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THE ECONOMICS OF BANK CROSS-FIRM SELLING: THE VALUE OF BORROWER BOARD CONNECTEDNESS AND OPACITY

Jianxin Zhao

A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Kenan-Flagler Business School.

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Approved by:

William H. Beaver

Robert M. Bushman

Jennifer S. Conrad

Wayne R. Landsman

Edward L. Maydew

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ABSTRACT

Jianxin Zhao: The Economics of Bank Cross-Firm Selling: The Value of Borrower Board Connectedness and Opacity
(Under the direction of Wayne R. Landsman)

This study provides evidence that banks value their existing borrowers' board network because it can give banks an advantage in cross-selling services to other firms in the network. I posit that banks gain an informational advantage from a common shared director between the existing borrower and firms in the borrower's network. I find that if a bank has a lending relationship with a well-connected borrower, then the bank's likelihood of winning loan business from a firm in the borrower's board network increases. I also find that banks are willing to compensate well-connected borrowers with larger board networks by offering lower loan spreads because these borrowers provide greater opportunities for their bank lenders to sell loans to firms in their networks. Moreover, consistent with board networks providing connected banks with an informational advantage over other *de novo* lenders, I find that the probability of a connected bank winning loan business from a firm in its existing borrower's network is higher if the firm is more informationally opaque. As further evidence of a network-based information advantage, I also find that banks offer lower loan spreads to a well-connected borrower if firms in that borrower's board network are on average more opaque. This finding indicates that a borrower can benefit from the opacity of its connected firms via lower loan spreads.

To my lovely wife and beloved parents

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CHAPTER 1: INTRODUCTION

Firms are connected through complex social and economic networks. One important source of connectedness is board networks formed by shared board directorates across firms. Individuals who are executives or directors at two or more companies become conduits for information, knowledge, and experiences that travel across the active links in the board network (e.g., Stuart and Yim, 2010; Chiu, Teoh, and Tian, 2012; Larcker, So, and Wang, 2013). Whereas recent studies suggest that board networks can function as a means for information transmission and play an important role in the financial markets, there is little research examining whether information flows through board networks can affect relative information asymmetries across potential lenders and thereby influence competition among bank lenders in the private lending market. I investigate the extent to which bank lenders are able to exploit their existing borrowers' board networks to increase their chances of winning loan business from firms in such networks (hereafter connected firms). Further, I examine whether banks compensate well-connected borrowers for access to the cross-firm selling opportunities provided by their board networks, and whether the value of a borrower's board network to a bank is increasing in the opacity of firms in the network.

Bank lenders potentially have multiple advantages over other *de novo* lenders when competing for making loans to firms in their existing borrower's board network, including access to the connected firms' boards and managers and better information about the connected firms' credit worthiness. Common directors, who serve as board members in a borrower and its connected firms, can act as informal financial intermediaries between the borrower's bank and these connected firms, which provide banks with information that enhances their competitive advantage relative to other potential lenders. In this regard, Garmaise and Moskowitz (2003) analyzes a model in which informal financial intermediaries (e.g., brokers) and lenders play a cooperative repeated game. Lenders cooperate with informal financial intermediaries by expending effort to expedite the evaluation of loan applications made by the intermediaries' clients, which results in more service fees to the intermediaries. In return, the informal financial intermediary advises its clients to seek a loan from the lender.

Building on the cooperation theory in Garmaise and Moskowitz (2003), I posit that there is a form of cooperation between a bank and a borrower with a well-connected board (i.e., a board with directors that sit on the boards of many other firms). Specifically, the borrower's directors, who also serve as board members in its connected firms, can help the bank win future lending business from its connected firms because they can act as informal financial intermediaries. In return, the bank lender cooperates with the borrower by offering better loan contract terms. Hence, I predict that if a bank has a lending relationship with a well-connected borrower, then the bank's likelihood of winning the loan business from a firm in the borrower's board network increases. State differently, if a bank has made a loan to a potential borrower's connected firm before, then the bank becomes a connected bank of that borrower and thus the bank's chances of winning the loan business from that borrower increases. In addition, I predict that the well-connected borrower is rewarded with more favorable loan contract terms as reflected by a lower cost of debt.

To illustrate, Barbara Bass served on the board of both Starbucks Corp and Bebe Stores Inc. from 2000 to 2011. In 2005, Starbucks received a syndicated loan from Wells Fargo. Thus, in years 2005–2011 (but not 2000–2004), Wells Fargo may have a connection with Bebe Stores because Wells Fargo is connected to Bebe Stores via a common director. In other words, Wells Fargo becomes a connected bank of Bebe. Director Bass may act as an informal financial intermediary between Wells Fargo and Bebe Stores, which could increase Wells Fargo's likelihood of winning loan business from Bebe Stores during 2005–2011. In return, Starbucks may have received a lower cost of debt or other favorable loan terms from Wells Fargo on its 2005 syndicated loan.

To analyze empirically whether having made a loan to a borrower's connected firm increases a bank's likelihood of winning loan business from that borrower when competing with other banks, I use and augment data from Boardex to retrieve all the connections between firms through shared common directors and Dealscan to retrieve loan information for the sample period between 2000 and 2015. Following prior studies such as Bharath et al. (2008) and Hellmann et al. (2008), I directly model a firm's lender-choice problem in which a firm selects its lender from a pool of potential banks. Specifically, in my lender choice model, for each loan, a borrower has a choice set of all possible bank lenders. My empirical model examines whether a potential bank lender's likelihood of winning the loan business depends on whether the potential bank lender has made previous loans to a firm connected to the borrower, controlling for other determinants of lender choices, including the potential bank lender's prior lending relationship with the borrower, the bank's market power and reputation, the bank's industry specialization, and the geographic proximity between the bank and the borrower.

I find that having a prior lending relationship with a borrower's connected firm significantly increases a bank's chance of becoming the lender for that borrower. Specifically, conditional on having made a loan to a borrower's connected firm, a bank's probability of granting a loan to that borrower more than doubles from approximately 1.6% to 4.5%. I include loan fixed effects in the regressions as controls for various sources of observed and unobserved heterogeneity in lender choice and to minimize correlated omitted variable (and related endogeneity) concerns. This fixed effect structure implies that my analysis provides within-loan estimates for the key variables of interest, eliminating all common determinants of lender choice within a loan, including firms' and actual/realized lenders' characteristics.

Next, I examine whether borrowers with well-connected boards are compensated by bank lenders for their role in facilitating the bank's efforts to win loan business from other firms in the borrowers' board network. Analogous to the cooperation game in Garmaise and Moskowitz (2003), a bank can curry favor with a well-connected borrower by offering favorable loan contracts in return for their cooperation in increasing the bank's likelihood of subsequently winning loan business from the borrower's connected firms. I test this prediction by constructing a measure of board connectedness for each borrower and by comparing loan spreads between borrowers with a well-connected board and borrowers with a less well-connected board. I find that borrowers with a well-connected board have a lower cost of debt, even after controlling for credit risk and past and future performance. Specifically, loan spreads decrease by approximately 10% when the firm's board connectedness ranking moves from the bottom quintile to the top quintile. This finding is consistent with well-connected borrowers being rewarded with better loan contracts because they provide greater potential for cross-firm selling.

Next, I analyze the mechanism through which a bank that previously made a loan to a potential borrower's connected firm is more likely to win the loan from that new borrower. One important mechanism is that common directors, who link the new borrower and its connected firms, can serve as information intermediaries for the bank. Specifically, the intermediation role of the common directors can improve information flow and communication between the new borrower and the bank, and allow the bank to gain private information that provides the bank with a comparative advantage when competing with other *de novo* banks. The private information can include hard information, such as borrowers' financial projections and plans for acquisitions or dispositions, as well as softer information, such as observations about a management team's abilities and honesty (Petersen, 2004; Bushman, Williams, and Wittenberg-Moerman, forthcoming). Such private information would plausibly have higher value to a bank in situations where borrower opacity obscures the firm's fundamentals and makes it more difficult for other *de novo* lenders to assess the borrower's creditworthiness.

This analysis builds on Rajan (1992) and Hauswald and Marquez (2006), which model the competition between an informed bank and less informed banks to supply loan business to a risky borrower. The models show that informed banks have a competitive advantage in winning the loan by virtue of their information advantage. In my setting, I designate as informed lenders banks that have a lending relationship with the borrower's connected firm, where common directors can serve as information channels for private information about the borrower. Less informed banks are those without privileged access to the borrower. The greater is opacity in the borrowing firm's activities, the greater is the relative information advantage of the informed lenders, which in turn implies a greater competitive advantage. As a result, I predict that an informed bank's probability of winning the loan increases with a borrower's informational opacity. I find evidence consistent with this prediction: the probability of a connected bank lender winning the loan from a new borrower is higher when the borrower's financial reporting is more opaque.

Building on this result, I next examine whether the average opacity of firms in a well-connected borrower's board network increases the value of the network to a connected bank by increasing cross-firm selling potential. If the value of a board network is increasing in opacity, I expect banks to compensate well-connected borrowers that have opaque networks by offering lower loan spreads. Consistent with this expectation, I find that the loan spread discount for an existing well-connected borrower is greater if firms in that borrower's board network are on average more opaque. Overall, these findings are consistent with common directors serving as information intermediaries between the connected bank and the borrower and allowing the connected bank to gain an information advantage when competing for the borrower's loans.

One caveat regarding the inferences I draw from my findings is that, as with much of the work on social networks, it is difficult to definitively establish causality. Directors and firms do not match randomly. Prior studies suggest that because board members are chosen, board characteristics therefore are endogenously related to firm outcomes (e.g., Hermalin and Weisbach, 2003). As a result, a concern for my analysis is that the presence of a director on two firms' boards could reflect an underlying similarity between the two firms, and it could be this commonality that causes each to select the same bank lenders. This is effectively a correlated omitted variable problem, in which a potentially omitted factor is anything that both determines director matching to firms and is correlated with a firm's propensity to select certain bank lenders. To address this problem, I explicitly include controls for time-variant firm heterogeneity through loan fixed effects, time-invariant bank heterogeneity through bank fixed effects and time-varying bank characteristics through observable control variables (e.g., market power) in my lender-choice model. However, even after including these controls, an omitted variable can still operate at the firm and bank pair level, e.g., because the firm and bank operate in the same geographic region. To mitigate this concern, I exploit my data structure and include firm-bank fixed effects in the lender-choice model. In addition, I include controls for industry- and geography-proximity effects because these are two dimensions along which bank lending activities can cluster and board service is determined. My inferences are robust to using these fixed effects structure and control variables. Further, although I cannot fully rule out similarity between two connected firms as an alternative explanation for my findings, findings from the cross-sectional tests mitigate this concern. That is, the findings showing that borrower opacity increases the probability of a connected bank winning the loan and that connected banks offer lower loan spreads to well-connected borrowers with more opaque networks are inconsistent with this alternative explanation.

