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Information Intermediaries: How Commercial Bankers Facilitate Strategic Alliances

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Abstract

We investigate how bankers use information from lending relationships to help borrowers find partners for strategic alliances. Firms that have borrowed from the same banker or share an indirect connection through a network of bankers are significantly more likely to enter an alliance. Consistent with bankers overcoming informational frictions, their ability to facilitate alliances decreases with banker-network distance, and is stronger for opaque borrowers. Firms connected to more potential partners via banker networks enter more alliances. These alliances are associated with positive announcement returns, and brokering banks are more likely to receive future underwriting mandates.

I. Introduction

Banks choosing their loan portfolio face a trade-off between specialization and diversification. A straightforward portfolio diversification argument suggests that banks should spread lending risk across different industries. On the other hand, industry expertise can improve both loan screening and monitoring (Acharya, Hasan, and Saunders (2006)), and can allow banks to effectively internalize externalities such as bankruptcy spillovers (Favara and Giannetti (2017), Giannetti and Saidi (2018), and Saidi and Streitz (2019)). Borrowers, too, face trade-offs when deciding whether to borrow from an industry-specialized bank. On the negative side, there is wide anecdotal evidence of banks allegedly passing on privileged

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information obtained in lending relationships.[1] The academic literature on information transmission in the banking sector has focused on these possible negative consequences for borrowers (Ivashina, Nair, Saunders, Massoud, and Stover (2009), Asker and Ljungqvist (2010)).[2]

We investigate a novel, potentially positive side of bank specialization for borrowers, whether banks can use their expertise to provide value to borrowers by matchmaking them with potential collaboration partners. We find evidence consistent with banks acting as matchmakers between borrowers, and that this activity benefits both borrowers and the banks themselves. The link between borrowers comes through individual bankers, and our evidence suggests that bankers help bridge asymmetric information between borrowers to broker collaboration between them.

We focus on a broad set of collaborations between borrowers in the form of strategic alliances, formalized collaborations that are between arm's length, market-based transactions, and intrafirm relationships.[3] Our analysis documents that banks, and individual bankers, in particular, act as information intermediaries between potential partners, thereby facilitating alliances, and creating value for borrowers.

These collaborations are an ideal laboratory to study information transmission through banks since they are publicly observable forms of collaboration that are sensitive to information asymmetries and create value for firms (Chan, Kensinger, Keown, and Martin (1997)). Most alliances are formed to benefit from specific knowledge or capabilities of the partner firm (Mariti and Smiley (1983)), therefore requiring partners to possess specific, potentially nonpublic information about each other's capabilities ex ante. One potential source to obtain this information is capital providers associated with both firms (e.g., Lindsey (2008), He and Huang (2017)). For example, Greg Becker, CEO of Silicon Valley Bank, describes his bank's advantage as its "ability to make an introduction to a potential partnership, because we understand that business better than maybe one of our competitors would, […] the value added we give to our clients, whether it is making an introduction to a potential client or making an introduction to a potential partnership."[4]

To link borrowers to specific commercial bankers, we use data from the signature pages of loan contracts. These data allow us to identify connections between bankers and borrowers and to assess whether two firms have borrowed

[1]A prominent lawsuit involving M&A transactions is Dana Corporation v. UBS *(Dana Corporation v. UBS Securities LLC, New York Southern District Court, Case No. 1:03-cv-05820).* In 2018, there were similar allegations in an M&A transaction advised by Goldman Sachs (The *New York Times* (2018)).

[2]Other examples are Acharya and Johnson (2007), Bodnaruk, Massa, and Simonov (2009), Griffin, Shu, and Topaloglu (2012), and Kedia and Zhou (2014).

[3]The literature on strategic alliances sometime focuses on a more narrow set of research-oriented alliances, for example, in the biotechnology sector. Although we use the term strategic alliances, we look into collaborations more broadly, including marketing and production alliances. As an illustration, consider supplier–customer relationships. At the arm's length level, a firm can purchase input material on a transaction-by-transaction basis. Alternatively, it can formalize the relationship in a customer–supplier agreement, a specific type of alliance. The closest form of collaboration would be a takeover of the supplier to internalize the relationship.

[4]See the interview "Meet Your Partner: The Bank as Matchmaker" in the 2016 PwC U.S. CEO survey, starting at 4:04, available at https://youtu.be/t3wAOBeG81o?t=244. Section A of the Supplementary Material provides a more extensive transcript of this interview and presents additional anecdotal evidence from news stories and our own conversations with practitioners suggesting that bankers actively arrange collaborations for their borrowers.

not just from the same bank, but from the same specific banker in the past. We hypothesize that individual bankers are the specific economic channel through which information is transmitted. Commercial bankers for lead lenders play a key role in negotiating, structuring, and monitoring loan agreements, which allows them to form a close relationship with firms' management and gives them access to private information (Uzzi (1999), Esty (2001), and Uzzi and Lancaster (2003)).

We first test directly whether strategic alliances between pairs of firms are more likely if the pair is connected through a network of bankers using a simple univariate *t*-test. The results show that firms are significantly more likely to enter strategic alliances with partners they are connected to (either directly or indirectly) as compared to the overall universe of potential partner firms.

We then estimate deeply saturated panel regressions that allow us to control for all alternative, time-invariant firm-pair explanations such as geographic proximity, industry, and firm quality through firm-pair fixed effects. In addition, these regressions include industry-year fixed effects for both firms, which absorb time-varying confounding factors at the industry level. We find that sharing the same banker significantly increases the likelihood of entering a strategic alliance at a rate that is economically about 5 times as large as that of sharing the same bank. In additional robustness tests, we control for time-varying firm-level unobservables by including firm-year fixed effects for both firms in a potential alliance pair. The result persists in this heavily saturated specification.

The highly saturated fixed effects models we estimate can control for all unobservable, time-invariant firm-pair specific tendencies to collaborate. There might, however, still be time-varying variation in the likelihood to collaborate on the firm-pair level, such as the appointment of an executive at one firm with social ties to both the same banker and CEO of the other one. We provide instrumental variable (IV) estimates to address this potential source of endogeneity. Our IV estimates exploit bankers changing from one employing bank to another as a source of quasi-exogenous variation in banker networks between firms. Borrowers keep borrowing from the same set of banks over time (Bharath, Dahiya, Saunders, and Srinivasan (2011), Chodorow-Reich (2013)). Therefore, when a banker moves to a new bank, the network distance between the existing borrowers of that bank (the banker's new employer) and the banker's previous borrowers is likely to decrease in the future. We find that all our results hold after accounting for endogeneity in this way.

Since each banker has only a limited set of direct borrowers, it can be hard for them to match firms within their own portfolio of borrowers. We therefore also investigate whether indirect connections between borrowers through a network of bankers can facilitate alliances. For our purposes, connected bankers are defined as two or more individuals who have previously syndicated loans together. Previous co-syndication is a good proxy for personal connections since the bankers involved in a lending syndicate interact with each other repeatedly during the origination process (Esty (2001)). After origination, bankers stay in touch over the life of the loan for the purpose of monitoring covenants and renegotiating terms.[5] We hypothesize that bankers can use these connections to find suitable collaboration partners for their portfolio of borrowers, similar to board members connecting firms in

[5]The average loan is modified 5 times (Roberts (2015)), and more than 90% of loans undergo at least one such renegotiation (Roberts and Sufi (2009)).

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mergers and acquisitions (M&A) transactions (Cai and Sevilir (2012)). We then test whether these indirect network connections between bankers can help broker collaborations for borrowers in the same way as direct ones from sharing the same banker. We find that even indirectly connected borrowers are significantly more likely to engage in a strategic alliance, albeit at a lower rate than directly connected firms.

Brokering alliances between borrowers requires coordination and effort on the part of bankers. Therefore, the ability of bankers to facilitate alliances between clients should decrease as more links in the banker network are needed to connect the firms. This prediction is borne out in the data, where we find that the likelihood that two firms enter an alliance is monotonically decreasing in the network distance between their bankers. Our results are robust to a wide range of alternative definitions and estimation techniques of banker networks, firm–bank relationship, and fixed effects. We further perform a number of tests that rule out that our results are driven by firms initiating collaborations first, before starting to borrow from the same banker later.

If bankers facilitate collaborations due to their knowledge of borrowers, their role should be more pronounced when information asymmetries are large. We indeed find that banker connections are more important for informationally opaque borrowers, in particular those that lack a public credit rating or have a high share of intangible assets.

In our final set of results, we investigate whether commercial bankers' involvement in the formation of strategic alliances benefits borrowers and their banks. First, we document that firms with well-connected bankers form a larger number of alliances than those with less well-developed networks. In addition, in an event study, we find that the average strategic alliance increases market value by 0.7% (consistent with Chan et al. (1997), Allen and Phillips (2000), and Bodnaruk, Massa, and Simonov (2013)), and that strategic alliances in which firms are connected through the banker network create as much value as those without such a connection. Together, these results suggest that banker networks benefit firms on the extensive rather than the intensive margin when forming strategic alliances.

On the other side of the lending relationship, we find that borrowers reward banks for facilitating collaborations by awarding them additional business. After a firm initiates a strategic alliance with another firm it is connected to through the banker network, the connecting banks are substantially more likely to be chosen as the lead arranger for an additional syndicated loan or as the underwriter for a bond or seasoned equity offering. Banks also get rewarded through slightly higher interest rates on future loans by these firms, and, consistent with the literature of star analysts attracting deal flow in the IPO market (e.g., Krigman, Shaw, and Womack (2001)), banks with more well-connected bankers attract more business in the future.

Our article contributes to two different strands of the literature. The first one is concerned with the impact of investors and financial intermediaries on different forms of collaboration between firms. Ivashina et al. (2009) and Fee, Subramaniam, Wang, and Zhang (2017) show that banks use private information about borrowers in merger transactions. We show that information transmission through lenders does not just lead to M&A transactions, but also less intense forms of collaborations. Importantly, our setting allows us to go beyond the effect of institutions, and we show that it is individual bankers and their networks drive the transmission, and that even *indirect* banker connections can transmit information. Similarly, our article extends the work of Lindsey (2008) and He and Huang (2017), who illustrate the importance of capital providers other than banks in facilitating collaborations between firms.[6]

Our results are perhaps more surprising than those of the previous literature, because commercial banks generally neither have board seats nor equity stakes in the companies they arrange alliances for. Our findings imply that they nevertheless have both the ability and incentives to provide these services to borrowers. The second literature we contribute to relates to the importance of personal relationships in bank lending. We find that individual bankers are the primary conduit through which information is transmitted, and document the importance of professional networks beyond executives (Engelberg, Gao, and Parsons (2012), Karolyi (2017)). We also add to a growing number of studies investigating the role of individual bankers in the lending process (Ceccarelli, Herpfer, and Ongena (2021), Bushman, Gao, Martin, and Pacelli (2021), and Herpfer (2021)).

