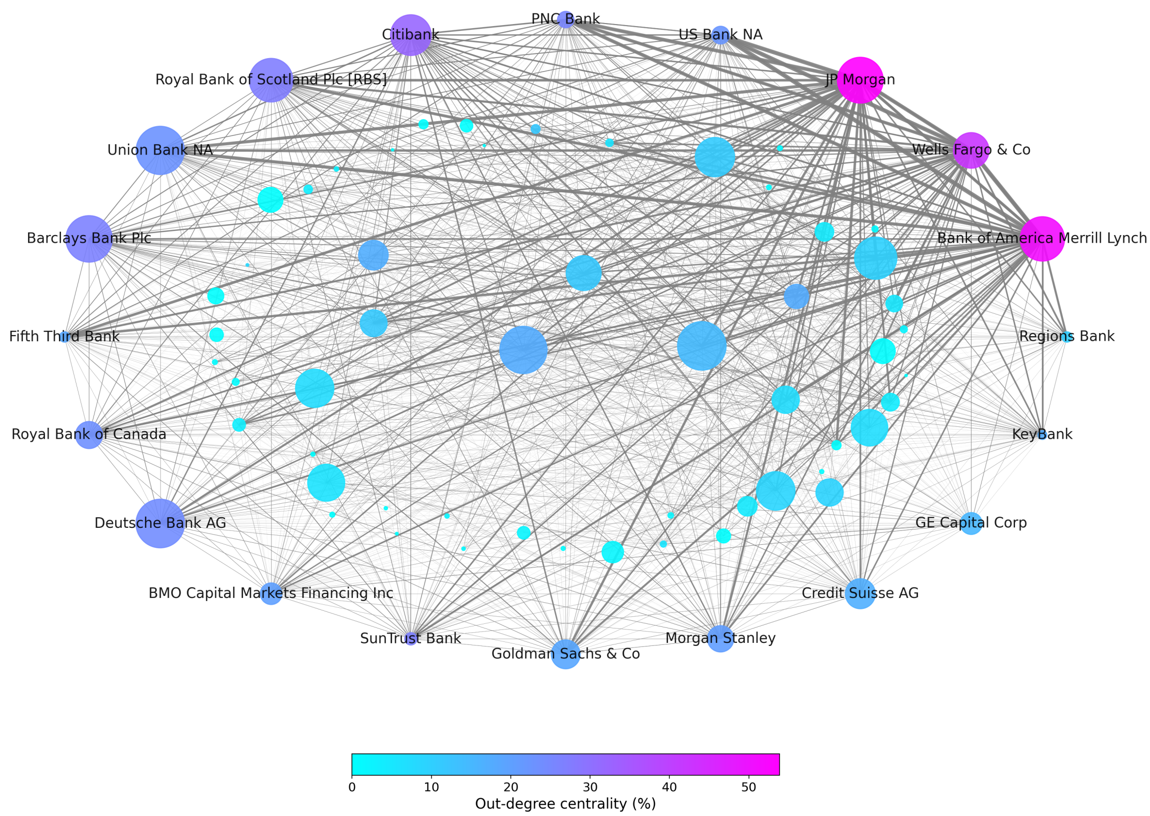


Figure 4: Lenders' network centrality and loan characteristics

Loan pricing structure: This figure shows the average residualized loan spread and total loan fees grouped by lender degree, in-degree, out-degree, betweenness, eigenvector, and closeness network centrality measures. The residuals are calculated using regression (6) excluding lender centrality from the model. We define each centrality measure in the Variable definitions Table.

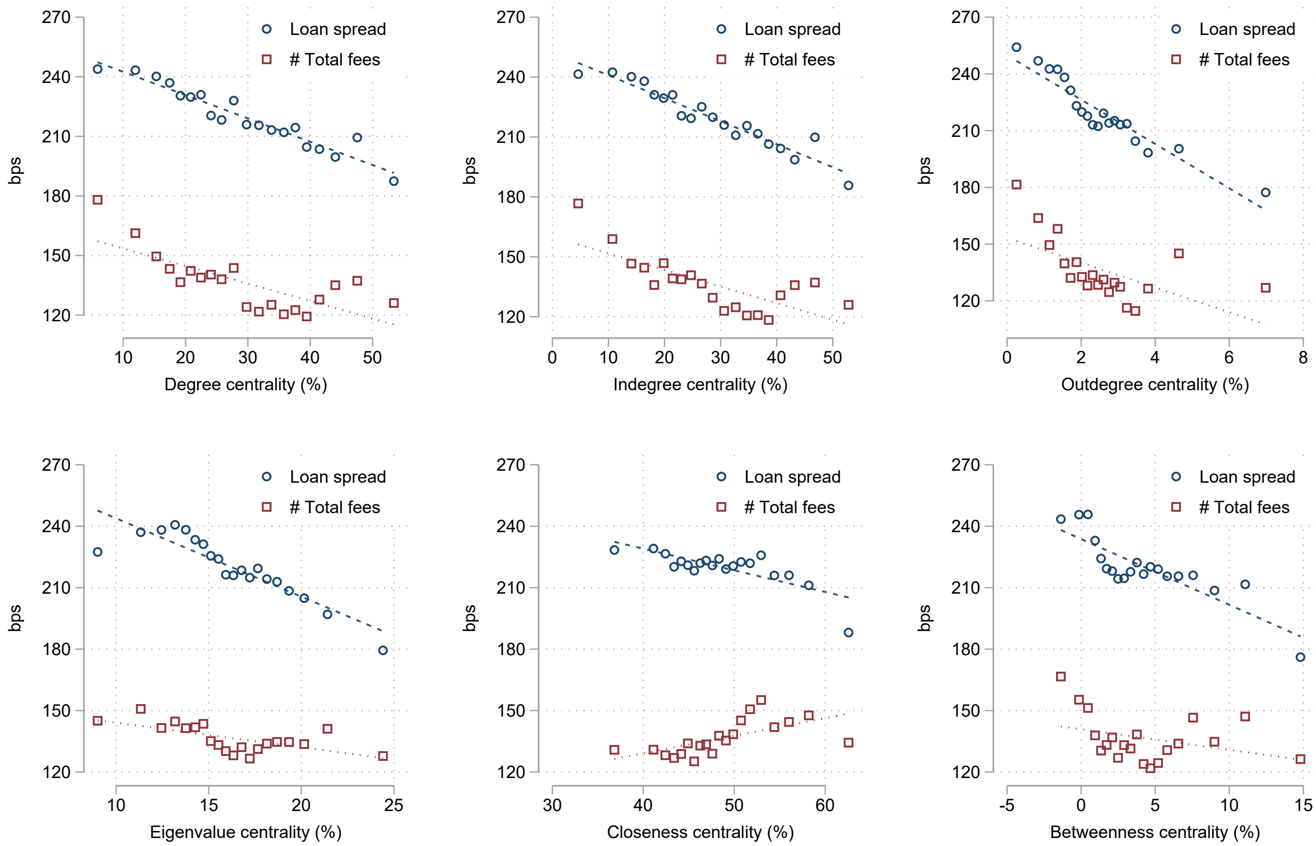


Figure 5: Loan syndicate structure: This figure shows the average residualized number of junior participants (circles) and lead arrangers (boxes) in a loan syndicate grouped by lender degree, in-degree, out-degree, betweenness, eigenvector, and closeness network centrality measures. The residuals are calculated using regression (6) excluding lender centrality from the model. We define each centrality measure in the Variable definitions Table.

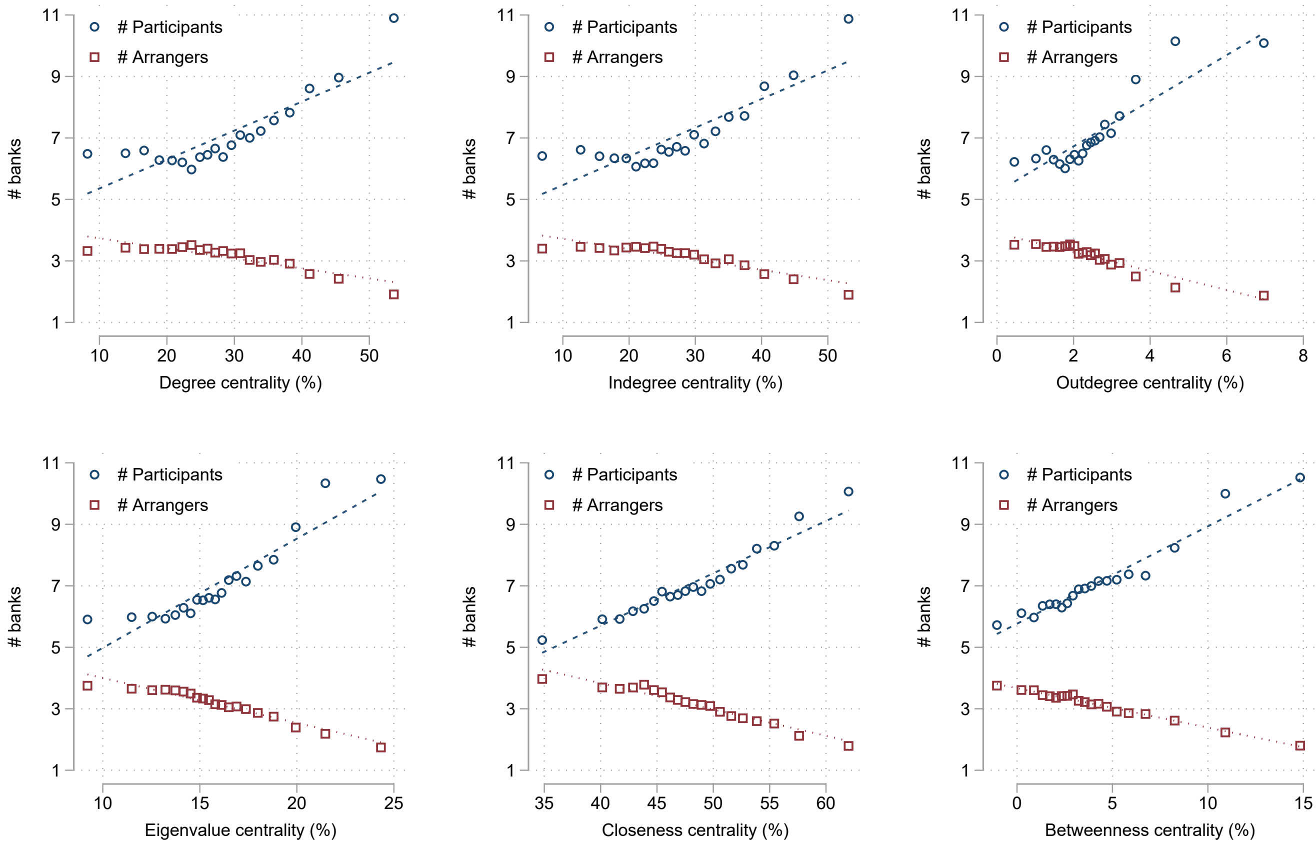
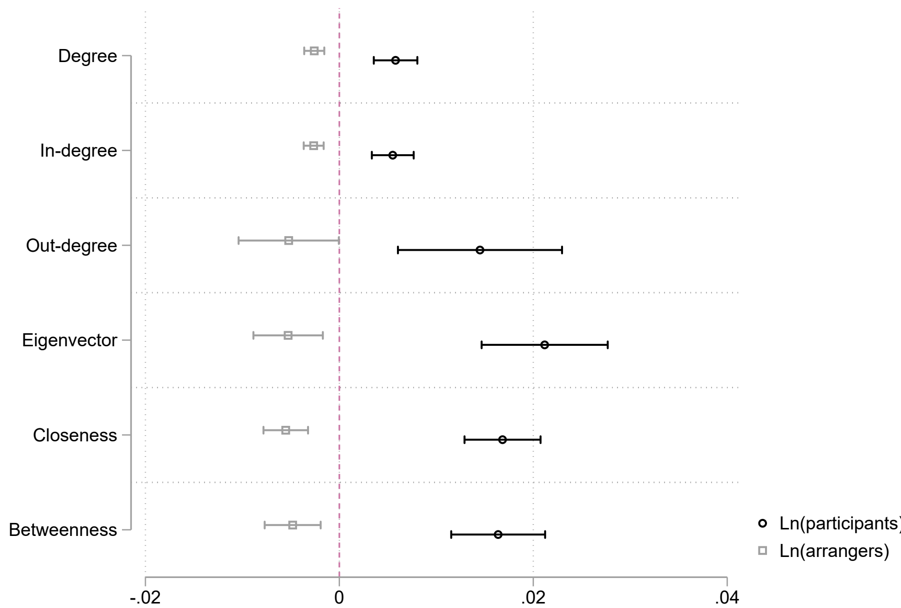


Figure 6: Loan syndicate structure estimation results

The figures present the estimated effect of lenders' degree, in-degree, out-degree, betweenness, eigenvector, and closeness centrality measures on syndicate structure based on regressions of the model in equation (6). In figure (a) (top), the dependent variable is the natural log of participants and arrangers in the syndicate. In figure (b) (bottom), the dependent variable is the lead arranger's allocation, and the natural log of the deal's total fee income. All regressions include firm, year-quarter, loan type, loan purpose, and rating fixed effects. Horizontal lines indicate 95% confidence intervals of centrality estimates (γ) based on robust standard errors, clustered at the firm and year level. Definitions for all variables are in the Variable definitions Table. We tabulate all estimates of the regressions in panels (a) and (b) in Tables B.1, B.2, B.3, and B.4 of the Online Appendix, respectively.