This study makes several contributions to the literature. First, prior research on board networks suggests that a board's social network is beneficial (e.g., Larcker et al., 2013; Houston et al., 2015). However, the mechanism through which the board network creates value is not yet well understood. This study complements this literature by documenting one mechanism for value creation—cross-firm selling potential for the firm's bank lenders provided by board connectedness. My findings suggest that board connectedness benefits not only borrowers, but also their bank lenders. In addition, although prior studies suggest that board networks can function as a means of information transmission, this paper is among the first to provide direct evidence on the information intermediation role of common directors. Second, this paper extends the extant accounting literature relating the quality of accounting information to debt contracting (e.g., Armstrong, Guay, and Weber, 2010; Dechow, Ge, and Schrand, 2010). Although much of this literature suggests that the quality of a firm's financial reporting positively affects its debt contracting outcomes, this paper adopts a contrasting perspective on the issue by considering the possibility that the opacity of a well-connected borrowers' network can be valuable to a bank and that the borrower can benefit from the opacity of its connected firms via lower loan spreads.

The remainder of the paper is organized as follows. Section 2 presents prior research that motivates my analyses and the hypotheses development. Section 3 presents the research design, section 4 describes the sample and data, and section 5 presents the results. Section 6 provides concluding remarks.

CHAPTER 2: RELATED LITERATURE AND PREDICTIONS

2.1. Borrower board connectedness and bank cross-firm selling

Sociologists have long viewed each company's board as a node in a firm-to-firm network that arises because a large fraction of public company directors are either directors or executives of other firm (e.g., Stuart and Yim, 2010). Individuals who are executives or directors at two or more companies become conduits for information, knowledge, and experiences that travel across the active links in the board network. Recent studies suggest that board networks play an important role in the financial markets. Larcker, So, and Wang (2013) documents a positive association between board connectedness and firm performance, and posits that the positive relation is attributable to networks providing better access to information. Several studies suggest that board networks function as the transmission route for the diffusion of financial practices. For example, board networks contribute to the dissemination of the stock option backdating practice (Bizjak et al., 2009) and earnings management (Chiu et al., 2012). Board members and their social networks influence which companies become targets in change-of-control transactions in the private equity market (Stuart and Yim, 2010). I build on these insights and investigate the extent to which bank lenders are able to exploit their existing borrowers' board networks to increase their chances of winning loan business from firms in such networks.

When a bank makes a syndicated loan to a firm, the ongoing interactions between the bank and the firm during the syndication process and over the life of the loan provide the bank and firm directors opportunities to build informal relationships with each other. When these directors also simultaneously serve as board members in other firms, their relationship with a bank allows these directors to act as informal financial intermediaries between the bank and other firms in the directors' networks. The role of these directors as an informal financial intermediary can increase the bank's likelihood of winning the loan business.[1] This line of reasoning is closely related to Garmaise and Moskowitz (2003), which presents a model of a general informal financial network that demonstrates that informal financial intermediaries, who do not supply loans, can facilitate their clients' access to financing through informal relationships with lenders. In the study's model, informal financial intermediaries and lenders play a cooperative repeated game. Lenders cooperate with informal financial intermediaries by expending effort to expedite the evaluation of loan applications made by the informal financial intermediary's clients, this results in more service fees to the intermediaries. In return, the informal financial intermediary advises its clients to seek a loan from the lender.

Building on the cooperation theory in Garmaise and Moskowitz (2003), I posit that there is a form of cooperation between a bank and a firm with a well-connected board, i.e., a board with directors that sit on the boards of many other firms. Specifically, when a bank syndicates a loan to a firm with a well-connected board, the bank cooperates with the firm by offering better loan contract terms. In return, the firm's directors, who also sit on other firms' boards, can help the bank win future lending business from those firms because these common directors act as informal financial intermediaries between the bank and the connected firms. In section 2.2, I investigate the mechanism through which the bank can win the loan business from the connected firms. Specifically, I analyze whether the bank gains privileged information about the connected firms, which gives the bank comparative advantage over other *de novo* lenders when competing

[1] As advisers to senior management, directors generally play an important role in major corporate decisions, including lending decisions (e.g., Engelberg, Gao, and Parsons, 2012).

for winning loans from these connected firms. One important reason that the well-connected firm' directors are willing to act in the interest of the firm and thus help the firm's bank is their reputational concern. Ample evidence suggests that directors seek to develop their reputation to gain more board seats and thereby obtain prestige, power, and compensation (e.g., Coles and Hoi, 2003; Lel and Miller, 2015; Levit and Malenko, 2016).[2] To sum up, if a bank has made a loan to a new borrower's connected firm before, then the bank's chance of winning the loan business from that borrower increases. My first hypothesis is the following:

H1: *Having a prior lending relationship with a borrower's connected firm increases a bank's likelihood of providing a loan to that borrower.*

My next prediction considers whether banks compensate well-connected borrowers for their role in facilitating the banks' efforts to win loan business from other firms in the borrowers' board network. As part of the cooperation game in Garmaise and Moskowitz (2003), a bank can curry favor with a well-connected borrower by offering favorable loan contracts in return for their cooperation in increasing the bank's likelihood of subsequently winning loan business from the borrower's connected firms. Accordingly, my second hypothesis is:

H2: *Borrowers with a well-connected board (i.e., well-connected borrowers) can obtain loans at a lower spread.*

This prediction is consistent with Ivashina and Kovner (2008), which examines the impact of leveraged buyout firms' bank relationships on the terms of their syndicated loans. The study suggests that bank pricing decisions take fees across all products into account and thus the potential for additional business from the leveraged buyout firms' other investments would

[2] Another potential reason that the common directors have incentives to help the connected bank is that the directors may benefit directly from their relationship with the connected bank. For example, they might receive special loan terms if they borrow from the connected bank.

improve the terms for any given loan. My study complements Ivashina and Kovner (2008) by examining whether banks offer favorable loan terms to a well-connected borrower to curry favor with the borrower to help the bank sell loans to the borrower's connected firms.

Whereas my study focuses on bank cross-firm selling, there is an extensive banking literature that focuses on banks' incentives to cross-sell different products to the same firm. For example, a number of studies examine how a bank's past lending relationships with a firm affect the bank's chance of becoming underwriter of the firm's debt and equity. Yasuda (2005) examines the impact of prior lending relationships on the choice of debt underwriter and finds that past lending relationships are associated with a significantly higher probability of securing the debt underwriting business. Drucker and Puri (2005) focuses exclusively on seasoned equity offerings and reports that concurrent lending—a loan six months before or six months after the issue—is associated with a higher likelihood of winning the underwriting business. Bharath et al. (2007) finds that prior lending relationships are associated with a significantly higher probability of winning underwriting business for initial public offerings. Instead of examining the relation between prior lending relationship and the choice of underwriter, Hellmann Lindsey and Puri (2008) considers the relation between a bank's venture capital investments and its subsequent lending. The study finds that having a prior relationship with a firm in the venture capital market increases a bank's chance of subsequently granting a loan to that firm. My study builds on this literature by investigating the extent to which the bank lenders exploit their existing borrowers' board networks to sell loans to other firms in such networks.

2.2. Bank cross-firm selling, borrower board connectedness and borrower opacity

In section 2.1, I predict that a bank's chance of winning a loan from a borrower increases if the bank previously made loans to the borrower's connected firm. I term those banks as connected banks. An explanation for this prediction is that common directors, who link the borrower and its connected firms, act as informal financial intermediaries for the bank. The question arises as to whether the intermediation role of common directors is associated with the ability of the connected bank to gain privileged information regarding the borrower, which provides the bank a comparative advantage when competing with other lenders. I analyze this question in this section.

Building relationships with common directors potentially enables a bank to gain extensive inside knowledge of the borrowers operations and to develop private channels of communication with the managers.[3] The inside information gained by the bank can include hard information, such as financial projections and plans for acquisitions or dispositions, as well as softer information, such as observations about a management team's abilities and honesty (Petersen, 2004). In addition, the inside information can be new information not available to the bank from other sources, or it could be a signal that confirms, corroborates, or substantiates noisy information that the bank received from a different source (Bushman, Williams, and Wittenberg-Moerman, forthcoming). In the latter case, the common directors can, for example, confirm soft information the bank obtained elsewhere about the borrower, or allow the bank to filter noise from signals received from other sources.

Because of this informational advantage, the bank has a comparative advantage over outside lenders without such connections. Thus, when the connected bank lenders compete with other lenders to arrange a loan for the borrower, *de novo* unconnected lenders face higher adverse selection risk than connected bank lenders because of their pre-bidding informational

[3] Although securities law prohibits investors from obtaining unequal access to firms' confidential information in the equity market, private debt markets are not subject to such securities laws. As a result, investors in the debt market, i.e., lenders, have significant access to borrowers' private information.

disadvantage. This line of reasoning is motivated by Rajan (1992) and Hauswald and Marquez (2006), which provide the theoretical underpinning for the tests that follow.[4]

Rajan (1992) and Hauswald and Marquez (2006) model competitive dynamics in private lending markets in a setting where an informed (inside) bank competes for a borrower's loan with less informed (outside) banks. The models assume that the informed bank acquires private information through its privileged access to the borrower, whereas an uninformed bank does not have such access. [5] The models assume that the informed bank has superior (or perfect) information about whether the firm will succeed or fail, and that an uninformed bank has no private information. The informed bank can use its ability to distinguish good from bad credit risks to adjust its lending strategy accordingly and thus to subject less informed lenders to problems of adverse selection. As a result, an uninformed bank will bid for the loan less aggressively by offering loans less frequently.

Hauswald and Marquez (2006) also shows that the probability that a borrower receives a loan offer from an uninformed bank decreases in the informational advantage of the informed bank. Specifically, because the improved informational advantage increases the threat of adverse selection to the uninformed bank, the uninformed bank will bid less aggressively and thus is less likely to win the loan contract. This theory leads to the prediction that the probability of an informed bank winning the loan from the borrower is higher when the informed bank's informational advantage is higher. Assuming that the informed bank would have a greater informational advantage relative to the uninformed bank if the borrower's information

[4] These models are used by Bushman, Williams, and Wittenberg-Moerman (forthcoming) to examine the informational role of the media in private lending.

