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Abstract

We investigate how bankers use information from lending relationships to help borrowers combine resources in 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 network distance, and is stronger for opaque borrowers. Alliances are associated with positive announcement returns and brokering banks are more likely to receive future underwriting mandates. We exploit quasi-exogenous variation in banker networks from interstate branching deregulation to show that this relationship is causal.

JEL Classifications: G20; G21; G30.

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1 Introduction

Banks obtain detailed, private information about their corporate clients through lending (Fama, 1985; Diamond, 1984; Petersen and Rajan, 1994) and advisory relationships. Such privileged access to information can create agency conflicts when banks use information from a lending relationship in other areas to their own advantage. There is wide anecdotal evidence of banks allegedly passing on information to the opposing party in M&A transactions or using it for insider trading, with a number of cases resulting in high profile lawsuits.[1] As a consequence, much of the academic literature on information spillovers in the banking sector has focused on possible negative consequences for clients.[2]

Our paper identifies a potentially beneficial side to information spillovers for clients of commercial banks in the US syndicated loan market. We investigate how commercial bankers create value for borrowers by brokering collaborations between them. We focus on a broad set of collaborations in the form of strategic alliances, formalized collaborations that are somewhere between arm's length, market based transactions and intra firm relationships.[3] Our analysis documents that banks, and individual bankers in particular, act as information intermediaries between potential partners and thereby facilitate alliances.

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).

[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). Possibly as a result of these lawsuits, some large advisory clients now require banks to enter non-compete agreements (Financial Times, 2018). Examples for cases involving insider trading include ASIC v. Citigroup (Financial Times, 2006) and the SEC against Barclay's (Securities and Exchange Commission, 2007).

[2] E.g., Lowry, Rossi, and Zhu (2019), Bodnaruk, Massa, and Simonov (2009), Acharya and Johnson (2007), Griffin, Shu, and Topaloglu (2012), Kedia and Zhou (2014) and Ivashina, Nair, Saunders, Massoud, and Stover (2009).

[3] The literature on strategic alliances sometime focuses on a more narrow set of research oriented alliances, for example in the biotechnology sector. While 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.

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 non-public information about each other's capabilities ex ante. One potential source to obtain this information are capital providers associated with both firms (e.g., Lindsey, 2008; He and Huang, 2017).

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 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 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 (Esty, 2001; Uzzi, 1999; 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 panel regressions that allow us to control for time-invariant firm-pair characteristics such as geographic proximity, industry, firm quality and compatible corporate culture and strategy through firm-pair fixed effects. In addition, these specifications also allow us to separate the effect of connections through bankers as people from that of banks as institutions by directly controlling for whether a potential alliance pair has borrowed from the same bank in the past. We find that sharing the same banker significantly increases the likelihood of entering a strategic alliance at a rate that is economically about five times as large as that of sharing the same bank.

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.[4] 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 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 the 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.

Firms have limited use and capacity for alliances. Once a firm has decided to collaborate with a certain partner, it is less likely to engage in another alliance for the same purpose with another firm. Because the level of observation in our sample is a pair of firms, the result

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

is a correlation structure that conventional clustering of standard errors in panel regressions cannot fully account for (Cameron and Miller, 2014). To account for the interconnected nature of alliance formation, we estimate a sequenced conditional logit model. This discrete choice model developed by Lindsey (2008) allows us to explicitly model firms' choice of alliance partners over time. The tests confirm that firms sharing a banker or an indirect connection through a network are significantly more likely to enter an alliance and that the influence of indirect connections is decreasing in the network distance between bankers.

The highly saturated fixed effects models we estimate can control for all unobservable, time invariant firm-pair specific tendencies to collaborate. These models cannot, however, fully control for time varying unobservable 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 the other one. We therefore exploit restrictions to interstate bank branching (Rice and Strahan, 2010) as a source of quasi-exogenous variation in the banker network connecting firms. Less restrictive branching laws make it more likely that firms borrow from out-of-state banks (Keil and Müller, 2019; Saidi and Streitz, 2019) whose bankers are more central in the network, thereby decreasing their network distance in relation to potential alliance partners. We find that all our results hold after accounting for endogeneity in this way.

If bankers facilitate collaborations due to their knowledge of borrowers, their role should be more pronounced when information asymmetries are large. We investigate this conjecture in cross-sectional tests and 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. In an event study, we find that the average strategic alliance increases market value by 0.7%. We find that strategic alliances in which firms are connected through the banker network create as much value as those without such a connection. This result is consistent with the literature on the benefits of strategic alliances for firms (Chan et al., 1997; Allen and Phillips, 2000; Bodnaruk, Massa, and Simonov, 2013).

We also find that borrowers reward banks for facilitating collaborations by awarding them additional business. We find that after a firm initiates a strategic alliance with another firm that 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 by those firms in the next five years. Similarly, borrowers are significantly more likely to choose such banks as the underwriter for a bond or seasoned equity offering, albeit to a lower extent.

Our paper 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 add to those findings by showing that information transmission through banks does not just lead to M&A transactions, but also less intense forms of collaborations. Similarly, our paper 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.[5] 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. Our paper finds that as firms grow and switch from venture capital to bank funding, bankers do not just take over funding but also play a role in the arrangement of strategic alliances.

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

[5]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 that firms sharing the same lender compete less aggressively.

executives (Engelberg, Gao, and Parsons, 2012; Karolyi, 2017). We also add to a growing number of studies that investigates the role of individual commercial bankers in the lending process to large, publicly traded corporations (Herpfer, 2018; Gao, Martin, and Pacelli, 2017; Gao, Karolyi, and Pacelli, 2018a).

2 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. First, since they interact with a number of different borrowers, bankers likely have access to public and private information regarding potential partners which can speed up searches. In addition, if an alliance requires a certain non-publicly observable (e.g. managerial or technological) capability, bankers can identify potential partners using private information obtained through their lending. 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." We therefore formulate

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 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, 2018b). Bankers can facilitate alliances even if none of their own borrowers are directly involved in it, 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

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 illustrates a simplified example of how firms are connected through the banker network. Consider three bankers (1 to 3) and four firms (A to 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 with banker 2, the network distance between firms A and B takes the value 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 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 for firms A and B from t=0 to t=1 in the example above.

Lindsey (2008) finds that venture capital funds facilitate alliances between portfolio companies by overcoming informational frictions and contracting problems. Because bankers hold little formal influence over their borrowers, we hypothesize that it is primarily information frictions and the challenge to find an alliance partner ex ante that bankers can help overcome, 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. If an alliance is valuable for participating firms, this should be reflected in their market value.

Hypothesis 4a: Alliances facilitated by one or more banks are associated with an increase participating firms' market value.

One reason for why bankers might assist firms in finding partners for strategic alliances is an expectation of being compensated through lucrative mandates in the future. While there is 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.[6] We hypothesize that future mandates are the primary motivation for bankers to get involved in the facilitation of strategic alliances.

Hypothesis 4b: Borrowers reward banks for brokering alliances by giving them additional business.

3 Data

3.1 Data on bankers

We follow a number of recent papers (e.g. Gao et al., 2018b; Herpfer, 2018) 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.[7] The majority of loan contracts contains 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

[6] In 2018 a consortium of banks underwrote a $1.3bn 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). Finally, we want to note that an increase in firm value benefits banks not just through potential future business, but also directly as they hold the firm's debt. This effect through a lower likelihood of bankruptcy is, however, likely a smaller incentive than the promise of additional business.

[7] Since loan contracts are considered material under item 601(b) of Regulation S-K, EDGAR provides 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)

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 Herpfer (2018) and Gao et al. (2018b).

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 intra-layer 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 inter-layer 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.[8] In our sample, bankers have personal relationships with between 1 and 13 distinct borrowers. The relatively small number of relationships makes it more likely that bankers have intense relationships with each borrower.[9]

Existing work provides evidence that these signatures correctly identify the bankers involved in the lending decision process, and that the data is of high quality (Herpfer, 2018; Gao et al., 2018b). To the degree that there is measurement error, e.g. 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

[8]See Esty (2001) for a case study on the syndication process and the relationship formation between lead banks and borrowers.

[9]We likely understate the true number of clients since our dataset 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.

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, e.g. due to word of mouth recommendations or to raise funding for a joint project. To rule out that strategic alliance precede connections through the banker network, we lag the network characteristics by one period in all estimations.[10]

3.2 Data on strategic alliances

Data on strategic alliances comes from Standard and Poor's (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 covers 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. 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. 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

[10]In un-tabulated results we confirm that both the OLS and sequenced conditional logit estimates are robust to increasing this lag to two years. In addition, the sequenced conditional logit estimates eliminate firm pairs after an alliance has been recorded, meaning these results cannot be driven by collaborations that precede borrowing from the same banker.

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. Note that our data covering bankers goes back to 1996, which gives us six years prior to the sample to let the banker network build up. Given an average loan maturity of about four years, our network should sufficiently approximate the underlying, unobservable connections between individuals at the start of our estimation sample in 2002. We treat alliances between more than two firms as a set of bilateral alliances between all parties involved.

Finally, we merge the strategic alliances with financial data from Compustat and the personal relationship measures discussed above.[11] The final sample covers 3,189 strategic alliances between publicly listed, non-financial US firms with non-missing accounting data.

3.3 Sample characteristics

Table 2 displays summary statistics for alliance pairs in the year they are first observed. All variables are calculated as defined in Table 1.

[Table 2 here]

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.

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

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 two are rare (less than two percent of the sample), we censor the banker network distance at three (i.e. we pool all distances exceeding two).[12]

4 Results

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

4.1 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 US 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:

$$\textit{within-network alliance ratio}_j = \frac{C_j}{n_j} \tag{1}$$

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

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:

$$total\ alliance\ ratio_j = \frac{A_j}{n-1} \tag{2}$$

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 three (firms B, C and D).