(a) $Ln(Participants),\ Ln(Arrangers)_{i,b,t} = \alpha_i + \alpha_t + \beta_1 C_{b,t} + \beta_2 X_{i,t} + \gamma Lender\ Centrality_{b,t} + \epsilon_{i,b,t}$



(b) $Ln(fee\text{-}income),\ Lead\ allocation_{i,b,t} = \alpha_i + \alpha_t + \beta_1 C_{b,t} + \beta_2 X_{i,t} + \gamma Lender\ Centrality_{b,t} + \epsilon_{i,b,t}$

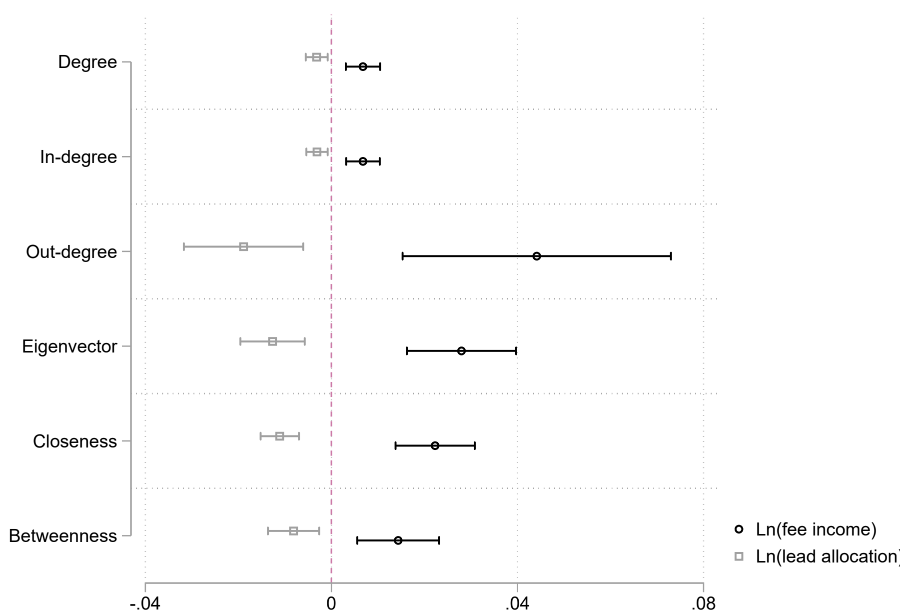


Figure 7: Overview of the identification strategy

This figure illustrates the identification strategy and underlying assumptions of our empirical strategy. The regressions use bank mergers to identify shifts in a firm's credit relationship from a low centrality bank to a high centrality bank. In this example, Firm 1 has a credit relationship with the high centrality lender Bank A. Firm 2 has a credit relationship with a low centrality lender Bank B, which later merges with Bank B and creates bank AB. In the post-merger period, we observe both Firm 1 and Firm 2 borrowing from the merged bank AB. However, only Firm 2 experiences a large change in the centrality of its lead lender, and thus this loan serves as a treated unit. Firm 1, which also borrows from bank AB, does not experience a large change in lead-lender centrality and thus the loan to Firm 1 is a control unit. After Bank AB (high-centrality) merges with Bank C (low-centrality), subsequent loans of bank ABC to Firms 1 and 2 are control units because AB experiences no change in centrality. By contrast, the loan to Firm 3 is a treated unit because the credit relationship is transferred from the portfolio of the low-centrality lender.

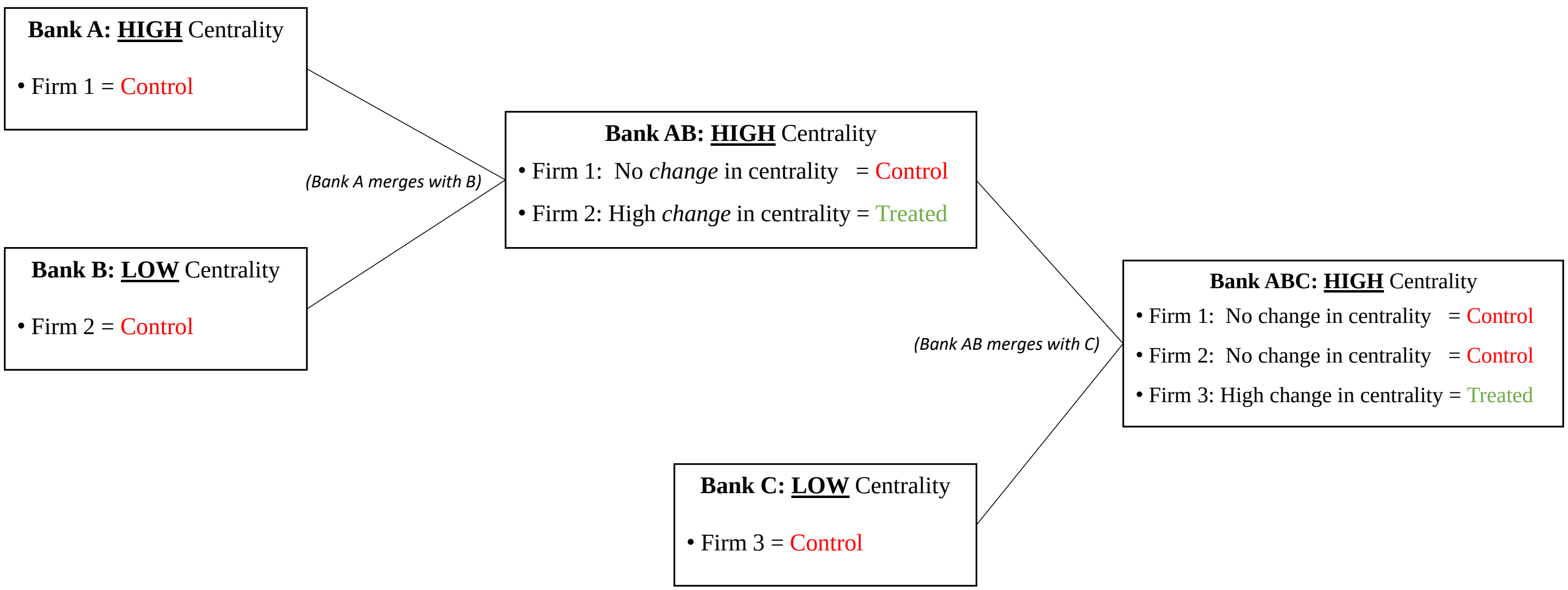
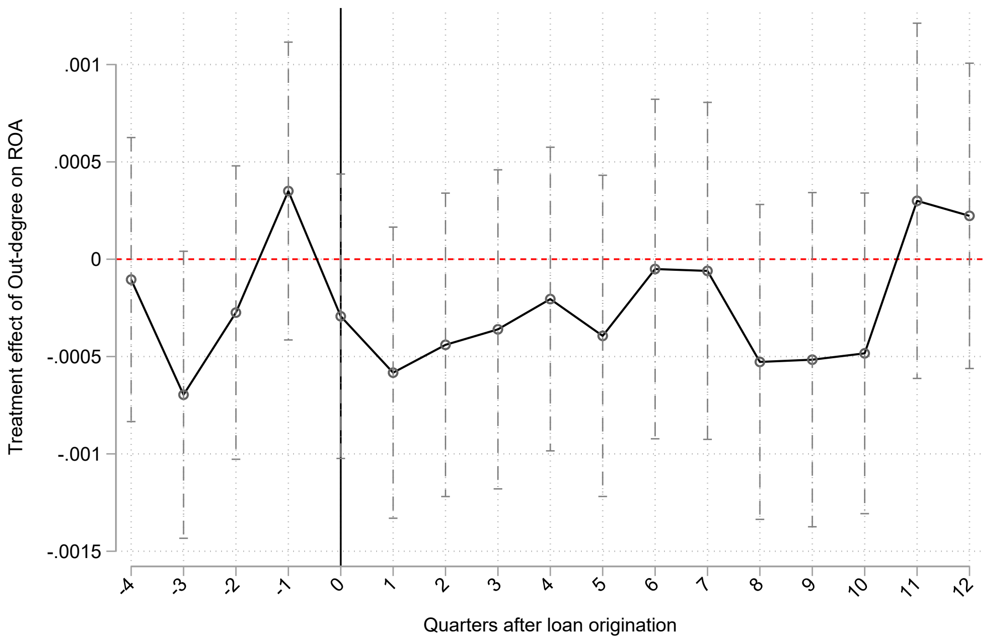


Figure 8: Bank centrality and firms' post-origination performance

This figure shows event-study estimates of changes in firms' operating performance and value before and after loan origination for firms borrowing from lenders with high out-degree centrality. Each figure plots the estimate of high out-degree centrality from a regression of return on assets (top sub-figure) and market-to-book ratio (bottom sub-figure) on the lender's out-degree centrality similar to equation (7)

(a) Treatment effect of out-degree centrality on ROA



(b) Treatment effect of out-degree centrality on Mkt-to-Book

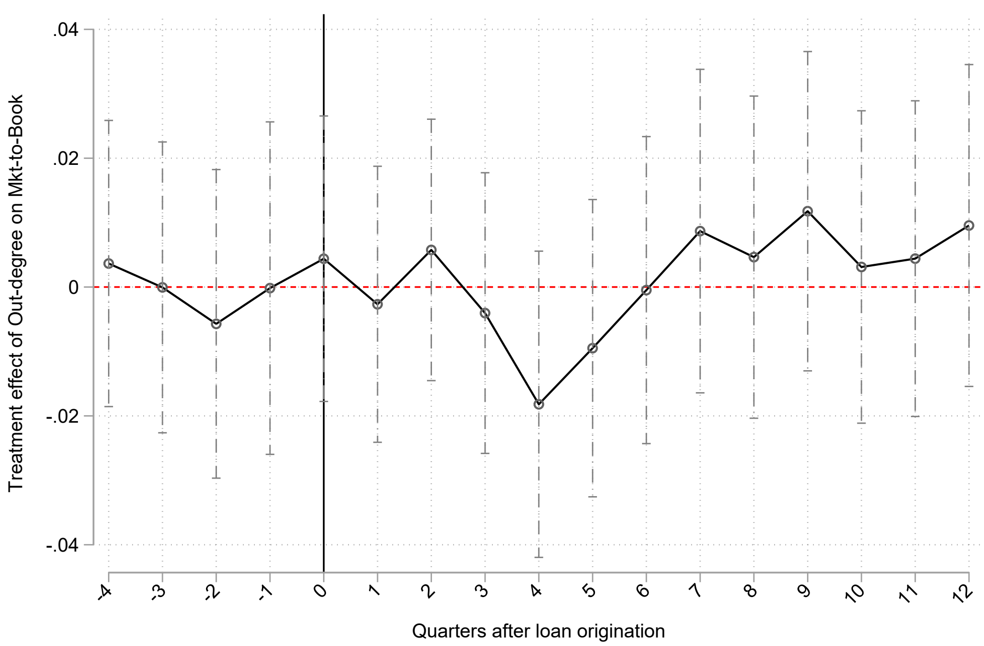


Table 1: Summary statistics

This table presents summary statistics of firm, loan, and bank characteristics. A detailed description of each variable is available in the Variables definitions Table.