[5] In Rajan (1992), the informed bank is a relationship bank that has made loans to the borrower and thus can acquire private information. In Hauswald and Marquez (2006), the informed bank is a bank that is located in close geographic proximity to the borrower and the short distance between the bank and borrower allows the bank to acquire private information.

environment is more opaque, the probability of the informed bank granting a loan is increasing in the borrower's information opacity. In my context, I designate as informed lenders banks that have a lending relationship with the borrower's connected firm where common directors can serve as information channels for private information about the borrower. Therefore I predict that the effect of the bank's prior lending relationship with the borrower's connected firm on the likelihood of granting a loan to the borrower is stronger if the borrower is more opaque.

I further predict that the loan spread discount for an existing well-connected borrower is greater if firms in that borrower's board network are more informationally opaque. As discussed above, if firms in the borrower's board network are more opaque, then the borrower's bank would have higher probability of winning the loan business from these firms in the network. Therefore, the board network of the borrower would be more valuable to the bank lender, and the bank would compensate the well-connected borrower with lower spreads.

This prediction is related to the literature on the role of financial reporting quality in debt contracting. Prior studies primarily show that a firm's information quality is positively related to its debt contracting outcomes such as cost of debt (e.g., Ball et al., 2008; Bharath et al., 2008; Graham et al., 2008; Zhang, 2008).[6] My paper adopts a contrasting perspective on the issue by considering the possibility that a well-connected borrower's cost of debt is related to the information quality of firms in its board network and that the borrower can benefit from the opacity of firms in its board network. The underlying mechanism for the benefit is that the opacity of the connected firms provides greater cross-firm selling potential for the borrower's bank and therefore is valuable to the bank. This mechanism is distinct from those studied in the extant literature, including agency costs and renegotiation costs (e.g., Armstrong et al., 2010).

[6] See Armstrong et al. (2010) for detailed review of this literature.

CHAPTER 3: RESEARCH DESIGN

I organize the discussion of research design into three subsections. Section 3.1 describes the network measures used in empirical tests. Section 3.2 discusses the regression model that I use to examine whether having a prior lending relationship with a borrower's connected firms increases a bank's probability of granting a loan to that borrower. Section 3.3 explains the regression model for testing whether a borrower with a well-connected board is rewarded with a lower cost of debt. Section 3.4 presents the regression model for analyzing whether the connected bank's likelihood of granting a loan to a new borrower is higher if the borrower is more informationally opaque. Section 3.5 explains the regression model for testing whether the loan pricing discount for a well-connected borrower is higher if firms in the borrower's board network are more informationally opaque.

3.1. Connection measures

In my study, two firms are linked or connected if they share at least one common director. To conduct my tests, I create two different types of connection measures based on director network or experience. My first connection measure relates to board connectedness. I define *Aggregate_Connectedness*, which is the total number of links to outside firms to which a given firm is connected by sharing its directors. For example if a firm has two directors, one of which sits on 4 other firms' boards and antoher of which sits on 3 non-overlapping firms' boards, then *Aggregate_Connectedness* equals 7. This is a general measure of firm's connectedness in the board network. One drawback of this connectedness measure is that larger firms tend to have larger boards, giving rise to a mechanical positive association between firm size and the board connectedness measure. Therefore, following Larcker et al. (2013), I create a ranked version of the connectedness measure that reduces the association with size. Specifically, for each year, I rank all firms into quintiles based on total assets. Within each total asset quintile, I sort firms into quintiles based on *Aggregate_Connectedness,* where the highest (lowest) value of connectedness is assigned a value of four (zero). I further deflate this connectedness measure by four, so that the range of this variable is between 0 and 1. I term this connectedness measure *Connectedness*. The use of quintiles ranks reduces the influence of extreme values, eases the interpretation of the regression results, and provides a non-parametric method to mitigate the impact of firm size on the connectedness measure. To further mitigate the effect of size, I include other size proxies in the regressions such as total asset and board size.

The second measure relates to whether a bank has a lending relationship with a given borrower's connected firms. This variable, $Connected\_Bank_{i,m}$ is an indicator variable that equals one if any of firm *i*'s directors serve on the board of a second or more firm that has a lending relationship with bank *m*. I use $Connected\_Bank_{i,m}$ to test H1, i.e., whether having a prior lending relationship with a borrower's connected firm increases a bank's likelihood of providing a loan to that borrower.

3.2. The effect of prior lending relationship with borrower's connected firm on likelihood of being chosen as the lead bank

In this section, I develop the empirical analysis I use to test the hypothesis that having a prior lending relationship with a borrower's connected firm increases a bank's likelihood of providing a loan to that borrower. Following prior research such as Hellmann, Lindsey, and Puri (2008) and Cai, Saunders, and Steffen (2016), I directly model a firm's lender-choice problem for its syndicated loans and evaluate the effect of prior lending relationships with connected firms on the choice of lenders. I focus on syndicated loans because they are the dominant way in which firms obtain loans from banks and other financial institutions.[7] Because the lead arranger bank is the key lender in a syndicated loan, I focus on the firm's choice of lead banks rather than all lenders (I use the terms lead arranger and lead bank interchangeably).[8]

To evaluate the effect of prior lending relationships with the borrower's connected firm, for each loan, I focus on any bank *m*'s likelihood of winning the loan business as the lead arranger from borrower *i* at time *t*. I need to consider both realized matches in the loan market (where a specific bank grants a loan to a specific firm), and unrealized matches (where a specific bank does not grant a loan to a specific firm). This implies that the unit of analysis is the potential pairing between a firm and a bank at a specific time. That is, I need to consider not only the realized pairs of firms and banks but also those cases in which there is potential to pair even if the pairing does not actually happen. The number of potential lead banks is quite large, and a handful of banks account for the bulk of lending. Therefore, following Sufi (2007) and Cai et al. (2016), I limit the analysis to the top 100 lead banks in my sample because such banks account for 99% of the aggregate market share. For each loan I create a choice set of 100 potential lead banks, thereby creating 100 loan-bank pairs. I estimate the following linear probability regression model:

[7] Syndicated loans are large deals that typically require board approval. The average loan size in my sample is approximately $500 million.

[8] In contrast to a traditional bank loan, which involves a single lender, a syndicated loan involves a group of lenders. The loan is originated by a lead bank (i.e., lead arranger) which sells pieces of the loan to other participant banks. Although the lead bank retains only part of the loan, it acts as the manager for the loan with primary responsibility for ex ante due diligence and for ex post monitoring of the borrower. Participant banks depend on the information collected by the lead bank.

$$Realized\_Lender_{i,m,k,t} = \alpha + \beta_1 Connected\_Bank_{i,m,t} + Controls + LoanFE + \varepsilon \quad (1)$$

$Realized\_Lender_{i,m,k,t}$ is an indicator variable that equals one if borrower *i* selects bank *m* as the lead arranger/bank in loan *k* that is originated in month *t* and zero otherwise. My central independent variable is $Connected\_Bank_{i,m,t}$, which is an indicator variable that equals one if bank *m* has originated a loan to the borrower's connected firm prior to the month *t* and during the period in which the connection is active, and zero otherwise. As noted earlier, a borrower's connected firms are other firms that share directorates with firm *i* at time *t*.[9] If a bank's prior lending relationship with a borrower's connected firm is associated with an increase (decrease, no change) in the bank's likelihood of originating a loan to the borrower, then I predict $\beta_1 > 0$ ($\beta_1 < 0$, $\beta_1 = 0$).

Based on prior literature, I also include controls for other variables that determine bank *m*'s likelihood of originating a loan to a borrower (e.g., Cai et al., 2016). The first control, $Prior\_lending\_relationship_{i,m,t}$, a proxy for direct bank to borrower relationships, is an indicator variable for whether bank *m* has originated any loans to the borrower prior to month *t*. Inclusion of $Prior\_lending\_relationship_{i,m,t}$ serves as a control for effects of prior relationships between the borrower and bank *m*.[10] *Market_Share* is the market share of bank *m* as a lead arranger in the US syndicated loan market during the twelve months prior to month *t*, and is a proxy for the bank's reputation and market size or power. *Industry_Specialization* is the loan portfolio weights for each bank *m* in each industry specialization category, which I measure

[9] Borrower *i* may begin to share directorates with connected firm *j* several years before the month *t*, and this connection could last several years after the month *t*. In other words, connections are essentially predetermined.

[10] Untabulated findings reveal that the inferences remain the same if I exclude lenders who have a direct lending relationship with the borrower.

based on 2-digit SIC. I include it as a proxy for bank *m* specialization in the borrower's industry. *Same_Region* is an indicator variable that equals one if the headquarters of borrower and bank *m* are located in the same region (i.e., the same 3-digit Zip code), and zero otherwise. I use this variable as a proxy for the geographic proximity between bank *m* and the borrower. *LoanFE* is a vector of loan fixed effects, which are included as controls for various sources of observed and unobserved heterogeneity in lender choice and to minimize correlated omitted variable (and related endogeneity) concerns. This fixed effect structure implies that my analysis provides within-loan estimates for the key variable of interest, *Connected_Bank*. That is, the loan fixed effects eliminate all common determinants of lender choice within a loan. For a given loan, all variables that do not vary across observations (loan-bank pairs) are subsumed by the fixed effects. As a result, I omit all firm-specific, loan-specific and lead bank specific variables and time fixed effects in the regression. Standard errors are heteroscedasticity robust and clustered at the firm level.

3.3. The effect of board connectedness on loan pricing

In this section, I develop the empirical analysis I use to test the hypothesis of whether banks compensate firms with a well-connected board by offering better loan contract terms as reflected by lower loan spreads. To examine the effect of board connectedness on loan pricing, I estimate the following regression model:

$$LoanSpread_{it} = \alpha + \beta_1 Connectedness_{it-1} + Controls + FirmFE + YearFE + \varepsilon \qquad (2)$$

The dependent variable, *LoanSpread*, is loan spread based on the all-in-drawn spreads over LIBOR at issue date for loans issued to firm *i* in year *t*. Because loan spreads are highly skewed, following prior studies (e.g., Graham et al., 2008; Chava et al., 2009), I measure *LoanSpread* as the natural logarithm of the actual loan spread. The central independent variable is

Connectedness.[11] If board connectedness is associated with lower (higher, no change) loan spreads, then I predict $\beta_1 < 0$ ($\beta_1 > 0$, $\beta_1 = 0$). Since larger board and older firms are likely to have more aggregate connections, I also include controls for board size (*Board_Size*) and firm age (*Age*). *FirmFE* and *YearFE* are firm and year fixed effects.