The results of this test in our sample are displayed in Panel A of Table 3. There are 669 observations, equal to the number of sample firms. Means and standard errors in Table 3 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 ten 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.[13]

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 (also see Lindsey, 2008). The *within-portfolio alliance ratio* for banker i is defined as:

$$within\text{-}portfolio\ alliance\ ratio_i = \frac{W_i}{n_i(n_i - 1)} \tag{3}$$

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:

$$total\ alliance\ ratio_i = \frac{A_i}{n_i(n - 1)} \tag{4}$$

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

[13] 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.

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's *within 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), while 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 displayed in Panel B of Table 3. 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.

[Table 3 here]

There are numerous 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, non-financial US firms during 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 one 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):

$$alliance_{it} = \beta network\ connection_{it} + \gamma same\ bank_{it} + \theta_t + \xi_i + \varepsilon_{it} \tag{5}$$

where i indexes firm-pairs and t years. The main explanatory variables – different measures of network connectivity between firms – are represented by $network\ connection_{it}$. 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).

Since both the rate of alliance formation and bank lending can vary over time, we include year fixed effects (θ_t). Finally, 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 (ξ_i). Finally, ε_{it} is the error term. We double-cluster standard errors by firm one and firm two in all specifications.

[Table 4 here]

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 one if a pair of firms has ever shared a banker. The results are presented in Column 1 of Table 4 and show that two firms are about 0.7 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 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 0.13 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 one percent level. Given that the effect of sharing a banker is five 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.

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 we estimate the same model as in Column 1 but replace *same banker* with *banker network connection*, an indicator that takes the value of one 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 Column 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 zero therefore corresponds to two firms sharing the same banker and a distance of one indicates that the shortest connection between two firms involves two bankers that have worked together on loans for third companies.

We test hypothesis 2 in two ways. First, 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 4 . 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 $distance = 0$ (0.0081), $distance = 1$

(0.0022) and *distance* $= 2$ (0.0010) are all statistically significant at the 5% and 1% level. The coefficient estimate for distances larger than two (which we pool into a single group due to the small number of such observations) is still positive (0.0007), but statistically only marginally significant.

These result suggests that, while 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 three people there is 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.[14]

4.2 Additional robustness on the OLS specification

For robustness, we re-estimate the specification in Table 4 with additional firm-year fixed effects for both firms. We thereby control for both observable and unobservable time-varying characteristics on the firm level. The results are displayed in Appendix A. Even in this heavily saturated fixed effect specification, sharing the same banker remains a statistically and economically significant predictor for whether two firms enter a strategic alliance.

Another potential concern with the fixed effect specification in Table 4 is that it cannot fully distinguish whether a network connection precedes a strategic alliance or whether the opposite is the case. Strategic alliances could therefore systematically precede network connections, in which case the results could be driven by reverse causality. To alleviate this concern, Appendix A presents results from first difference regressions that relate changes in alliance status to concurrent changes in network connections. The first difference setup

[14] In un-tabulated results, we estimates the regression based only on the control variables to determine the impact of sharing the *same bank*. The resulting coefficient resembles those in the main specification both in terms of size and statistical significance.

is substantially more conservative than the baseline OLS results because it identifies the impact of banker networks on alliance formation only based on alliances entered in the first period after the network connection is first established.[15] All results retain their statistically significance in the first difference specifications. As expected, the economic magnitude of the estimated coefficients is lower, reflecting that they only represent the increase in the probability that two firms enter an alliance immediately after becoming connected through a banker network. Since in addition both the sequenced conditional logit results in Section 4.3 and the instrumental variable results in Section 4.4 hereafter are unaffected by this issue by construction, the overall evidence strongly suggests that our results are not driven by alliances preceding connections through the banker network.

An additional robustness test presented in Appendix A is concerned with the time-dimension of the network. The main specification in Table 4 assumes that connections between firms, bankers and banks last forever. The robustness test introduces time-phased connections by limiting the lifetime of all connections (bank to firm, banker to banker and banker to firm) to five years. The results of this specification are both economically and statistically close to those in Table 4 as well.

Finally, there are relatively few alliances (about 3000) compared to the overall sample size. We are unaware of any evidence indicating that the skewed nature of the dependent variable in the estimation above could render our coefficient estimates biased or inconsistent. Nevertheless, we repeat the LPM analysis on a reduced sample consisting of all firm-pairs that enter an alliance over the sample period and a single control pair for each one in a final robustness test. We select the control firm pair by matching both firms in an observed alliance to their nearest neighbor given a number of observable characteristics including industry, size and age and construct the control pair from the two nearest neighbors. The results displayed in Appendix A confirm that sharing a banker, or being connected through

[15] As mentioned in section 3.1, network connections are lagged by one period in all estimations.

the banker network, are associated with a higher likelihood of forming a strategic alliance.[16]

4.3 A dynamic model of alliance formation based on the sequenced conditional logit model

The fundamental unit of observation in our data is that of a firm-pair-year. Because a firm's choice of entering a strategic alliance might affect its decision to enter additional alliances in the future, observations for a particular firm-pair are potentially correlated with all other observations involving either of the two firms forming the pair. The result is a complicated correlation structure that conventional clustering of standard errors cannot fully account for.[17] Robust inference in the presence of such *dyadic* data, where the unit of observation is a pair, is still an active area of research (Fafchamps and Gubert, 2007; Cameron and Miller, 2014; Tabord-Meehan, 2018). Unfortunately, the size of our data set and the large number of corresponding fixed effects means implementing the existing estimators for dyadic data is impossible for computational reasons. According to the results of Monte-Carlo simulations in Cameron and Miller (2014), however, our choice of clustering standard errors twice both along the first and second dimension of the dyad is the most conservative among the alternatives and provides the closest approximation to full dyadic clustering.

To account for the firm-level dependence in alliance choice more comprehensively, we instead apply the sequenced conditional logit model developed by Lindsey (2008), a discrete choice model based on the standard conditional logit model (e.g., Chamberlain, 1980) but different in that it allows the set of conditioning outcomes to vary over time. This approach allows us to explicitly model the sequential way in which alliances form over time while also

[16]The only difference is that the effect does not fall in network distance in these specifications. The failure to pick up on this nuanced effect might be due to the fact that these regressions draw inference from a sample comprising less than 1% of our main sample.

[17]For example, consider a sample consisting of the firms A, B and C. Possible pair-wise combinations are {A,B}, {A,C} and {B,C}; at least one firm (in this case, B) will show up once as the first and once as the second entry, no matter how the combinations are chosen. Therefore, the observations {A,B} and {B,C} are possibly correlated, but even standard errors double-clustered by firm one and firm two will not account for this fact.

incorporating the group structure of the data.[18]

The probability of an observed alliance under the sequenced conditional logit model is parameterized as

$$pr(alliance = 1) = \frac{e^{X_s^t \beta}}{\sum_{s \in S} e^{X_s^t \beta}} \tag{6}$$

where X is a vector of explanatory variables, β is the coefficient vector to be estimated, t indexes time, s indexes firm-pairs and S is the set of feasible alliances constructed from firms in the two alliance partners' industries. The set of conditioning outcomes S varies over time as alliances are formed. Lindsey (2008) develops two different implementations of the model, the *variable capacity* and the *fixed capacity* version, which differ in the way in which S is restricted over time. In both versions of the model, when an alliance between a particular pair of firms is realized, the pair is removed from S in subsequent years.

The variable capacity model places no additional restrictions on S, therefore it assumes that firms could have entered any number of alliances. Hence the variable capacity model does not account for the possibility that the realization of one alliance can affect the same firm's probability of entering additional alliances in the future, but has the benefit of not imposing any additional restrictions on the estimation. The fixed capacity version of the model, on the other hand, assumes that firms have a maximum alliance capacity corresponding to the total number of alliances they enter over the sample period. Once a firm has reached its alliance capacity, all firm-pairs containing it are removed from the set of conditioning outcomes S in subsequent periods, thereby accounting for the dynamic way in which the realization of one alliance can preclude others in the future.

The likelihood L^p for industry-pair p, with N_p realized alliances between time 1 and T is

[18] While the sequenced conditional logit allows us to model firms' choices in more detail, including the group structure of the data, it also comes with drawbacks. The reported coefficients are logit coefficients and can therefore not be economically interpreted (except in the form of an odds ratio). Unlike in standard logit models, it is not possible to directly calculate margins in conditional logit models due to the different reference group for each firm pair.

then the product of the probability of all realized alliances, i.e.

$$L^p = \left(\frac{e^{X^1_{s_1}\beta}}{\sum_{s\in S^p} e^{X^1_s\beta}}\right)\left(\frac{e^{X^2_{s_2}\beta}}{\sum_{s\in S^{pf(s_1)}} e^{X^2_s\beta}}\right)\cdots\left(\frac{e^{X^T_{s_{N_p}}\beta}}{\sum_{s\in S^{pf(s_1,s_2,\ldots,s_{N_p-1})}} e^{X^T_s\beta}}\right) \tag{7}$$

And the overall likelihood, multiplied across industry pairs, can be expressed as

$$L = \prod_{p\in P} L^p(s_1, ..., s_{N_p}) \tag{8}$$

Appendix B illustrates the sequenced conditional logit model in detail using examples. We apply the two versions of the sequenced conditional logit model to our estimation of the effect of banker network connections on alliance propensity. We first present the results of the less restrictive variable capacity model in Table 5.