Panel A: Firm and loan characteristics

	N	Mean	SD	10%	50%	90%
Assets	45717	13839.51	35090.11	273.67	3153.48	30882.66
ROA	45717	0.03	0.02	0.01	0.03	0.06
Market-to-Book value	45717	1.40	0.90	0.64	1.15	2.47
Tangibility	45717	0.32	0.25	0.05	0.24	0.71
Has SP rating	45717	0.55	0.50	0.00	1.00	1.00
Book leverage	45717	0.36	0.21	0.10	0.34	0.63
Loan spread (bps)	45717	210.02	131.47	75.00	175.00	375.00
Total fees (bps)	32161	109.92	124.03	12.50	50.00	287.50
Amount	45717	720.73	1014.79	35.00	350.00	1800.00
Maturity	45717	53.07	21.14	12.00	60.00	78.00
Credit line	45717	0.62	0.49	0.00	1.00	1.00
Participants #	45717	7.25	7.28	0.00	5.00	17.00
Arrangers #	45717	3.10	2.51	1.00	2.00	7.00
Lead lender share	10718	25.02	27.41	5.83	13.33	67.57
Days in market	7701	27.53	24.05	10.00	21.00	50.00
Cov. violation	21806	0.03	0.18	0.00	0.00	0.00
Cov. Strictness	30570	25.87	21.04	0.00	29.82	57.30
Syndicate concentration	11011	22.49	27.62	4.72	10.53	59.68

Panel B: Bank characteristics

	N	Mean	SD	10%	50%	90%
Lender assets	4487	578.92	714.05	18.93	256.49	1736.34
Market share	4487	8.17	7.86	0.84	6.35	17.40
Industry market share	4487	5.14	2.94	1.95	4.64	8.88
Lender capitalization	4487	7.48	3.27	3.43	7.31	11.84
Share of rel. lending	4487	13.01	10.61	2.17	9.65	29.91
Lender equity	4487	35.52	48.17	1.72	15.99	87.70
Degree	4487	13.51	11.16	1.89	10.39	27.49
In-degree	4487	12.03	11.46	0.29	9.01	26.39
Out-degree	4487	4.43	2.24	1.31	4.41	7.37
Eigenvector	4487	10.88	5.11	3.43	11.20	16.99
Closeness	4487	41.96	9.78	31.72	43.96	50.70
Betweenness	4487	1.42	2.46	0.00	0.56	3.59

Table 2: Network position and loan prices

The dependent variable in the regressions is the natural logarithm of loan spread, excluding fees. *Degree, In-degree, Out-degree, Eigenvector, Closeness,* and *Betweenness* are normalized measures of lead arrangers' network centrality. All regressions include firm, year-quarter, loan type, loan purpose, and rating fixed effects. We define all variables in the Variable definitions Table. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Ln(Loan Spread)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Degree	-0.001*						
	(0.001)						
In-degree		-0.001*					
		(0.001)					
Out-degree			-0.015***				-0.012***
			(0.003)				(0.003)
Eigenvector				-0.008***			-0.006**
				(0.002)			(0.003)
Closeness					-0.005***		-0.001
					(0.001)		(0.002)
Betweenness						-0.003*	0.000
						(0.002)	(0.002)
Ln(Amount)	-0.101***	-0.101***	-0.102***	-0.100***	-0.101***	-0.101***	-0.100***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ln(Maturity)	0.064***	0.064***	0.064***	0.063***	0.064***	0.064***	0.064***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Ln(Lender assets)	-0.010	-0.010	-0.011	-0.004	-0.008	-0.013*	-0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Lender capitalization	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Market share	-0.001	-0.001	0.000	0.000	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry market share	-0.001	-0.001	-0.005**	-0.001	-0.001	-0.001	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Ln(Firm assets)	-0.085***	-0.085***	-0.085***	-0.083***	-0.083***	-0.085***	-0.083***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Market-to-Book value	-0.084***	-0.084***	-0.084***	-0.084***	-0.084***	-0.084***	-0.084***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Book leverage	0.516***	0.516***	0.514***	0.518***	0.517***	0.515***	0.517***
	(0.042)	(0.042)	(0.041)	(0.042)	(0.042)	(0.042)	(0.042)
Tangibility	-0.182**	-0.182**	-0.180**	-0.177**	-0.178**	-0.181**	-0.176**
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
ROA	-2.241***	-2.241***	-2.238***	-2.240***	-2.246***	-2.243***	-2.237***
	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)	(0.266)
Observations	44659	44659	44659	44659	44659	44659	44659
Adjusted R^2	0.754	0.754	0.754	0.754	0.754	0.754	0.754

Table 3: Network position and syndicate structure

The dependent variable in all regressions is *Syndicate concentration*, which is the HHI of lenders' loan shares retained in the syndicate. *Degree, In-degree, Out-degree, Eigenvector, Closeness,* and *Betweenness* are measures of lead arrangers' network centrality. All regressions include firm, year-quarter, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We define all variables in the Variable definitions Table. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Syndicate concentration						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Degree	-0.037						
	(0.029)						
In-degree		-0.039					
		(0.028)					
Out-degree			-0.768***				-0.537***
			(0.206)				(0.188)
Eigenvector				-0.338***			0.054
				(0.106)			(0.173)
Closeness					-0.332***		-0.447**
					(0.096)		(0.175)
Betweenness						-0.014	0.267**
						(0.072)	(0.109)
Ln(Amount)	-5.063***	-5.062***	-5.065***	-5.029***	-5.004***	-5.073***	-5.005***
	(0.589)	(0.589)	(0.588)	(0.587)	(0.587)	(0.589)	(0.587)
Ln(Maturity)	-3.580***	-3.581***	-3.511***	-3.570***	-3.562***	-3.572***	-3.483***
	(0.484)	(0.484)	(0.483)	(0.484)	(0.482)	(0.484)	(0.481)
Ln(Lender assets)	0.316	0.328	0.296	0.606*	0.564*	0.245	0.715**
	(0.331)	(0.333)	(0.331)	(0.327)	(0.332)	(0.339)	(0.342)
Lender capitalization	0.114	0.114	0.130	0.118	0.106	0.114	0.156*
	(0.094)	(0.094)	(0.094)	(0.093)	(0.093)	(0.094)	(0.094)
Market share	0.004	0.005	0.042	0.032	0.042	-0.022	0.044
	(0.052)	(0.052)	(0.052)	(0.050)	(0.051)	(0.047)	(0.052)
Industry market share	-0.081	-0.075	-0.205	-0.024	0.005	-0.108	-0.119
	(0.142)	(0.142)	(0.147)	(0.141)	(0.140)	(0.145)	(0.145)
Ln(Firm assets)	-3.648***	-3.644***	-3.690***	-3.540***	-3.473***	-3.687***	-3.518***
	(0.795)	(0.795)	(0.794)	(0.796)	(0.797)	(0.796)	(0.796)
Market-to-Book value	0.155	0.153	0.144	0.139	0.139	0.167	0.150
	(0.585)	(0.585)	(0.584)	(0.581)	(0.581)	(0.586)	(0.581)
Book leverage	-3.716	-3.715	-3.633	-3.536	-3.488	-3.733	-3.352
	(2.945)	(2.944)	(2.934)	(2.910)	(2.891)	(2.950)	(2.876)
Tangibility	4.491	4.516	4.505	4.925	4.994	4.407	5.088
	(4.171)	(4.172)	(4.163)	(4.189)	(4.166)	(4.165)	(4.157)
ROA	-31.670	-31.634	-32.405*	-31.685	-32.281*	-31.915	-33.274*
	(19.401)	(19.397)	(19.343)	(19.352)	(19.344)	(19.424)	(19.240)
Observations	10070	10070	10070	10070	10070	10070	10070
Adjusted R^2	0.771	0.771	0.772	0.772	0.772	0.771	0.773

Table 4: Network position and loan prices: Evidence from bank mergers

In regressions (1)–(7), the dependent variable is the natural logarithm of loan spread measured in basis points. *Post Merger* is an indicator variable that equals one if the firm extends a relationship with a bank that merged with the previous lender of the firm. Δ.*Degree high,* Δ.*In-degree high,* Δ.*Out-degree high,* Δ.*Eigenvector high,* Δ.*Closeness high*, and Δ.Betweenness high are indicator variables that equal one if the firm extends a relationship with a lender whose network centrality changes from the bottom or middle tercile to the top tercile of the yearly distribution of each (respective) centrality measure, and zero otherwise. The regressions also include as controls the following lender characteristics: *Market share high*, which equals one if the lender's share of loans it underwrites in a given year is at the top tercile of the yearly distribution and zero otherwise; *Industry Market Share high*, which equals one if the lender's share of loans it underwrites in a given SIC-3 industry and year is at the top tercile of the yearly distribution, and zero otherwise; and *Ln(Lender assets)*, which is the natural logarithm of lenders' assets. All regressions include firm controls (Ln(firm assets), market-to-book ratio, book leverage, tangibility, and ROA) and loan controls (loan maturity, loan amount, and Ln(participants)), as well as firm, year-quarter, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Ln(Total Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Merger	-0.009	-0.010	-0.007	-0.010	-0.014	-0.010	-0.006	-0.008
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Degree high	-0.020*							
	(0.011)							
Post merger*Δ.Degree high	-0.030*							
	(0.016)							
In-degree high		-0.021**					-0.018*	0.002
		(0.010)					(0.011)	(0.011)
Post merger*Δ.In-degree high		-0.020					0.038	0.031
		(0.021)					(0.032)	(0.028)
Out-degree high			-0.060***				-0.056***	-0.002
			(0.014)				(0.015)	(0.025)
Post merger*Δ.Out-degree high			-0.043***				-0.078***	-0.068***
			(0.015)				(0.023)	(0.021)
Betweenness high				-0.022			-0.020	-0.023
				(0.014)			(0.015)	(0.015)
Post merger*Δ.Betweenness high				-0.011			0.059*	0.050*
				(0.018)			(0.030)	(0.028)
Eigenvector high					0.005		0.030	0.072***
					(0.024)		(0.022)	(0.026)
Post merger*Δ.Eigenvector high					-0.031		-0.061*	-0.043
					(0.051)		(0.035)	(0.035)
Closeness high						-0.014	0.013	0.012
						(0.013)	(0.017)	(0.017)
Post merger*Δ.Closeness high						-0.039**	-0.037	-0.047*
						(0.019)	(0.028)	(0.026)
Ln(Lender Assets)	-0.019**	-0.021**	-0.010	-0.020**	-0.022**	-0.020**	-0.012	0.026
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.029)
Market share high	-0.013	-0.017	0.005	-0.015	-0.014	-0.016	0.005	0.005
	(0.011)	(0.011)	(0.012)	(0.011)	(0.013)	(0.010)	(0.011)	(0.016)
Industry market share high	0.016	0.016	0.018	0.016	0.021	0.016	0.019	0.020*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Lead Arranger FEs	No	No	No	No	No	No	No	Yes
Observations	13954	13954	13954	13954	13954	13954	13954	13948
Adjusted R^2	0.792	0.792	0.793	0.792	0.785	0.792	0.793	0.798

Table 5: Time on the market and lender loan share retention

In column (1), the dependent variable (*Days in Market*) is the total number of days from the loan launch date until the loan underwriting process is completed. In column (2), the dependent variable (*Lead Bank Share*) is the lead arranger's share of the total loan amount. *Post Merger* is an indicator variable that equals one if the firm extends a relationship with a bank that merged with the previous lender of the firm. Δ.*Out-degree high* is an indicator variable that equals one if the firm extends a relationship with a lender whose network centrality changes from the bottom or middle tercile to the top tercile of the yearly distribution of out-degree centrality and zero otherwise. All regressions include firm controls (Ln(firm assets), market-to-book ratio, book leverage, tangibility, and ROA) and loan controls (loan maturity and loan amount), as well as firm, year-quarter, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1) Days in market	(2) Lead lender allocation
Post merger*Δ.Out-degree high	-5.003**	-1.113*
	(2.499)	(0.622)
Δ.Out-degree high	1.408**	-3.236***
	(0.638)	(1.002)
Post Merger	-8.513*	-2.920***
	(5.128)	(0.797)
Ln(Lender Assets)	0.470	-0.606
	(0.489)	(0.480)
Market share high	-0.547	0.571
	(0.881)	(0.663)
Industry market share high	-3.100***	5.518***
	(1.172)	(0.908)
Ln(Maturity)	0.579	-3.287***
	(1.195)	(0.867)
Ln(Amount)	1.583	-4.416***
	(0.992)	(1.105)
Book Leverage	-12.804	-6.955
	(10.338)	(5.165)
ROA	50.576	-18.342
	(80.221)	(34.754)
Market-to-Book	-10.313**	-0.579
	(4.948)	(0.979)
Tangibility	-64.625**	-20.530***
	(26.989)	(6.524)
Ln(Firm Assets)	-8.583**	-4.584***
	(3.735)	(1.173)
Observations	4645	4561
Adjusted R^2	0.616	0.651