II. Hypotheses Development

Being connected through lenders can help borrowers looking for a collaboration partner to overcome asymmetry in both public and private information. First, selecting the right alliance partner can be difficult if alliance success relies on private information. Second, even if all relevant information is public, search costs can impede the formation of collaborations. Bankers play a role in overcoming both these challenges. Since they interact with a number of different borrowers, bankers have access to public and private information regarding potential partners which can speed up searches. In addition, if an alliance requires a certain nonpublicly observable (e.g., managerial or technological) capability, bankers can identify potential partners using private information obtained through their lending.[7] We therefore formulate the following hypothesis:

Hypothesis 1. Two firms are more likely to enter a strategic alliance if they share the same banker.

The ability of bankers to find matching alliance partners is limited by the number of firms about which they have information. One way a banker can increase

[6]He and Huang (2017) find that strategic alliances are more likely between firms that have a high degree of institutional cross-ownership. Lindsey (2008) shows that venture capital funds broker strategic alliances within their portfolio of startup firms as long as at least one of them is private. See Brinster and Tykvová (2021) for connected venture capital funds. Additional evidence for the role of banks in shaping collaborations between firms can be found in Coiculescu (2018), who finds that firms sharing the same bank are more likely to enter a customer–supplier relationship, and Saidi and Streitz (2019), who find evidence that firms sharing the same lender compete less aggressively.

[7]One banker interviewed by Uzzi and Lancaster (2003) describes the process through which bankers form connections between borrowers: "You happen to find out that a firm is having problems sourcing a certain raw material, and the banker happens to know someone that provides that material. […] the banker happens to know someone that they can trust that can help out. On and on, that's a network." Another banker states that "there are costs to the entrepreneur to gather [select] information. A relationship can set me apart if I deliver the information. That's the concept of value-added provider."

the number of potential partners she has access to is by reaching out to her network. If alliances are beneficial to borrowers, bankers might be willing to assist in arranging an alliance even if one of the partners is not their own client but somebody else's (e.g., because improved borrower performance aids bankers' career, see Gao, Kleiner, and Pacelli (2020)). Bankers can facilitate alliances even if none of their own borrowers are directly involved in them, by connecting other bankers to each other. Such transmission of information across two degrees of separation would imply that bankers can trade favors to each other. Transmitting private information over longer network paths (i.e., a larger number of bankers) likely increases the cost of coordination. We therefore formulate the following hypothesis:

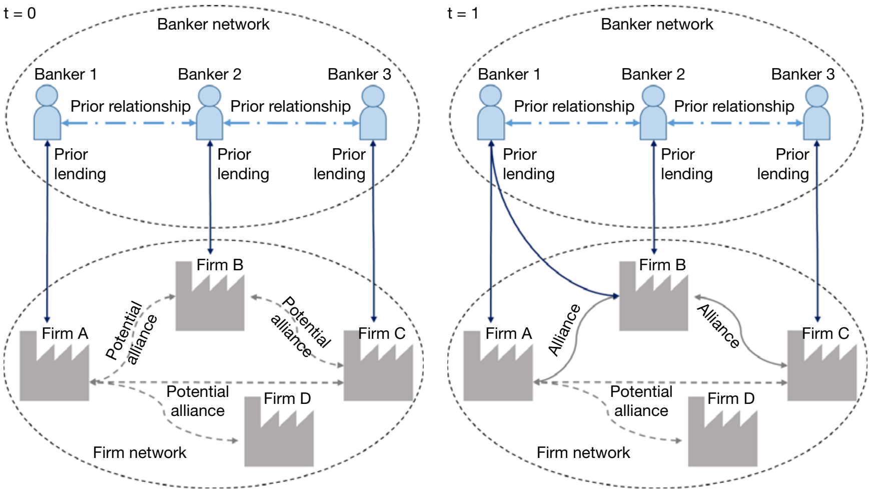
Hypothesis 2. Firms are more likely to enter an alliance if they deal with different bankers that know each other, either directly or through one or several acquaintances. The magnitude of this effect decreases as the number of links required to connect the bankers increases.

Figure 1 shows a simplified example of how firms are connected through the banker network. Consider three bankers (1–3) and four firms (A–D). At time $t = 0$, each firm has borrowed from one banker each. Both banker 1 and banker 3 have previously co-syndicated one loan each with banker 2. If firm A was to consider a potential collaboration at this point, it could obtain information about its three potential partners from its banker, banker 1. Since banker 1 has previously worked

FIGURE 1

Illustration of the Banker Network

Figure 1 shows a simplified illustration of the multilayer network structure. The upper bubble represents the banker network between three bankers. The lower bubble represents the firm network of borrowers. Connections between bankers exist if the bankers have co-syndicated loans in the past. Connections between firms and bankers are established when the banker signs a syndicated loan contract with the firm, but only when serving as lead arranger. At time 0, firms A–C borrow from bankers 1–3, respectively. Firm D is unconnected to the banker network. Banker 2 has co-syndicated separate loans with both bankers 1 and 3 in the past. The network distance between firm A to its potential collaboration partners is therefore 1 to firm B, and 2 to firm C. Its network distance to firm D is undefined. At time 1, firm B takes out a new loan from banker 1. The network distance between firms A and B therefore shrinks to 0. Dotted (full) gray lines between firms denote potential (realized) alliances. For clarity, we only display the potential alliances for firm A.



with banker 2, the network distance between firms A and B takes the value of 1. It would be relatively easy to obtain information about banker 2's client, firm B. The network distance between firm A and firm C takes the value of 2, since their bankers have not previously co-syndicated loans and are only indirectly connected through banker 2. Finally, there is no way for firm A to obtain information about firm D through the banker network.

At time $t = 1$, firm B has taken out a new loan from banker 1. Accordingly, the network distance between firms A and B has decreased to 0. In the context of this example, Hypotheses 1 and 2 suggest that firm A is more likely to engage in a strategic alliance with firm B than with firm C, both at $t = 0$ and at $t = 1$. Our main specification includes firm-pair fixed effects, and hence identifies correlations between network distances and the likelihood of entering an alliance only based on *changes* in network distance, such as for firms A and B from $t = 0$ to $t = 1$ in the example above.

Anecdotal evidence from news stories and our conversations with practitioners detailed in Section A of the Supplementary Material suggest that bankers mainly aid firms through lowering search frictions, leading to faster and more efficient outcomes for finding partners. Since strategic alliances often rely on specific, hard-to-observe firm characteristics (Mariti and Smiley (1983)), we hypothesize that the banker's help in finding a collaboration partner is most valuable when search costs for borrowers are highest, which leads to our next hypothesis:

Hypothesis 3. The role of bankers in facilitating alliances is more pronounced in circumstances with high information asymmetries.

Finally, we ask why firms would want bankers to facilitate alliances for them, and why bankers would exert effort to do so. To explain these behaviors, alliances arranged through bankers should benefit both the alliance partners as well as the bank(s) brokering the alliance. More well-connected banks can add value both on the intensive and extensive margins. First, if bankers indeed lower search costs for firms looking for alliance partners, firms with more well-connected bankers should enter a larger number of alliances even if the value of the alliance is unaffected by the involvement of a banker. The reason is that the potential benefit from an alliance will exceed the cost of arranging the alliance in a larger number of cases when the search costs are lower. We therefore formulate the following hypothesis:

Hypothesis 4a. Firms with more well-connected bankers enter a larger number of strategic alliances.

Second, if the alliances brokered by bankers are value-enhancing, firms' market value should increase upon the announcement of such an alliance. We explicitly do not have a prior on whether strategic alliances arranged through a bank should create more, less, or the same amount of value as the average alliance. Accordingly, we formulate the next hypothesis:

Hypothesis 4b. Alliances facilitated by bankers are associated with an increase in participating firms' market value.

One reason why bankers might assist firms in finding partners for strategic alliances is an expectation of being compensated through lucrative mandates in the future. Although there is a little academic research on the topic (with the exception of Bharath, Dahiya, Saunders, and Srinivasan (2007)), there is ample anecdotal evidence of banks providing free services to their corporate customers in the hope of building relationships.[8] Such relationships benefit banks if they lead to recurring business or increase the customer's willingness to pay for the same service. We hypothesize that future mandates are the primary motivation for bankers to get involved in the facilitation of strategic alliances.

Hypothesis 4c. Borrowers reward banks for facilitating alliances by giving them additional business or by paying higher fees in future transactions.

III. Data

A. Data on Bankers

We follow a number of recent articles (e.g., Gao et al. (2020), Herpfer (2021)) and obtain data from the signature pages of publicly available loan contracts to link individual bankers to specific corporations. All U.S. companies with publicly traded securities are obliged to file "material contracts" with the Securities and Exchange Commission (SEC). The SEC makes these filings available to the public through its electronic archive system EDGAR.[9] The majority of loan contracts contain a signature page featuring the names and functions of all banks involved in the deal and the names of all bankers representing those banks.

We use a search algorithm to identify loan contracts from EDGAR and extract the name of each banker involved in the deals. Figure 2 shows the layout of such a signature page and marks the data items extracted by the algorithm. Most loans to large, publicly traded borrowers are syndicated between multiple banks. Since the algorithm extracts the names of all bankers involved in a syndicated loan, our data do not just allow us to track individual bankers, but also to construct a network of linkages between bankers based on whether they have syndicated a loan in the past. A more detailed description of the extraction procedure, the resulting data set, and various quality controls can be found in both Gao et al. (2020) and Herpfer (2021).

[8]In 2018, a consortium of banks underwrote a $1.3-billion bond offering by three Indian state-owned companies for free. *The Wall Street Journal* (2018) commented that "banks that agree to arrange bond offerings for ultralow fees are generally hoping to build relationships with corporate clients for future deals." Similarly, observers have speculated that banks who provide certain types of loans to corporate clients primarily do so to build client loyalty (*Financial Times* (2016a), *The Wall Street Journal*, (2017)). As a final example, in the course of a parliamentary investigation in the United Kingdom, Goldman Sachs stated that it "often carries out unpaid work for longstanding clients," listing a total of 25 unpaid assignments it had carried out for one particular client over a period of 12 years (*Financial Times* (2016b)).

[9]Since loan contracts are considered material under Item 601(b) of Regulation S-K, EDGAR has provided a comprehensive list of all loan contracts since the inception of mandatory electronic filing in 1996. Information from these contracts is also a primary source for DealScan (see Chava and Roberts (2008)).

FIGURE 2

Example of Simple Signature Page with a Single Bank

The red circles in Figure 2 indicate information extracted by the text search algorithm. This information includes the name and role of the bank, as well as the name and title of the signatory. The names of the banker, corporation, and corporate executive are anonymized for the sake of privacy. The prior literature offers additional, detailed descriptions of the data as well as extensive quality checks (e.g., Gao et al. (2020), Herpfer (2021)).

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          IN WITNESS WHEREOF, the parties hereto have caused
this Agreement to be duly executed and delivered by their
respective officers thereunto duly authorized as of the date
first written above.