[Table 5 here]

As in the OLS specification, we include controls for sharing the same bank. Furthermore, we include a control *previous alliances* for the number of alliances the two firms in each pair have previously entered. Note that the sequenced conditional logit estimation setup controls for industry-year effects by construction since the industry-pair-year is used as the reference group.

The specification in Column 1 estimates the sequenced conditional logit model in its variable capacity version with the *same banker* as the main explanatory variable. The estimated coefficient of *same banker* on initiating a strategic alliance is 0.380 and statistically significant at the 1% level. As in the OLS analysis we therefore conclude that having shared the same banker increases the likelihood of two firms initiating a strategic alliance. In Column 2, we replace *same banker* with *banker network connection*, an indicator of whether two firms are in any way connected. As in the OLS setting, the estimated coefficient is positive at 0.290 and statistically significant at the 1% level. In the next column, we limit the sample to those firms that are connected through the banker network and estimate the effect of an increase in network distance on the likelihood of alliance formation. The coefficient estimate is -0.175 and statistically significant at the 10% level. The sequenced conditional logit model therefore finds that greater network distance between bankers reduces their ability to broker strategic alliances. When we include each distance level individually in our final specification – with unconnected firm-pairs forming the base category – we find that the propensity of a banker network connection to broker a strategic alliance decreases monotonously as the distance increases, from 0.427 for a distance of zero to 0.256 for a distance of one (both significant at the 1% level), with all additional coefficients being statistically insignificant.

Unlike in the OLS analysis, there are no firm-pair fixed effects subsuming time invariant firm-pair features in the sequenced conditional logit regressions. This allows us to include an indicator whether two firms are headquartered in the same state to specifically test for the effect of geographic proximity between firms. Consistent with the results in Reuer and Lahiri (2013), we find that firms headquartered in the same state are significantly more likely to form alliances. The coefficient for *same bank* is positive but statistically insignificant in the variable capacity model.

The conditional logit model, in general, does not allow for the unconditional marginal effects associated with individual regression coefficients to be recovered, but the exponential of the estimated coefficients can be interpreted as an odds ratio. If a pair of firms shares a banker (*same banker=1*) it is 1.462 times as likely to enter a strategic alliance in any given year as it would be if it did not. Similarly, the odds ratio for being connected through the banker network in any manner (*banker connection=1*) is 1.336, so a firm-pair is 1.336 as likely to enter an alliance if it is connected every year. The base case for the interpretation of the odds ratio in Column 3 is a firm-pair that shares the same banker. Hence a firm pair connected indirectly with *distance=1* is only 0.839 times as likely to enter a strategic alliance as it would be if it shared the same banker, decreasing further to 0.705 for *distance=2*, 0.592 for *distance=3* and so on. Finally, in the discrete specification in Column 4 the base case is that of a firm-pair unconnected through the network, implying a pair of firms connected directly (*distance=0*) is 1.533 times as likely to enter a strategic alliance than it would be if it was unconnected, decreasing to 1.292 times for an indirect connection of order 1 (*distance=1*).[19]

In summary, Table 5 shows that our results hold in the sequenced conditional logit specification. Because our unit of observation is a firm-pair, we do not have a clear prior on the impact of individual firms' financial characteristics on a pair's propensity to enter an alliance and therefore do not control for them in our main specification. A robustness test in Appendix A adds controls for sales, tangibility of assets and financial leverage, and shows that our results remain economically and statistically very similar.

We next estimate the sequenced conditional logit model in its more restrictive fixed capacity specification. The corresponding results are presented in Table 6.

[Table 6 here]

The specifications presented follow those from Table 5. The *previous alliances* control is absent in the fixed capacity version of the model since the estimation already controls for it by design. While our power shrinks significantly due to the 40% lower sample size in the fixed capacity setting, the coefficient estimates are both economically and statistically very similar to the variable capacity model. The coefficient estimate on sharing the same banker (Column 1) is about 0.3 and statistically significant at the 1% level. The coefficient estimate on the indicator of sharing any connection through the banker network (Column 2) is 0.181 and equally statistically significant. The estimate for the relationship between banker network distance and the propensity to form strategic alliances is -0.156 and marginally statistically significant in the continuous setting (Column 3).

As in our prior specifications, the ability of bankers to broker alliances between their clients is monotonously decreasing in the discrete specification (Column 4), with the coefficient for *distance* $= 0$ remaining statistically significant at the 1% level. The coefficient

[19] Note that the odds ratio for *same banker* in Column 1 and *distance* $= 0$ in column four are different because the base case is a different one; in Column 1 the base case is not sharing the same banker, in Column 4 it is not having any connection, even an indirect one, through a banker network.

estimate for *same bank* is positive and statistically significant in all specifications. Taken together, the results from this section show that our main result, that bankers broker strategic alliances both between their own portfolio firms and those of connected bankers, holds even in the most restrictive regression settings.

4.4 Instrumental variable estimates

Firms that share certain unobservable characteristics might be both more likely to enter a strategic alliance and borrow from the same banker. While our result that bankers broker alliances even through indirect connections somewhat alleviates this concern, we cannot rule out that bankers are more likely to jointly appear on a loan contract due to the same unobservable variable that makes them lend to similar borrowers. One example for such a scenario could be that the CEOs of two companies went to the same college as the CEOs of two banks (Engelberg et al., 2012). While firm-pair fixed effects in our model absorb time invariant unobservable connections, these tests cannot rule out that time varying unobservable connections drive our results.

We address this endogeneity concern by instrumenting for firms' banker-network position using interstate banking regulations.[20] The relevance condition in this setting requires a potential instrument to influence a firm-pair's distance in the network. The exclusion restriction requires that the instrument does not affect the pair's likelihood of entering a strategic alliance through any other channel. We exploit interstate bank branching regulation, as measured by the average Rice and Strahan (2010) index of the states the two firms are headquartered in, as an instrument for the network distance between two borrowers.

Rice and Strahan (2010) track provisions in state statutes enacted under the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994 that impede the establishment of branches by out-of-state banks. The four provisions are a minimum age requirement of at

[20] In addition to partially observable variables such as shared CEO educational history or interlocking boards, there are many completely unobservable, time varying variables, such as a shared golfing hobby. Exploiting an exogenous shock to network distance allows us to simultaneously control for both observable and unobservable alternative connections.

least three years for banks to be acquired by an out-of-state bank, a ban on the establishment of de novo branches by out-of-state banks, a ban on the acquisition of individual branches from local banks and finally a ceiling lower than 30 for the maximum percentage of deposits that any bank may control within the state following the entry of an out-of-state bank. As the original index only tracks changes in state statutes until 2005, we update it through 2016 by tracking changes in state statutes since. A list of such changes is provided in Appendix C. The Rice-Strahan index counts the number of these provisions, so a higher index value stands for more restrictive rules.

The relevancy condition in our setting is that firms located in states with more restrictions on the establishment of branches by out-of-state banks are more likely to borrow from local banks, whose bankers are less central in the network. Accordingly, high index values should be associated with larger banker-network distances between firm pairs. Consistent with this intuition, both Keil and Müller (2019) and Saidi and Streitz (2019) find that states that remove impediments to interstate bank branching indeed show an increase in lending from out-of-state banks, not just for small borrowers, but also for large borrowers from the DealScan-Compustat dataset.[21]

A potential challenge to the exclusion restriction is that lifting state-level restrictions might increase the amount of funding available for expansion and therefore impact firms' general propensity to ally. However, Rice and Strahan (2010) find that firms located in states that lifted restrictions on interstate branching did not increase their debt levels subsequently. Hence the introduction of interstate bank branching is unlikely to have loosened financial constraints for firms in affected states, and the improved access to bank borrowing should not have led to an overall increase in firms' likelihood of entering strategic alliances. Of course, we cannot completely rule out a scenario in which borrowing from banks somehow

[21] Keil and Müller (2019) also find a shift from syndicated loans to single-lender loans. The aggregate effect of deregulation on network size is therefore ambiguous: borrowers interact with fewer bankers, but those have wider networks since they are from out of state banks. Our data cover both syndicated and bilateral loans and our first stage results, discussed below, indicate that, on aggregate, banker networks expanded for the average firm after deregulation.

improves alliance formation compared to borrowing from non-bank sources through another channel than banks' matchmaking.

Because the sequenced conditional logit model presented in Section 4 is nonlinear, a consistent estimation via the standard two-stage least squares (2SLS) procedure is not possible. We therefore implement a two-stage residual inclusion (2SRI) estimator as first suggested by Hausman (1978) and illustrated in Terza, Basu, and Rathouz (2008).[22] For robustness, we also implement a 2SLS estimator in which the OLS specification discussed in Section 4.1 serves as the second stage, and our results carry through in both specifications. For the 2SLS estimation, the first stage regression is

$$network\ connection_{it} = \beta z_{it} + \gamma same\ bank_{it} + \theta_t + \xi_i + \varepsilon_{it} \tag{9}$$

where i indexes firm-pairs and t years, $network\ connection_{it}$ is either *same banker*, *banker network distance* or *banker network connection*, $same\ bank_{it}$ is an indicator variable for whether to firms have borrowed from the same lead bank, θ_t a year fixed effect, ξ_i a firm-pair fixed effect and ε_{it} the error term. z_{it} stands for the instrumental variable, which is the firm-pair average of the Rice-Strahan index described above. The second stage estimate follows equation 5 except that the fitted value for $network\ connection_{it}$ from the first stage is used as the independent variable.