Table 6: Lender networks and information asymmetry

In regressions (1)–(2), the dependent variable is the natural logarithm of loan spreads. *Post-merger* is an indicator variable that equals one if the firm extends a relationship with a bank that merged with the previous lender of the firm. Δ.*Out-degree high* is an indicator variable that equals one if the firm extends a relationship with a lender whose network centrality changes from the bottom or middle tercile to the top tercile of the yearly distribution of out-degree centrality, and zero otherwise. *Private* is an indicator variable that equals one if the firm is not publicly listed, and zero otherwise; *Small* is an indicator variable that equals one if the firm is at the lowest tercile of the yearly distribution of firm assets in our sample, and zero otherwise. All regressions include firm controls (Ln(firm assets), market-to-book ratio, book leverage, tangibility, and ROA) and loan controls (loan maturity and loan amount), as well as firm, year-quarter, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1) Ln(Spread)	(2) Ln(Spread)
Post merger*Δ.Out-degree high*Private	-0.141**	
	(0.065)	
Δ.Out-degree high*Private	-0.016	
	(0.031)	
Post merger*Δ.Out-degree high*Small		-0.080*
		(0.047)
Δ.Out-degree high*Small		0.031
		(0.034)
Post merger*Δ.Out-degree high	-0.051***	-0.040**
	(0.018)	(0.019)
Δ.Out-degree high	0.003	-0.012
	(0.025)	(0.034)
Post Merger	-0.009	-0.015
	(0.020)	(0.016)
Ln(Lender Assets)	0.039	0.023
	(0.028)	(0.043)
Market share high	0.007	0.018
	(0.017)	(0.027)
Industry market share high	0.018	0.023**
	(0.012)	(0.011)
Ln(Maturity)	0.073***	0.068***
	(0.013)	(0.013)
Ln(Amount)	-0.080***	-0.083***
	(0.010)	(0.012)
Book Leverage	0.465***	0.483***
	(0.072)	(0.069)
ROA	-2.731***	-2.649***
	(0.487)	(0.406)
Market-to-Book	-0.100***	-0.110***
	(0.016)	(0.016)
Tangibility	-0.099	-0.104
	(0.143)	(0.145)
Ln(Firm Assets)	-0.110***	-0.104***
	(0.024)	(0.027)
Observations	13948	13948
Adjusted R^2	0.799	0.792

Table 7: This Table presents regressions of loan spreads on lender network centrality. In columns (1)–(2), we examine the effect of lead arrangers' out-degree centrality on loan spreads. We limit our sample to firm-loan observations that involve consolidations between banks with different levels of pre-merger out-degree centrality and the out-degree centrality of the combined bank is high. The variable Δ.*Out-degree high* equals one if the firm's previous relationship lender had low out-degree centrality before the merger, and zero if its out-degree centrality was high. *Post Merger* is an indicator variable that equals one for loans originated after the underwriter merged with (or acquired) the borrower's relationship lender. All regressions include firm controls (Ln(firm assets), market-to-book ratio, book leverage, tangibility, and ROA) and loan controls (loan maturity and loan amount), as well as firm, year-quarter, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1) Ln(Spread)	(2) Ln(Spread)
Post merger*Δ.Out-degree high	-0.097***	
	(0.024)	
Δ(Out-degree high)		-0.027**
		(0.013)
Ln(Lender Assets)	-0.002	
	(0.010)	
Industry market share high	0.034**	
	(0.016)	
Market share high	-0.024	
	(0.016)	
Ln(Maturity)	0.056**	0.097***
	(0.023)	(0.028)
Ln(Amount)	-0.048***	-0.046**
	(0.013)	(0.019)
Ln(Firm Assets)	-0.146***	-0.066***
	(0.038)	(0.012)
Market-to-Book	-0.157***	-0.182***
	(0.028)	(0.020)
Book Leverage	0.427***	0.592***
	(0.127)	(0.072)
Tangibility	-0.171	0.076
	(0.168)	(0.054)
ROA	-2.451***	-3.500***
	(0.725)	(0.652)
Firm FEs	Yes	No
Year-quarter FEs	Yes	No
Bank*Year-quarter FEs	No	Yes
Observations	9182	8993
Adjusted R^2	0.809	0.698

Table 8: Bank centrality and screening

In columns (1)–(2), the dependent variable is the change in ROA four and eight quarters after loan origination, respectively. In columns (3)–(4) the dependent variable is the change in market-to-book four and eight quarters after loan origination, respectively. Δ.*Out-degree high* is an indicator variable that equals one if the lead arranger's out-degree centrality changes from the lowest or middle tercile to the top tercile of the distribution across lenders, and zero otherwise. *Post merger* is an indicator variable that equals one for loans originated after the underwriter merged with (or acquired) the borrower's relationship lender, and zero otherwise. The regressions include firm controls (assets, book leverage, ROA, market-to-book ratio, and Altman's Z-score) and loan controls (loan maturity, loan amount, and number of participants), as well as industry (SIC-3), year, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	$\Delta(ROA)_{t+4}$	$\Delta(ROA)_{t+8}$	$\Delta(MB)_{t+4}$	$\Delta(MB)_{t+8}$
	(1)	(2)	(3)	(4)
Post merger*Δ.Out-degree high	0.001	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.018)	(0.021)
Out-degree high	-0.000	0.000	-0.016	0.009
	(0.001)	(0.001)	(0.014)	(0.014)
Post Merger	-0.000	-0.001	0.001	0.028
	(0.001)	(0.001)	(0.022)	(0.025)
Ln(Lender Assets)	-0.000	0.000	-0.005	-0.001
	(0.000)	(0.000)	(0.010)	(0.008)
Industry market share high	0.000	0.001	0.012	0.010
	(0.001)	(0.001)	(0.016)	(0.017)
Market share high	0.001	0.000	0.026*	0.013
	(0.000)	(0.000)	(0.014)	(0.014)
Ln(Firm Assets)	-0.000	-0.000	-0.033***	-0.043***
	(0.001)	(0.000)	(0.009)	(0.012)
Market-to-Book	0.005***	0.005***	-0.333***	-0.413***
	(0.001)	(0.001)	(0.029)	(0.033)
Book Leverage	0.003	0.004	0.235***	0.226**
	(0.003)	(0.003)	(0.069)	(0.092)
Tangibility	0.004	0.007	-0.072	-0.015
	(0.005)	(0.005)	(0.091)	(0.113)
ROA	-0.635***	-0.684***	2.660***	1.805**
	(0.031)	(0.034)	(0.649)	(0.710)
Observations	12437	12437	12437	12437
Adjusted R^2	0.569	0.615	0.536	0.576

Table 9: Bank centrality and monitoring

In columns (1)–(3), the dependent variable is, respectively, as follows: (1) an indicator variable that equals one if the firm violates a covenant within two years after loan origination, and zero otherwise; (2) the number of financial covenants in the contract; and (3) the stringency of financial covenants, which represents the probability that the firm will violate at least one covenant over the next quarter (see Murfin, 2012). Δ.*Out-degree high* is an indicator variable that equals one if the lead arranger's out-degree centrality changes from the lowest or middle tercile to the top tercile of the distribution across lenders, and zero otherwise. *Post merger* is an indicator variable that equals one for loans originated after the underwriter merged with (or acquired) the borrower's relationship lender, and zero otherwise. The regressions include firm controls (Ln(assets), Book leverage, ROA, Market-to-Book, and Altman's Z-score) and loan controls (loan maturity, loan amount, and number of participants), as well as firm, year, loan type, loan purpose (e.g., acquisition), and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1) Cov. Violation	(2) Covenants (#)	(3) Ln(Cov. Strictness)
Post merger*Δ.Out-degree high	-0.004	-0.018	-0.223
	(0.018)	(0.039)	(0.173)
Δ.Out-degree high	0.013	-0.058*	-0.131
	(0.013)	(0.032)	(0.146)
Post merger	-0.004	-0.047	0.148
	(0.022)	(0.053)	(0.204)
Ln(Lender Assets)	-0.001	0.013	-0.254***
	(0.007)	(0.019)	(0.084)
Market share high	-0.004	-0.032	0.219**
	(0.010)	(0.024)	(0.104)
Industry market share high	-0.002	-0.017	-0.088
	(0.013)	(0.028)	(0.120)
Book Leverage	0.144	0.157	10.852***
	(0.089)	(0.185)	(1.343)
ROA	-1.529***	-1.737	-35.088***
	(0.577)	(1.261)	(7.680)
Market-to-Book	-0.003	-0.025	-0.079
	(0.026)	(0.043)	(0.269)
Tangibility	-0.077	0.100	-0.664
	(0.146)	(0.371)	(1.737)
Ln(Firm Assets)	0.012	-0.127**	-0.140
	(0.025)	(0.053)	(0.245)
Observations	4378	5255	5255
Adjusted R^2	0.541	0.689	0.665

Table 10: Formation of loan syndicate connections

This tables presents estimates from exponential random graph models (ERGM). The dependent variable in both Panels is the creating of a new connection between lenders in the loan syndication network, constructed from ties they develop in joint loan underwriting syndicates. The coefficients are the contribution of lenders' characteristics (*Market share, Industry market share* and *bank assets*) on the conditional log-odds that any two lenders will engage in a new tie. The conditional log-odds coefficients represent the effect on the formation of an individual tie holding all other ties fixed. The intercept estimate (*Edges*) indicates the homogeneous probability of forming a new connection when a random lender is added to the network. The ERG model is estimated via MCMC maximum likelihood. We calculate standard errors using the standard deviations of the posterior distribution of the corresponding parameter estimates and report them in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Dependent variable: Prob(New connection)					
	(1)	(2)	(3)	(4)	(5)	(6)
Edges	-6.179^{***}	-6.179^{***}	-6.318^{***}	-6.315^{***}	-2.381^{***}	-2.390^{***}
	(0.004)	(0.004)	(0.007)	(0.007)	(0.129)	(0.129)
Market Share	0.009^{***}				0.008^{***}	
	(0.002)				(0.002)	
Market Share (junior)		0.002				-0.003
		(0.002)				(0.003)
Market Share (lead)		0.016^{***}				0.018^{***}
		(0.002)				(0.003)
Industry market share			0.011^{***}		0.017^{***}	
			(0.0004)		(0.002)	
Industry market share (junior)				0.003^{***}		0.015^{***}
				(0.001)		(0.003)
Industry market share (lead)				0.019^{***}		0.019^{***}
				(0.001)		(0.003)
Bank assets					0.050^{***}	
					(0.006)	
Bank assets (junior)						0.036^{***}
						(0.008)
Bank assets (lead)						0.064^{***}
						(0.008)
Akaike Inf. Crit.	101542	101541	101475	101439	3491	3484

Online Appendix

A.1. Proof of Lemma 1

LEMMA 1: An arranger would exhaust junior participants before inviting co-arrangers in the syndicate. PROOF: We proceed by contradiction and assume that $n^* < N$ and $m^* > 0$. Since $\min(N - n^*, m^*) > 0$ we can pick $\theta > 0$ such that $\theta < \min(N - n^*, m^*)$. It is easy to verify that $U(n^* + \theta, m^* - \theta) > U(n^*, m^*)$ which violates the optimality of (n^*, m^*).

A.2. Proof of Lemma 2

LEMMA 2: Given a large enough N (and by extension Q), the derivatives $\frac{\partial V(.)}{\partial R} > 0$, $\frac{\partial^2 V(.)}{\partial R \partial \alpha} < 0$ and $\frac{\partial^2 V(.)}{\partial \alpha \partial N} > 0$.

PROOF: Note that $\frac{\partial V(.)}{\partial R} = \frac{1}{R} - \frac{1-\alpha}{C+R-R_f} + \frac{(C-c)W\,R_f}{(R-R_f)^2} \frac{(1-\alpha)N}{WR_f+(C-c)N\,q^*}$, $\frac{\partial V(\cdot)}{\partial N} = \frac{(C-c)q^*}{WR_f+(C-c)N\,q^*}$, and that $\frac{\partial q^*}{\partial \alpha} = \frac{WR}{R-R_f}$. Given that the term $\frac{(C-c)W\,R_f}{(R-R_f)^2} > 0$ and $q^* > 0$ then The last term of $\frac{\partial V(.)}{\partial R}$ is positive. Note that $\frac{1}{R} - \frac{1-\alpha}{C+R-R_f} = \frac{C+\alpha R-R_f}{R(C+R-R_f)} > 0$. Therefore $\frac{\partial V(.)}{\partial R} > 0$.