Eq. (2) also includes a set of control variables for a variety of firm- and loan-specific characteristics suggested by prior research to affect loan spread. The firm characteristics include return on assets, *ROA*; the tangibility of firm's asset, *Tangible*, the debt-to asset-ratio, *Leverage*; firm size as measured by the natural logarithm of total assets, *Log_asset*, and a set of indicator variables corresponding to each of 22 possible credit ratings (e.g., AAA, AA+, AA, etc.).[12] Loan characteristics include revolver lines, *Revolver*; term loan B or below, *TermLoanB*; presence of performance pricing provisions, *Performance_pricing*; the natural logarithm of loan dollar amount in millions, *LoanAmt*; the loan term in months, *Maturity*; the number of financial covenants, *NCOV*; an indicator variable that equals one if a loan is secured and zero otherwise, *Securdum*; and a set of 30 indicator variables for loan purpose, e.g., whether a loan is used to finance an acquisition or whether a loan is used to execute a leveraged buyout. All firm-level variables are measured as of the most recent quarterly financial reporting date. The appendix provides details of all variable definitions. I cluster standard errors at the firm level.

[11] Untabulated finings reveal that the references reported in the paper remain the same if I use *Aggregate_Connectedness*.

[12] These variables also include an indicator for whether a firm has a credit rating.

3.4. The *effect of borrower information opacity on a connected bank's likelihood of winning a loan*

In this section, I test the prediction that the effect of a bank's prior lending relationship with a borrower's connected firm on the likelihood of granting a loan to the borrower is stronger if the borrower is more opaque. I estimate the following regression model:

$$\begin{aligned} Realized\_Lender_{i,m,k,t} &= \alpha + \beta_1 Connected\_Bank_{m,i,t} + \beta_2 Opacity_{i,t} + \\ &\beta_3 Connected\_Bank_{m,i,t} \times Opacity + Controls + LoanFE + \varepsilon \end{aligned} \quad (3)$$

Eq. (3) modifies Eq. (1) by including a measure of financial reporting opacity, *Opacity*, and its interactions with the central independent variable, *Connected_Bank*. To create this financial reporting opacity measure, I borrow from Ball, Bushman, and Vasvari (2008) and Dou (2012), which develop a transparency measure, the debt-contracting value measure of a borrower's accounting information, *DCV*. The *DCV* measure reflects the inherent ability of firms' public accounting information to reflect credit quality. *DCV* is the Somers' D-statistic derived from the explanatory power of accounting variables (i.e., earnings, leverage, equity book value and interest coverage) in an industry-specific probit model of firm credit ratings and ranges from zero—low transparency—to one—high transparency. As such, *DCV* reflects the inherent ability of firms' accounting amounts to capture credit quality measured at the industry rather than the firm level (see Appendix for details). I multiply *DCV* by –1 such that a high value of *DCV* indicates an opaque financial reporting system. Further, I rank *DCV* into deciles, then divide the resulting measure by nine to convert the decile rank to a zero to one range. This procedure allows me to more easily interpret coefficients in my empirical tests. If a borrower's opacity increases a connected bank's likelihood of winning the loan business from that borrower, then I predict the coefficient on the two-way interaction term, *Connected_Bank* $\times$ *Opacity*, is positive ($\beta_3 > 0$).

I use *DCV*, a measure of financial statement transparency, rather than equity bid-ask spread or analysts' coverage as our measure of transparency for several reasons. First, whereas *DCV* relates specifically to the credit market, equity bid-ask spread and analysts' coverage relate primarily to the equity market. Second, *DCV* is particularly relevant to the credit markets at the time of loan initiation because accounting information is the primary source of information lenders use when they initiate loans. In this regard, prior studies provide consistent evidence that accounting information plays an important role in the design of debt contracts (e.g., Ball et al., 2008; Armstrong et al., 2010; Amiram, 2013; Amiram et al., 2016).

3.5. The effect of information opacity and loan pricing

In this section, I test the prediction that the loan spread discount for an existing well-connected borrower is greater if firms in that borrower's board network are more opaque. I estimate the following regression:

$$\begin{aligned} LoanSpread_{it} &= \alpha + \beta_1 Connectedness_{it} + \beta_2 Opacity\_Net_{i,t} + \\ &\quad \beta_3 Connectedness_{it} \times Opacity\_Net_{i,t} + Controls + FirmFE + YearFE + \varepsilon \end{aligned} \tag{4}$$

Eq. (4) modifies Eq. (2) by including a measure of network opacity for the borrower, *Opacity_Net*, and its interactions with the central independent variable, *Connectedness*. To create this financial reporting opacity measure for the borrower's board network, I calculate the average *DCV* value for all firms in the borrowers' board network.[13] I then multiply this average *DCV* by –1 such that a high value of *DCV* indicates an opaque financial reporting system.

[13] The calculation of *Opacity_Net* requires borrowers to have a least one firm in their board network. As a result, borrowers without board networks are excluding from the sample used to estimate Eq. (4).

Observations that are in the top quintile of this transformed average *DCV* value are classified as having high network opacity. If, as I predict, the loan pricing discount is greater for borrowers with more opaque board networks, then the coefficient on the two-way interaction term, *Connectedness* $\times$ *Opacity_Net*, is negative ($\beta_3 < 0$).

CHAPTER 4: DATA AND SAMPLE

I collect the data in this study from several sources. I obtain board connections information from the Boardex database, which reports extensive information regarding the characteristics of board members and executives for US public firms from 2000 onwards. The Boardex data include board size and composition along with each board member's complete history of other board memberships and socio-demographics such as age, gender, education, and nationality. Stock prices and accounting variables are from CRSP and Compustat. Using the Dealscan database, I also collect information on bank loans made to US public firms, the majority of which are syndicated between multiple banks that share lending risk. The unit of observation in Dealscan is a loan facility. For each facility, Dealscan lists a number of borrower and lender characteristics including the interest rate, the identity of the borrower and participant banks, the stated purpose of the loan, information about covenants, loan amount, maturity, and presence or absence of collateral. As mentioned earlier, a syndicated loan typically has multiple lenders who are classified broadly into two categories: lead arranger (or lead bank) and participant lenders. The lead arranger is the key lender, who originates the loan with the borrower and is responsible for screening borrowers before loan syndication and for monitoring borrowers throughout the life of the loans.[14] To test hypothesis 1, I focus on a borrowers' choice

[14] Following Sufi (2007), I use two variables to classify lenders as either lead arrangers or participants. Both are available from Dealscan. One variable is "Lead arranger credit" and the other is "Lender role". I designate as lead arrangers any lender for which the field "lead arranger credit" is marked "Yes". If this field is unavailable, then lenders that act as an administrative agent, agent, arranger, bookrunner, lead arranger, lead bank, or lead manager are defined to be lead arrangers.

of lead arranger for each loan facility. The sample for hypothesis 1 contains 15,974 loan facilities from 2,868 firms over the sample period of 2000–2015.[15] For each of those loan facilities, I consider all possible matches with the top 100 banks during my sample period, generating a total of 1,597,400 possible matches. I use this sample for hypothesis 1. Table 1, Panel A, provides summary statistics for the potential loan-bank matches sample. The mean value of *Realized_Lender* is 0.019, which indicates that the unconditional probability of being chosen as the lead arranger is 1.9%. The mean value of *Connected_Bank* is 0.074, which suggests that 7.4% of the bank lenders have made a loan to the borrower's connected firm before. The mean value of *Prior_lending_relationship* is 0.031, which indicates that 3.1% of the bank lenders have an existing lending relationship with the borrower before the current loan. The average market share of the bank lenders, *Market_Share*, is 0.99% with standard deviation of 3.616%. The average loan portfolio weight for a lender in the borrower's industry, *Industry_Specialization*, is 2.5% with standard deviation of 9.5%. The mean value of *Same_Region* is 0.014, which suggests that 1.4% of the firm-bank pair are located in the same 3-digit Zip Code region.

The sample for hypothesis 2 contains 11,934 loan facilities from 2,436 non-financial firms over the sample period of 2000–2015. Table 1, Panel B, reports the summary statistics for this loan sample. The mean *Aggregate_Connectedness* is 8.559, which implies that the average board in this sample has 8.559 aggregate connections, and the median and standard deviation are 7 and 7.134 connections. Untabulated statistics suggests that the Pearson correlation between *Aggregate_Connectedness* and the natural logarithm of assets is 0.551. The Pearson correlation

[15] I exclude financial firms, that is, firms with two-digit SIC between 60 and 64, inclusive (Ivashina, 2009). In addition, my sample includes only loan deals that were successfully syndicated.

between *Connectedness* and the natural logarithm of assets is 0.084, which suggests that *Connectedness* effectively mitigates the size effect associated with *Aggregate_Connectedness*. The average return on asset, *ROA*, is 0.008 with standard deviation of 0.051. The average proportion of tangible assets to total assets, *Tangible*, is 0.32. The average leverage ratio, *Leverage* is 0.314. The average log of total asset, *Log_asset*, is about 7.524, which is larger than average firms in Compustat. The average firm age, *Age*, is about 24 years. The average board in my sample has 9 directors (*Board_Size*). The average loan spread, *Log_spread*, is 5.021 with standard deviation of 0.808. The average natural logarithm of loan amount, *LoanAmt* is 19.153 with standard deviation of 1.418. Debt maturity, *Maturity* has a mean of 48.569 months. The average number of financial covenants, *NCOV* is 1.543, and 47.3% of the loans are secured (*Securedum*). Revolvers and institutional loans (term loan B or below) comprise 71.3% and 10.5% of the sample (*Revolver* and *TermLoanB*). 48.1% of the loans have performance pricing provisions (*Performance_Pricing*).

CHAPTER 5: RESULTS

5.1. The effect of prior lending relationship with a borrower's connected firm on a bank's likelihood of being chosen as the lead bank

Table 2, Column 1, reports the regression summary statistics associated with estimation of Eq. (1). The key finding is that the *Connected_Bank* coefficient, 0.029, is significantly positive (t-statistic = 17.75).[16] This finding indicates that having a lending relationship with a borrower's connected firm increases a bank's chances of granting a loan to that borrower. In addition to being statistically significant, the effect is also economically significant. The conditional probability of a potential lender without such a connection to the borrower being chosen as the lead bank, i.e., when *Connected_Bank* = 0, is 1.6% (evaluated at the mean of the independent variables), whereas this probability increases by 2.9% to 4.5% if the lender has such a connection to the borrower. This suggests that having a relationship with a borrower's connected firm more than doubles the probability of granting a loan to that borrower. Because the dependent variable, *Realized_Lender*, is binary, I also estimate Eq. (1) using logistic regression. Column 2 reports the odds ratio estimates from the logistic regression. As in Column 1, Column 2 shows that the coefficient on *Connected_Bank* is positive and significant. The odds ratio for *Connected_Bank* is 3.74, which suggests that banks that have a lending relationship with a borrower's connected firm are 3.7 times more likely to make a loan to that borrower relative to banks that do not have such connection. Overall, these results confirm my

[16] Throughout, when discussing a coefficient, I use the term significant to denote a 5% significance level under a two-sided alternative.

hypothesis about the importance of building a relationship with a borrower's connected firm in the syndicated loan market.