For the sequenced conditional logit models, we estimate the first stage equation:

$$network\ connection_{st} = f(z_{st}, same\ bank_{st}, \varepsilon_{st}^{first\ stage}) \tag{10}$$

where s indexes firm pairs and estimation technique $f(.)$ is either OLS for *banker network distance* and logistic regression for *same banker* and *banker network connection*, respectively. We then retain the residual $\varepsilon_{st}^{first\ stage}$ and include it as an additional independent variable in

[22] Terza et al. show that the 2SRI estimator is consistent in case either one or both stages in the estimation are nonlinear, whereas 2SLS is not. For an application of 2SRI in finance, see Chen, Hong, Jiang, and Kubik (2013).

the second stage, which is a variable capacity sequenced conditional logit model as described in Section 4.3.

For each specification, we estimate the effect of sharing the same banker, sharing any banker connection, and the effect of increasing distance through the banker network on alliance formation as before. For ease of exposition, the results of the first stage regressions are displayed in Appendix A; the first stage estimates show that higher index values are associated with lower likelihood of being directly or indirectly connected through the banker network, and higher banker-network distances. The instrumental variable is not just highly statistically significant as determinant of the variables of interest, but exhibits strong economic significance as well. We therefore conclude that the Rice Strahan Index appears to fulfill the relevancy criterion. The results for the second stage are presented in Table 7 below.

[Table 7 here]

Columns 1 to 3 of Table 7 show the second stage results for the 2SLS model. The coefficient on sharing the same banker is 0.283. As in our previous specifications, the instrumental variable results therefore suggest that sharing the same banker increases the likelihood of two firms entering a strategic alliance. Similarly, the coefficient estimate for the indicator variable *banker network connection* is 0.043. Finally, the coefficient for *banker network distance* is -0.012, suggesting that the ability of bankers to facilitate strategic alliances decreases as their degree of separation through the network increases. All three coefficients are statistically significant at the 1% level.

Columns 4 to 6 of Table 7 implements the two-stage residual inclusion estimator to account for the nonlinear nature of the variable capacity sequenced conditional logit model from Lindsey (2008) in the second stage. The *first stage residual* is statistically significant and positive in Columns 4 and 5, which supports an endogenous relationship between network connections and the likelihood of entering a strategic alliance. The results exhibit a positive effect, with the coefficients for *same banker* (0.326) and *banker network connection* (0.264) being of similar magnitude as those in the main specification in Table 5 and statistically significant at the ten and one percent level, respectively. The coefficient on *banker network distance* on the other hand is not statistically significant in these regressions. Overall, the results in this section provide evidence that our main finding, that bankers broker alliances between their clients both directly and indirectly, holds after accounting for the potentially endogenous nature of relationship formation by exploiting plausibly exogenous variations in the banker network from changes in the regulatory framework.

4.5 Bankers are more 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 8.

[Table 8 here]

The results in Columns 1 and 2 of Table 8 are for the variable capacity version of the sequenced conditional logit model.[23] For robustness, we repeat the same tests using a linear probability model in Columns 3 and 4. The specifications in Table 8 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 one 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 un-interacted variable *one unrated* enters the regression negative and 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

[23] 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.

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.

Similarly, Column 2 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 statistical significance at the 1% level.[24] The main effect for *one high intangibles* on the other hand is statistically insignificant.

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.

Columns 3 and 4 repeat the same tests based on the linear probability model. The results show only limited robustness to such a specification change. The coefficient for the interaction with *one unrated* has the opposite sign compared to the main specification, although it does not reach statistical significance at the 5% level. The interaction term for *one high intangibles* on the other hand is positive and statistically significant at the 5% level, consistent with the main specification.

4.6 Alliances facilitated by bankers are valuable for firms

To investigate whether strategic alliances arranged by bankers are beneficial for firms, we perform an event study around their announcement. The dependent variable in these re-

[24]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.

gressions is the cumulative abnormal return (CARs) for every alliance announcement over a three-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 1 and 99% level. We require at least 220 observations in the estimation window to be non-missing and use the value-weighted return of all CRSP firms as the market benchmark and the 1-month US treasury bill for the risk-free rate. The estimated market beta has been shrunk towards the cross-sectional mean based on the Vasicek (1973) estimator. We use the value-weighted return of all US-incorporated stocks in CRSP and the one-month US treasury bill rate provided by Kenneth French on his website[25] as proxies for the market return and the risk-free rate, respectively. For robustness, we repeat the same tests on 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 9.

[Table 9 here]

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 zero. 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 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 there exists any *banker network connection*. The estimated

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

coefficients for all of the network characteristics are statistically insignificant, therefore not providing any evidence that alliances facilitated through banker networks are either better or worse than the average alliance. We interpret this result as alliances facilitated by bankers adding to firms on the extensive, rather than the intensive margin: they benefit firms if they constitute additional strategic alliances, which are valuable but not of higher quality than the average strategic alliance.[26]

4.7 Banks are compensated through additional mandates

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. We therefore ask whether banks that broker strategic alliances get rewarded through additional mandates, for example when raising debt or equity capital, or engaging in M&A transactions.[27]

We test for the existence of compensation through additional mandates explicitly 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 the subsequent five-year period, i.e. 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 mergers

[26]Consistent with alliances facilitated by bankers adding to firms' total number of alliances we find a positive pairwise correlation of 0.12 between firms' yearly number of new alliances and their number of banker network connections.

[27]A bank that holds a borrower's debt also experiences a small benefit through the rise in firm (and therefore debt) value from increased firm performance after brokering an alliance. This more direct channel of how facilitating alliances benefits banks is, however, likely to be small.

and acquisitions comes from Capital IQ, data on syndicated loans from LPC DealScan.[28] 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 is that the shared bank connection played a role in brokering the strategic alliance). For robustness, we perform all tests both using a logit model as well as a linear probability model. Standard errors for the latter are clustered by firm. The linear probability model further contains firm-year and bank-year fixed effects. To avoid the incidental parameter problem, the logit specification only contains year fixed effects. In addition, the logit model controls for the firm's number of strategic alliances announced during the year of reference and its total number of mandates (e.g. M&A advisory mandates) of a particular type for the year.[29]

Table 10 below displays 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 mixed. Whereas the logit model indicates a positive impact, also statistically significant at the 1% level, the coefficient estimate in the linear probability model is insignificant.

[Table 10 here]

The estimated coefficients are not only of statistical, but also economic significance. The average marginal effect for an increase of one in the number of alliances brokered by the bank increases the probability of that bank becoming the lead arranger for at least one syndicated loan over the following five 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). This difference in magnitude might have both economic and mechanical

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

[29]These controls are absorbed by the firm-year fixed effects in the linear probability specification.

reasons, as the firm-bank relationships for our tests are formed based on syndicated lending. The economic argument is that a bank's syndicated loan department and its employees are likely more directly and visibly compensated through an additional syndicated loan than through security underwriting or M&A advisory services.

The control variables in the logit specifications indicate that, as expected, the likelihood of a bank receiving any mandate (syndicated loan, securities underwriting, M&A advisory) is positively related to the firm's number of such mandates for the period and the number of alliances, which could potentially be explained by an increased need for financing and/or investment following the announcement of an alliance, adding another reason for why a bank might be interested in facilitating alliances.

5 Conclusion

We investigate how individual bankers facilitate collaboration between firms in the form of strategic alliances by helping them overcome asymmetric information. Bankers can use their knowledge of borrowers obtained from prior lending transactions to help match firms to an alliance partner. Consistent with this intuition, we find that two firms are significantly more likely to enter a strategic alliance if they share the same banker. The role of bankers in transmitting information extends beyond firms inside a single banker's portfolio. We show that two firms are significantly more likely to engage in a strategic alliance even if they borrow from two different bankers, as long as those have a connection through joint prior lending. The impact of sharing a banker on the likelihood of entering a strategic alliance is strongest for informationally opaque firms. Consistent with costs to transmitting information between multiple bankers, the ability of bankers to facilitate alliances decreases as the network distance between them increases.

We find that both firms and banks profit from their involvement in strategic alliances. The announcement of strategic alliances is associated with significant positive abnormal stock returns, and banks that were likely involved in their arrangement are more likely to be chosen to underwrite loans, bonds and seasoned equity offerings in the future.

Our results are robust to a range of controls and estimation techniques. We address endogeneity through instrumental variable estimates that exploit interstate bank branching restrictions (Rice and Strahan, 2010) as quasi-exogenous variation in firms' banker networks.

Our results highlight a novel way through which banking relationships benefit borrowers besides providing access to capital. They lead to positive information spillover that create value for borrowers by helping them combine resources in strategic alliances.

References

Acharya, V., Johnson, T., 2007. Insider trading in credit derivatives. Journal of Financial Economics 84, 110–141.

Allen, J. W., Phillips, G. M., 2000. Corporate equity ownership, strategic alliances, and product market relationships. Journal of Finance 55, 2791–2815.

Bharath, S., Dahiya, S., Saunders, A., Srinivasan, A., 2007. So what do I get? The bank's view of lending relationships. Journal of Financial Economics 85, 368–419.

Bodnaruk, A., Massa, M., Simonov, A., 2009. Investment banks as insiders and the market for corporate control. Review of Financial Studies 22, 4989–5026.

Bodnaruk, A., Massa, M., Simonov, A., 2013. Alliances and corporate governance. Journal of Financial Economics 107, 671–693.

Cai, Y., Sevilir, M., 2012. Board connections and M&A transactions. Journal of Financial Economics 103, 327–349.

Cameron, A. C., Miller, D. L., 2014. Robust inference for dyadic data. Working paper, University of California, Davis.

Chamberlain, G., 1980. Analysis of covariance with qualitative data. Review of Economic Studies 47, 225–238.

Chan, S. H., Kensinger, J. W., Keown, A. J., Martin, J. D., 1997. Do strategic alliances create value? Journal of Financial Economics 46, 199–221.

