Information intermediaries: How commercial bankers facilitate inter-firm alliances*

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Abstract

We investigate how bankers use private information to facilitate strategic alliances between borrowers. Firms that have borrowed from the same banker in the past are significantly more likely to enter an alliance, and the same is true for firms borrowing from different bankers that have co-syndicated loans previously. We find that bankers can facilitate strategic alliances even across banks. Consistent with bankers overcoming informational frictions, their ability to facilitate alliances decreases with network distance, and is stronger for opaque borrowers. We exploit quasi-exogenous variation in firms' banker networks from interstate bank branching deregulation to show that this relationship is causal.

JEL Classifications: G20; G21; G30; D74.

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1 Introduction

We investigate a novel channel through which banks create value for borrowers and allocate resources in the economy: the ability of commercial bankers to transmit information across firm boundaries and facilitate strategic alliances between borrowers. The ability of banks to create information about their borrowers is at the core of banking (Diamond, 1984; Petersen and Rajan, 1994; Berger and Udell, 1995). We build on the established finding that banks obtain private information about borrowers and investigate the effect of information spillovers between existing borrowers. We provide evidence that the banking system transmits information between firms and helps them identify potential collaboration partners.

We document that banks can act as information intermediaries between potential alliance partners and thereby facilitate, or broker, alliances. We identify individual bankers as the specific economic channel through which information is transmitted. Commercial bankers play a key role in negotiating and structuring initial loan agreements, which allows them to form a close relationship with firms' management and gives them access to private information.[1] Importantly, bankers can broker alliances not just between two of their own borrowers, but between one of their own clients and clients of other bankers they had a prior working relationship with. This ability of two bankers to facilitate alliances between their clients even holds for two bankers employed at different banks.

Strategic alliances, "voluntary arrangements involving durable exchange, sharing, or co-development of new products and technologies" (Gulati, 1995), contribute significantly to corporate valuation and efficiency (Chan, Kensinger, Keown, and Martin, 1997; Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Robinson, 2008). As contracts that are somewhere between arm's length, market based transactions and intra firm relationships, alliances blur the boundaries of individual firms to combine resources. These alliances are particularly sensitive to information asymmetries since a firm looking for an alliance partner needs infor-

[1] See Esty (2001) and Uzzi (1999) for detailed descriptions of the loan origination process and the role of bankers.

mation on the partner's capabilities that is not necessarily publicly available. One potential channel to overcome this information asymmetry is through capital providers that are associated with both firms.

Lindsey (2008), for example, documents that sharing the same venture capital firm greatly increases the likelihood of a strategic alliance between private firms. Similarly, Ivashina, Nair, Saunders, Massoud, and Stover (2009) find evidence that banks pass on information they obtain about borrowers to potential acquires in the M&A market. Brokering alliances is not only beneficial for borrowers; we find that, all else equal, firms become substantially more likely to mandate a particular bank with administering a loan syndicate or underwriting a securities offering if that bank facilitated a strategic alliance for the firm recently.

Our results are therefore not just evidence of a novel way in which banks provide value to their borrowers, but also add to a growing literature that highlights the importance of individual bankers in the lending market to large, public borrowers (Herpfer, 2017; Gao, Martin, and Pacelli, 2017). While banks as financial intermediaries can therefore blur firm boundaries for borrowers (Lindsey, 2008; Ivashina et al., 2009), bankers can blur boundaries across different banks by allowing information to flow from one bank to another.

We use data from publicly available loan contracts that allow us to link individual bankers to specific loans for a sample of U.S. non-financial borrowers from 1996 to 2012. 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.