The Table 2 findings for the primary control variables are consistent with prior research(e.g., Bharath et al., 2007; Hellmann et al., 2008; Cai et al., 2016). Having a prior lending relationship with the borrower itself (*Prior_lending_relationship*) increases the probability of subsequently granting a loan to the same borrower. Lenders with higher loan market share or reputation in the syndicated loan market (*Market_Share*) have higher probabilities of granting a loan. Bank industry specialization (*Industry_Specialization*) increases a bank's likelihood of making a loan to that specialized industry. Banks that are located in the same region (*Same_Region*) as a borrower's headquarter have higher probabilities of making a loan to that borrower.

5.2. The effect of board connectedness on loan pricing

Table 3, Column 1, reports the regression summary statistics associated with estimation of Eq. (2). The key finding is that the *Connectedness* coefficient is significantly negative (coefficient = –0.104; t-statistic = –3.34). The magnitude of the coefficient is also economically significant, implying that loan spreads decrease by approximately 10% when a firm's board connectedness ranking moves from the bottom quintile to the top quintile. This implies that for a firm that faces a loan spread of 200bp when its board connectedness is in the bottom quintile, which is the average loan spread in my sample, the loan spread decreases to180bp if the firm's connectedness ranking moves to the top quintile. Finding that there is a loan pricing discount for well-connected borrowers is consistent with banks valuing board connectedness because the borrowers can help the banks win loans from other firms in the borrower's network.

The findings in Table 3 also reveal that the majority of the control variables' coefficients are significant, with signs that are largely consistent with prior research (e.g., Zhang, 2008; Ivashina, 2009; Bushman et al., forthcoming). For example, firms with high return on assets (*ROA*) and larger firms (*Log_asset*) on average have a lower cost of debt. More highly leveraged firms (*Leverage*) pay higher spreads. Regarding the non-price loan terms, the loan amount (*LoanAmt*) and loan maturity (*Maturity*) coefficients are statistically negative. Both collateral (*Securedum*) and number of covenants (*NCOV*) are positively related to loan spread, which perhaps reflects the endogenous determination of loan contractual terms. The significantly negative coefficient on *Revolver* and significantly positive coefficient on *TermLoanB* indicate that revolver loans and term loans B (i.e., those in which syndicate participants are non-bank institutions) face lower and higher rates. The significantly negative coefficient on *Performance_Pricing* indicates that loans with performance pricing provisions have lower interest rates.

Larcker et al., (2013) finds that companies with boards at a more central location in the board network tend to have better future performance. Hence one potential alternative explanation for the loan pricing discount for well-connected borrowers is that bank lenders anticipate better future performance of well-connected firms and thus charge lower interest rates. To mitigate this concern, I re-estimate Eq. (2) and include *ROA* in the next 3 years as a control for future performance. Table 3, Column 2, reports the regression summary statistics associated with this estimation. As expected, coefficients on *ROA* in years t+1 and year t+2 are significantly negatively related to loan spread. However, the *Connectedness* coefficient is significantly negative (coefficient = –0.107; t-statistic = –3.05). In addition, the *Connectedness* coefficients and t-statistics are of similar magnitudes whether or not subsequent years ROA are included as controls, which suggests that future growth has no impact on the relation between loan spread and connectedness. Furthermore, my inference remains the same if I use stock return as an alternative measure for performance.

Taken together, the findings in Table 3 indicate that borrowers with a well-connected board obtain loans at a lower spread. These findings, together with the findings in Table 2, portray a consistent picture: a borrower's board connectedness creates a potential for its bank lender to sell loan to the borrower's connected firms. In return for this opportunity for future growth, the lender offers a well-connected borrower favorable loan contracts.

5.3. The information intermediation role of common directors

5.3.1. The effect of borrower opacity on a connected bank's likelihood of winning a loan

Table 4 reports summary statistics associated with estimation of Eq. (3). The key finding is that the coefficient on the interaction term, $Connected\_Bank \times Opacity$, is significantly positive (coefficient = 0.013; t-statistic = 2.37), which is consistent with the prediction that a connected bank's likelihood of winning loan business from a new borrower is higher if the borrower is more opaque. The *Connected_Bank* coefficient is also significantly positive (coefficient = 0.023; t-statistic = 6.94), suggesting that a connected bank's probability of granting a loan to a borrower will increase by 2.3% even if the borrower is informationally transparent. If the borrower is opaque then this probability will increase by 3.6% (= 0.023 + 0.013). Overall, this finding supports the view that a bank that has a prior lending relationship with a borrower's connected firm gains privileged information about that borrower and thus has an informational advantage over *de novo* bank lenders when competing for loan business.

5.3.2. The effect of board network informational opacity on loan pricing

Table 5 reports regression summary statistics associated with estimation of Eq. (4). The key finding is that the coefficient on the interaction term, *Connectedness* $\times$ *Opacity_Net*, is significantly negative (coefficient = –0.124; t-statistic = –2.12), which is consistent with the prediction that a well-connected borrower that has more opaque firms in its board network receives more loan pricing discount from the bank lender. The *Connectedness* coefficient is also significantly negative (coefficient = – 0.091; t-statistic = –2.66), suggesting that a well-connected borrower still receives a loan pricing discount even if firms in the borrower's network have transparent information. However, if firms in the borrower's network are opaque, then the loan pricing discount increases to 0.215 (= 0.091 + 0.124). Overall, this finding supports the view that banks perceive the cross-firm selling potential to a borrower's connected firms is higher if the connected firms are more opaque and thus are willing to offer more loan pricing discount. This finding extends the extant accounting literature relating the quality of accounting information to debt contracting (e.g., Armstrong, Guay and Weber, 2010; Dechow, Ge and Schrand, 2010). Although much of this literature suggests that the quality of a firm's financial reporting positively affects its debt contracting outcomes, this paper demonstrates that the debt contracting outcomes of a borrower also depend on the financial reporting quality of its connected firms and that the borrower can benefit from the opacity of its connected firms.

5.4. Robustness: bank heterogeneity

The findings in Table 2 indicate that having made a loan to a potential borrower's connected firm, *Connected_Bank*, increases a bank's likelihood of winning loan business from that borrower. To mitigate the effects of endogeneity, it is important that *Connected_Bank* does not simply reflect other bank lender attributes that could affect the bank's likelihood of winning loan business from a borrower. To further mitigate the effects of lender attribute heterogeneity, I re-estimate Eq. (1) by including bank fixed effects in the regression. Untabulated findings reveal that the *Connected_Bank* coefficient is significantly positive (coefficient = 0.024; t-statistic = 15.41). The t-statistics and coefficient are of similar magnitudes whether or not bank fixed effects are included as controls, which indicates that other omitted bank characteristics have minimal impact on the relation between the probability of being selected as a lender and being a connected bank, *Connected_Bank*.

For Eq. (2), the majority of the control variables are defined at the firm level and not at the lender level. When capital providers are relatively homogeneous, lender specific attributes are unikely to influence lending outcomes (e.g., loan pricing). However, in the syndicated loan market, the ability to screen and monitor borrowers could differ significantly between banks. To that extent that such differences are correlated with my board connectedness measure, *Connectedness*, the coefficient I report would be biased. To further mitigate the effects of lender attribute heterogeneity, I re-estimate Eq. (2) by including bank fixed effects in the regression. Untabulated findings reveal that the *Connectedness* coefficient is significantly positive (coefficient = 0.101; t-statistic = –3.24). The t-statistics and coefficient essentially remain unchanged whether or not bank fixed effects are included as controls, which suggests that other omitted bank characteristics have no effect on the relation between loan spread and board connectedness.

5.5. Endogeneity

The findings in Table 2 indicate that a bank's chance of winning loan business from a borrower increases if the bank previously made loans to the borrower's connected firm. An explanation for this finding is that common directors, who sit on the borrower's board and the connected firm's board with which the bank has an existing lending relationship, act as informal financial intermediaries between the bank and the borrower and help the bank to win the loan business from the borrower. However, two broad sources of endogeneity challenges the credibility of this effect: reverse causality, as a bank lender may recommend directors to sit on their borrower's board, and (2) director-firm matching on an ommited attribute that determines both board composition and lender choice.

5.5.1. Reverse causality

The first endogeneity concern is reverse causality. That is, during the loan negotiation process and before the final loan origination date, a bank lender is selected by the new borrower, and then the lender recommends a director with which the lender has developed a relationship in the past to sit on the borrower's board. One approach to address this possibility is to consider the role of the individual director's tenure on the new borrower. If the director has served on the new borrower's board for a relatively long period of time before the loan origination, for instance, 2 or more years, then it is unlikely that the findings in Table 2 are attributable to reverse causality. Hence, I re-estimate Eq. (1) by using observations that exclude loans where the common directors have served on the borrower's board for less than 2 years before loan origination. Table 6, Panel A, reports the regression summary statistics associated with estimation of Eq. (1) using the new sample. The key finding in Column (1) is that the *Connected_Bank* coefficient, 0.030, is significantly positive (t-statistic = 14.58). Column 2 reports the odds ratio estimates from the logistic regression. As in Column 1, Column 2 shows that the coefficient on *Connected_Bank* is positive and significant (coefficient = 2.435, t-statistic = 19.70). Taken together, these findings provide additional support that the inferences I draw from Tables 2 and 3 findings are not the result of reverse causality.

5.5.2. Director-firm matching

Directors and firms are not matched randomly.[17] The fact that a director sits on two firms' board could just indicate a similarity between the two firms, and this commonality may cause each firm to select the same bank lenders. This is effectively a correlated omitted variable problem, in which a potentially omitted factor is anything that both determines director matching to firms and is correlated with a firm's propensity to select certain bank lenders. To address this problem, in above sections, I explicitly include controls for time-variant firm heterogeneity through loan fixed effects, time-invariant bank heterogeneity through bank fixed effects and time-varying bank characteristics through observable control variables (e.g., market power) in my lender-choice model Eq. (1). However, even after including these controls, an omitted variable can still operate at the firm and bank pair level, e.g., because the firm and bank operate in the same geographic region.