Chava, S., Roberts, M. R., 2008. How does financing impact investment? The role of debt covenants. Journal of Finance 63, 2085–2121.

Chen, J., Hong, H., Jiang, W., Kubik, J. D., 2013. Outsourcing mutual fund management: Firm boundaries, incentives, and performance. Journal of Finance 68, 523–558.

Coiculescu, G., 2018. Banking relationships and the formation of supply-chain relationships. Working paper, Yeshiva University.

Diamond, D. W., 1984. Financial intermediation and delegated monitoring. Review of Economic Studies 51, 393–414.

Engelberg, J., Gao, P., Parsons, C. A., 2012. Friends with money. Journal of Financial Economics 103, 169–188.

Esty, B. C., 2001. Structuring loan syndicates: A case study of the Hong Kong Disneyland project loan. Journal of Applied Corporate Finance 14, 80–95.

Fafchamps, M., Gubert, F., 2007. Risk sharing and network formation. American Economic Review 97, 75–79.

Fama, E. F., 1985. What's different about banks? Journal of Monetary Economics 15, 29–39.

Fee, C. E., Subramaniam, V., Wang, M., Zhang, Y., 2017. Bank lenders as matchmakers? When acquirers and targets share a common lender. Working paper, Tulane University.

Financial Times, 2006. Australia accuses Citigroup of insider trading. V. Marsh, April 1.

Financial Times, 2016a. City rainmakers unfazed by FCA capital markets report. M. Arnold, April 14.

Financial Times, 2016b. Goldman Sachs faces further questions from MPs. M. Vandevelde, July 31.

Financial Times, 2018. Alibaba and Tencent tell bankers to pick sides. L. Lucas, D. Weinland, June 5.

Gao, J., Karolyi, S. A., Pacelli, J., 2018a. Screening and monitoring by inattentive corporate loan officers. Working paper, Indiana University.

Gao, J., Kleiner, K., Pacelli, J., 2018b. Credit and punishment: Career incentives in corporate banking. Working paper, Indiana University.

Gao, J., Martin, X., Pacelli, J., 2017. Do loan officers impact lending decisions? Evidence from the corporate loan market. Working paper, Indiana University.

Griffin, J., Shu, T., Topaloglu, S., 2012. Examining the dark side of financial markets: Do institutions trade on information from investment bank connections? Review of Financial Studies 25, 2155–2188.

Hausman, J. A., 1978. Specification tests in microeconometrics. Econometrica 46, 1251–1271.

He, J., Huang, J., 2017. Product market competition in a world of cross-ownership: Evidence from institutional blockholdings. Review of Financial Studies 30, 2674–2718.

Hellmann, T., Lindsey, L., Puri, M., 2007. Building relationships early: Banks in venture capital. The Review of Financial Studies 21, 513–541.

Herpfer, C., 2018. The role of bankers in the US syndicated loan market. Working paper, Emory University.

Ivashina, V., Nair, V. B., Saunders, A., Massoud, N., Stover, R., 2009. Bank debt and corporate governance. Review of Financial Studies 1, 41–77.

Karolyi, S. A., 2017. Personal lending relationships. Journal of Finance 73, 5–49.

Kedia, S., Zhou, X., 2014. Informed trading around acquisitions: Evidence from corporate bonds. Journal of Financial Markets 18, 182–205.

Keil, J., Müller, K., 2019. Bank branching deregulation and the syndicated loan market. Journal of Financial and Quantitative Analysis, forthcoming.

Lindsey, L., 2008. Blurring firm boundaries: The role of venture capital in strategic alliances. Journal of Finance 63, 1137–1168.

Lowry, M., Rossi, M., Zhu, Z., 2019. Informed trading by advisor banks: Evidence from option holdings. Review of Financial Studies 32, 605–645.

Mariti, P., Smiley, R., 1983. Co-operative agreements and the organization of industry. Journal of Industrial Economics 31, 437–451.

Petersen, M. A., Rajan, R. G., 1994. The benefits of lending relationships: Evidence from small business data. Journal of Finance 49, 3–37.

Reuer, J. J., Lahiri, N., 2013. Searching for alliance partners: Effects of geographic distance on the formation of R&D collaborations. Organization Science 25, 283–298.

Rice, T., Strahan, P. E., 2010. Does credit competition affect small-firm finance? Journal of Finance 65, 861–889.

Roberts, M. R., 2015. The role of dynamic renegotiation and asymmetric information in financial contracting. Journal of Financial Economics 116, 61–81.

Roberts, M. R., Sufi, A., 2009. Renegotiation of financial contracts: Evidence from private credit agreements. Journal of Financial Economics 93, 159–184.

Saidi, F., Streitz, D., 2019. Bank concentration and product market competition. Working paper, Stockholm School of Economics.

Securities and Exchange Commission, 2007. SEC v. Barclays Bank PLC and Steven J. Landzberg, 07-CV-04427. Litigation Release No. 20132, May 30.

Tabord-Meehan, M., 2018. Inference with dyadic data: Asymptotic behavior of the dyadic-robust t-statistic. Journal of Business & Economic Statistics.

Terza, J. V., Basu, A., Rathouz, P. J., 2008. Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modelling. Journal of Health Economics 27, 531–543.

The New York Times, 2018. A top Goldman banker raised ethics concerns. Then he was gone. E. Flitter, K. Kelly, D. Enrich, September 11.

The Wall Street Journal, 2017. Goldman Sachs embraces banking's bland side: Lending money. L. Hoffman, May 1.

The Wall Street Journal, 2018. The new floor for bond underwriting fees: $1. M. Dalal, January 3.

Uzzi, B., 1999. Embeddedness in the making of financial capital: How social relations and networks benefit firms seeking financing. American Sociological Review 64, 481–505.

Uzzi, B., Lancaster, R., 2003. Relational embeddedness and learning: The case of bank loan managers and their clients. Management Science 49, 383–399.

Vasicek, O. A., 1973. A note on using cross-sectional information in Bayesian estimation of security betas. Journal of Finance 28, 1233–1239.

Figures

Figure 1: Illustration of the banker network
The figure presents 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, B, and C borrow from bankers 1, 2, and 3, respectively. Firm D is unconnected to the banker network. Banker 2 has co-syndicated separate loans with both banker 1 and banker 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 firm A and firm 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.

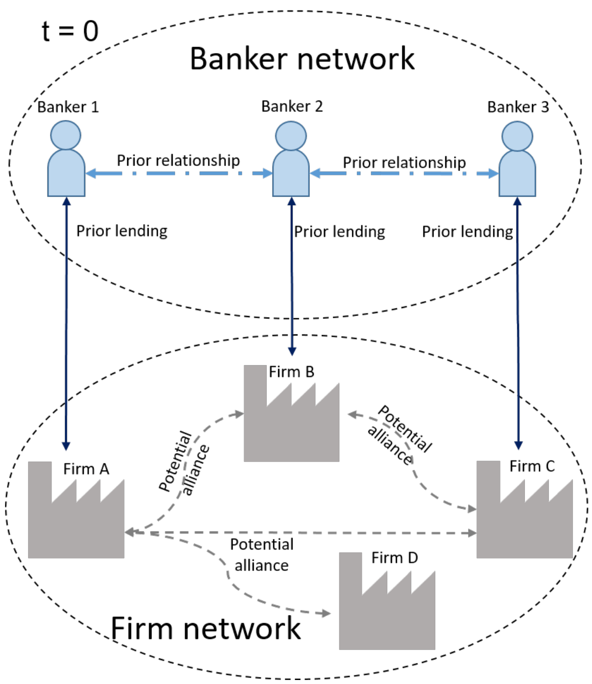
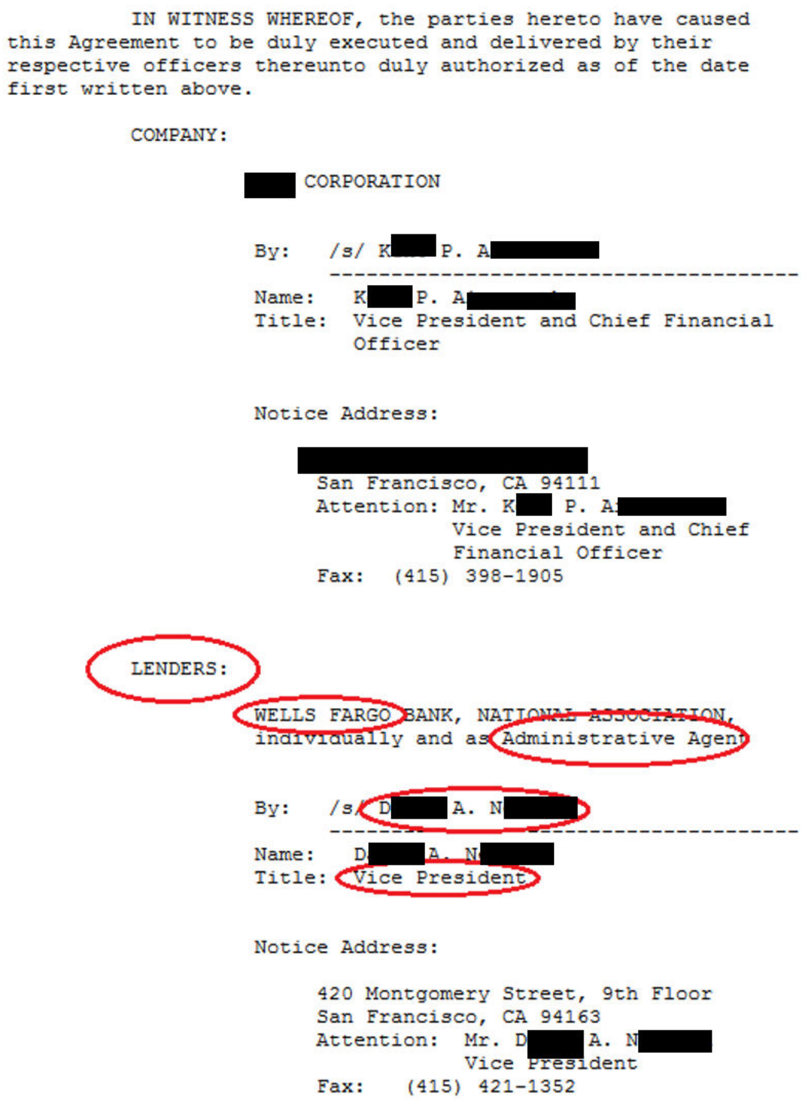


Figure 2: Example of simple signature page with a single bank
The red circles indicate information extracted by the text search algorithm. This information includes the name and role of the bank, as well as the name and title of the signatory. The names of the banker, corporation, and corporate executive 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. Herpfer, 2018; Gao et al., 2018b).