          COMPANY:

                   [redacted] CORPORATION

                   By:   /s/ K[redacted] P. A[redacted]
                         --------------------------------------
                   Name:    K[redacted] P. A[redacted]
                   Title:   Vice President and Chief Financial
                            Officer


                   Notice Address:

                      [redacted]
                        San Francisco, CA 94111
                        Attention: Mr. K[redacted] P. A[redacted]
                                   Vice President and Chief
                                   Financial Officer
                        Fax:   (415) 398-1905


          LENDERS:

                   WELLS FARGO BANK, NATIONAL ASSOCIATION,
                   individually and as Administrative Agent

                   By:   /s/ D[redacted] A. N[redacted]
                         --------------------------------------
                   Name:    D[redacted] A. N[redacted]
                   Title:   Vice President


                   Notice Address:

                        420 Montgomery Street, 9th Floor
                        San Francisco, CA 94163
                        Attention:  Mr. D[redacted] A. N[redacted]
                                    Vice President
                        Fax:    (415) 421-1352
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To formally model the effect of bankers on the formation of strategic alliances, we employ a rudimentary multilayer network approach. The first network consists of firms, which form the nodes of that network. Connections between firms, the intralayer edges, represent strategic alliances between firms. The network's second layer consists of bankers in the syndicated loan market. Each banker is a node, and links are constructed through bankers' joint appearance on loan contracts (i.e., we assume two bankers are acquainted after they show up as signatories on the same loan contract). The interlayer edges, representing connections between bankers and firms, are created when a banker signs a loan contract with the firm, but only while representing the loan syndicate's lead arranger. In this case, the syndicate's lead banker has a professional relationship with the borrowing firm.[10]

[10]See Esty (2001) for a case study on the syndication process and the relationship formation between lead banks and borrowers. In our sample, bankers have personal relationships with between 1 and

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Existing work provides evidence that these signatures correctly identify the bankers involved in the lending decision process, and that the data are of high quality (Gao et al. (2020), Herpfer (2021)). To the degree that there is measurement error, for example, because bankers make loans to private firms which are unobservable, we will tend to underestimate the degree to which borrowers are connected through the banker network, which biases our analysis *against* finding an effect of banker networks on alliance formation.

One potential concern with the estimation is reverse causality: Two firms might enter a strategic alliance and subsequently both start borrowing from the same bank, for example, due to word of mouth recommendations or to raise funding for a joint project. To rule out that strategic alliances precede connections through the banker network, we lag the network characteristics by one period in all estimations.[11]

B. Data on Strategic Alliances

Data on strategic alliances come from S&P's Capital IQ and SDC Platinum. Importantly, both databases classify a wide range of collaborations as "strategic alliances," including collaborations in marketing, production, and customer–supplier agreements. Capital IQ has covered announcements regarding the initiation or modification of strategic alliances between two or more firms since 2002. A database entry consists of the names and identifiers of the firms involved, a headline that briefly mentions the participating firms, and the alliance's content and purpose, a detailed description and a reference to the source of the information.[12] SDC Platinum lists announcements of strategic alliances ranging back to the 1960s, covering the initiation of strategic alliances and a multitude of attributes such as the alliance's purpose and announcement date.

We collect strategic alliances announced between 2002 and 2013 from both databases and merge the resulting data sets. We aggregate all strategic alliances by the ultimate parent of the announcing firm and retain only those alliances where all parties involved have an ultimate parent that is publicly listed and incorporated in the United States. For every firm pair, we only retain the first alliance announcement over the sample period. Our data covering bankers starts 1996, which gives us 6 years prior to the sample to let the banker network build up. We treat alliances between more than two firms as a set of bilateral alliances between all parties involved.

13 distinct borrowers. The relatively small number of relationships makes it more likely that bankers have intense relationships with each borrower. We likely understate the true number of clients since our data set limits us to publicly traded borrowers. Uzzi (1999) finds that bankers in the mid-market segment have between 6 and 50 clients, using proprietary data from a mid-market lender.

[11]In untabulated results, we confirm that both the OLS and sequenced conditional logit estimates are robust to increasing this lag to 2 years.

[12]Capital IQ does not classify database entries by their timing (i.e., whether the announcement concerns the initiation of a new alliance or the termination of an existing alliance). Since we are only interested in initiations, we apply pattern-matching programs to the database entries' headlines to filter out items referring to the termination of an existing alliance.

Finally, we merge the strategic alliances with financial data from Compustat and the personal relationship measures discussed above.[13] The final sample covers 3,189 strategic alliances between publicly listed, nonfinancial U.S. firms with nonmissing accounting data.

C. Sample Characteristics

Table 1 reports summary statistics for alliance pairs in the year they are first observed. All variables are calculated as defined in Section D of the Supplementary Material.

The syndicated loan market is a common source of funding for the firms in our sample: For 88% of observed alliances, at least one firm has borrowed in the syndicated loan market before entering the alliance, and for 44% of alliances, both have done so. At the time they enter a strategic alliance, firms are substantially more likely to have borrowed from the SAME_BANK (mean = 0.18) than from the SAME_BANKER (mean = 0.03) at any point in the past. About 11% of all firm pairs are connected through the banker network at the time an alliance is initiated (BANKER_NETWORK_CONNECTION = 1). Note that our sample is limited to formalized collaborations between firms, because arm's length transactions are usually unobservable. Because smaller, informal collaborations are unobservable, our analysis provides a lower bound for the role of banker connections in facilitating collaboration between borrowers. Banker-network distance is expressed as the number of connections between bankers needed to connect two firms. Accordingly, a network distance of 0 corresponds to two firms sharing the same banker. The firm pairs that are connected via the banker network have a mean distance of only 0.91, with the modal distance being one. Low distances are therefore most common. Because distances exceeding 2 are rare (less than 2% of

TABLE 1

Summary Statistics for Observed Initial Alliance Pairs

Table 1 presents descriptive statistics for firm pairs at the time they form an alliance. Variables are defined as described in Section D of the Supplementary Material.

	No. of. Obs.	Mean	Std. Dev.	Min	Max
Panel A. Bank Loan Characteristics					
SAME_BANK	3,189	0.18	0.39	0.00	1.00
SAME_BANKER	3,189	0.03	0.18	0.00	1.00
BANKER_NETWORK_CONNECTION	3,189	0.11	0.31	0.00	1.00
BANKER_NETWORK_DISTANCE	348	0.91	0.77	0.00	3.00
ONE_HAS_A_SYNDICATED_LOAN	3,189	0.88	0.32	0.00	1.00
BOTH_HAVE_A_SYNDICATED_LOAN	3,189	0.44	0.50	0.00	1.00
Panel B. Firm-Pair Characteristics					
SAME_STATE	3,189	0.17	0.38	0.00	1.00
ONE_HIGH_INTANGIBLES	2,938	0.32	0.47	0.00	1.00
ONE_UNRATED	3,189	0.69	0.46	0.00	1.00
PREVIOUS_ALLIANCES	3,189	17.13	27.35	0.00	220.00

[13]Data from Capital IQ can be directly merged on Compustat's *gvkey*, whereas firms in the SDC data are identified by their CUSIP code.

the sample), we censor the banker-network distance at 3 (i.e., we pool all distances exceeding 2).[14]

IV. Results

This section presents various specifications estimating the impact of shared banker connections on the formation of alliances between borrowers.

A. Univariate Test and OLS Results

We begin our analysis with a simple, univariate estimate for whether firms' connections through bankers affect their propensity to enter strategic alliances. For this test, we consider all network connections and alliances established over the entire sample period. The sample consists of all publicly listed U.S. firms in Compustat between 2002 and 2013 that enter at least one strategic alliance over that same period. We implement the univariate test on two different levels: by firm and by banker portfolio. The firm-level test compares firms' propensity to enter alliances with potential partners they are connected to through the banker network to their unconditional propensity to ally. For this purpose, we calculate two ratios; a firm's WITHIN_NETWORK_ALLIANCE_RATIO, intended to capture the firm's propensity to enter strategic alliances with other firms it is connected to via the banker network, is defined as follows:

$$\text{(1)} \qquad \text{WITHIN\_NETWORK\_ALLIANCE\_RATIO}_j = \frac{C_j}{n_j},$$

where C_j is the number of firms j is connected to and enters a strategic alliance with and n_j is its total number of connections. This ratio is compared to its TOTAL_ALLIANCE_RATIO, which is designed to capture a firm's unconditional propensity to enter strategic alliances, defined as follows:

$$\text{(2)} \qquad \text{TOTAL\_ALLIANCE\_RATIO}_j = \frac{A_j}{n-1},$$

where A_j is the total number of firms that j enters a strategic alliance with and n is the number of sample firms. The two ratios are then compared to each other by means of a simple t-test.

For illustration, consider the situation in Figure 1 at time $t = 1$. Firm A has entered only one strategic alliance, the partner for that alliance being firm B. Firm A's within-network alliance ratio as defined by equation (1) is then $\frac{1}{2}$; there are two firms it is connected to via its banker network (B and C), and it has entered an alliance with one of them. Its total alliance ratio as defined by equation (2), on the other hand, is $\frac{1}{3}$. It has still only entered one alliance (with firm B), but the total number of potential alliance partners across network boundaries is 3 (firms B–D).

The results of this test in our sample are reported in Panel A of Table 2. There are 669 observations, equal to the number of sample firms. Means and standard

[14]Our results are both statistically and economically similar when we do not make this change.

TABLE 2

Univariate Tests for Propensity to Ally Given Network Connections

Panel A of Table 2 tests whether firms are more likely to enter strategic alliances with counterparties that they are connected to through the banker network. Panel B tests whether firms are more likely to enter strategic alliances with potential partners that they share a banker with. Reported means and standard errors have been multiplied by 100 for legibility.