For $\frac{\partial^2 V(R,\alpha)}{\partial R \partial \alpha}$, we have:

$$\frac{\partial^2 V(R,\alpha)}{\partial R \partial \alpha} = \frac{1}{C+R-R_f} - \frac{\Big((C-c)R_f N\Big)\Big(R_f + (C-c)N\Big)}{\Big((R-Rf)R_f + (C-c)(\alpha R - R_f)N)\Big)^2}.$$

Note that the first term is bounded ($\frac{1}{C+R-R_f} < 1/C$) and the second term can be arbitrarily large depending on N since it is increasing in N and $\lim_{N\to\infty} \frac{\Big((C-c)R_f N\Big)\Big(R_f+(C-c)N\Big)}{\Big((R-Rf)R_f+(C-c)(\alpha R-R_f)N)\Big)^2} = \infty$.

Therefore, for large enough N, we get $\frac{\partial^2 V(R,\alpha)}{\partial R \partial \alpha} < 0$.

Finally, considering $\frac{\partial^2 V(\cdot)}{\partial N \partial \alpha}$, we have:

$$\frac{\partial^2 V(R,\alpha;N)}{\partial N \partial \alpha} \propto (C-c)WR_f \frac{\partial q^*}{\partial \alpha} > 0.\blacksquare$$

A.3. Proof of Theorem 1

We prove that a unique equilibrium in regular strategies exists. We first define regular and mixed strategies, as well as other notions used in the proofs. The first part of the proof shows that mixed strategies cannot exist in equilibrium and that the bidding strategies satisfy certain regularity conditions. Afterward, the proof proceeds in three steps: Initial conditions, no crossing, and relative toughness. We elaborate on each step below.

A.3.1. Definitions

In the following parts of the proof, we adopt the definitions in Lizzeri and Persico (2000). We use these definitions to replicate their proofs for the existence and uniqueness of an equilibrium in our setting.

Definition 1: A pure strategy is measurable function $b_i : [\underline{\theta}, \theta] \to (-\infty, +\infty)$. Furthermore, a regular strategy is a pure strategy that is nondecreasing on the whole range, and for bids strictly above $\underline{p}$ are continuous, strictly increasing, differentiable and Lipschitz continuous.

Pure and regular strategies can be thought of in terms of deterministic mappings between a player's signal and her bid. Another possibility is the player mixes her strategies, and upon observing a signal θ, she bids an amount p with some probability distribution, i.e., each signal θ defines a probability measure over the set of possible bids.

Let $\mathcal{B}$ be the class of Borel subsets of the real line, and let $A \in \mathcal{B}$.

Definition 2: A function $\eta_j : \mathcal{B} \times [\underline{\theta}, \theta] \to [0, 1]$ is a mixed strategy for player j if:

1. $\eta_j(\cdot, \theta) : \mathcal{B} \to [0, 1]$ is a probability measure for all $\theta \in [\underline{\theta}, \theta]$.
2. $\eta_j(A, \cdot) : [\underline{\theta}, \theta] \to [0, 1]$ is measurable.

Definition 3: A mixed strategy $\eta_j(\cdot, \cdot)$ is nondecreasing if whenever $\theta' > \theta$, every element of the support of $\eta_j(\cdot, \theta')$ is greater than or equal to every element of the support of $\eta_j(\cdot, \theta)$.

If player j adopts a mixed strategy, then we can define the probability measure induced by the mixed strategy of j in i's opinion (based on observing signal θ_i).

Definition 4: Let $T \in \mathcal{B} \cap [\underline{\theta}, \theta]$, and $A \in \mathcal{B}$. The probability measure $\mu_i(\cdot|\theta_i)$ for player i of type θ_i induced by the mixed strategy $\eta_j(\cdot, \cdot)$ is given by:

$$\mu_i(T, A|\theta_i) := \int_T \eta_j(A, \theta_j) f_j(\theta_j|\theta_i) d\theta_j$$

and

$$\mu_i(T|\theta_i) := \mu_i(T, [\underline{\theta}, \theta]|\theta_i).$$

The unconditional probability measure $\mu_i(\cdot)$ for player i induced by the mixed strategy $\eta_j(\cdot,\cdot)$ is given by:

$$\mu_i(T, A) := \int_T \eta_j(A, \theta_j) f_j(\theta_j) d\theta_j$$

and

$$\mu_i(T) := \mu_i(T, [\underline{\theta}, \theta]).$$

Denote $P_j := \sup\{p : p \in \mathit{support}(\mu_j(\cdot))\}$ and let $P = P_1 \vee P_2$. Hence, P is the maximum bid that any of the players will ever play.

DEFINITION 5: We say that a function $F(x)$ is quasimonotone in x if $F(x_0) = 0$ then $F(x) \geq 0$, $\forall x > x_0$. We say that the F is strictly quasimonotone if $F(x) > 0$, $\forall x > x_0$.

A.3.2. Regularity of Equilibrium Strategies

In this section, we establish that all equilibrium strategies must be regular. We first rule out mixed strategies. The first lemma shows that mixed strategies have to be nondecreasing.

LEMMA IA1: In our setting, if the signals Θ_1 and Θ_2 are independent, then all equilibrium mixed strategies are nondecreasing.

PROOF: Let us proceed by contradiction and assume that for some $\theta' > \theta \in [\underline{\theta}, \bar{\theta}]$ we have $p' \in \mathit{support}(\eta_i(\cdot, \theta'))$ and $p \in \mathit{support}(\eta_i(\cdot, \theta))$ such that $p' < p$.

Given that the bidding functions are optimal it has to be the case that the expected payoff from playing p' is higher than that of playing p upon observing θ'. Likewise, the expected payoff from playing p is higher than that of playing p' upon observing θ. Formally:

$$\int_{(\underline{p},p')\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta',\theta_j,p',p_j)\mu_j(dp_j,d\theta_j) + \frac{1}{2}\int_{\{p'\}\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta',\theta_j,p',p_j)\mu_j(dp_j,d\theta_j)$$
$$\geq$$
$$\int_{(\underline{p},p)\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta',\theta_j,p,p_j)\mu_j(dp_j,d\theta_j) + \frac{1}{2}\int_{\{p\}\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta',\theta_j,p,p_j)\mu_j(dp_j,d\theta_j),$$

and

$$\int_{(\underline{p},p)\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta,\theta_j,p,p_j)\mu_j(dp_j,d\theta_j) + \frac{1}{2}\int_{\{p\}\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta,\theta_j,p,p_j)\mu_j(dp_j,d\theta_j)$$
$$\geq$$
$$\int_{(\underline{p},p')\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta,\theta_j,p',p_j)\mu_j(dp_j,d\theta_j) + \frac{1}{2}\int_{\{p'\}\times[\underline{\theta},\bar{\theta}]} \pi_i^W(\theta,\theta_j,p',p_j)\mu_j(dp_j,d\theta_j).$$

To help with the notation, let us define the expression $\Delta_\theta(p;p_j,\theta_) := \pi_i^W(\theta,\theta_j,p,p_j) - \pi_i^W(\theta,\theta_j,p,p_j)$. If we rearrange the expressions and take their difference we get the following inequality:

$$\begin{aligned}
&\int_{(\underline{p},p')\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p';p_j,\theta_j)\mu_j(dp_j,d\theta_j) + \frac{1}{2}\int_{\{p'\}\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p';p_j,\theta_j)\mu_j(dp_j,d\theta_j) \\
&\geq \\
&\int_{(\underline{p},p)\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j)\mu_j(dp_j,d\theta_j) + \frac{1}{2}\int_{\{p\}\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j)\mu_j(dp_j,d\theta_j).
\end{aligned} \tag{1}$$

Note that we can decompose:

$$\int_{(\underline{p},p)[\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j)\mu_j(dp_j,d\theta_j) = \Big[\int_{(\underline{p},p')\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j) + \int_{\{p'\}\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j)$$
$$+ \int_{(p',p)\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j)\Big]\mu_j(dp_j,d\theta_j).$$

Let us first compare the two terms:

$\int_{(\underline{p},p')\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p;p_j,\theta_j)\mu_j(dp_j,d\theta_j)$ and $\int_{(\underline{p},p')\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p';p_j,\theta_j)\mu_j(dp_j,d\theta_j)$.

Recall from Lemma 2 that the second derivative of $\pi_i^W(\cdot)$ with respect to p_i and θ_i is positive. Therefore $\Delta_\theta(p'; p_j, \theta_j) < \Delta_\theta(p; p_j, \theta_j)$, $\forall p_j, \theta_j$. removing these two terms from the inequality (1), we get:

$$\Big[\int_{\{p'\}\times[\underline{\theta},\bar{\theta}]} \Big(\Delta_\theta(p) - \frac{1}{2}\Delta_\theta(p')\Big) + \int_{(p',p)\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p) + \frac{1}{2}\int_{\{p\}\times[\underline{\theta},\bar{\theta}]} \Delta_\theta(p)\Big]\mu_j(dp_j, d\theta_j) \leq 0.$$

Note that the integrands are all positive since we just established that $\Delta_\theta(p) > \Delta_\theta(p')$ and $\Delta_\theta(p) > 0$ since $\pi_i^W(\cdot)$ is increasing in θ_i. The inequality is therefore a contradiction unless the bounds of integration have zero measure with respect to μ_j. But if that is the case (i.e. player j bids in the interval $[p', p]$ with probability 0), then player i should never p and opt for p' instead upon observing θ. ■

Lemma IA2: Consider any open interval $A = (a, b) \subset (\underline{p}, P)$. Then, in a nondecreasing strategies equilibrium of our setting, $\mu_j(A) > 0$ for $j = 1, 2$.

Proof: Assume by contradiction that the lemma does not hold. It cannot be that $\mu_i(A) > 0$ and $\mu_j(A) = 0$ for $i \neq j$. To see why not, consider a player i who bids $p \in A$. By bidding any amount in (a, p), she wins with the same probability measure as bidding p (since j bids in the interval (a, p) with measure 0). But since $\pi_i^W(\cdot)$ is strictly decreasing in p_i, it is not optimal to bid p.

Therefore for the lemma to not hold we need $\mu_j(A) = 0$ for $j = 1, 2$. Let the interval $B = (a', b')$ be the largest interval containing A such that $\mu_j(B) = 0$ for $j = 1, 2$. We have three cases:

Case 1: $\mu_i(\{b'\}) > 0$ and $\mu_j(\{b'\}) = 0$ for $i \neq j$, i.e. there is a mass of player i bidding b' and no such mass for player j. Using the same argument as before, player i is better off playing any amount in (a', b').

Case 2: $\mu_i(\{b'\}) = 0$ for $i = 1, 2$. Then players i and j bid with positive measure over open intervals above p'. However, picking p arbitrarily close to b' the mass of player's j bidding in such interval becomes arbitrarily small. Consider a player i bidding an amount $p > b'$ that is arbitrarily close to b'. The expected payoff to player i is:

$$\int_{(-\infty,b)\times[\underline{\theta},\bar{\theta}]} \pi_i^W(p, s \vee \underline{p}, \theta_i, \theta_j) d\mu_j(ds, d\theta_j|\theta_i)$$

Player i bidding an amount in (b', p) instead reduces the limits of integration in the expression above by a negligible mass but increases the integrand by a non negligible amount. Therefore the player will not bid p.

Case 3: $\mu_i(\{b'\}) > 0$ for $i = 1, 2$. We did not explicitly define this rule of the auction, but we assume that if two bidders submit the same bid, one of them is picked at random. So, we represent this setting with each getting half of their expected payoff in these cases. Now consider the payoff to a player i bidding either $b' + \epsilon$ or $b' - \epsilon$ for an arbitrarily small $\epsilon > 0$. Let $\Pi_i(b, \theta)$ be the expected payoff to player i upon bidding b with signal θ, then:

$$\lim_{\epsilon\to 0} \Big(\Pi_i(b' + \epsilon, \theta_i) - \Pi_i(b', \theta_i)\Big) = \frac{1}{2}\int_{\{b'\}\times[\underline{\theta},\bar{\theta}]} \pi_i^W(b', b', \theta_i, \theta_j) d\mu_j(\{b'\}|\theta_i)$$

and

$$\lim_{\epsilon\to 0} \Big(\Pi_i(b', \theta_i) - \Pi_i(b' - \epsilon, \theta_i)\Big) = \frac{1}{2}\int_{\{b'\}\times[\underline{\theta},\bar{\theta}]} \pi_i^W(b', b', \theta_i, \theta_j) d\mu_j(\{b'\}|\theta_i).$$

Since no player that bids b' would bid $b' + \epsilon$, the expressions above have to be arbitrarily small. Therefore, bidding $b' - \epsilon$ has a payoff that is arbitrarily close to the payoff from b'. But then bidding an amount $\frac{a'+b'}{2}$ dominates bidding $b' - \epsilon$ and hence b'. ■

COROLLARY: An equilibrium in our setting has to be in pure strategies. Additionally, the equilibrium strategies $p_i(\cdot)$ are continuous over the their support $p_i^{-1}(\underline{p}, P]$.