To mitigate this concern, I use two approaches. First, as discussed in section 3, I explicitly include controls for relevant firm-bank level variables in the lender choice model Eq. (1). I consider two dimensions: industry- and geography-proximity effects, because these are dimensions along which bank lending activities can cluster and board service is determined. With respect to industry effects, prior research suggests that different banks may specialize in different industries (e.g., Cai et al., 2016). Moreover, links in the director network could reflect patterns of demand for directors with industry-specific expertise that enhances the value of their advice. To mitigate this concern, I include in Eq. (1) a bank specialization variable measured at the firm-bank level, *Industry_Specialization*, which reflects a bank's degree of specialization in

[17] Several authors have modeled board composition as a response to firms' relative needs for monitoring versus advising (e.g., Hermalin and Weisbach, 1998; Adams and Ferreira, 2007; Harris and Raviv, 2008), and empirical studies have also found associations between board composition and firm characteristics (e.g., Boone, Field, Karpoff, and Raheja, 2007; Linck, Netter, and Yang, 2008; Coles, Daniel, and Naveen, 2008).

the borrower's industry. With respect to geography proximity effects, the concern is that if banks close to their borrowers have information or monitoring advantages over other competing banks and directors serve on geographically proximate firms, then the documented findings simply reflect the local information networks in the private debt lending market (e.g., Brickley, Linck, and Smith, 2003). To address this issue, I include in Eq. (1) an indictor variable for whether the bank and the borrower are located in the same 3-digit Zip code region as a control for a firm's proximity to the bank lender.

My second approach to mitigate the effect of omitted correlated variable that operates at the firm-bank level is to include firm-bank fixed effects (i.e., firm-bank pair) in the lender-choice model Eq. (1). Because many firms borrow multiple times over the fifteen-year sample period and a bank's connection to a firm can change over time, I can estimate Eq. (1) with firm-bank fixed effects.[18] Table 6, Panel B, reports the regression summary statistics associated with estimation of Eq. (1) using the new fixed effects structure. The key finding in Column (1) is that the *Connected_Bank* coefficient, 0.014, is significantly positive (t-statistic = 7.12). As in Column 1, Column 2 shows that the coefficient on *Connected_Bank* is positive and significant (coefficient = 1.432, t-statistic = 5.77). These findings provide additional support that the inferences I draw from Tables 2 and 3 findings are not the result of director-firm matching.

5.6. Loan pricing for firms in a well-connected borrower's board network

The findings in Table 2 indicate that a bank's chance of winning a loan from a new borrower increases if the bank previously made loans to the borrower's connected firm. In this section, I investigate whether the bank offers favorable loan contract terms to the new borrower

[18] To allow for firm-bank fixed effects in the model, loan fixed effects (i.e., firm-year fixed effects) need to be excluded, and year fixed effects are added to the model. In addition, firms that borrowed only once during the sample period will not be used to identify the coefficient of interest because the effects of these observations are subsumed by the firm-bank fixed effects.

as reflected in lower interest spreads. On the one hand, the common directors allow the connected bank to gain inside information about the borrower, which reduces information asymmetries between the borrower and the connected bank. This reduced information asymmetry implies that the borrower can obtain loans at a lower interest spread (Diamond 1984; Bharath et al., 2011). On the other hand, theory suggests that banks' private information lets them hold up borrowers for higher interest rates. As formulated by Rajan (1992) and Hauswald and Marquez (2006), the information advantage of inside banks decreases the aggressiveness of outside lenders in bidding for a loan, which increases the rents that inside lenders can extract from borrowers and thus results in higher interest rate spreads. Prior studies such as Hale and Santo (2009) provides evidence consistent with the theoretical predication: banks price their information monopoly. Hence, because of the two competing forces, whether a connected bank offers favorable loan contract terms to a new borrower is an empirical question.

To analyze this question, I re-estimate Eq. (2) by including an indicator variable *Connected_lending* that equals one if the lead bank of a loan has made a loan to the borrower's connected firm before, and zero otherwise. Table 7 reports the regression summary statistics associated with estimation of the modified version of Eq. (2). In Column 1, the *Connected_lending* coefficient is significantly negative (coefficient = –0.053; t-statistic = –2.68), which indicates that a borrower can obtain loans at a lower interest rate from a connected bank because of lower information asymmetry. However, after including lender fixed effects to control for lender attributes heterogeneity, the *Connected_lending* coefficient ceases to be significant (coefficient = –0.025; t-statistic = –1.32). Therefore, I do not find reliable evidence that connected banks offer favorable loan contracts to their new borrowers because of lower information asymmetry. However, the *Connectedness* coefficient is positive and significant in both columns, indicating that banks value their borrowers' board connectedness. Taken together, these findings suggest that banks do not offer lower loan spreads to firms in their existing borrower's board network because of lower information asymmetry but do compensate well-connected borrowers for access to the cross-firm selling opportunities provided by their networks.

CHAPTER 6: SUMMARY AND CONCLUDING REMARKS

Whereas recent studies suggest that board networks can function as a means for information transmission and play an important role in the financial markets, there is little research examining whether information flows through board networks can affect relative information asymmetries across potential lenders and thereby influence competition among bank lenders in the private lending market. This paper provides evidence that a bank can exploit its existing borrower's board network to gain an informational advantage relative to other potential lenders when competing for loan business from firms in the borrower's board network. This informational advantage, which arises from there being a common director in the existing borrower's board and firms in the borrower's board network, enhances the likelihood of winning new loan business from these connected firms. Specifically, I find that having made a previous loan to a borrower's connected firm more than doubles a bank's likelihood of granting a loan to that new borrower. In addition, I find that banks are willing to compensate well-connected borrowers by offering lower loan spreads because these borrowers provide greater cross-firm selling opportunities.

Moreover, consistent with board networks providing connected banks with an informational advantage over *de novo* lenders, I also find that the probability of a connected bank winning loan business from a new borrower is higher if the borrower is more informationally opaque. Moreover, as further evidence of a network-based information advantage, I find that the loan spread discount for an existing well-connected borrower is greater if firms in that borrower’s board network are more opaque. The explanation is that well-connected borrowers with more opaque firms in their board networks have higher cross-firm selling potential, and thus bank lenders are willing to offer more favorable contract terms to them. Hence, this paper contrasts prior studies by considering the possibility that the opacity of a well-connected borrowers’ network can be valuable to a bank and that the borrower can benefit from the opacity of its connected firms via lower loan spreads.

TABLE 1: SUMMARY STATISTICS

This table presents summary statistics for the sample of syndicated loans used in this study. The data period is from 2000–2015. The unit of analysis is a loan-bank pair in Panel A and loan facility in Panel B. *Realized_Lender* is an indicator variable that equals one if a bank is the lead arranger of the loan, and zero otherwise. *Connected_Bank* is an indicator variable that equals one if a potential bank lender has previously originated a loan to the borrower's connected firm, and zero otherwise. I define two firms/boards as connected/linked if they share at least one board member. *Prior_lending_relationship* is an indicator variable that equals one if a bank has originated loans to the borrower prior to the current loan, and zero otherwise. *Market_Share* is the market share of a bank as a lead arranger in the US syndicated loan market. *Industry_Specialization* is loan portfolio weight for a bank in the borrower's industry. *Same_Region* is an indicator that equals one if the headquarters of the borrower and the bank in a loan-bank pair are located in the same region (i.e., same 3-digit ZIP code), and zero otherwise. *Aggregate_Connectedness* is a firm's total number of links to outside boards (firms). *Connectedness* is transformed quantile rank of *Aggregate_Connectedness* with a range from 0 to 1 (orthogonal to firm size as well). *ROA* is return on assets, defined as operating income after depreciation, divided by total assets. *Leverage* is total debt divided by total assets. *Tangible* is defined as property, plant and equipment (PPE), divided by total assets. *Log_asset* is the natural logarithm of a firm's total asset. *Opacity* is a credit market-based financial reporting opacity measure for a borrower. *Board_Size* is the number of directors on a firm's board. *Age* is firm age in years. *Opacity_Net* is a credit market-based financial reporting opacity measure for all firms in a borrower's board network. *Log_spread* is the natural logarithm of interest spread of a loan measured in basis points. *LoanAmt* is the natural logarithm of loan dollar amount in millions. *Maturity* is loan term in months. *NCOV* is the number of financial and net worth covenants for a loan deal. *Securedum* is an indicator variable that equals one if the debt is secured and zero otherwise. *TermLoanB* is an indicator variable that equals one if the loan is term loan B, C, or D, and zero otherwise. *Revolver* is an indicator variable that equals one if the loan is a revolver, and zero otherwise. *Performance_Pricing* is an indicator variable equal to one when borrower has a guarantor, and zero otherwise.

Panel A: loan-bank pairs

Variable	N	Mean	Std Dev	P25	Median	P75
Realized_Lender	1,597,400	0.019	0.137	0	0	0
Connected_Bank	1,597,400	0.074	0.262	0	0	0
Prior_lending_relationship	1,597,400	0.031	0.173	0	0	0
Market_Share(%)	1,597,400	0.994	3.616	0.001	0.041	0.329
Industry_Specialization	1,597,400	0.025	0.095	0	0	0.004
Same_Region	1,597,400	0.014	0.116	0	0	0
Opacity	1,496,500	–0.487	0.123	–0.550	–0.461	–0.411

Panel B: syndicated loans

Variable	N	Mean	Std Dev	P25	Median	P75
Connectedness	11,934	0.487	0.360	0.250	0.500	0.750
Aggregate_Connectedness	11,934	8.559	7.134	3.000	7.000	12.000
ROA	11,934	0.008	0.051	0.001	0.010	0.019
Tangible	11,934	0.320	0.252	0.112	0.246	0.491
Leverage	11,934	0.314	0.218	0.169	0.292	0.418
Log_asset	11,934	7.524	1.612	6.429	7.486	8.583

Table 1 (*continued*)

Age	11,934	24.359	17.449	10.000	18.000	39.000
Board_Size	11,934	9.000	2.428	7.000	9.000	10.000
Opacity_Net	11,166	–0.486	0.073	–0.531	–0.480	–0.437
Log_spread	11,934	5.021	0.808	4.605	5.165	5.541
LoanAmt	11,934	19.153	1.418	18.421	19.254	20.055
Maturity	11,934	48.569	20.886	36	60	60
NCOV	11,934	1.543	1.414	0	2	3
Securdum	11,934	0.473	0.499	0	0	1
Revolver	11,934	0.713	0.452	0	1	1
TermLoanB	11,934	0.105	0.307	0	0	0
Performance_pricing	11,934	0.481	0.500	0	0	1

TABLE 2: THE EFFECT OF PRIOR LENDING RELATIONSHIP WITH A BORROWER'S CONNECTED FIRM ON A BANK'S LIKELIHOOD OF BEING CHOSEN AS THE LEAD ARRANGER