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

Tables

Table 1: Variable descriptions

Variable name	Description
Firm-pair characteristics	
Previous alliances	Number of alliances the two firms have entered into collectively between the beginning of the sample period and the time of observation.
Same state	The headquarters of the two firms are located in the same state.
One unrated	Either one or both parties do not have a long-term issuer credit rating from S&P's, Moody's or Fitch.
One high intangibles	Either one or both parties to a strategic alliance have an intangibles-to-assets ratio in the top quintile.
Avg. Rice-Strahan index	Firm-pair average of the Rice and Strahan (2010) index of the states the firms are headquartered in. Changes in the index between 2006 and 2016 are documented in Appendix C.
Bank loan related characteristics	
Banker network distance	Minimum distance between the two firms' loan officers through the network, zero meaning both have the same loan officer. The measure has been winsorized from above at three.
Same bank	Both firms have taken out at least one loan from the same lead arranger/lead agent.
Same banker	Both firms have taken out a loan from the same banker.
Banker connection	The two firms are connected through the banker network (regardless of distance).
One has a syndicated loan	At least one party to a strategic alliance has borrowed in the syndicated loan market since the inception of electronic filing.
Both have a syndicated loan	Both parties to an alliance have borrowed in the syndicated loan market since the inception of electronic filing.

Table 2: Summary statistics for observed initial alliance pairs
The table presents descriptive statistics for firm-pairs at the time they form an alliance. Variables are defined as discussed in Table 1.

Panel A: Bank loan characteristics					
	Obs.	Mean	SD	Min	Max
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					
	Obs.	Mean	SD	Min	Max
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
Avg. Rice-Strahan index	3,139	1.78	0.90	0.00	4.00
Previous alliances	3,189	17.13	27.35	0.00	220.00

Table 3: Univariate tests for propensity to ally given network connections
Panel A 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.

Panel A: By firm			
Variable	Mean	Standard Error	Observations
Within-network alliance ratio	0.2765	0.0241	669
Total alliance ratio	0.0282	0.0023	669
t-statistic	10.2507	p-value	0.0000
Panel B: By banker portfolio			
Variable	Mean	Standard Error	Observations
Within-portfolio alliance ratio	0.2937	0.0527	4’632
Total alliance ratio	0.0062	0.0002	4’632
t-statistic	5.4517	p-value	0.0000

Table 4: Influence of banker networks on the formation of strategic alliances: OLS results
The table displays 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 observations is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance before or during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. *Same banker* is equal to one 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, zero indicating none (i.e. the firms share the same banker). *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double-clustered by firm one and firm two. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.0071***			
	(4.64)			
Banker network connection		0.0021***		
		(3.76)		
Banker network distance			0.0004	
			(0.80)	
Distance = 0				0.0081***
				(4.80)
Distance = 1				0.0022***
				(3.04)
Distance = 2				0.0010**
				(2.33)
Distance > 2				0.0007*
				(1.68)
Same bank	0.0013***	0.0012***	0.0012	0.0010***
	(3.70)	(3.51)	(1.54)	(3.12)
Firm-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,370,774	6,370,774	359,678	6,370,774
R^2	0.7440	0.7440	0.8349	0.7440

Table 5: Influence of banker networks on the formation of strategic alliances: Variable capacity model

The table displays results from a maximum likelihood estimation of the variable capacity sequenced conditional logit model. The unit of observation is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. A firm's maximum alliance capacity is assumed to be unlimited. *Same banker* is equal to one 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, zero indicating none (i.e. the firms share the same banker). *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. The (omitted) base category for the indicator variables in Column 4 is two firms *not* being connected through the network. Parentheses contain z-statistics. Industry-pair-year fixed effects are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.380***			
	(3.31)			
Banker network connection		0.290***		
		(4.28)		
Banker network distance			-0.175*	
			(-1.92)	
Distance = 0				0.427***
				(3.69)
Distance = 1				0.256***
				(2.81)
Distance = 2				0.244
				(1.63)
Distance > 2				0.071
				(0.24)
Same bank	0.042	0.019	0.017	0.006
	(0.71)	(0.31)	(0.12)	(0.11)
Same state	0.382***	0.390***	0.452***	0.387***
	(7.57)	(7.72)	(2.72)	(7.65)
Previous alliances	0.025***	0.025***	0.019***	0.025***
	(30.17)	(30.21)	(7.92)	(30.19)
N	529,323	529,323	24,844	529,323
Prob > χ^2	0.000	0.000	0.000	0.000

Table 6: Influence of banker networks on the formation of strategic alliances: Fixed capacity model

The table displays results from a maximum likelihood estimation of the fixed capacity sequenced conditional logit model. The unit of observations is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. A firm's maximum alliance capacity is assumed to be fixed and equal to the number of strategic alliances the firm enters over the sample period. Once firms have exhausted their alliance capacity they are excluded from the panel in subsequent periods. *Same banker* is equal to one 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, zero indicating none (i.e. the firms share the same banker). *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. The (omitted) base category for the indicator variables in Column 4 is two firms *not* being connected through the network. Parentheses contain z-statistics. Industry-pair-year fixed effects are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.298***			
	(2.59)			
Banker network connection		0.181***		
		(2.63)		
Banker network distance			-0.156*	
			(-1.67)	
Distance = 0				0.327***
				(2.81)
Distance = 1				0.156*
				(1.69)
Distance = 2				0.080
				(0.52)
Distance > 2				0.008
				(0.03)
Same bank	0.176***	0.167***	0.008	0.153**
	(2.94)	(2.77)	(0.06)	(2.50)
Same state	0.319***	0.324***	0.398**	0.321***
	(6.26)	(6.37)	(2.35)	(6.30)
N	308,459	308,459	12,866	308,459
Prob > χ^2	0.000	0.000	0.031	0.000

Table 7: Instrumental variable estimates

The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. The instrument is the firm-pair average Rice and Strahan (2010) index of interstate bank branching deregulation. Standard errors for the two-stage residual inclusion (2SRI) estimates have been calculated using block bootstrap, re-sampling industry-pair-years 500 times. The first stage of the 2SRI estimator is a logit regression for the independent variables *same banker* and *banker network connection* and OLS for *banker network distance*. Its second stage is the variable capacity conditional logit model as in Table 5. First stage estimates are provided in Appendix A. *First stage residual* is the residual of the first stage regression. Parentheses contain z-statistics. Standard errors for the 2SLS estimates have been double-clustered by firm one and firm two. Industry-pair-year fixed effects for Columns 4 to 6 are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Two-stage least squares			Two-stage residual inclusion		
	(1)	(2)	(3)	(4)	(5)	(6)
Same banker	0.283***			0.326*		
	(5.86)			(1.93)		
Banker network connection		0.043***			0.264***	
		(6.43)			(3.34)	
Banker network distance			-0.012***			0.205
			(-4.89)			(0.06)
Same bank	-0.005***	-0.003***	0.001	0.031	0.004	0.241
	(-3.93)	(-3.41)	(0.82)	(0.53)	(0.06)	(0.12)
Same state				0.395***	0.379***	0.481
				(8.27)	(7.94)	(1.00)
Previous alliances				0.025***	0.025***	0.020**
				(13.44)	(13.24)	(2.26)
First stage residual				0.055***	0.026***	-0.381
				(4.46)	(3.23)	(-0.12)
Year FE	Yes	Yes	Yes	No	No	No
Firm-pair FE	Yes	Yes	Yes	No	No	No
N	6,220,593	6,220,593	356,359	517,136	517,136	24,888

Table 8: Banker networks by firm opacity

The sample consists of all publicly listed non-financial US 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 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 one and firm two. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Sequenced cond. logit		LPM	
	(1)	(2)	(3)	(4)
Same banker × one unrated	0.660**		-0.005*	
	(2.52)		(-1.92)	
Same banker × one high intangibles		0.615***		0.004**
		(2.67)		(2.09)
One unrated	-0.439***		-0.001**	
	(-8.05)		(-2.38)	
One high intangibles		-0.040		0.000
		(-0.87)		(1.47)
Same banker	0.174	0.039	0.008***	0.005***
	(1.37)	(0.22)	(4.45)	(3.94)
Same bank	-0.130**	0.052	0.001***	0.001***
	(-2.07)	(0.86)	(3.44)	(3.67)
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
Year FE	No	No	Yes	Yes
N	529,323	480,006	6,370,774	5,846,850
Prob > χ^2	0.000	0.000		
R^2			0.744	0.756

Table 9: Do alliances brokered through banker networks increase firm value?