PROOF: Assume by contradiction that a player θ_i plays a mixed strategy whereby two bids a and b ($a < b$) are played with non-zero probability. Then by Lemma IA1, all players with signals above or below θ_i would have $\mu_i((a, b)) = 0$ but that contradicts Lemma IA2. therefore equilibrium strategies have to be pure.

Since the equilibrium strategies are nondecreasing and pure, Lemma IA2 establishes continuity.■

LEMMA IA3: Equilibrium strategies are strictly increasing on $p_i^{-1}(\underline{p}, P)$.

PROOF: Assume that the strategy for player j is not constant at p over some interval $(\underline{\phi}, \bar{\phi})$. Without loss of generality, assume that this interval is the largest interval, i.e. $p_j^{-1}(p) = (\underline{\phi}, \bar{\phi})$. Note that because we are interested in pure strategies, we do not need to consider closed intervals since each point has measure 0 in $\eta_j(\cdot)$.

First, we will establish that $p_i(\cdot)$ is strictly increasing at p. Since $p_i(\cdot)$ is nondecreasing, we only need to show that it is not constatnt at p. Assume that is not the case, i.e., $\exists \theta_i < \theta_i'$ such that $p_i(\theta_i) = p_i(\theta_i') = p$. Since $\pi_i^W(\cdot)$ is strictly increasing in θ_i, we can order the expected payoffs to types θ_i and θ_i':

$$\begin{gathered}
\Big[\int_{(\underline{\theta},\underline{\phi})} \pi_i^W(\theta_i', \theta_j, p, p_j(\theta_j)) + \frac{1}{2}\int_{(\underline{\phi},\bar{\phi})} \pi_i^W(\theta_i', \theta_j, p, p_j(\theta_j))\Big] df(\theta_j) \\
> \\
\Big[\int_{(\underline{\theta},\underline{\phi})} \pi_i^W(\theta_i, \theta_j, p, p_j(\theta_j)) + \frac{1}{2}\int_{(\underline{\phi},\bar{\phi})} \pi_i^W(\theta_i, \theta_j, p, p_j(\theta_j))\Big] df(\theta_j) \geq 0.
\end{gathered} \tag{2}$$

Since $\pi_i^W(\cdot)$ is strictly increasing in θ_j, then $\int_{(\underline{\phi},\bar{\phi})} \pi_i^W(\theta_i', \theta_j, p, p_j(\theta_j)) df(\theta_j) > 0$. Therefore, player θ_i' can increase her payoff by a nontrivial amount $(\frac{1}{2}\int_{(\underline{\phi},\bar{\phi})} \pi_i^W(\theta_i', \theta_j, p, p_j(\theta_j)) df(\theta_j))$ by raising her bid arbitrarily above p. Not that bu the continuity of $\pi_i^W(\cdot)$ with respect to p_i such increase decreases here payoff by a trivial amount. This contradicts the optimality of $p_i(\theta_i')$.

Now, we will establish that i will not bid in a an interval below $p_i^{-1}(p)$. Let us denote the expected payoff from playing p as a type θ_i by $\Pi_i(p, \theta_i)$. Let $\theta_i^* = p_i^{-1}(p)$. Since $\pi_i^W(\cdot)$ is continuous in both p_i and θ_i then:

$$\lim_{\epsilon \downarrow 0} \Big(\Pi_i(p_i(\theta_i^* + \epsilon), \theta_i^* + \epsilon) - \Pi_i(p_i(\theta_i^* - \epsilon), \theta_i^* - \epsilon)\Big) = \int_{\underline{\phi}}^{\bar{\phi}} \pi_i^W(p, p, \theta_i^*, \theta_j) df(\theta_j) > 0.$$

Since $\pi_i^W(\cdot)$ is continuous, players of type $\theta_i^* - \epsilon$ for an arbitrarily small ϵ would find it optimal to bid right above p. This contradicts Lemma IA3.■

LEMMA IA4: The inverse bidding strategies are differentiable in the interior of the bidding range.

PROOF: Note that since $p_i(\cdot)$ is strictly increasing, we can define an inverse function $\phi_i(p) := p_i^{-1}(p)$ for $i = 1, 2$. Let $\theta_i \in p_i^{-1}(\underline{p}, P)$ and let $p_i = p_i(\theta_i)$. Also, consider a sequence $\{\theta_i^n\} \uparrow \theta_i$. By the continuity of p_i, $p_i^n := p_i(\theta_i^n) \uparrow p_i$.

Since p_i^n is an optimal response to θ_i^n, the expected payoff from bidding p_i^n is higher than that from bidding p_i given signal θ_i^n:

$$\int_{\underline{\theta}}^{\phi_j(p_i^n)} \pi_i^W(\theta_i^n, \theta_j, p_i^n, p_j(\theta_j)) df_j(\theta_j|\theta_i^n) \geq \int_{\underline{\theta}}^{\phi_j(p_i)} \pi_i^W(\theta_i^n, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i^n). \tag{3}$$

Subtracting $\int_{\underline{\theta}}^{\phi_j(p_i^n)} \pi_i^W(\theta_i^n, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i^n)$ from both sides of the inequality, we get:

$$\begin{aligned} \int_{\underline{\theta}}^{\phi_j(p_i^n)} \Big[\pi_i^W(\theta_i^n, \theta_j, p_i^n, p_j(\theta_j)) - \pi_i^W(\theta_i^n, \theta_j, p_i, p_j(\theta_j))\Big] df_j(\theta_j|\theta_i^n) \geq \\ \int_{\phi_j(p_i^n)}^{\phi_j(p_i)} \pi_i^W(\theta_i^n, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i^n). \end{aligned} \tag{4}$$

If we divide both sides by $p_i - p_i^n$ and take limits:

$$\begin{aligned} \limsup_{n\to\infty} \int_{\underline{\theta}}^{\phi_j(p_i^n)} \Big[\pi_i^W(\theta_i^n, \theta_j, p_i^n, p_j(\theta_j)) - \pi_i^W(\theta_i^n, \theta_j, p_i, p_j(\theta_j))\Big] df_j(\theta_j|\theta_i^n) = \\ = \int_{\underline{\theta}}^{\phi_j(p_i)} -\frac{\partial}{\partial b_i}\pi_i^W(\theta_i, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i) \end{aligned} \tag{5}$$

and, given the continuity of π_i^W:

$$\limsup_{n\to\infty} \int_{\phi_j(p_i^n)}^{\phi_j(p_i)} \pi_i^W(\theta_i^n, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i^n) = \pi_i^W(\theta_i, \phi_j(p_i), p_i, p_i) f_j(\phi_j(p_i)|\theta_i) \limsup_{n\to\infty} \int_{\phi_j(p_i^n)}^{\phi_j(p_i)} \frac{d\theta_j}{p_i - p_i^n}.$$

Using the two above expressions in the previous inequality, we get that:

$$\limsup_{n\to\infty} \frac{\phi_j(\theta_i) - \phi_j(\theta_i^n)}{p_i - p_i^n} \leq \frac{\int_{\underline{\theta}}^{\phi_j(p_i)} -\frac{\partial}{\partial b_i}\pi_i^W(\theta_i, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i)}{\pi_i^W(\theta_i, \phi_j(p_i), p_i, p_i) f_j(\phi_j(p_i)|\theta_i)}. \tag{6}$$

If we repeat the same analysis starting from the optimality of p_i as a strategy for type θ_i:

$$\int_{\underline{\theta}}^{\phi_j(p_i)} \pi_i^W(\theta_i, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i) \geq \int_{\underline{\theta}}^{\phi_j(p_i^n)} \pi_i^W(\theta_i, \theta_j, p_i^n, p_j(\theta_j)) df_j(\theta_j|\theta_i).$$

and repeat the same step (taking liminf as opposed to limsup) we get:

$$\liminf_{n\to\infty} \frac{\phi_j(\theta_i) - \phi_j(\theta_i^n)}{p_i - p_i^n} \geq \frac{\int_{\underline{\theta}}^{\phi_j(p_i)} -\frac{\partial}{\partial b_i}\pi_i^W(\theta_i, \theta_j, p_i, p_j(\theta_j)) df_j(\theta_j|\theta_i)}{\pi_i^W(\theta_i, \phi_j(p_i), p_i, p_i) f_j(\phi_j(p_i)|\theta_i)}. \tag{7}$$

Note that $f_j(\phi_j(p_i)|\theta_i) > 0$ by assumption, and that $\pi_i^W(\theta_i, \phi_j(p_i), p_i, p_i) > 0$ since $pi_i^W(\cdot)$ is strictly increasing in θ_j and $E[\pi_i^W(\theta_i, \theta_j, p_i, p_j(\theta_j))1_{\{\theta_j < \phi_j(p_i)|\theta_i\}}] \geq 0$. Therefore, the $\phi_j(p_i)$ is differentiable from below.

One can carry out a similar argument with a decreasing sequence to establish differentiability from above. ■

Lemma IA5: The equilibrium trajectories satisfy the Lipschitz condition in the interior of the bidding range.

Proof: Note that in our case the FOC is a differential equation of the form:

$$\phi_j'(p) = \frac{\int_{\underline{\theta}}^{\phi_j(p)} \frac{\partial}{\partial p_i}\pi_i^W(\phi_i(p), \theta_j, p, p) df_j(\theta_j|\phi_i(p))}{f_j(\phi_j(p)|\phi_i(p))\pi_i^W(\phi_i(p), \phi_j(p), p, p)}.$$

Therefore, we only need to show that the term $f_j(\phi_j(p)|\phi_i(p))\pi_i^W(\phi_i(p), \phi_j(p), p, p)$ is bounded away from 0 to prove the Lipschitz condition. Note that by assumption A1, $f_j(\phi_j(p)|\phi_i(p)) > 0$, so that we only need to show that $\exists \epsilon > 0$, $s.t.$ $\pi_i^W(\phi_i(p), \phi_j(p), p, p) > \epsilon$.

Note that the expected payoff from bidding p upon observing $\phi_i(p)$ is given by:

$$\int_{\underline{\theta}}^{\phi_j(p)} \pi_i^W(\phi_i(p), \theta_j, p, p) df_j(\theta_j|\phi_i(p)) \geq 0.$$

By assumption A3, $\phi_j(p) > \underline{\theta}$ since at $\underline{\theta}$ player j does not bid. Given that $\pi_i^W(\cdot)$ is strictly increasing in θ_j and $f_j(\theta_j|\phi_i) > 0$, it has to be the case that at some point in the range $(\underline{\theta}, \phi_j(p))$, π_i^W

becomes positive, i.e. $\exists \epsilon > 0\, and\; \theta^* \in (\underline{\theta}, \phi_j(p)),\; s.t.\; \pi_i^W(\phi_i(p), \theta, p, p) > \epsilon$ for all $\theta > \theta^*$ including $\phi_j(p)$. ■

A.3.3. Existence and Uniqueness of Equilibrium

As stated above, now that we have established the regularity conditions, we can proceed to establish existence and uniqueness. Lemma IA5 demonstrates that the equilibrium is characterized by a differential equation that satisfies the requirements of the fundamental theorem in Hirsch and Smale (1974). Furthermore, the theorem states that the differential equation has a unique solution for each starting point. Therefore, to verify existence and uniqueness, one only needs to verify the uniqueness of a starting point (and ensure that the starting point doesn't violate the equilibrium requirements).

A.3.3.a. Initial Conditions

Uniqueness of Initial Conditions: We define initial conditions as a pair (θ_1^0, θ_2^0) such that $R_i(\theta_i^0) = \bar{R}$, $i = 1, 2$. Note that the equilibrium is a solution of a first order differential equation given our assumption of regular strategies. Such differential equation has a unique solution for each starting point (θ_1^0, θ_2^0). Therefore we have many potential solutions given by a starting condition. Here we will show that the starting conditions are nested, i.e. for a pair of starting conditions (θ_1^0, θ_2^0) and $(\hat{\theta}_1^0, \hat{\theta}_2^0)$, if $\theta_1^0 < \hat{\theta}_1^0$ then $\theta_2^0 > \hat{\theta}_2^0$.

Define the function $H_i(\psi_i, \psi_j) = \int_{-\infty}^{\psi_j} \pi_i^W(\psi_i, \theta_j, \underline{p}, \underline{p}) df_j(\theta_j|\psi_i)$. This functions represents the payoff to player i observing $\theta_i = \psi_i$ upon bidding an amount p just above $\underline{p}$ (or R below $\bar{R}$) and winning the bid when the opposing bidder does not bid if $\theta_j < \psi_j$ and $p_j(\psi_j) = \underline{p}$.