This table reports coefficient estimates from regressions relating the likelihood of a potential lender being chosen as the lead arranger by the borrower to whether the potential lender has originated loans to the borrower's connected firm before. Each observation corresponds to one loan-bank pair (i.e., each loan is matched to 100 potential bank lenders, who are among the top 100 lead arrangers in the sample). The dependent variable, *Realized_Lender* is an indicator variable that equals one if the potential bank lender is the lead arranger of the loan, and zero otherwise. *Connected_Bank* is an indicator variable that equals one if the potential bank lender has previously originated a loan to the borrower's connected firm, and zero otherwise. I define two firms/boards as connected/linked if they share at least one board member. *Prior_lending_relationship* is an indicator variable that equals one if the potential bank lender has originated loans to the borrower prior to the current loan, and zero otherwise. *Market_Share* is the market share of the potential bank as lead arranger in the US syndicated loan market. *Industry_Specialization* is loan portfolio weight for the potential bank lender in the borrower's industry. *Same_Region* is an indicator that equals one if the headquarters of the borrower and the potential bank lender are located in the same region, and zero otherwise. All regressions include loan facility fixed effects, which are used to rule out any facility-specific effects, including the effects from the borrower, the lead arranger, the time trend in a particular year, and any loan characteristics. t-statistics based on robust standard errors allowing for clustering by borrower are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Dependent variable: *Realized_Lender*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	Logit	OLS	OLS	OLS	OLS	OLS
		Odds ratio					
Connected_Bank	0.029***	3.740***	0.143***	0.062***	0.060***	0.142***	0.142***
	(17.75)	(30.26)	(60.83)	(38.18)	(26.39)	(60.58)	(60.78)
Prior_lending_relationship	0.351***	47.505***		0.395***			
	(52.76)	(98.44)		(62.65)			
Market_Share	0.638***	1,389.190***			1.251***		
	(30.93)	(31.45)			(54.11)		
Industry_Specilization	0.012***	6.757***				0.034***	
	(7.27)	(25.78)				(15.74)	
Same_Region	0.008***	1.549***					0.025***
	(2.92)	(3.23)					(5.98)
Loan FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,597,400	1,597,400	1,597,400	1,597,400	1,597,400	1,597,400	1,597,400
Adjusted (Pseudo) R-squared	0.318	0.531	0.074	0.297	0.161	0.075	0.074

TABLE 3: THE EFFECT OF BOARD CONNECTEDNESS ON LOAN SPREAD

This table reports the results of OLS regressions investigating the effect of board connectedness on loan spread. Each observation in the analysis corresponds to one loan facility. The dependent variable, *Log_spread,* is the natural logarithm of loan spread (in basis points). *Aggregate_Connectedness* is a firm's total number of links to outside boards (firms). *Connectedness* is transformed quintile rank of *Aggregate_Connectedness* with a range from 0 to 1 (orthogonal to firm size as well). *ROA* is return on assets, defined as operating income after depreciation, divided by total assets. *Leverage* is total debt divided by total assets. *Tangible* is defined as property, plant and equipment (PPE), divided by total assets. *Log_asset* is the natural logarithm of a firm's total asset. *Board_Size* is the number of directors on a firm's board. *Age* is firm age in years. *LoanAmt* is the natural logarithm of loan dollar amount in millions. *Maturity* is loan term in months. *NCOV* is the number of financial and net worth covenants for a loan deal. *Securedum* is an indicator variable that equals one if the debt is secured and zero otherwise. *TermLoanB* is an indicator variable that equals one if the loan is term loan B, C, or D, and zero otherwise. *Revolver* is an indicator variable that equals one if the loan is a revolver, and zero otherwise. *Performance_Pricing* is an indicator variable equal to one when borrower has a guarantor, and zero otherwise. t-statistics in parentheses are based on standard errors clustered by borrower. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)
Variables	*Log_spread*	*Log_spread*
Connectedness	–0.104***	–0.107***
	(–3.34)	(–3.05)
Firm characteristics		
ROA	–1.141***	–0.433
	(–4.08)	(–1.18)
Tangible	–0.082	–0.093
	(–0.58)	(–0.58)
Leverage	0.555***	0.556***
	(7.46)	(6.39)
Log_asset	–0.064***	–0.081***
	(–2.71)	(–3.03)
Age	–0.017	–0.021
	(–0.72)	(–0.76)
Board_Size	0.007	0.007
	(1.09)	(1.08)
Loan characteristics		
LoanAmt	–0.050***	–0.050***
	(–6.42)	(–5.42)
Maturity	–0.001**	–0.001**
	(–2.09)	(–2.54)
NCOV	0.022***	0.025***

Table 3 (*continued*)

	(3.30)	(3.36)
Securdum	0.085***	0.075***
	(4.22)	(3.30)
Revolver	–0.137***	–0.136***
	(–10.33)	(–9.14)
TermLoanB	0.131***	0.107***
	(6.40)	(4.79)
Performance_Pricing	–0.057***	–0.047***
	(–3.91)	(–2.86)
Future performance		
ROA (t+1)		–0.315***
		(–2.74)
ROA (t+2)		–0.260***
		(–2.87)
ROA (t+3)		–0.100
		(–1.28)
Credit Rating FE	YES	YES
Loan Purpose FE	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
Observations	11,934	9,794
Adjusted R–squared	0.811	0.825

TABLE 4:THE EFFECT OF PRIOR LENDING RELATIONSHIP WITH A BORROWER'S CONNECTED FIRM ON A BANK'S LIKELIHOOD OF BEING CHOSEN AS THE LEAD ARRANGER, DOES THE BORROWER'S FINANCIAL REPORTING OPACITY MATTER

This table reports coefficient estimates from regressions relating the likelihood of a potential lender being chosen as the lead arranger by the borrower to whether the potential lender has originated loans to the borrower's connected firm before. Each observation corresponds to one loan-bank pair (each loan facility is matched to 100 potential lenders, who are among the top 100 lead arrangers in the sample). The dependent variable, *Realized_Lender* is an indicator variable that equals one if the potential bank lender is the lead arranger of the loan, and zero otherwise. *Connected_Bank* is an indicator variable that equals one if the potential bank lender has previously originated a loan to the borrower's connected firm, and zero otherwise. I define two firms/boards as connected/linked if they share at least one board member. *Opacity* is a transformed decile rank of a credit market-based financial reporting opacity measure for a borrower and ranges from 0 to 1. *Prior_lending_relationship* is an indicator variable that equals one if the potential bank lender has originated loans to the borrower prior to the current loan, and zero otherwise. *Market_Share* is the market share of the potential bank lender as lead arranger in the US syndicated loan market. *Industry_Specialization* is loan portfolio weight for the potential bank lender in the borrower's industry. *Same_Region* is an indicator that equals one if the headquarters of the borrower and the potential bank lender are located in the same region, and zero otherwise. All regressions include loan facility fixed effects, which are used to rule out any facility-specific effects, including the effects from the borrower, the lead arranger, the time trend in a particular year, and any loan characteristics. t-statistics based on robust standard errors allowing for clustering by borrower are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)
Variables	*Realized_Lender*
Connected_Bank	0.023***
	(6.94)
Connected_Bank × *Opacity*	0.013**
	(2.37)
Prior_lending_relationship	0.353***
	(50.94)
Market_Share	0.633***
	(29.83)
Industry_Specialization	0.012***
	(7.08)
Same_Region	0.009***
	(2.91)
Loan FE	YES
Observations	1,496,500
Adjusted R-squared	0.319

TABLE 5: THE EFFECT OF BORROWER'S BOARD CONNECTEDNESS ON LOAN SPREAD, DOES INFORMATIONAL OPACITY OF FIRMS IN THE BORROWER'S BOARD NETWORK MATTER

This table reports the results of OLS regressions investigating the effect of board connectedness on loan spread. Each observation in the analysis corresponds to one loan facility. The dependent variable, *Log_spread*, is the natural logarithm of loan spread (in basis points). *Aggregate_Connectedness* is a firm's total number of links to outside boards (firms). *Connectedness* is transformed quintile rank of *Aggregate_Connectedness* with a range from 0 to 1 (orthogonal to firm size as well). *Opacity_Net* is an indicator variable that equals one if firms in the borrower's network are on average opaque (see appendix for detail), and zero otherwise. *ROA* is return on assets, defined as operating income after depreciation, divided by total assets. *Leverage* is total debt divided by total assets. *Tangible* is defined as property, plant and equipment (PPE), divided by total assets. *Log_asset* is the natural logarithm of a firm's total asset. *Board_Size* is the number of directors on a firm's board. *Age* is firm age in years. *LoanAmt* is the natural logarithm of loan dollar amount in millions. *Maturity* is loan term in months. *NCOV* is the number of financial and net worth covenants for a loan deal. *Securedum* is an indicator variable that equals one if the debt is secured and zero otherwise. *TermLoanB* is an indicator variable that equals one if the loan is term loan B, C, or D, and zero otherwise. *Revolver* is an indicator variable that equals one if the loan is a revolver, and zero otherwise. *Performance_Pricing* is an indicator variable equal to one when borrower has a guarantor, and zero otherwise. t-statistics in parentheses are based on standard errors clustered by borrower. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)
Variables	*Log_spread*
Connectedness	–0.091***
	(–2.66)
Opacity_Net	0.068**
	(2.19)
Connectedness × Opacity_Net	–0.124**
	(–2.12)
ROA	–1.098***
	(–3.77)
Tangible	–0.066
	(–0.44)
Leverage	0.546***
	(6.91)
Log_asset	–0.059**
	(–2.36)
Age	–0.010
	(–0.41)
Board_Size	0.005
	(0.84)
LoanAmt	–0.050***
	(–6.16)

Table 5 (*continued*)

Maturity	–0.001**
	(–1.97)
NCOV	0.024***
	(3.39)
Securdum	0.090***
	(4.19)
Revolver	–0.132***
	(–9.52)
TermLoanB	0.131***
	(6.20)
Performance_Pricing	–0.059***
	(–3.95)
Credit Rating FE	YES
Loan Purpose FE	YES
Firm FE	YES
Year FE	YES
Observations	11,166
Adjusted R-squared	0.815

TABLE 6: THE EFFECT OF PRIOR LENDING RELATIONSHIP WITH A BORROWER'S CONNECTED FIRM ON A BANK'S LIKELIHOOD OF BEING CHOSEN AS THE LEAD ARRANGER, TENURED DIRECTORS AND BORROWER-BANK FIXED EFFECTS