Variable	Mean	Std. Error	No. of Obs.
Panel A. By Firm			
WITHIN_NETWORK_ALLIANCE_RATIO	0.2765	0.0241	669
TOTAL_ALLIANCE_RATIO	0.0282	0.0023	669
t-Stat	10.2507	*p*-Value	0.0000
Panel B. By Banker Portfolio			
WITHIN_PORTFOLIO_ALLIANCE_RATIO	0.2937	0.0527	4,632
TOTAL_ALLIANCE_RATIO	0.0062	0.0002	4,632
t-Stat	5.4517	*p*-Value	0.0000

errors in Table 2 have been scaled by 100 to improve readability. If firms are as likely to enter collaborations with firms they are connected to through the banker network as they are with those they are not connected to, the two ratios should be identical. The average within-network alliance ratio is 0.27%. Firms are almost 10 times as likely to form alliances within their banker network compared to the overall sample, and the t-test rejects the null hypothesis of equality in means at the 1% level.[15]

The banker portfolio test compares firms' propensity to enter strategic alliances with other firms they share a banker with to their unconditional propensity to ally. For this purpose, we calculate two statistics for every banker in the sample, similar to the firm-level test above (Lindsey (2008)). The WITHIN_PORTFOLIO_ALLIANCE_RATIO for banker i is defined as follows:

$$\text{(3)} \qquad \text{WITHIN\_PORTFOLIO\_ALLIANCE\_RATIO}_i = \frac{W_i}{n_i(n_i-1)},$$

where W_i is the number of nodes (i.e., firms in an observed alliance) in alliances between firms that both belong to banker i's portfolio and n_i is the total number of firms in the portfolio. The denominator represents the total number of potential alliance nodes that could be formed within a banker's portfolio. This ratio therefore captures firms' propensity to form strategic alliances conditional on sharing the same banker. We compare it to the banker's total alliance ratio, defined as follows:

[15]To illustrate this test further, assume that a firm has an unconditional propensity of forming an alliance with any firm of p_1. If there are n potential partners in the world, the expected number of alliances A_j equals $n \times p_1$. Similarly, if there are n_j firms inside a firm's network, the expected within-network number of alliances C_j is $n_j \times p_2$, where p_2 is the propensity to form within-network alliances. Equations (1) and (2) form the sample analogues of p_2 and p_1, respectively, and we then test the null hypothesis of $p_1 = p_2$. One misconception could be that, as n goes up, $\frac{A_j}{n-1}$ falls and the test mechanically rejects the null. This intuition is misleading for two reasons: First, as n increases, firm j's network n_j expands. Second, even if n_j stayed constant, C_j should decrease as n increases, if alliances are being entered completely independently from firms' banker networks.

$$\text{(4)} \qquad \text{TOTAL\_ALLIANCE\_RATIO}_i = \frac{A_i}{n_i(n-1)},$$

where A_i is the total number of alliance nodes in the banker's portfolio, regardless of whether only one or both alliance partners are part of the banker's portfolio. n is the total number of sample firms, so the denominator represents the maximum number of alliance nodes that *could* form in banker i's portfolio if each of her borrowers entered an alliance with every other sample firm. This second ratio is again designed to capture firms' unconditional propensity to form alliances.

As a numeric example, consider once more the situation in Figure 1 at $t = 1$. Firms A and B and firms B and C have entered pairwise alliances. Firms A and B have borrowed from banker 1, the others have not. The number of nodes in alliances formed between firms that are both within banker 1's portfolio, W_1, is equal to 2 (because firms A and B have entered an alliance), which is also the total number of such nodes possible, $n_1(n_1 - 1)$. Banker 1'sWITHIN_PORTFOLIO_ALLIANCE_RATIO, captured by equation (3), is therefore 1. For the same banker, the total number of alliances nodes in the portfolio is $A_1 = 3$ (firm A once and firm B twice), whereas the maximum number of nodes possible is $n_1(n-1) = 6$. Therefore, banker 1's TOTAL_ALLIANCE_RATIO, captured by equation (4), is equal to $\frac{1}{2}$.

For our sample, we compare the two ratios by means of a t-test for equal means. The results are reported in Panel B of Table 2. The number of observations is 4,632, equal to the number of bankers that are connected to at least two sample firms (the within-portfolio alliance-ratio is undefined for loan officers with less than two connections). The t-test rejects the null hypothesis at the 1% level, implying that firms are significantly more likely to form alliances if they share a banker. The difference between the two ratios is large, with the mean within-portfolio alliance ratio of 0.3% being almost 50 times the mean total alliance ratio.

There are of course other reasons why firms sharing the same banker should be more likely to initiate a strategic alliance, such as bankers specializing in certain industries and regions, combined with a higher propensity of firms to ally with others in their own industry and geographic proximity. These attributes are likely partly responsible for the large economic magnitudes of the results of the univariate tests above. In our next step, we therefore extend our analysis to a panel setting which allows us to control for alternative drivers of the propensity to ally, such as sharing the same bank, industry, or location.

We assemble a panel data set where the unit of observation is a pair of publicly listed, nonfinancial U.S. firms from 2002 to 2013. The panel consists of all possible firm pairs, subject to two restrictions. First, we only consider firms that enter at least one alliance over the whole sample period. Second, we only consider firm pairs in two industries if there is at least one reported alliance between firms in those two industries in the data. We define a firm's industry based on the 30 Fama–French industry portfolios. This choice is a compromise between trying not restrict firms' choice of alliance partners too much while also avoiding numerical issues that would arise in the estimation of the conditional logit model in the next section if the number of observations per industry-pair becomes too large. These two conditions restrict the size of the panel to a manageable dimension and ensure that only firm pairs that could realistically have formed an alliance enter the estimation. The panel then consists of 6.4-million firm-pair-years. Firms are not allowed to self-match, and we eliminate duplicates from permutations of the same pair of firms. The main dependent variable of interest, an indicator variable labeled ALLIANCE_{it}, equals 1 in case a pair of firms has entered a strategic alliance during the reference year or any preceding year. We then estimate the linear probability model (LPM):

$$\text{ALLIANCE}_{it} = \beta\text{NETWORK\_CONNECTION}_{it} + \gamma\text{SAME\_BANK}_{it} + \lambda_{it}\delta + \theta_i + \varepsilon_{it}, \tag{5}$$

where i indexes firm pairs and t years. The main explanatory variables (different measures of network connectivity between firms) are represented by $\text{NETWORK\_CONNECTION}_{it}$. The variable SAME_BANK_{it} controls for whether the two potential alliance partners have borrowed from the same (lead) bank in the past, since not just bankers as individuals but also banks as institutions can transmit information between borrowers (Ivashina et al. (2009)).

In addition, there might be time-varying factors, potentially at the industry level (e.g., technological developments or changes in the competitive landscape) that affect both borrowing and the rate of alliance formation. Our specification therefore includes industry-year fixed effects for both firm 1and firm 2, represented by the vector λ_{it}. In addition, the likelihood of alliance formation can vary along a number of observable (e.g., higher alliance propensity between related industries) and unobservable dimensions such as the compatibility of two companies' corporate culture. We therefore control for time-invariant, firm-pair specific variation in the propensity to form alliances by adding firm-pair fixed effects (θ_i). Finally, ε_{it} is the error term. We double-cluster standard errors by firm 1 and firm 2 in all specifications. For ease of exposition, we have multiplied the coefficient estimates of all LPMs that are presented hereafter by 100, so that the results can be directly interpreted as percentage changes.

We begin our investigation by testing Hypothesis 1, which states that two firms should be more likely to engage in a strategic alliance if they share the same banker, as measured by the indicator variable SAME_BANKER, which takes the value of 1 if a pair of firms has ever shared a banker. The results are presented in column 1 of Table 3 and show that two firms are about 0.67 percentage points more likely to engage in a strategic alliance if they share the same banker, even after controlling for the effect of sharing the same bank, time variation in the overall number of alliances and connections at the industry level, and time-invariant observable and unobservable firm-pair characteristics.

We therefore only draw inference from observations that change from not sharing the same banker to doing so during our sample period. We also find that firms are 0.12 percentage points more likely to ally if they have at some point shared the same bank. One potential concern might be that bankers are a more granular unit of observation than banks. Two firms sharing the same banker are, for example, significantly more likely to be in the same industry. Our firm-pair fixed effects capture such similarities as long as they are time-invariant. Both of these estimates are statistically significant at the 1% level. Given that the effect of sharing a banker is 5 times the effect of sharing a bank, the economic magnitude of our estimate of the impact of sharing the same banker is high in both absolute and relative terms.

TABLE 3

Influence of Banker Networks on the Formation of Strategic Alliances: OLS Results

Table 3 reports estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers. The unit of observation is a firm-pair-year, and the dependent variable is an indicator variable equal to 1 if a certain firm pair has entered a strategic alliance before or during the year of observation. The sample consists of all publicly listed nonfinancial U.S. firms in Compustat that enter at least one strategic alliance between 2002 and 2013. SAME_BANKER is equal to 1 if the firm pair has a banker in common. BANKER_NETWORK_DISTANCE measures how many banker-to-banker connections are required to establish a connection between the two firms, 0 indicating none (i.e., the firms share the same banker). BANKER_NETWORK_CONNECTION is an indicator equal to 1 if the two firms are connected through the network of bankers. Parentheses contain *t*-statistics calculated from standard errors double-clustered by firm 1 and firm 2. For ease of exposition, all coefficients have been multiplied by 100. The second panel shows *F*-statistics from pairwise Wald tests for equality for the regression coefficients in column 4. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4
SAME_BANKER	0.6705***			
	(4.56)			
BANKER_NETWORK_CONNECTION		0.2091***		
		(3.81)		
BANKER_NETWORK_DISTANCE			0.0347	
			(0.78)	
DISTANCE = 0				0.7801***
				(4.76)
DISTANCE = 1				0.2278***
				(3.13)
DISTANCE = 2				0.1064**
				(2.46)
DISTANCE > 2				0.0684
				(1.60)
SAME_BANK	0.1246***	0.1165***	0.1315	0.1046***
	(3.88)	(3.69)	(1.62)	(3.34)
Firm-pair FE	Yes	Yes	Yes	Yes
Industry 1-year FE	Yes	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes	Yes
N	6,370,758	6,370,758	359,668	6,370,758
R^2	0.7444	0.7444	0.8360	0.7444

	Wald-Tests for Equality of Coefficients		
	DISTANCE = 1	DISTANCE = 2	DISTANCE > 2
DISTANCE = 0	16.25***	19.11***	19.21***
DISTANCE = 1		5.20**	4.36**
DISTANCE = 2			0.74

Hypothesis 2 states that two firms should be more likely to ally even if they do not share the same banker, but are indirectly connected through a banker network. In column 2 of Table 3, we estimate the same model as in column 1, but replace SAME_BANKER with BANKER_NETWORK_CONNECTION, an indicator that takes the value of 1 if the two firms in a pair are in any way connected through their banker network from past loans. The estimated coefficient on this indicator is 0.21 percentage points and highly statistically significant, consistent with our prediction.

Hypothesis 2 also predicts that the effect of an indirect banker connection should become weaker as the distance between bankers increases. We explicitly test this conjecture in columns 3 and 4 of Table 3, where our main explanatory variable is BANKER_NETWORK_DISTANCE, a measure of the shortest network path between all bankers associated with the two firms. A distance of 0 therefore corresponds to two firms sharing the same banker, and a distance of 1 indicates that the shortest connection between two firms involves two bankers that have worked together on loans to other companies.

We test Hypothesis 2 in two ways. In column 3 of Table 3, we limit our sample to only those firms that do share a connection through the banker network, and run a regression of our alliance indicator on BANKER_NETWORK_DISTANCE. Note that the sample shrinks significantly in this specification, since we can only consider pairs of firms that are in any way connected through a banker network, as the distance between two firms that are unconnected is undefined. While Hypothesis 2 would predict a negative and significant effect of network distance on the propensity to form an alliance, the estimated coefficient on BANKER_NETWORK_DISTANCE is both statistically and economically insignificant in this specification. Since firm-pair fixed effects absorb any time-invariant firm-pair-level characteristics, these specifications can only draw inference from firm–bank pairs that are connected through the banker network with different levels of distance. The power of this test is significantly lowered since we cannot draw inference from firms that move from being unconnected to being connected.