Lemma IA6: In equilibrium (θ_1^0, θ_2^0), $H_i(\theta_i^0, \theta_j^0) \geq 0$, $i = 1, 2$ with equality for at least one player.

Proof: Suppose that $H_i(\theta_i^0, \theta_j^0) < 0$. Note that by the continuity of $\pi_i^W(\cdot)$, the expected payoff is also continuous. Then there exists a type $\theta_i > \theta_i^0$ that is actively bidding yet her payoff is arbitrarily close to $H_i(\theta_i^0, \theta_j^0) < 0$. This is a contradiction since this player is better off not bidding.

To prove that the equality holds for at least one player, assume that $H_i(\theta_i^0, \theta_j^0) > 0$ for both $i = 1, 2$. Recall that at θ^* the expected payoff for both players is strictly negative. Then by the continuity of the expected payoffs, $\exists \hat{\theta}_i < \hat{\theta}_i^0$, $i = 1, 2$ such that $p_i(\hat{\theta}_i) = \underline{p}$. By definition, that means there is a mass of players bidding $\underline{p}$ which violates the equilibrium conditions.

Proposition IA1: If $H_i(\psi_i, \psi_j) = H_i(\hat{\psi}_i, \hat{\psi}_j) = 0$ and $\psi_i > \hat{\psi}_i$ then $\psi_j < \hat{\psi}_j$.

Proof: It is sufficient to show that $H_i(\cdot)$ is strictly increasing in ψ_i and ψ_j at $H_i(\psi_i, \psi_j) = 0$. It is easy to see that the term inside the integral is strictly increasing in ψ_i and by the assumption that the payoff is negative at $\underline{\theta}$, then $\psi_j > 0$ if $H_i(\psi_i, \psi_j) = 0$ and therefore the bounds of integration have non-zero mass. So $H_i(\cdot)$ is increasing in ψ_i.

For ψ_j, note that the derivative with respect to ψ_j: $\frac{\partial H_i(\psi_i, \psi_j)}{\partial \psi_j} = \pi_i^W(r, r, \psi_i, \psi_j)$. Given that $\pi_i^W(\cdot)$ is strictly increasing in θ_i and $H_i(\psi_i, \psi_j) = 0$, $\pi_i^W(r, r, \psi_i, \psi_j)$ must be positive (otherwise $H_i(\psi_i, \psi_j) < 0$). So, $H_i(\cdot)$ is increasing in ψ_j.■

Notes: The initial condition in our setting boils down to $V_i(\bar{R}, \theta_i^0) \geq 0$ with equality for either i or j or both. The FOC_i can be interpreted as characterizing the optimal response to observing a given θ_i. A more aggressive bid (lower R_i) increases the probability of winning the auction (the first term), but decreases the value to the arranger conditional on winning (the second term). The optimal solution balances these opposing forces.

A.3.3.b. Uniqueness and the No Crossing Property

Proposition IA2: Let two trajectories $\phi_i(\cdot)$ and $\hat{\phi}_i(\cdot)$ with different starting points $((\theta_1^0, \theta_2^0) \neq (\hat{\theta}_1^0, \hat{\theta}_2^0))$ satisfy the FOC at a bid p^*. If $\phi_i(p^*) > \hat{\phi}_i(p^*)$ then $\phi_j'(p^*) < \hat{\phi}_j'(p^*)$ for $i \neq j$.

Proof: To simplify notation drop p^* as an argument to ϕ_i and $\hat{\phi}_i$. Assume that $\phi_j' \geq \hat{\phi}_j'$. The FOC at p^* for the two trajectories:

$$\phi_j' f_j(\phi_j|\phi_i)\pi_i^W(\phi_i, \phi_j, p^*, p^*) + \int_{\underline{\theta}}^{\phi_j} \frac{\partial}{\partial p_i}\pi_i^W(\phi_i, \theta_j, p^*, p_j(\theta_j)) df_j(\theta_j|\phi_i) = 0,$$

and

$$\hat{\phi}_j' f_j(\hat{\phi}_j|\hat{\phi}_i)\pi_i^W(\hat{\phi}_i,\hat{\phi}_j,p^*,p^*) + \int_{\underline{\theta}}^{\hat{\phi}_j} \frac{\partial}{\partial p_i}\pi_i^W(\hat{\phi}_i,\theta_j,p^*,p_j(\theta_j))df_j(\theta_j|\hat{\phi}_i) = 0.$$

Note that all the terms in the expression are larger for (ϕ_i,ϕ_i') than for $(\hat{\phi}_i,\hat{\phi}_i')$. $\phi_j' \geq \hat{\phi}_j' > 0$ by assumption and the fact that the bidding trajectories are strictly increasing. $f_j(\phi_j|\phi_i) \geq f_j(\hat{\phi}_j|\hat{\phi}_i) > 0$ by affiliation. $\pi_i^W(\phi_i,\phi_j,p^*,p^*) \geq \pi_i^W(\hat{\phi}_i,\hat{\phi}_j,p^*,p^*) > 0$. Finally,

$$\int_{\underline{\theta}}^{\phi_j} \frac{\partial}{\partial p_i}\pi_i^W(\phi_i,\theta_j,p^*,p_j(\theta_j))df_j(\theta_j|\phi_i) \geq \int_{\underline{\theta}}^{\hat{\phi}_j} \frac{\partial}{\partial p_i}\pi_i^W(\hat{\phi}_i,\theta_j,p^*,p_j(\theta_j))df_j(\theta_j|\hat{\phi}_i)$$

using Lemma 2 and the affiliation assumption. Then the difference between the two FOC is strictly positive.■

PROPOSITION IA3: Two trajectories $\phi_i(\cdot)$ and $\hat{\phi}_i(\cdot)$ with different starting points $((\theta_1^0,\theta_2^0) \neq (\hat{\theta}_1^0,\hat{\theta}_2^0))$ cannot cross.

PROOF: Assume by contradiction that the two trajectories cross, and let p^* be the lowest point at which the two trajectories $\phi_i(\cdot)$ and $\hat{\phi}_i(\cdot)$ cross for either i. Without loss of generality, let $\phi_1(p^*) = \hat{\phi}_1(p^*)$ and we have $\forall p < p^*$, $\phi_1(p) < \hat{\phi}_1(p)$ then by the nested nature of initial conditions it has to be that $\phi_2(p) > \hat{\phi}_2(p)$. If $\phi_2(p^*) = \hat{\phi}_2(p^*)$, then using the fundamental theorem of Hirsch and Smale (1974) the two trajectories have to be identical (i.e., the starting positions are the same, a contradiction). Given that $\phi_i(\cdot)$ and $\hat{\phi}_i(\cdot)$ are continuous then $\phi_2(p^*) > \hat{\phi}_2(p^*)$. By the previous result, we have $\phi_1'(p^*) < \hat{\phi}_1'(p^*)$ but that contradict the fact that $\phi_i(\cdot)$ approaches $\hat{\phi}_i(\cdot)$ from below at p^*. ■

A.3.3.c. Existence and the final condition

First, we recap what the Lemmas and Propositions we covered thus far say about the equilibrium. Focusing on regular strategies, we are assured that any equilibrium strategies must strictly increase and satisfy the FOCs. It is easy to see that upon observing $\bar{\theta}$, both players should be playing the same bid P. Because of the no crossing result, at most one set of initial conditions can satisfy the equilibrium requirements. Otherwise, starting from nested initial conditions and arriving at a single point at $\bar{\theta}$ will require crossing.

In this section, we show that every set of starting points satisfying $H_i(\theta_1^0, \theta_2^0) = 0$ provides a valid equilibrium. Then we show that only one such set of points has the same final condition, and establish both existence and uniqueness.

LEMMA IA7: All points satisfying $H_i(\theta_1^0, \theta_2^0) = 0$ are valid candidates for initial conditions.

PROOF: To indicate dependence on a set of starting points, let us denote the inverse bidding trajectories $\phi_i(p; \theta_i^0, \theta_j^0)$. Now define $P(\theta_i^0, \theta_j^0) := min\{p : \phi_1(p; \theta_1^0, \theta_2^0) = \bar{\theta}\, or\, \phi_2(p; \theta_1^0, \theta_2^0) = \bar{\theta}\}$. We need to show that for every player $\theta_i < \theta_i^0$, they would not bid any amount $\hat{p} > r$ (i.e., they are not actively bidding) and that every player $\theta_i' > \theta_i^0$ is actively bidding.

Fix $\theta_i < \theta_i^0$ and let $\hat{\theta}_i > \theta_i^0$ such that $p_i(\hat{\theta}_i) = \hat{p}$. By the QM Lemma, the FOC at $(\hat{\theta}_i, \hat{p})$ is quasimonotone in θ_i. In other words, the derivative of the payoff at any point below $\hat{\theta}_i$ w.r.t. p is negative. Therefore, θ_i cannot bid p.

Consider now $\theta_i' > \theta_i^0$, this player can bid r and guarantee a payoff greater than $H_i(\theta_1^0, \theta_2^0) = 0$ because $H_i(\cdot)$ is strictly increasing. Therefore, they will be bidding actively.■

THEOREM: A unique equilibrium exists.

PROOF: We have established that every pair (θ_i^0, θ_j^0) satisfying $H_i(\theta_i^0, \theta_j^0) \geq 0$ with equality for at least i or j are valid starting points. To prove existence, we need to show that there is such pair whereby the $\phi_i(P(\theta_i^0, \theta_j^0); \theta_i^0, \theta_j^0) = \phi_j(P(\theta_i^0, \theta_j^0); \theta_i^0, \theta_j^0) = \bar{\theta}$.

Given the regularity conditions of the differential equation, Hirsch and Smale (1974) show that $\phi_i(\cdot)$ are continuous in the initial conditions (θ_i^0, θ_j^0). Therefore, $P(\theta_i^0, \theta_j^0)$ is also continuous. Define the function:

$$G(\theta_i^0, \theta_j^0) := \left[\bar{\theta} - \phi_1(P(\theta_i^0, \theta_j^0); \theta_i^0, \theta_j^0)\right] + \left[\phi_2(P(\theta_i^0, \theta_j^0); \theta_i^0, \theta_j^0) - \bar{\theta}\right] \tag{8}$$

For $\theta_2^0 < \bar{\theta}$, if we select θ_1^0 arbitrarily close to $\hat{\theta}$ then $G(\cdot)$ becomes negative (since $\phi_1' > 0$ and $\phi_2' < \infty$. Using a similar logic, fixing $\theta_1^0 < \bar{\theta}$ and picking θ_2^0 arbitrarily close to $\hat{\theta}$ we can make $G(\cdot)$ positive. It is clear the the function $G(\cdot)$ is continuous, therefore there is point at which it is 0.■

A.4. Proof of Theorem 2

THEOREM 2: Assuming that the signals (θ_1, θ_2) that the two arrangers observe are identically distributed and that the repayment probability is symmetric in θ_i, θ_j (i.e., $\alpha(\theta_i, \theta_j) = \alpha(\theta_j, \theta_i)$, $\forall \theta_i, \theta_j$), then arranger 1 offers a lower rate than arranger 2 given the same signal $R_1(\theta) \leq R_2(\theta)$, or equivalently the inverse rate $p_1(\theta) \geq p_2(\theta)$, $\forall \theta \in (\underline{\theta}, \bar{\theta}]$.

PROOF: We will first prove that the initial conditions satisfy: $\theta_1^0 \leq \theta_2^0$, where the pair (θ_1^0, θ_2^0) is implicitly defined by $p_i(\theta_i^0) = \underline{p}$. Define the function $H_i(\psi_i, \psi_j) = \int_{\underline{\theta}}^{\psi_j} \pi_i^W(\psi_i, \theta_j, \underline{p}, \underline{p}) df_j(\theta_j|\psi_i)$. This functions represents the payoff to player i observing $\theta_i = \psi_i$ upon bidding an amount p just above $\underline{p}$ (or $R = 1/p - R_f$ just below $\bar{R}$) and winning the bid when the opposing bidder does not bid if $\theta_j < \psi_j$ and $p_j(\psi_j) = \underline{p}$. Lizzeri and Persico show that $H_i(\theta_i^0, \theta_j^0) \geq 0$ with strict equality for at least one.