The table displays coefficient estimates from regressions of cumulative abnormal returns (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 non-financial US 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 towards the cross-sectional mean based on the Vasicek (1973) estimator. Standard errors have been clustered by alliance. The unit of observation in Columns 1 to 2 is a firm in an observed alliance. The unit of observation in Columns 3 to 4 is a strategic alliance, with the CAR having been calculated by taking the market value weighted average of the alliance members' CARs.

	Firm-level CAR		Alliance-level CAR	
	(1)	(2)	(3)	(4)
Intercept	0.006***	0.007***	0.002***	0.002***
	(8.11)	(8.10)	(2.90)	(2.79)
Same banker	-0.001		0.002	
	(-0.32)		(0.90)	
Banker network connection		-0.002		0.001
		(-1.35)		(0.62)
Same bank	-0.003*	-0.002	-0.001	-0.001
	(-1.95)	(-1.56)	(-0.97)	(-0.96)
N	5,526	5,526	2,976	2,976
R^2	0.000	0.001	0.000	0.000

Table 10: Are relationship banks compensated for brokering alliances?
The unit of observation for the tests displays in the table 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 five 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 LPM. Standard errors for the LPM estimates have been clustered by firm.

	Bank-based financing		Market-based financing		M&A advisory	
Probability model	Logit	LPM	Logit	LPM	Logit	LPM
	(1)	(2)	(3)	(4)	(5)	(6)
No. of alliances facilitated by bank	0.336***	0.193***	0.033***	0.046***	0.002***	0.005
	(30.02)	(14.20)	(12.36)	(4.92)	(3.58)	(1.02)
Number of syndicated loans	0.112***					
	(87.32)					
Number of bond issues and SEOs			0.000***			
			(15.40)			
Number of M&A transactions					0.001***	
					(19.33)	
Number of alliances	0.010***		0.009***		0.000***	
	(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

Appendix for
"Information Intermediaries: How Commercial Bankers Facilitate Strategic Alliances"

A Additional results

Table A1: Linear probability model with firm-year fixed effects
The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers. The tests follow Table 4 but are augmented with firm 1-year and firm 2-year fixed effects. The unit of observations is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance before or during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. *Same banker* is equal to one 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, zero indicating none. *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double clustered by firm one and firm two. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.0042***			
	(3.26)			
Banker network connection		0.0008*		
		(1.93)		
Banker network distance			0.0005	
			(0.90)	
Distance = 0				0.0048***
				(3.40)
Distance = 1				0.0008
				(1.51)
Distance = 2				0.0002
				(0.62)
Distance > 2				0.0000
				(0.01)
Same bank	-0.0000	-0.0000	0.0001	-0.0000
	(-0.06)	(-0.04)	(0.17)	(-0.21)
Firm 1-year FE	Yes	Yes	Yes	Yes
Firm 2-year FE	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes
N	6,370,712	6,370,712	359,605	6,370,712
R^2	0.7493	0.7493	0.8436	0.7493

Table A2: First difference model

The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers based on a first difference model. The unit of observations is a firm-pair-year and the dependent variable is the first difference in alliance status, i.e. an indicator variable equal to one if a certain firm-pair enters a strategic alliance during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. *Same banker* is equal to one 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, zero indicating none. *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double clustered by firm one and firm two. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Δ Same banker	0.0015***			
	(2.79)			
Δ Banker network connection		0.0005**		
		(2.55)		
Δ Banker network distance			0.0001	
			(0.37)	
Δ (Distance = 0)				0.0019***
				(3.18)
Δ (Distance = 1)				0.0005*
				(1.96)
Δ (Distance = 2)				0.0003**
				(2.05)
Δ (Distance > 2)				0.0003
				(1.01)
Δ Same bank	0.0003***	0.0003***	0.0008**	0.0003***
	(2.80)	(2.75)	(2.03)	(2.65)
Year FE	Yes	Yes	Yes	Yes
N	5,533,295	5,533,295	309,541	5,533,295
R^2	0.0000	0.0000	0.0001	0.0000

Table A3: Linear probability model with time-phased network connections

The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers. The tests follow Table 4 but banker-to-firm, bank-to-firm and banker-to-banker connections require that at least one interaction between the parties took place *within the last five years*. The unit of observations is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance before or during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. *Same banker* is equal to one 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, zero indicating none. *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double clustered by firm one and firm two. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.0019*			
	(1.91)			
Banker network connection		0.0012***		
		(2.84)		
Banker network distance			0.0002	
			(0.64)	
Distance = 0				0.0024**
				(2.23)
Distance = 1				0.0015***
				(2.79)
Distance = 2				0.0007*
				(1.89)
Distance > 2				0.0006
				(1.50)
Same bank	0.0001	0.0001	0.0002	0.0001
	(0.49)	(0.32)	(0.58)	(0.31)
Firm-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,370,774	6,370,774	189,318	6,370,774
R^2	0.7440	0.7440	0.8672	0.7440

Table A4: Influence of banker networks on the formation of strategic alliances: matched-pairs OLS regression results

The table displays 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 observations is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance during the year of observation or earlier during the sample period. For each firm-pair that ever enters a strategic alliance, a pair of control firms is chosen and added to the sample. Control firms are selected by choosing the firm in the same industry group that, during the year in which the alliance is observed, minimizes the Mahalanobis-distance for the natural logarithm of sales, the natural logarithm of age, the ratio of intangibles to total assets and the market-to-book ratio between the original and the matched firm and that is not a member of the original firm-pair entering the alliance. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. *Same banker* is equal to one 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, zero indicating none. *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors clustered by firm one and firm two. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.0381			
	(1.43)			
Banker network connection		0.0904***		
		(4.36)		
Banker network distance			0.0265	
			(1.09)	
Distance = 0				0.0843***
				(2.68)
Distance = 1				0.0892***
				(3.91)
Distance = 2				0.0993***
				(3.45)
Distance > 2				0.0903
				(1.42)
Same bank	-0.0010	-0.0073	0.0515*	-0.0071
	(-0.05)	(-0.39)	(1.70)	(-0.38)
Firm-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	43,960	43,960	5,685	43,960
R^2	0.7029	0.7039	0.7730	0.7039

Table A5: Variable capacity sequenced conditional logit model with additional control variables

The table displays results from a maximum likelihood estimation of the variable capacity sequenced conditional logit model as the one displayed in Table 5 but controlling for additional firm-pair characteristics. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. The unit of observation is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance during the year of observation. A firm's maximum alliance capacity is assumed to be unlimited. *Same banker* is equal to one 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, zero indicating none (i.e. the firms share the same banker). *Banker connection* is an indicator equal to one if the two firms are connected through the network of bankers. The (omitted) base category for the indicator variables in Column 4 is two firms *not* being connected through the network (i.e. infinite distance). Financial characteristics have been winsorized at the 2 and 98% level. Parentheses contain z-statistics. Industry-pair-year fixed effects are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.291**			
	(2.44)			
Banker network connection		0.238***		
		(3.39)		
Banker network distance			-0.052	
			(-0.53)	
Distance = 0				0.333***
				(2.77)
Distance = 1				0.197**
				(2.12)
Distance = 2				0.253*
				(1.69)
Distance > 2				0.083
				(0.27)
Ln(total sales)	0.296***	0.295***	0.284***	0.295***
	(20.06)	(19.94)	(3.46)	(19.93)
Avg. tangiblity ratio	0.152	0.189	-0.826	0.191
	(0.90)	(1.12)	(-1.52)	(1.13)
Avg. market leverage	-1.019***	-1.044***	-0.981	-1.042***
	(-4.83)	(-4.94)	(-1.50)	(-4.93)
Same bank	-0.051	-0.066	-0.022	-0.073
	(-0.81)	(-1.06)	(-0.15)	(-1.15)
Same state	0.371***	0.376***	0.450***	0.374***
	(6.57)	(6.67)	(2.59)	(6.62)
Previous alliances	0.014***	0.014***	0.013***	0.014***
	(13.25)	(13.35)	(4.28)	(13.35)
N	414,409	414,409	22,846	414,409
Prob > χ^2	0.000	0.000	0.000	0.000

Table A6: First stage results of IV estimation

First stage estimates for the IV results displayed in Table 7. Parentheses contain t-statistics (z-statistics for the logit models). Standard errors for the two stage least squares estimates have been double clustered by firm one and firm two. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013.

	Two-stage least squares			Two-stage residual inclusion		
Dependent variable	Same banker	Network connection	Network distance	Same banker	Network connection	Network distance
Probability model	OLS	OLS	OLS	Logit	Logit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Rice-Strahan index	-0.006***	-0.039***	0.187***	-0.237***	-0.115***	0.053***
	(-7.98)	(-10.90)	(12.69)	(-15.12)	(-15.77)	(4.17)
Same bank	0.028***	0.143***	-0.237***	3.430***	2.389***	-0.596***
	(10.10)	(13.67)	(-10.98)	(115.43)	(184.50)	(-27.84)
Same state				0.574***	-0.145***	-0.120***
				(16.65)	(-7.85)	(-3.19)
Previous alliances				0.003***	0.012***	-0.002***
				(5.54)	(41.45)	(-4.30)
Year FE	Yes	Yes	Yes	No	No	No
Firm-pair FE	Yes	Yes	Yes	No	No	No
Kleibergen-Paap F.	63.72	118.78	161.14			17.42
N	6,220,593	6,220,593	356,359	525,399	525,399	33,035