To overcome this limitation and increase the power of our test, we instead treat BANKER_NETWORK_DISTANCE as a discrete variable and estimate coefficients for each level of distance separately in column 4 of Table 3. In that way, we are able to use unconnected firms as the reference group, and draw inference from firm pairs that move from being unconnected to being connected. The magnitude of the coefficient estimates is monotonously decreasing in the distance in these specifications. The coefficients on DISTANCE = 0 (0.78), DISTANCE = 1 (0.23), and DISTANCE = 2 (0.11) are all statistically significant at the 5% or 1% level. The coefficient estimate for distances larger than 2 (which we pool into a single group due to the small number of such observations) is still positive (0.07), but statistically insignificant. We perform pairwise Wald tests for equality to establish that the differences between the individual coefficient estimates are statistically significant. The results of these tests are provided at the bottom of Table 3. All but one test reject the null hypothesis of equality at the 5% level or below. These results support our interpretation that the impact of banker networks on alliance formation is a decreasing function of network distance.

The results in column 4 of Table 3 are particularly interesting since they alleviate a number of endogeneity concerns. The firm-pair fixed effects in these specifications mean that we draw inference only from cases in which the banker-network distance between two existing firms changes. The coefficients on distances larger than 0 therefore mostly reflect events in which the two bankers associated with two firms jointly issue a loan to a *third*, unrelated borrower, that is, without any of the two firms taking out a new loan. These cases therefore really isolate changes in banker-network connections from any confounding effects on the firm level. We then conduct pairwise Wald tests between the coefficients of the various network distances. We find that all coefficients are statistically significantly different from each other, with the exception of the difference between distances equal to 2, and those larger than 2. This result is unsurprising, as few firm pairs have a network distance larger than 2 and the coefficient for DISTANCE > 2 itself is not statistically significant.

Section C of the Supplementary Material provides a number of robustness tests for our OLS specification. Principally among those are a model with firm-year fixed effects for both firms, a first-difference model, and a specification in which we limit the lifetime of network connections to 5 years. Our core result remains intact in all these additional tests.

Results in Section E of the Supplementary Material also show that our results remain robust when estimating them using the sequenced conditional logit model developed by Lindsey (2008). Section C of the Supplementary Material describes this model in more detail and provides an example. Throughout the remaining analysis, we present both our LPM and logit results whenever applicable.

These result suggests that, although sharing the same banker is the strongest predictor of two firms entering into a strategic alliance, even indirect connections still increase the likelihood of two firms to ally. At the same time, larger network distance between bankers reduces their matchmaking ability, with the estimated coefficient monotonically decreasing in network distance. Once the chain of bankers exceeds 3 people, there is a very little impact on alliance formation. Across all specifications, the estimated effect of sharing the same bank has a positive and statistically significant impact on the likelihood of alliance formation.

B. Exogenous Shocks to Banker Connections from Banker Turnover

Although our fixed effects models allow us to control tightly for many potentially confounding factors, there is still the possibility of time-varying, firm-pair-banker specific shocks that cause both changes in banker-network connections and increase the likelihood of collaboration for a specific set of firms.

For illustration, consider a pair of firms, Firm A and Firm B, and that there is a change in the CEO in Firm A. The new CEO might have a personal network both with a new banker and the CEO of Firm B. If the CEO of Firm B has also borrowed from the same banker in the past, the appointment of the new CEO at Firm A will both induce a new banker-network connection between firms A and B, while also increasing the likelihood of a future collaboration between the firms due to their CEO connection. To rule out that such contemporaneous shocks to both banker networks and specific firm pairs drive our results, we use cases in which bankers switch employers as shocks to banker-network connections. In these cases, we can trace the change in firm–network distance to an event that is unrelated to firm (or firm-pair) specific events.

The IV estimates we provide are for our OLS sample. The variables we instrument are the measures of network distance between firm pairs (i.e., SAME_BANKER, BANKER_NETWORK_CONNECTION, and BANKER_NETWORK_DISTANCE). Our instrument is an indicator variable we label BANKER_MOVED. It takes a value of 1 for firm-pair years in which *Firm A* has previously borrowed from a certain banker, and that banker has subsequently switched to *Firm B's* bank (or the other way around).

The IV is based on the fact that firms generally keep borrowing from the same bank. When a bank acquires a new banker, that bank's clients are likely to establish a connection with the new banker when they get a new loan from their bank, which also establishes a network link with the banker's previous clients that he lent to while working for his previous employer. The banker turnover therefore impacts the

TABLE 4

Instrumental Variable Estimates

Table 4 reports results from the second stage of 2SLS instrumental variable regressions on the firm-pair level. The first stage is an OLS regression for the independent variables SAME_BANKER and BANKER_NETWORK_CONNECTION and BANKER_NETWORK_DISTANCE on an indicator for whether a banker with a previous relationship with one firm moved to a new employing bank that has previously extended a loan to the other firm. The second stage is the OLS model as in Table 3. First-stage estimates are provided in Section E of the Supplementary Material. The sample consists of all publicly listed nonfinancial U.S. firms in Compustat that enter at least one strategic alliance between 2002 and 2013. Standard errors have been double-clustered by firm 1 and firm 2. For ease of exposition, all coefficients have been multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
SAME_BANKER	8.1758**		
	(2.23)		
BANKER_NETWORK_CONNECTION		4.8602**	
		(2.37)	
BANKER_NETWORK_DISTANCE			−3.9908*
			(−1.80)
SAME_BANK	−0.0203	−0.3513*	−0.1685
	(−0.27)	(−1.67)	(−0.92)
Firm-pair FE	Yes	Yes	Yes
Industry 1-year FE	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes
N	6,370,752	6,370,752	359,662

network distance only between a banker's *previous borrowers*, and the *existing borrowers* (at the time of turnover) of his new bank.[16]

For ease of exposition, we report the results of the first-stage regression separately in Section E of the Supplementary Material. We find that our instrument appears to fulfill the relevancy condition, and the first-stage Kleibergen–Paap F-statistic between 10 and 13 alleviates concerns of a weak instrument. The years after a banker switches to a new bank see a significant drop in banker-network distance between the banker's old clients, and the existing borrowers of his new bank. Importantly, we only consider moves by bankers between legally independent banks, that is, we do not assign the BANKER_MOVED indicator after a merger between two banks. We use the linking table provided by Schwert (2018) to determine the precise cutoffs for these bank mergers. Table 4 presents the results of the second-stage regressions.

Column 1 of Table 4 reports the result for SAME_BANKER. As in our main specification, the coefficient is positive at 0.10, and statistically significant at the 5% level. As in our other tests, the coefficient on NETWORK_CONNECTION is smaller at 0.05, and statistically equally significant. As in the main test, the coefficient estimate on BANKER_NETWORK_DISTANCE is negative at −0.04, although it is only marginally significant at the 10% level.[17]

[16]We specifically do not assign the indicator to borrowers that borrow from the new bank only after the banker switched. We use the same instrument for three separate measures of network distance, but these 3 variables are just different measures of the same underlying network change.

[17]The size of the instrumental variable local average treatment effects in Table 4 is significantly larger than the average sample OLS estimates in our main specification. There are two likely explanations for this discrepancy in treatment effects. First, the economic explanation for this difference is that the estimates in Table 4 reflect the effects of banker connections for the subset of bankers that move. This relatively small subset of bankers is different in that these are the bankers that appear most often in our sample, and are therefore both more central in our banker network and more senior than the average

The exclusion restriction in these tests requires that banker turnover only impacts firms through its effect on the network distance. Despite banking relationships being sticky (Bharath et al. (2011), Chodorow-Reich (2013)), it could be that a banker's former clients might eventually follow her to her new bank. In that case, the banker switching would impact not just banker-network distance, but also the likelihood of sharing the same bank. To limit this potentially confounding factor, for every firm-pair-year, we construct the IV based only on banker moves that happened over the preceding 2 years. Since bankers often face noncompete clauses immediately after leaving a bank, limiting the instrument to these 2 years reduces the potentially confounding impact of borrowers following their bankers. In addition, borrowers following bankers could not explain our findings for our measure of indirect connections (represented by the variable BANKER_NETWORK_CONNECTION).

Overall, the results of these IV regressions support a causal interpretation of our main findings.

C. Bankers Are Important when Information Asymmetry Is High

Our third hypothesis predicts that bankers' ability to broker alliances should exhibit cross-sectional differences based on borrower characteristics. We test the prediction that greater opacity should amplify the role of bankers in brokering alliances in Table 5.

The results in columns 1 and 2 of Table 5 are for the variable capacity version of the sequenced conditional logit model.[18] For robustness, we repeat the same tests using an LPM in columns 3 and 4. The specifications in Table 5 interact the independent variable SAME_BANKER with two measures of opacity: lack of credit ratings and high intangibility of assets. In column 1, we interact SAME_BANKER with ONE_UNRATED, an indicator variable that takes the value of 1 for pairs in which at least one firm has no domestic long-term issuer credit rating from S&P's, Moody's, or Fitch. We find that the coefficient estimate on the interaction of sharing the same banker and ONE_UNRATED is 0.660, and statistically significant at the 5% level. Interestingly, we find that the uninteracted variable ONE_UNRATED enters the regression negatively and is statistically significant at the 1% level, which implies that firm pairs in which one is unrated indeed are less likely to join a strategic alliance. This result shows that sharing the same banker has a significantly more positive impact on the formation of strategic alliances when there is less publicly available information about the participants.

banker. These bankers are likely to have a heightened ability to match clients because of their wider network, longer experience, and higher seniority. Second, the OLS specifications feature many firm pairs for which we do not observe bankers. To the degree that we undercount the connections made by bankers for these firms, we underestimate the effect of those bankers that we do observe. The IV regressions, in contrast, draw inference only from those firm pairs for which we do observe bankers. The magnitude of the IV regressions is, in fact, very similar to that in the matched-pairs OLS regressions of Table E4 in the Supplementary Material, suggesting that there is significant downward pressure in our main OLS estimates, making them very conservative.

[18]In unreported analyses, we repeat all tests in this table using the fixed capacity model. All estimates are both statistically and economically very close to the variable capacity estimates.