Let us proceed by contradiction and assume that $\theta_1^0 > \theta_2^0$. Then it has to be the case that $H_2(\theta_i^0, \theta_j^0) = 0$ since otherwise players 1 with signals $\theta_i \in (\theta_2^0, \theta_1^0)$ will find it beneficial to bid aggressively (their payoff from winning is higher than that of player 2). Clearly if $H_1(\theta_i^0, \theta_j^0) > 0$ then by the continuity of H_i there are players just below θ_1^0 not bidding yet their expected payoff is positive. Yet these players by the definition of θ_1^0 are not bidding. This violated the equilibrium outcome. Then $H_1(\theta_1^0, \theta_2^0) = H_2(\theta_2^0, \theta_1^0) = 0$. But since $\pi_1^W \geq \pi_2^W$, then $H_1(\theta_1^0, \theta_2^0) > H_2(\theta_2^0, \theta_1^0)$ when $\theta_1^0 > \theta_2^0$. This contradicts our assumption.

Now, we proceed by contradiction and assume the for some $\hat{\theta} \in (\underline{\theta}, \bar{\theta}]$ we have $\underline{p} \leq p_1(\theta) < p_2(\theta)$. Appealing to the continuity of the of the trajectories $p_i(\theta)$ and the fact that p_1 is below p_2 at θ_0^2, then there exists a point $\theta^* < \bar{\theta}$ where the $p_1(\theta^*) = p_2(\theta^*) = p^*$. Note that the payoff to player i at this point is given by $\int_{\underline{\theta}}^{\theta^*} \pi_i^W(\theta^*, \theta_j, p^*, p^*) f_j(\theta_j|\theta^*) d\theta_j$. The optimality of θ^* for player i indicates that $\int_{\underline{\theta}}^{\theta^*} \left[\frac{\partial}{\partial \theta_i} \pi_i^W(\theta_i, \theta_j, p^*, p^*) f_j(\theta_j|\theta_i)\right]_{\theta_i = \theta^*} d\theta_j = 0$. Note also that $f_i(\theta|\theta^*) = f_j(\theta|\theta^*) = f(\theta|\theta^*)$ since the signals are identically distributed. If we take the difference of the two FOCs we get:

$$\int_{\underline{\theta}}^{\theta^*} \left[\frac{\partial}{\partial \theta_1} \pi_1^W(\theta_1, \theta, p^*, p^*) f_2(\theta|\theta_1)\right]_{\theta_1 = \theta^*} - \left[\frac{\partial}{\partial \theta_2} \pi_2^W(\theta, \theta_2, p^*, p^*) f_1(\theta|\theta_2)\right]_{\theta_2 = \theta^*} d\theta = 0. \quad (9)$$

Focusing on the term between brackets, we only need to show that $\frac{\partial}{\partial\theta_1}\pi_1^W(\theta_1,\theta,p^*,p^*)|_{\theta_1=\theta^*} > \frac{\partial}{\partial\theta_2}\pi_2^W(\theta,\theta_2,p^*,p^*)|_{\theta_2=\theta^*}$ and $\pi_1^W(\theta^*,\theta,p^*,p^*) > \pi_2^W(\theta,\theta^*,p^*,p^*,)$ to prove the theorem. First, by Lemma 2, $\frac{\partial}{\partial\alpha}\pi_1^W(\theta^*,\theta,p^*,p^*) > \frac{\partial}{\partial\alpha}\pi_2^W(\theta,\theta^*,p^*,p^*,)$ and since $\alpha(\cdot)$ is symmetric and increasing in both parameters then $\frac{\partial}{\partial\theta_1}\pi_1^W(\theta_1,\theta,p^*,p^*)|_{\theta_1=\theta^*} > \frac{\partial}{\partial\theta_2}\pi_2^W(\theta,\theta_2,p^*,p^*)|_{\theta_2=\theta^*}$. In the proof to Lemma 2, we also established the π_i^W is increasing in N so that $\pi_1^W(\theta^*,\theta,p^*,p^*) > \pi_2^W(\theta,\theta^*,p^*,p^*)$.■

Table B.1: Network centrality and number of participants

The dependent variable in the regressions is the number of participants in the loan syndicate. *Degree, In-degree, Out-degree, Eigenvector, Closeness,* and *Betweenness* are normalized measures of lead arrangers' network centrality. We define all variables in the Variable Definitions Appendix. All regressions include firm, year-quarter, loan type, loan purpose, and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Number of Participants					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	0.059***					
	(0.008)					
In-degree		0.057***				
		(0.008)				
Out-degree			0.086***			
			(0.033)			
Eigenvector				0.170***		
				(0.022)		
Closeness					0.121***	
					(0.014)	
Betweenness						0.148***
						(0.021)
Ln(Amount)	1.502***	1.502***	1.520***	1.494***	1.496***	1.506***
	(0.085)	(0.085)	(0.086)	(0.085)	(0.085)	(0.085)
Ln(Maturity)	1.228***	1.229***	1.218***	1.228***	1.222***	1.228***
	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)	(0.116)
Ln(Lender assets)	-0.226***	-0.233***	-0.134*	-0.282***	-0.217***	-0.081
	(0.069)	(0.069)	(0.070)	(0.070)	(0.070)	(0.069)
Lender capitalization	-0.003	-0.003	-0.003	0.002	0.000	0.013
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Market share	-0.026**	-0.023**	0.015	-0.012	-0.006	-0.011
	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
Industry market share	-0.035	-0.041	0.018	-0.024	-0.023	-0.036
	(0.027)	(0.028)	(0.029)	(0.027)	(0.028)	(0.028)
Ln(Firm assets)	1.035***	1.037***	1.087***	1.031***	1.030***	1.044***
	(0.156)	(0.156)	(0.156)	(0.157)	(0.156)	(0.156)
Market-to-Book value	0.265**	0.266**	0.271**	0.266**	0.258**	0.265**
	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)	(0.119)
Book leverage	-1.823***	-1.827***	-1.774***	-1.836***	-1.830***	-1.789***
	(0.563)	(0.563)	(0.568)	(0.563)	(0.563)	(0.563)
Tangibility	-0.881	-0.878	-0.847	-0.943	-0.942	-0.893
	(1.129)	(1.128)	(1.125)	(1.127)	(1.126)	(1.129)
ROA	8.169**	8.162**	8.238**	8.201**	8.338**	8.254**
	(3.446)	(3.446)	(3.472)	(3.452)	(3.450)	(3.445)
Observations	44659	44659	44659	44659	44659	44659
Adjusted R^2	0.479	0.479	0.477	0.479	0.479	0.479

Table B.2: Network centrality and number of lead arrangers

The dependent variable in the regressions is the number of lead arrangers as a share of all banks participating in the syndicate. *Degree, In-degree, Out-degree, Eigenvector, Closeness,* and *Betweenness* are normalized measures of lead arrangers' network centrality. We define all variables in the Variable Definitions Appendix. All regressions include firm, year-quarter, loan type, loan purpose, and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Arrangers/Total syndicate participants					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	-0.001***					
	(0.000)					
In-degree		-0.001***				
		(0.000)				
Out-degree			-0.003***			
			(0.001)			
Eigenvector				-0.003***		
				(0.000)		
Closeness					-0.003***	
					(0.000)	
Betweenness						-0.002***
						(0.000)
Ln(Amount)	-0.022***	-0.022***	-0.023***	-0.022***	-0.022***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Maturity)	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(Lender assets)	0.005***	0.005***	0.003**	0.006***	0.005***	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lender capitalization	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market share	-0.000	-0.000	-0.001***	-0.000**	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry market share	0.002***	0.002***	0.000	0.001***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Firm assets)	-0.010***	-0.010***	-0.011***	-0.010***	-0.009***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Market-to-Book value	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Book leverage	0.040***	0.040***	0.039***	0.040***	0.040***	0.039***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Tangibility	-0.001	-0.001	-0.002	0.000	0.001	-0.001
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
ROA	-0.125**	-0.125**	-0.126**	-0.126**	-0.129**	-0.127**
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Observations	44659	44659	44659	44659	44659	44659
Adjusted R^2	0.544	0.544	0.543	0.545	0.546	0.544

Table B.3: Network centrality and lead lender allocation

The dependent variable in the regressions is the lead arranger's percentage of the loan amount retained in their portfolio after loan origination. *Degree, In-degree, Out-degree, Eigenvector, Closeness,* and *Betweenness* are normalized measures of lead arrangers' network centrality. We define all variables in the Variable Definitions Appendix. All regressions include firm, year-quarter, loan type, loan purpose, and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Lead lender allocation					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	-0.077**					
	(0.030)					
In-degree		-0.076***				
		(0.029)				
Out-degree			-0.807***			
			(0.210)			
Eigenvector				-0.419***		
				(0.107)		
Closeness					-0.404***	
					(0.090)	
Betweenness						-0.121
						(0.076)
Ln(Amount)	-4.032***	-4.030***	-4.041***	-3.996***	-3.965***	-4.045***
	(0.434)	(0.434)	(0.431)	(0.430)	(0.430)	(0.435)
Ln(Maturity)	-3.966***	-3.966***	-3.882***	-3.947***	-3.941***	-3.962***
	(0.455)	(0.455)	(0.453)	(0.454)	(0.453)	(0.455)
Ln(Lender assets)	0.162	0.178	0.075	0.469	0.415	-0.007
	(0.355)	(0.358)	(0.346)	(0.354)	(0.354)	(0.353)
Lender capitalization	0.159	0.159	0.178*	0.166	0.153	0.143
	(0.102)	(0.102)	(0.102)	(0.102)	(0.101)	(0.103)
Market share	0.045	0.043	0.055	0.056	0.065	0.011
	(0.051)	(0.051)	(0.051)	(0.049)	(0.050)	(0.047)
Industry market share	0.024	0.031	-0.139	0.068	0.102	-0.001
	(0.149)	(0.148)	(0.150)	(0.149)	(0.146)	(0.152)
Ln(Firm assets)	-4.280***	-4.279***	-4.373***	-4.187***	-4.108***	-4.327***
	(0.714)	(0.713)	(0.715)	(0.716)	(0.718)	(0.716)
Market-to-Book value	-0.126	-0.128	-0.115	-0.138	-0.133	-0.111
	(0.519)	(0.519)	(0.516)	(0.515)	(0.514)	(0.520)
Book leverage	-5.212*	-5.214*	-5.138*	-5.034*	-4.961*	-5.243*
	(2.706)	(2.704)	(2.708)	(2.672)	(2.650)	(2.715)
Tangibility	4.413	4.453	4.306	4.901	4.970	4.265
	(3.903)	(3.903)	(3.892)	(3.913)	(3.877)	(3.901)
ROA	-43.395**	-43.349**	-44.526***	-43.734**	-44.471***	-43.695**
	(17.060)	(17.057)	(16.995)	(16.985)	(16.979)	(17.104)
Observations	9778	9778	9778	9778	9778	9778
Adjusted R^2	0.792	0.792	0.792	0.792	0.793	0.792

Table B.4: Network centrality and total loan fee-income

The dependent variable in the regressions is the natural logarithm of the total amount of fee-income (loan amount $\times$ loan fees) received from a loan deal. *Degree, In-degree, Out-degree, Eigenvector, Closeness,* and *Betweenness* are normalized measures of lead arrangers' network centrality. We define all variables in the Variable Definitions Appendix. All regressions include firm, year-quarter, loan type, loan purpose, and rating fixed effects. We cluster at the firm and year level and report standard errors in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Ln(Fee Income)					
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	0.007***					
	(0.002)					
In-degree		0.007***				
		(0.002)				
Out-degree			0.047***			
			(0.012)			
Eigenvector				0.029***		
				(0.005)		
Closeness					0.023***	
					(0.004)	
Betweenness						0.015***
						(0.004)
Ln(Maturity)	0.475***	0.475***	0.475***	0.475***	0.475***	0.475***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Ln(Lender assets)	-0.013	-0.015	-0.007	-0.028	-0.015	0.004
	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)
Lender capitalization	-0.009*	-0.009*	-0.008*	-0.008*	-0.008	-0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Market share	-0.012***	-0.012***	-0.009***	-0.012***	-0.012***	-0.009***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Industry market share	0.019***	0.019***	0.019***	0.019***	0.018***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Ln(Firm assets)	0.348***	0.348***	0.349***	0.344***	0.344***	0.350***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Market-to-Book value	0.020	0.021	0.021	0.021	0.021	0.020
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Book leverage	0.244*	0.243*	0.247*	0.239*	0.239*	0.248**
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
Tangibility	-0.187	-0.187	-0.187	-0.197	-0.198	-0.188
	(0.213)	(0.213)	(0.213)	(0.212)	(0.212)	(0.213)
ROA	-0.244	-0.245	-0.231	-0.225	-0.236	-0.237
	(0.810)	(0.809)	(0.810)	(0.809)	(0.807)	(0.809)
Observations	31142	31142	31142	31142	31142	31142
Adjusted R^2	0.528	0.529	0.528	0.529	0.529	0.528