This table reports coefficient estimates from regressions relating the likelihood of a potential lender being chosen as the lead arranger by the borrower to whether the potential lender has originated loans to the borrower's connected firm before. In Panel A, I exclude loans where common directors have served on the borrower's board for less than 2 years before loan origination. Common directors are those who sit on the borrower's board and the connected firm's board with which a bank has an existing lending relationship. In Panel B, I include borrower-bank fixed effects in Eq. (1). Each observation corresponds to one loan (firm)-bank pair (each loan facility is matched to 100 potential lenders, who are among the top 100 lead arrangers in the sample). The dependent variable, *Realized_Lender* is an indicator that equals one if the potential bank lender is the lead arranger of the loan, and zero otherwise. *Connected_Bank* is an indicator variable that equals one if the potential bank lender has previously originated a loan to the borrower's connected firm, and zero otherwise. I define two firms/boards as connected/linked if they share at least one board member. *Prior_lending_relationship* is an indicator variable that equals one if the potential bank lender has originated loans to the borrower prior to the current loan, and zero otherwise. *Market_Share* is the market share of the potential bank as lead arranger in the US syndicated loan market. *Industry_Specialization* is loan portfolio weight for the potential bank lender in the borrower's industry. *Same_Region* is an indicator that equals one if the headquarters of the borrower and the potential bank lender are located in the same region, and zero otherwise. All regressions include loan facility fixed effects, which are used to rule out any facility-specific effects, including the effects from the borrower, the lead arranger, the time trend in a particular year, and any loan characteristics. t-statistics based on robust standard errors allowing for clustering by borrower are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A: tenured director sample

	Dependent variable: *Realized_Lender*	
	(1)	(2)
	OLS	Logit
	Coefficient	Odds ratio
Connected_Bank	0.030***	2.435***
	(14.58)	(19.70)
Prior_lending_relationship	0.351***	52.952***
	(52.32)	(103.55)
Market_Share	0.666***	5,361.845***
	(32.29)	(35.49)
Industry_Specilization	0.012***	6.348***
	(7.65)	(25.13)
Same_Region	0.008***	1.627***
	(2.95)	(3.54)
Loan FE	YES	YES
Observations	1,565,000	1,565,000
Adjusted (Pseudo) R-squared	0.317	0.523

Table 6 (*continued*)

Panel B: borrower-bank fixed effects

	Dependent variable*: Realized_Lender*	
	(1)	(2)
	OLS	Logit
	Coefficient	Odds ratio
Connected_Bank	0.014***	1.432***
	(7.12)	(5.77)
Prior_lending_relationship	0.156***	0.564***
	(13.01)	(-8.51)
Market_Share	–0.227***	914.663***
	(–2.99)	(7.58)
Industry_Specilization	0.005***	11.583***
	(3.87)	(6.78)
Borrower-Bank FE	YES	YES
Year FE	YES	YES
Observations	1,597,400	1,597,400
Adjusted (Pseudo) R-squared	0.593	0.623

TABLE 7: THE EFFECT OF CONNECTED LENDING ON LOAN SPREAD

This table reports the results of OLS regressions investigating whether a borrower pays lower loan spreads if the bank lender has made a loan to the borrower's connected firm before. Each observation in the analysis corresponds to one loan facility. The dependent variable, *Log_spread*, is the natural logarithm of loan spread (in basis points). *Connected_lending* is an indicator variable that equals one if the lead bank of a loan has made a loan to the borrower's connected firm before, and zero otherwise. *Connectedness* is transformed quintile rank of *Aggregate_Connectedness* with a range from 0 to 1 (orthogonal to firm size as well). *ROA* is return on assets, defined as operating income after depreciation, divided by total assets. *Leverage* is total debt divided by total assets. *Tangible* is defined as property, plant and equipment (PPE), divided by total assets. *Log_asset* is the natural logarithm of a firm's total asset. *Board_Size* is the number of directors on a firm's board. *Age* is firm age in years. *LoanAmt* is the natural logarithm of loan dollar amount in millions. *Maturity* is loan term in months. *NCOV* is the number of financial and net worth covenants for a loan deal. *Securedum* is an indicator variable that equals one if the debt is secured and zero otherwise. *TermLoanB* is an indicator variable that equals one if the loan is term loan B, C, or D, and zero otherwise. *Revolver* is an indicator variable that equals one if the loan is a revolver, and zero otherwise. *Performance_Pricing* is an indicator variable equal to one when borrower has a guarantor, and zero otherwise. t–statistics in parentheses are based on standard errors clustered by borrower. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	(1)	(2)
Variables	*Log_spread*	*Log_spread*
Connected_lending	–0.053***	–0.025
	(–2.68)	(–1.32)
Connectedness	–0.097***	–0.097***
	(–3.12)	(–3.14)
Firm characteristics		
ROA	–1.112***	–1.105***
	(–3.99)	(–4.23)
Tangible	–0.080	–0.061
	(–0.57)	(–0.44)
Leverage	0.561***	0.536***
	(7.56)	(7.13)
Log_asset	–0.061***	–0.052**
	(–2.61)	(–2.25)
Age	–0.018	–0.023
	(–0.75)	(–1.02)
Board_Size	0.007	0.006
	(1.21)	(1.00)
Loan characteristics		
LoanAmt	–0.049***	–0.047***
	(–6.24)	(–5.99)
Maturity	–0.001**	–0.001**
	(–2.06)	(–2.00)

Table 7 (*continued*)

NCOV	0.022***	0.021***
	(3.31)	(3.12)
Securdum	0.084***	0.076***
	(4.16)	(3.82)
Revolver	–0.136***	–0.124***
	(–10.26)	(–9.60)
TermLoanB	0.130***	0.119***
	(6.35)	(5.94)
Performance_Pricing	–0.056***	–0.056***
	(–3.85)	(–3.85)
Credit Rating FE	YES	YES
Loan Purpose FE	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
Bank FE	NO	YES
Observations	11,934	11,934
Adjusted R–squared	0.812	0.818

APPENDIX: VARIABLE DEFINITIONS

Variables	Description
Lender characteristics	
Realized_Lender	An indicator variable that equals one if a bank is the lead arranger of the loan, and zero otherwise.
Connected_Bank	An indicator variable that equals one if a bank has previously originated a loan to the borrower's connected firm, and zero otherwise. I define two firms/boards as connected/linked if they share at least one board member.
Prior_lending_relationship	An indicator variable that equals one if a bank has originated loans to the borrower prior to the current loan, and zero otherwise.
Market_Share	Market share of a bank as a lead arranger in the US syndicated loan market during the past twelve months.
Industry_Specialization	Loan portfolio weights for a bank in each industry specialization category (i.e., 2-digit SIC). It is included as a proxy for a bank's specialization in the borrower's industry.
Same_Region	An indicator variable that equals one if the headquarters of a borrower and a bank are located in the same region (i.e., the same 3-digit ZIP code), and zero otherwise. I use this variable as a proxy for the geographic proximity between the bank and the borrower.
Loan Characteristics	
Log_spread	The natural logarithm of loan spread, which equals the spread between the interest rate on the loan and the relevant Libor rate, per dollar of loan, measured in basis points.
LoanAmt	The natural logarithm of loan dollar amount in millions.
Maturity	The term of the loan in months.
NCOV	The number of financial and net worth covenants reported on Dealscan. If no data are available we assume the number of covenants in the contracts is zero. The variables are measured per facility.
Securedum	An indicator variable equal to one if the debt is collateralized and zero otherwise, if missing collateral data, I treat it as 0.
TermLoanB	An indicator variable equal to one if the loan is term loan B, C D, and zero otherwise.

Revolver	An indicator variable equal to one if the loan is a revolver, and zero otherwise.
Performance_Pricing	An indicator variable equal to one when borrower has a guarantor, and zero otherwise.
Firm characteristics	
Aggregate_Connectedness	A firm's total number of links to outside boards (firms). I define two firms/boards as connected/linked if they share at least one board member.
Connectedness	A quintile ranked version of *Aggregate_Connectedness* that reduces the association with firm size. Specifically, for each year, all firms are ranked into quintiles based on total assets. Within each total asset quintile, firms are sorted into quintiles based on the connectedness measure, where the highest (lowest) value of connectedness assume a value of four (zero). I further deflate this connectedness measure by four, so that range of this variable is between 0 and 1.
Connected_lending	An indicator variable that equals one if the lead bank of a loan has made a loan to the borrower's connected firm before, and zero otherwise.
ROA	Return on assets. It is defined as operating income after depreciation divided by beginning of period total assets.
Leverage	Total debt (short-term debt plus long-term debt) divided by total assets.
Tangible	Property, plant and equipment (PPE) divided by total assets.
Log_asset	The natural logarithm of a firm's total asset.
Board_Size	The number of directors on a firm's board.
Rating	A numeric rank of S&P credit ratings. We assign 1 to AAA, 2 to AA+, 3 to AA and etc. For firms without credit ratings, we follow the approach in Beaver et al. (1998) to use accounting measures to generate credit ratings.
Age	Firm age in years.
DCV	A credit market based earnings quality measure computed as the Somers' D association statistic obtained from industry-specific probit regressions that predict credit ratings; industries are based on Fama and French(1997) industry groupings. Specifically, for any given year, I estimate an ordered probit model using quarterly data in the past five years for each industry grouping: $P(Rating_{q,i} \leq N) = \Phi(\sum_{n=1}^{N}\mu_n + \sum_{k=1}^{4}\alpha_k E_{q-k,i} + \sum_{k=1}^{4}\beta_k COV_{q-k,i} + \sum_{k=1}^{4}\delta_k LEVERAGE_{q-k,i} + \sum_{k=1}^{4}\gamma_k NW_{q-k,i})$

	where *Rating* is constructed by assigning 1 to firms with the highest S&P credit rating AAA in quarter *q*, 2 to AA+ and so on. *E* is EBITDA in quarter *q-k* divided by total assets at the beginning of the quarter. *COV* is interest coverage in quarter *q-k* (EBITDA divided by total interest expense). *LEVERAGE* is the long-term debt in quarter *q-k* divided by total assets. *NW* is common equity in quarter *q-k* divided by total assets. Each regression requires at least 100 firm-quarter observations. *DCV* is measured as Somers's D, a goodness-of-fit statistic.
Opacity	A measure of a firm's financial reporting opacity. To obtain this measure, I first multiply *DCV* by -1, then rank this *DCV* into deciles, and then divide it by nine to convert the decile rank to a zero to one range.
Opacity_Net	An indicator that equals one if firms in a borrower's board network are on average opaque, and zero otherwise. Firm opacity is measured based on *DCV*. I calculate the average *DCV* value for all firms in the borrowers' board network. I then multiply this average *DCV* by –1 such that a high value of *DCV* indicates an opaque financial reporting system. Observations that are in the top quintile of this transformed average *DCV* value are classified as having high network opacity.

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