TABLE 5

Banker Networks and Firm Opacity

The sample in Table 5 consists of all publicly listed nonfinancial U.S. firms in Compustat that enter at least one strategic alliance between 2002 and 2013. Estimates for the sequenced conditional logit model are based on the variable capacity implementation. ONE_UNRATED means either one or both firms do not have a domestic long-term issuer credit rating from either S&P, Moody's, or Fitch. ONE_HIGH_INTANGIBLES means either one or both firms have an intangibles-to-assets ratio in the top quintile. Parentheses contain *z*-statistics for the conditional logit model and *t*-statistics for the linear probability model (LPM). Industry-pair-year fixed effects are implicit in the sequenced conditional logit model. Standard errors for the LPM have been double-clustered by firm 1 and firm 2. For ease of exposition, the coefficients for the LPM have been multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Sequenced Cond. Logit		LPM	
	1	2	3	4
SAME_BANKER × ONE_UNRATED	0.660**		−0.456*	
	(2.52)		(−1.88)	
SAME_BANKER × ONE_HIGH_INTANGIBLES		0.615***		0.408**
		(2.67)		(2.03)
ONE_UNRATED	−0.439***		−0.090**	
	(−8.05)		(−2.26)	
ONE_HIGH_INTANGIBLES		−0.040		0.012
		(−0.87)		(1.33)
SAME_BANKER	0.174	0.039	0.776***	0.462***
	(1.37)	(0.22)	(4.37)	(3.91)
SAME_BANK	−0.130**	0.052	0.117***	0.118***
	(−2.07)	(0.86)	(3.69)	(3.88)
SAME_STATE	0.394***	0.359***		
	(7.79)	(6.71)		
PREVIOUS_ALLIANCES	0.024***	0.025***		
	(27.97)	(28.61)		
Firm-pair FE	No	No	Yes	Yes
Industry 1-year FE	No	No	Yes	Yes
Industry 2-year FE	No	No	Yes	Yes
N	529,323	480,006	6,370,758	5,846,834
Prob > χ^2	0.000	0.000		
R^2			0.744	0.756

Similarly, column 2 of Table 5 tests whether the effect of bankers on alliance formation is larger when at least one of the potential partners has a particularly high (i.e., in the top quintile) fraction of intangible assets. We find that ONE_HIGH_INTANGIBLES indeed interacts positively with SAME_BANKER, with a coefficient of 0.615 and is statistical significance at the 1% level.[19] The main effect for ONE_HIGH_INTANGIBLES, on the other hand, is statistically insignificant.[20]

Columns 3 and 4 of Table 5 repeat the same tests based on the LPM. Inconsistent with the main specification, the coefficient for the interaction with

[19]Another cross-sectional dimension on which to measure opacity might be firm size. In unreported results, we find no statistically significantly different effect of network connection across small and large firms. That finding is consistent with Ivashina et al. (2009), who demonstrate that banks have sensitive inside information even for the largest, most transparent firms.

[20]Because the coefficients are from a conditional logit model, they again cannot be interpreted as a marginal effect without imposing unduly strict assumptions on the (unidentified) fixed effects. However, an interpretation in terms of odds ratios is possible. The exponential of the interaction term in column 1 indicates that when two firms share the same banker and do not have a credit rating, the odds they will subsequently enter an alliance increase by 1.935 times as much as they would if the firms did have a credit rating. In other words, unrated firms benefit almost twice as much from sharing the same banker as rated firms. The economic impact of a high share of intangible assets in column 2 is of a similar magnitude.

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ONE_UNRATED is negative, albeit statistically marginal. The interaction term for ONE_HIGH_INTANGIBLES, on the other hand, is positive and significant at the 5% level, consistent with the results in column 2.

D. Banker Networks Within and Across Industries

In this section, we investigate the process through which bankers facilitate alliances. We hypothesize that there are two sets of circumstances in which bankers should not be helpful in forming alliances: i) when firms are fundamentally incompatible and ii) when firms are obvious partners. On the one hand, a connection to an ex ante unlikely partner is not going to increase the likelihood of forming an alliances. For example, an automobile company that is connected to a Biotech company is not going to be any more likely to form a joint venture. If an alliance is ex ante not feasible, lower search costs are not going to matter. We test this hypothesis in Table 6 by estimating the effect of banker networks within and across industries.

The results in Table 6 are consistent with the hypothesis that banker networks mostly increase the likelihood of ex ante feasible alliances to form. Coding firm pairs as being in the same industry if both firms are in the same Fama–French 30 industry group, we find that the effect of both direct and indirect banker-network connections is concentrated among firms in the same industry, although the across-industry effect (the uninteracted coefficient) is still positive and statistically significant. The literature on growth and innovation has found that both within- and across-industry innovations impact growth (Glaeser, Kallal, Scheinkman, and Shleifer (1992)). Our results show that bankers seem to impact both types, and to

TABLE 6

Banker Networks Within and Across Industries

Table 6 reports results from linear probability models relating the effect of banker connections to the rate of alliance formation within and across industries. The unit of observation is a firm-pair-year, and the dependent variable is an indicator variable equal to 1 if a certain firm pair has entered a strategic alliance before or during the year of observation. The variable SAME_INDUSTRY is an indicator taking the value of 1 for firm pairs in the same industry (according to the 30 Fama–French industry groups). The sample consists of all publicly listed nonfinancial U.S. firms in Compustat that enter at least one strategic alliance between 2002 and 2013. Parentheses contain *t*-statistics. Standard errors have been double-clustered by firm 1 and firm 2. For ease of exposition, all coefficients have been multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2
SAME_BANKER	0.2758***	
	(2.59)	
SAME_BANKER × SAME_INDUSTRY	1.9117***	
	(3.74)	
BANKER_NETWORK_CONNECTION		0.0368
		(0.85)
BANKER_NETWORK_CONNECTION × SAME_INDUSTRY		1.0924***
		(5.65)
SAME_BANK	0.1258***	0.1196***
	(3.72)	(3.56)
Firm-pair FE	Yes	Yes
Year FE	Yes	Yes
N	6,370,774	6,370,774
R^2	0.7441	0.7441

the degree that across-industry innovation creates outsize value, the smaller coefficient on these cross-industry alliances might still carry a large economic impact.

We also investigate another dimension of ex ante feasibility of alliances, namely geography. Firms that are geographically very distant from each other have a harder time collaborating, and likely lack the necessary information about each other. Just as in the case of firms from unrelated industries, a shared banker connection should not impact firm pairs that are fundamentally unlikely to collaborate since they operate in different geographic markets. Consistent with this idea, the results reported in Table E10 in the Supplementary Material show that the effect of sharing the same banker decreases with the distance between firms, as does the effect of sharing the same bank.

In addition to distance between firms, Table E10 in the Supplementary Material also tests for heterogeneity in the effect of sharing the same banker based on the distance between banker and firm.[21] Interestingly, we find that bankers located further away from firms have a slightly higher effect on their likelihood to collaborate, although the effect is small. This result might be due to either bankers located further away helping expand the firms' network of potential partners, or bankers located further away from firms might be of higher quality than local bankers. For example, larger distance might proxy for bankers located in large financial hubs such as New York and Chicago. We leave the detailed examination of this question for future work.

E. Well-Connected Bankers Allow Borrowers to Forge More Alliances

We now test Hypothesis 4a, whether banker networks increase the number of alliances firms form. To test our hypothesis, we aggregate data on the firm-year level and run regressions of the number of (new) alliances on measures of the aggregate connectedness of each firm to its potential alliance partners in Table 7. The samples for the sequenced conditional logit regressions and the OLS regressions differ both in terms of sample construction and how they treat realized alliances. We therefore run these tests both on the data structure of the sequenced conditional logit panel (columns 1 and 2) as well as the OLS panel (columns 3 and 4).

In the sequenced conditional logit model, we remove firm pairs in the year following a realized alliance, so the dependent variable in the first two columns is the logarithm of the number of newly realized alliances plus 1 in each firm year. In column 1 of Table 7, we measure each firm's average level of connectedness through the banker network as the mean of the SAME_BANKER variable (i.e., the fraction of other firms it could have entered an alliance with and with which it shares the same banker). We control for unobservable firm-level characteristics through firm fixed effects, and time variation in the propensity to form alliances through year fixed effects. Our specifications therefore only draw inference from variation in each firm's network connections over time. We also control

[21]We obtain data on the location of bankers by manually collecting the office addresses for correspondence from loan contracts. We then supplement these data using location information from online sources. We then calculate the average geographic distance between the two firms in a pair and the banker they share.

TABLE 7

Banker Networks and Firms' Number of Strategic Alliances

The unit of observation for the tests displayed in Table 7 is a firm-year and the independent variable an indicator for the number of strategic alliances the firm enters in the current year (columns 1 and 2) or has entered over the sample period (columns 3 and 4). The set of potential alliance partners for each firm is constructed analogously to the tests in Table 3 and Table E6 in the Supplementary Material. The network characteristics (SAME_BANKER, BANKER_NETWORK_CONNECTION, and SAME_BANK) have then been averaged across this set of potential partners for each firm. In columns 1 and 2, potential alliance partners have been eliminated from a firm's set of possible matches in the first year after an alliance is first realized, analogous to the sequenced conditional logit sample. In columns 3 and 4, those pairs remain in the sample, analogous to the OLS sample. Standard errors have been clustered by firm. Financial variables have been winsorized at the 2% and 98% levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ln(1 + NEW_ALLIANCES)		ln(1 + TOTAL_ALLIANCES)	
	1	2	3	4
MEAN(SAME_BANKER)	0.1317* (1.92)		1.8297*** (3.54)	
MEAN(BANKER_NETWORK_CONNECTION)		0.0699** (2.09)		0.3865*** (3.94)
MEAN(SAME_BANK)	0.0603** (2.39)	0.0568** (2.23)	0.1875* (1.94)	0.1942** (2.02)
ln(TOTAL_ASSETS)	0.0397*** (6.09)	0.0395*** (6.05)	0.0374*** (3.61)	0.0348*** (3.37)
ln(FIRM_AGE)	−0.0000 (−0.00)	0.0013 (0.05)	−0.0055 (−0.14)	−0.0105 (−0.27)
MARKET_LEVERAGE	−0.0502* (−1.85)	−0.0499* (−1.84)	0.0392 (1.11)	0.0380 (1.07)
ROA	−0.0172 (−1.61)	−0.0173 (−1.62)	−0.0050 (−0.43)	−0.0044 (−0.38)
ln(NUM_POTENTIAL_ALLIANCES)	0.4033*** (16.96)	0.4053*** (16.99)	−0.1363 (−0.66)	−0.1216 (−0.59)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	13,589	13,589	14,020	14,020
R^2	0.4072	0.4072	0.8551	0.8549

for time-varying firm-level characteristics such as firm size, age, leverage, profitability, and the number of potential alliance partners. In addition, we control for the fraction of potential alliance partners the firm shares the same bank with (MEAN(SAME_BANK)). We find that the coefficient estimate on MEAN(SAME_BANKER) is 0.132, and statistically significant at the 10% level. Evaluated at the mean of all independent variables, this number implies that a 1-standard-deviation increase in MEAN(SAME_BANKER) leads to an additional 0.015 alliances for a particular firm-year, all else equal. The remaining coefficients imply that firms that share the same bank with more potential alliance partners initiate more new alliances, as do larger firms and those with a larger set of potential partners.

In column 2 of Table 7, we replace our main explanatory variable MEAN (SAME_BANKER) with MEAN(BANKER_CONNECTION), the mean of the BANKER_CONNECTION indicator that captures whether a firm-pair shares any direct or indirect links through the banker network. The coefficient estimate is 0.070, and statistically significant at the 5% level, implying that a 1-standard-deviation increase in MEAN(BANKER_CONNECTION) leads to an additional 0.018 alliances for a particular firm-year, evaluated at the means of all independent variables. Consistent with our earlier findings that indirect connections through the banker network have a lower impact on the formation of strategic alliances, we find that the coefficient estimates for MEAN(SAME_BANKER) exceeds both that for indirect connections (MEAN(BANKER_CONNECTION)) and sharing the same bank (MEAN(SAME_BANK)).