B Sequenced conditional logit estimation example

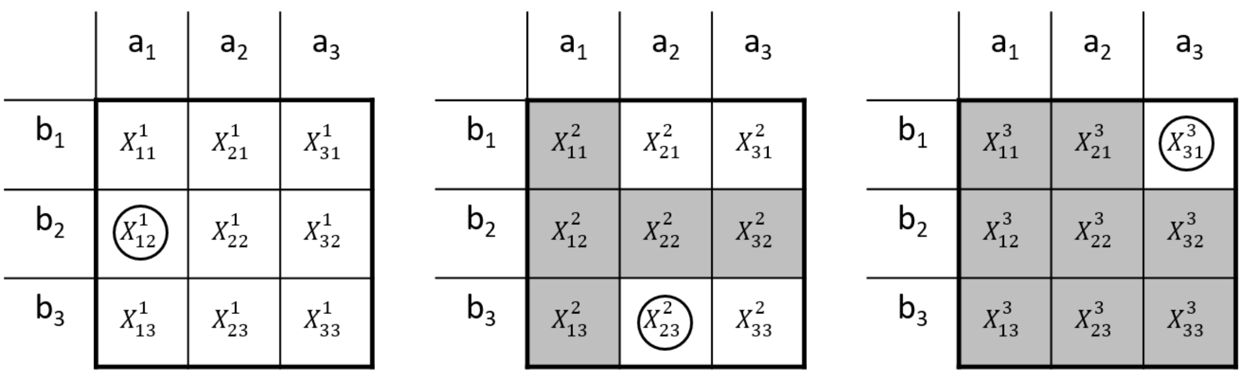
This section illustrates the sequenced conditional logit model developed by Lindsey (2008) on an example. Substantial parts of this example are reproduced from the same source. In practice, the sequential structure is accounted for when forming the data panel and the same maximum likelihood estimation procedure as for a standard conditional logit model can be applied.

Assume there are two industries, a and b, consisting of three firms (a_i and b_j, where $i, j \in \{1, 2, 3\}$) each. Further, denote the firm-pair characteristics at time t by X_{ij}^t and assume we observe three alliances: $\{a_1, b_2\}$ at $t = 1$, $\{a_2, b_3\}$ at $t = 2$, and $\{a_3, b_1\}$ at $t = 3$.

The fixed capacity model assumes that firms could not have entered more alliances than we observe in the data. Figure B1 illustrates the set of conditioning outcomes at each point in time for the fixed capacity model.

Figure B1: Fixed capacity model

The figure below illustrates the fixed capacity version of the sequenced conditional logit model developed by Lindsey (2008). Circles indicate realized alliances. Gray fields do not enter the estimation.



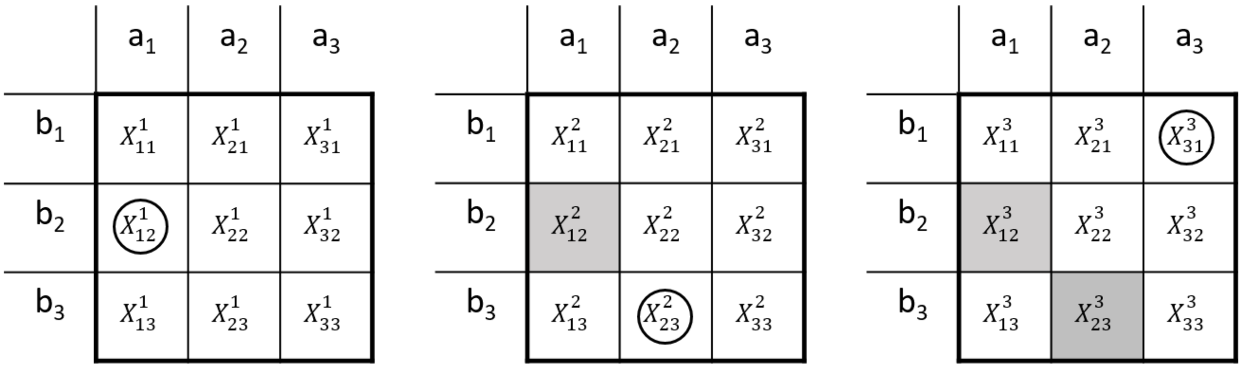
(a) $t = 1$ (b) $t = 2$ (c) $t = 3$

At $t = 1$, there are nine different alliances to choose from. The probability of observing $\{a_1, b_2\}$ is $\frac{e^{X_{12}^1 \beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X_{ij}^1 \beta}}$. Because both a_1 and b_2 only enter one alliance each, both have reached their alliance capacity and are removed from the set of possible alliances at $t = 2$ and $t = 3$. Thus the probability of the observed combination $\{a_2, b_3\}$ at $t = 2$ is given by $\frac{e^{X_{23}^2 \beta}}{e^{X_{21}^2 \beta} + e^{X_{23}^2 \beta} + e^{X_{31}^2 \beta} + e^{X_{33}^2 \beta}}$. Because a_2 and b_3 too have reached their alliance capacity, they are excluded from the set of possible alliances. At $t = 3$, only one possible alliance is left; its probability is equal to one regardless of the parameter vector β and it does therefore not enter the estimation. The likelihood function L^{ab} for industry-pair $\{a, b\}$ in the fixed capacity model is therefore given by

$$L^{ab} = \left(\frac{e^{X_{12}^1 \beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X_{ij}^1 \beta}} \right) \left(\frac{e^{X_{23}^2 \beta}}{e^{X_{21}^2 \beta} + e^{X_{23}^2 \beta} + e^{X_{31}^2 \beta} + e^{X_{33}^2 \beta}} \right) \tag{B.1}$$

Figure B2: Variable capacity model

The figure below illustrates the variable capacity version of the sequenced conditional logit model developed by Lindsey (2008). Circles indicate realized alliances. Gray fields do not enter the estimation.



(a) $t = 1$ (b) $t = 2$ (c) $t = 3$

In the variable capacity model, it is assumed that firms can enter any number of alliances. Hence only firm-pairs that have realized as alliances are removed from the estimation in subsequent periods. Figure B2 illustrates the set of conditioning outcomes at each point in time for the variable capacity model on the same two-industry, six-firm example as above. This time, the likelihood function L^{ab} for industry-pair $\{a, b\}$ is given by

$$L^{ab} = \left(\frac{e^{X^1_{12}\beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X^1_{ij}\beta}} \right) \left(\frac{e^{X^2_{23}\beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X^2_{ij}\beta} - e^{X^2_{12}\beta}} \right) \left(\frac{e^{X^3_{31}\beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X^3_{ij}\beta} - e^{X^3_{12}\beta} - e^{X^3_{23}\beta}} \right) \tag{B.2}$$

Now assume we add a second pair of industries $\{c, d\}$ to the estimation, and there are no alliances between firms in industries a and b and firms in either industry c or d. In both the fixed and the variable capacity model, calculating the overall likelihood is then just a matter of multiplying the likelihood L^{ab} for industry-pair $\{a, b\}$ with the likelihood L^{cd} of industry-pair $\{c, d\}$.

C Updates to the Rice-Strahan index

Table C1: Update of the Rice-Strahan index through 2016
This table displays changes to the four provisions that make up the Rice and Strahan (2010) index and that have become effective between 2006 and 2016. The data has been hand-collected from state statutes with the exception of changes effective on 22/07/2010. Those changes are due to the *Dodd Frank Wall Street Reform and Consumer Protection Act* of 2010 that removed restrictions to de novo branching across state borders nationwide.

State	Index	Date effective	Minimum age for acquisition	De novo branching	Acquisition of individual branches	Deposit cap
Alabama	1	01/06/2007	5	Yes	Yes	30
Alaska	1	22/07/2010	3	Yes	Yes	50
Arkansas	3	22/07/2010	5	Yes	No	25
Arkansas	2	30/03/2011	5	Yes	Yes	25
California	2	22/07/2010	5	Yes	No	30
Colorado	3	22/07/2010	5	Yes	No	25
Colorado	1	01/07/2013	No	Yes	Yes	25
Delaware	2	22/07/2010	5	Yes	No	30
Florida	2	22/07/2010	3	Yes	No	30
Florida	0	01/07/2011	No	Yes	Yes	30
Georgia	2	22/07/2010	3	Yes	No	30
Georgia	1	01/07/2016	3	Yes	Yes	30
Idaho	2	22/07/2010	5	Yes	No	None
Idaho	0	01/07/2015	No	Yes	Yes	None
Indiana	0	01/07/2011	No	Yes	Yes	30
Iowa	3	22/07/2010	5	Yes	No	15
Kansas	3	22/07/2010	5	Yes	No	15
Kentucky	2	22/07/2010	No	Yes	No	15
Louisiana	2	22/07/2010	5	Yes	No	30
Massachusetts	0	07/01/2015	No	Yes	Yes	30
Minnesota	2	22/07/2010	5	Yes	No	30
Mississippi	3	22/07/2010	5	Yes	No	25
Missouri	3	22/07/2010	5	Yes	No	13
Montana	3	22/07/2010	5	Yes	No	22
Nebraska	3	22/07/2010	5	Yes	No	14
Nebraska	1	06/04/2012	No	Yes	Yes	22
Nevada	2	22/07/2010	5	Yes	Limited	30
New Jersey	0	22/07/2010	No	Yes	Yes	30
New Mexico	2	22/07/2010	5	Yes	No	40
New York	1	21/07/2008	5	Yes	Yes	30
New York	0	18/07/2012	No	Yes	Yes	30
Oregon	2	22/07/2010	3	Yes	No	30
Oregon	0	07/06/2011	No	Yes	Yes	30
South Carolina	2	22/07/2010	5	Yes	No	30
South Dakota	0	10/03/2008	No	Yes	Yes	30
Texas	1	14/06/2013	No	Yes	Yes	20
Wisconsin	1	10/04/2006	5	Yes	Yes	30
Wyoming	2	22/07/2010	3	Yes	No	30
Wyoming	1	01/07/2013	No	Yes	No	30

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