In columns 3 and 4 of Table 7, we repeat this analysis using the OLS panel as the basis for the firm-year aggregation. In this sample, we do not remove firm pairs in the years after an alliance is first realized. Therefore, the appropriate dependent variable in this analysis has been the total number of alliances since the beginning of the sample period for each firm and year. The results confirm those from columns 1 and 2. The coefficient estimates on both MEAN(SAME_BANKER) and MEAN(BANKER_CONNECTION) are positive, and statistically significant at the 1% level.

Overall, the results are consistent with Hypothesis 4a, which states that more banker connections lead to firms engaging in more strategic alliances.

F. Alliances Facilitated by Bankers Are Valuable for Firms

To investigate Hypothesis 4b, whether strategic alliances arranged by bankers are beneficial for firms, we perform an event study around their announcement. The dependent variable in these regressions is the CARs for every alliance announcement over a 3-day event window centered on the announcement date. We then relate the CAR to the firm pair's network characteristics in OLS regressions. Cumulative abnormal returns are calculated based on the market model with a 250-day estimation period and winsorized at the 2% and 98% levels. We require at least 220 observations in the estimation window to be nonmissing and use the value-weighted return of all CRSP firms as the market benchmark and the 1-month U.S. treasury bill for the risk-free rate. The estimated market beta has been shrunk toward the cross-sectional mean based on the Vasicek (1973) estimator. We use the value-weighted return of all U.S.-incorporated stocks in CRSP and the 1-month U.S. treasury bill rate provided by Kenneth French on his website[22] as proxies for the market return and the risk-free rate, respectively. For robustness, we repeat the same tests on the alliance (instead of firm) level, where the CAR for an observed alliance is the market value weighted average CAR of all participating firms. The results of these regressions are presented in Table 8.

If alliances facilitated by bankers create more value than other alliances, the coefficient estimate for sharing the same banker should be positive. If they create less value, the coefficient should be negative, and if there is no difference, the coefficient should be 0. Consistent with the prior literature (e.g., Chan et al. (1997)), we find that strategic alliances are generally valuable for firms. In all model specifications, the intercept, which captures the general effect of alliances on firm value, is positive, and statistically significant at the 1% level. This result implies that a strategic alliance adds between 0.6% and 0.7% to a firm's market value on average. The intercepts for the weighted average CAR by alliance in columns 3 and 4 of Table 8 are lower at 0.2%, implying that small firms, in relative terms, benefit disproportionately from strategic alliances. The specifications in columns 1 and 3 control for whether the firms in an announced alliance share either the SAME_BANKER or the SAME_BANK, columns 2 and 4 do the same for whether

[22] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

TABLE 8

Do Alliances Brokered Through Banker Networks Increase Firm Value?

Table 8 reports coefficient estimates from regressions of CARs over a [−1;1] event window around alliance announcements on network characteristics. The sample consists of all initial strategic alliances entered by publicly listed nonfinancial U.S. firms that are listed in SDC Platinum or Capital IQ for the period from 2002 to 2013. CARs have been calculated according to the market model with market betas estimated from 250 daily observations and shrunk toward the cross-sectional mean based on the Vasicek (1973) estimator. Standard errors have been clustered by alliance. The unit of observation in columns 1 and 2 is a firm in an observed alliance. The unit of observation in columns 3 and 4 is a strategic alliance, with the CAR having been calculated by taking the market value weighted average of the alliance members' CARs. For ease of exposition, all coefficients have been multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Firm-Level CAR		Alliance-Level CAR	
	1	2	3	4
INTERCEPT	0.612***	0.624***	0.228***	0.226***
	(8.50)	(8.47)	(3.74)	(3.63)
SAME_BANKER	−0.088		0.230	
	(−0.38)		(1.02)	
BANKER_NETWORK_CONNECTION		−0.202		0.082
		(−1.34)		(0.56)
SAME_BANK	−0.213*	−0.171	−0.155	−0.150
	(−1.73)	(−1.36)	(−1.32)	(−1.24)
N	5,535	5,535	2,993	2,993
R^2	0.000	0.001	0.000	0.000

there exists any BANKER_NETWORK_CONNECTION. The estimated coefficients for all of the network characteristics are statistically insignificant at the 5% level, therefore not providing any evidence that alliances facilitated through banker networks are either better or worse than the average alliance.[23] These results suggest that banker networks benefit firms on the extensive rather than the intensive margin in the formation of alliances: Better connected networks allow firms to enter more alliances. These alliances are valuable but not of higher quality than the average strategic alliance.

G. Banks Are Compensated Through Additional Mandates, Higher Interest Rates, and More Clients

One reason why a bank might be interested in helping a borrower enter a strategic alliance is that it strengthens the lending relationship. Bharath et al. (2007) find that stronger lending relationships benefit banks through their ability to cross-sell other financial services, and Hellmann, Lindsey, and Puri (2007) find that banks which build a venture capital relationship to borrowers are more likely to be chosen as lenders later. Here, we present a number of tests motivated by that intuition.

1. Additional Mandates

We test for the existence of compensation through additional mandates on an annual panel of firm–bank pairs. For each firm in year t, we record all banks that served as lead arrangers on a loan in the past. The dependent variable of interest is an indicator, whether the bank is given a particular mandate from this borrower over

[23]Although the coefficient for sharing the same bank in column 1 is on the margin of statistical significance, it is only a third of the size of the intercept, that is, even if it was statistically significant, alliances between partners sharing the same bank would still have a positive overall impact on market value.

the subsequent 5-year period, that is, until $t+4$. We consider three types of mandates: arranging an additional syndicated loan ("bank-based financing"), serving as the underwriter in a bond or seasoned equity offering ("market-based financing"), or advising in an M&A transaction ("M&A advisory"). Data on seasoned equity offerings, bond issues, and advisory mandates in M&A come from Capital IQ, and data on syndicated loans from LPC DealScan.[24] Our main explanatory variable is the number of strategic alliances the firm has entered with a partner it shared the bank with ex ante, the underlying assumption being that the shared bank connection played a role in brokering the alliance. For robustness, we perform all tests both using a logit model as well as an LPM.

Table 9 reports the results of these tests. For the logistic regressions, we report marginal effects rather than the direct coefficient estimates. Both the OLS and logit estimates indicate a positive impact of the number of facilitated alliances on the probability of being selected to arrange a syndicated loan or underwrite a securities offering, statistically significant at the 1% level. The result for M&A advisory services are similar. The coefficient in the logit model is positive, and statistically significant at the 1% level. The LPM estimate is also positive, but not statistically significant.

The estimated coefficients are not only of statistical, but also economic significance. The average marginal effect for an increase of 1 in the number of alliances brokered by the bank increases the probability of that bank becoming the

TABLE 9

Are Relationship Banks Compensated for Brokering Alliances (Cross-Selling)?

The unit of observation for the tests displayed in Table 9 is a relationship bank-firm-year and the independent variable an indicator for whether the relationship bank is chosen at least once as the lead arranger of a loan syndicate in columns 1 and 2, the underwriter for a bond or seasoned equity offering in columns 3 and 4 or the adviser in an M&A transaction in columns 5 and 6 by the firm over the next 5 years, starting with the year of reference. For the logistic regressions, marginal effects are displayed. Parentheses contain z-statistics for logistic regressions and t-statistics for the linear probability model (LPM). Standard errors for the LPM estimates have been clustered by firm. For ease of exposition, all coefficients have been multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Bank-Based Financing		Market-Based Financing		M&A Advisory	
Probability Model	Logit	LPM	Logit	LPM	Logit	LPM
	1	2	3	4	5	6
NUM_ALLIANCES_FACILITATED_BY_BANK	33.555***	19.336***	3.264***	4.648***	0.200***	0.532
	(30.02)	(14.20)	(12.36)	(4.92)	(3.58)	(1.02)
NUMBER_SYNDICATED_LOANS	11.152***					
	(87.32)					
NUMBER_BOND_ISSUES_AND_SEOS			0.015***			
			(15.40)			
NUMBER_OF_M&A_TRANSACTIONS					0.085***	
					(19.33)	
NUMBER_OF_ALLIANCES	0.976***		0.938***		0.039***	
	(14.64)		(37.99)		(9.87)	
Year FE	Yes	No	Yes	No	Yes	No
Firm-year FE	No	Yes	No	Yes	No	Yes
Bank-year FE	No	Yes	No	Yes	No	Yes
N	255,556	212,235	255,556	212,235	255,556	212,235
(Pseudo) R^2	0.044	0.556	0.048	0.481	0.034	0.225

[24]The two databases are linked by matching banks on names.

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lead arranger for at least one syndicated loan over the following 5 years by 33.6 percentage points (the corresponding LPM estimate suggests a 19.3 percentage point increase). The marginal effect for securities underwriting services is lower at only 3.3 percentage points (the corresponding LPM estimate being 4.6 percentage points).

2. Higher Interest Rates

In this section, we test Hypothesis 4c, whether borrowers are willing to pay higher interest rates in return for banks facilitating strategic alliances for them. We start with the same panel of firm-bank-years used for the tests in Table 9 and restrict it to those observations in which at least one new loan is established. We then calculate the mean interest rate paid by the borrower to the bank across all loans new established in each particular year, and regress it on the number of alliances facilitated by the same bank in the past. The results of our tests are presented in Table 10.

In column 1 of Table 10, we present the base specification with firm, bank, and year fixed effects. The results imply that for every alliance potentially facilitated by the bank in the past, the borrower pays an additional 4 basis points in interest for the next loan, with statistical significance at the 5% level. In column 2, we augment this specification with bank-year fixed effects, and in column 3, we add both bank-year and firm-year fixed effects. The coefficient estimate is only marginally affected by the additional fixed effects, but its statistical significance decreases. In column 2, the coefficient estimate is still marginally statistically significant ($t = 1.88$). The coefficient stays economically the same, but becomes statistically insignificant once firm-year fixed effects are introduced in column 3. Note that the specification with firm-year fixed effects is highly restrictive as only a few firms ever take out more than one loan in a year.

3. Additional Clients

In this final section, we investigate if banks benefit from more well-connected bankers through attracting additional clients. Prior work has demonstrated that star

TABLE 10

Are Relationship Banks Compensated for Brokering Alliances (Interest Rates)?

Table 10 reports results from OLS regressions on the borrower-bank-year level, linking the interest rate paid on loans by borrowers to NUM_ALLIANCES_FACILITATED_BY_BANK, the number of alliances for the borrower that were potentially facilitated by the lending bank. The sample consists of all loans issued to firms in our main sample between 2002 and 2013. Standard errors have been clustered by firm. For ease of exposition, all coefficients have been multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	log(INTEREST_RATE)		
	1	2	3
NUM_ALLIANCES_FACILITATED_BY_BANK	3.678**	3.589*	3.658
	(2.02)	(1.88)	(0.96)
Firm FE	Yes	Yes	No
Bank FE	Yes	No	No
Year FE	Yes	No	No
Bank-year FE	No	Yes	Yes
Firm-year FE	No	No	Yes
N	14,427	13,947	6,600
R^2	0.863	0.860	0.825

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TABLE 11

Well-Connected Bankers and Banks' Business

Table 11 reports results from OLS regressions on the bank-year level, linking the amount of new business being done by a bank to measures of how well its bankers are connected. The dependent variable is the number of loans issued by the bank in a given year. The explanatory variable NUM_DEALS_BEST_BANKER is the maximum number of loans issued by a single banker within the bank, and the explanatory variable NUM_DEALS_AVERAGE_BANKER is the average number of loans issued by all bankers in the bank. Both explanatory variables are lagged by 1 year. The sample consists of all loans issued to firms in our main sample between 2002 and 2013. All variables have been winsorized at the 2% and 98% levels. Parentheses contain *t*-statistics. Standard errors have been double-clustered by bank and year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	No. of Loans			
	1	2	3	4
NUM_DEALS_BEST_BANKER	0.5335*** (4.02)			
NUM_DEALS_AVERAGE_BANKER		2.7240*** (3.83)		
NUM_DEALS_BEST_BANKER			3.0545*** (3.40)	
NUM_DEALS_AVERAGE_BANKER				5.4209*** (3.03)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,813	1,813	1,813	1,813
R^2	0.6550	0.6482	0.6587	0.6434

analysts attract deal flow in the IPO market (Krigman et al. (2001), Corwin and Schultz (2005)). We hypothesize that well-connected commercial bankers could have a similar role.

In Table 11, we estimate regressions linking the connectedness of a bank's bankers to future deal flow. We measure connectedness as the number of prior deals done by its bankers, both on the average and maximum levels. We then estimate panel models linking a bank's connectedness in year $t-1$ to the number of new loans it issues in year t. Exploiting within-bank variation of connectedness by including bank fixed effects, we find that both average and maximum connectedness are associated with higher future deal volume in columns 1 and 2. The effect is economically sizable. The average number of loans per bank-year is 21, with a standard deviation of 65. A 1-standard-deviation increase in the average number of prior deals per banker (2.1) therefore is associated with about 5.7 new loans, or about 27% of the unconditional sample mean.

To rule out that these results are driven by few, large clients, we measure connectedness as the number of clients per banker, rather than the number of prior loans in columns 3 and 4 of Table 11. We again find that both the average and maximum levels of connectedness in a bank increase its future deal flow substantially. These results are consistent with recent findings on the role of bankers in shaping the formation of lending relationships (Ceccarelli et al. (2021)).

V. Conclusion

We investigate how bankers use their knowledge of borrowers obtained from lending to help match firms to an alliance partner. Firms are significantly more likely to enter a strategic alliance if they share the same banker. Even firms that borrow from two different bankers are significantly more likely to engage in a strategic alliance, as long as those have a connection through joint prior lending. Both firms and banks benefit from their involvement in strategic alliances. Firms that have a larger number of connections to potential alliance partners through their network of bankers enter a larger number of value generating strategic alliances. Banks are subsequently more likely to be chosen to underwrite loans, bonds, and seasoned equity offerings, as well as receiving higher interest rates on future loans.

Our results highlight a novel way through which banking relationships benefit borrowers besides providing access to capital: positive information spillovers that create value for borrowers by helping them combine resources in strategic alliances. They highlight the importance of the scope of banking relationships, which goes beyond lending.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022000485.

References

Acharya, V., and T. Johnson. "Insider Trading in Credit Derivatives." *Journal of Financial Economics*, 84 (2007), 110–141.

Acharya, V. V.; I. Hasan; and A. Saunders. "Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios." *Journal of Business*, 79 (2006), 1355–1412.

Allen, J. W., and G. M. Phillips. "Corporate Equity Ownership, Strategic Alliances, and Product Market Relationships." *Journal of Finance*, 55 (2000), 2791–2815.

Asker, J., and A. Ljungqvist. "Competition and the Structure of Vertical Relationships in Capital Markets." *Journal of Political Economy*, 118 (2010), 599–647.

Bharath, S.; S. Dahiya; A. Saunders; and A. Srinivasan. "So What Do I Get? The Bank's View of Lending Relationships." *Journal of Financial Economics*, 85 (2007), 368–419.

Bharath, S.; S. Dahiya; A. Saunders; and A. Srinivasan. "Lending Relationships and Loan Contract Terms." *Review of Financial Studies*, 24 (2011), 1141–1203.

Bodnaruk, A.; M. Massa; and A. Simonov. "Investment Banks as Insiders and the Market for Corporate Control." *Review of Financial Studies*, 22 (2009), 4989–5026.

Bodnaruk, A.; M. Massa; and A. Simonov. "Alliances and Corporate Governance." *Journal of Financial Economics*, 107 (2013), 671–693.

Brinster, L., and T. Tykvová. "Connected VCs and Strategic Alliances: Evidence from Biotech Companies." *Journal of Corporate Finance*, 66 (2021), 101835.

Cai, Y., and M. Sevilir. "Board Connections and M&A Transactions." *Journal of Financial Economics*, 103 (2012), 327–349.

Ceccarelli, M.; C. Herpfer; and S. Ongena. "Inequality, Discrimination, and the Financial System: How Gender and Law Shape Banker Mobility, Bank-Firm Relationships and Bank Activity." Working Paper, University of Zurich (2021).

Chan, S. H.; J. W. Kensinger; A. J. Keown; and J. D. Martin. "Do Strategic Alliances Create Value?" *Journal of Financial Economics*, 46 (1997), 199–221.

Chava, S., and M. R. Roberts. "How Does Financing Impact Investment? The Role of Debt Covenants." *Journal of Finance*, 63 (2008), 2085–2121.

Chodorow-Reich, G. "The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008–2009 Financial Crisis." *Quarterly Journal of Economics*, 129 (2013), 1–59.

Coiculescu, G.. "Banking Relationships and the Formation of Supply-Chain Relationships." Working Paper, Yeshiva University (2018).

Corwin, S. A., and P. Schultz. "The Role of IPO Underwriting Syndicates: Pricing, Information Production, and Underwriter Competition." *Journal of Finance*, 60 (2005), 443–486.

Engelberg, J.; P. Gao; and C. A. Parsons. "Friends with Money." *Journal of Financial Economics*, 103 (2012), 169–188.

Esty, B. C. "Structuring Loan Syndicates: A Case Study of the Hong Kong Disneyland Project Loan." *Journal of Applied Corporate Finance*, 14 (2001), 80–95.

Favara, G., and M. Giannetti. "Forced Asset Sales and the Concentration of Outstanding Debt: Evidence from the Mortgage Market." *Journal of Finance*, 72 (2017), 1081–1118.

Fee, C. E.; V. Subramaniam; M. Wang; and Y. Zhang. "Bank Lenders as Matchmakers? When Acquirers and Targets Share a Common Lender." Working Paper, Tulane University (2017).

Financial Times. "City Rainmakers Unfazed by FCA Capital Markets Report." M. Arnold, Apr. 14 (2016a).

Financial Times. "Goldman Sachs Faces Further Questions from MPs." M. Vandevelde, July 31 (2016b).

Gao, J.; K. Kleiner; and J. Pacelli. "Credit and Punishment: Are Corporate Bankers Disciplined for Risk-Taking?" *Review of Financial Studies*, 33 (2020), 5706–5749.

Bushman, R.; J. Gao; X. Martin; and J. Pacelli. "The Influence of Loan Officers on Loan Contract Design and Performance." *Journal of Accounting and Economics*, 71 (2021), 101384.

Giannetti, M., and F. Saidi. "Shock Propagation and Banking Structure." *Review of Financial Studies*, 32 (2018), 2499–2540.

Glaeser, E. L.; H. D. Kallal; J. A. Scheinkman; and A. Shleifer. "Growth in Cities." *Journal of Political Economy*, 100 (1992), 1126–1152.

Griffin, J.; T. Shu; and S. Topaloglu. "Examining the Dark Side of Financial Markets: Do Institutions Trade on Information from Investment Bank Connections?" *Review of Financial Studies*, 25 (2012), 2155–2188.

He, J., and J. Huang. "Product Market Competition in a World of Cross-Ownership: Evidence from Institutional Blockholdings." *Review of Financial Studies*, 30 (2017), 2674–2718.

Hellmann, T.; L. Lindsey; and M. Puri. "Building Relationships Early: Banks in Venture Capital." *Review of Financial Studies*, 21 (2007), 513–541.

Herpfer, C. "The Role of Bankers in the U.S. Syndicated Loan Market." *Journal of Accounting and Economics*, 71 2-3 (2021), 101383.

Ivashina, V.; V. B. Nair; A. Saunders; N. Massoud; and R. Stover. "Bank Debt and Corporate Governance." *Review of Financial Studies*, 1 (2009), 41–77.

Karolyi, S. A. "Personal Lending Relationships." *Journal of Finance*, 73 (2017), 5–49.

Kedia, S., and X. Zhou. "Informed Trading Around Acquisitions: Evidence from Corporate Bonds." *Journal of Financial Markets*, 18 (2014), 182–205.

Krigman, L.; W. H. Shaw; and K. L. Womack. "Why Do Firms Switch Underwriters?" *Journal of Financial Economics*, 60 (2001), 245–284.

Lindsey, L. "Blurring Firm Boundaries: The Role of Venture Capital in Strategic Alliances." *Journal of Finance*, 63 (2008), 1137–1168.

Mariti, P., and R. Smiley. "Co-Operative Agreements and the Organization of Industry." *Journal of Industrial Economics*, 31 (1983), 437–451.

Roberts, M. R. "The Role of Dynamic Renegotiation and Asymmetric Information in Financial Contracting." *Journal of Financial Economics*, 116 (2015), 61–81.

Roberts, M. R., and A. Sufi. "Renegotiation of Financial Contracts: Evidence from Private Credit Agreements." *Journal of Financial Economics*, 93 (2009), 159–184.

Saidi, F., and D. Streitz. "Bank Concentration and Product Market Competition." Working Paper, Stockholm School of Economics (2019).

Schwert, M. "Bank Capital and Lending Relationships." *Journal of Finance*, 73 (2018), 787–830.

The *New York Times*. "A Top Goldman Banker Raised Ethics Concerns. Then He Was Gone." E. Flitter, K. Kelly, D. Enrich, Sept. 11 (2018).

The *Wall Street Journal*. "Goldman Sachs Embraces Banking's Bland Side: Lending Money." l. Hoffman, May 1 (2017).

The *Wall Street Journal*. "The New Floor for Bond Underwriting Fees: $1." M. Dalal, Jan. 3 (2018).

Uzzi, B. "Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing." *American Sociological Review*, 64 (1999), 481–505.

Uzzi, B., and R. Lancaster. "Relational Embeddedness and Learning: The Case of Bank Loan Managers and Their Clients." *Management Science*, 49 (2003), 383–399.

Vasicek, O. A. "A Note on Using Cross-Sectional Information in Bayesian Estimation of Security Betas." *Journal of Finance*, 28 (1973), 1233–1239.

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