Since each banker has only a limited set of direct borrowers, it can be hard for them to find a suitable partner inside their own portfolio of borrowers. We therefore investigate whether even indirect connections between borrowers through a network of bankers can broker alliances. To do so, we exploit that most loans to large borrowers are syndicated, i.e. have multiple lending institutions. Two borrowers that do not share the same banker can still be indirectly connected if their two bankers have worked together previously. We construct a network in which two bankers are connected if they have jointly signed a syndicated loan to any borrower in the past. The various bankers involved in a lending syndicate interact with each other repeatedly during the origination process (Esty, 2001). After origination, bankers stay in touch with borrowers during the maturity of the loan for the purpose of monitoring covenants and renegotiating loan terms.[2] Bankers form personal connections through jointly underwriting, monitoring and modifying loans and can use these connections to find suitable alliance partners for their portfolio firms. Bankers can therefore act as information intermediaries even across banks, allowing information to flow from one bank to the other.

We then directly test whether strategic alliances between pairs of firms are more likely if those firms are connected through the network of bankers. A simple univariate t-test shows 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. A variety of factors other than a shared connection through bankers impacts the likelihood of two firms forming an alliance. We therefore estimate panel regressions that allow us to control for factors like geographic proximity (Reuer and Lahiri, 2013) or time variation in the likelihood of forming strategic alliances. Importantly, these specifications 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.[3] In addition we control for any sort of observable or unobservable, time invariant propensity of firms to initiate strategic alliances through firm-pair fixed effects. We find that sharing the same banker significantly increases the likelihood of entering a strategic alliance. Sharing the same banker significantly increases the likelihood of two firms to engage in strategic alliances at a rate that is economically about six times as large as that of sharing the same bank.

[2] 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).

[3] Borrowers can be connected through bankers but not banks if bankers switch employers.

We then test whether this result also holds when considering all banker connections, including indirect ones. We find that even when two firms are indirectly connected through the banker network, they 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. The ability of bankers to broker alliances between clients should therefore decrease as more links in the banker network are needed to connect the two firms. This prediction is borne out in the data, where we find that the match making ability of bankers decreases monotonically as the distance between bankers increases.

One of the concerns with the linear probability setup is that it treats all firm-pairs as independent observations. In reality, firms likely 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. To account for this interconnected nature of alliance formation, we use the sequenced conditional logit model developed by Lindsey (2008) to model explicitly how strategic alliances form over time. The tests confirm that firms sharing a banker are significantly more likely to enter a strategic alliance and that this effect weakens as the distance between bankers increases.

Bankers and borrowers do not pair up randomly. One potential challenge to our inference is therefore that there could be both observable factors such as interlocking boards as well as unobservable factors such as shared interests that make firms both more likely to share the same banker and to engage in a strategic alliance. While our result that indirect connections through the banker network facilitate alliances somewhat alleviates this concern, it is possible that the same characteristics that make firms and bankers pair up also make bankers more likely to co-syndicate loans. We therefore implement two tests that address this endogeneity concern by exploiting restrictions to interstate bank branching (Rice and Strahan, 2010) as a source of quasi-exogenous variation in the banker network connecting firms. Restrictive branching laws make it more likely that firms borrow from local banks whose bankers are less central in the network, thereby increasing their network distance in relation to potential alliance partners. We find that more open inter-state branching laws indeed lowers the network distance between firm pairs and increases their likelihood of sharing the same banker, fulfilling the relevance condition. We find that all our results hold after accounting for endogeneity in this way.[4]

If bankers are able to broker alliances by overcoming information asymmetries, their role should be more pronounced when information asymmetries are large. We investigate this conjecture in cross sectional tests and find evidence that banker connections are more important in brokering alliances for informationally opaque borrowers, in particular those that lack a public credit rating and have a high share of intangible assets..

In our final set of results we investigate whether brokering alliances benefits borrowers and the brokering banks. In an event study, we find that brokered alliances are associated with positive market reactions, evidence that these alliances indeed create value for borrowers. Firms reward this service. Banks whose employees broker a strategic alliance for their borrower subsequently receive additional loan syndication as well as bond and equity underwriting mandates.

The paper closest to ours is Lindsey (2008), who finds that venture capital funds broker strategic alliances within their portfolio of start up firms as long as at least one of them is private. Our paper shows that, as firms grow and switch from venture capital funding to bank funding, bankers take over not just the funding of firms but also the brokering of alliances. We are also able to pin down the information transmission mechanism to individual bankers and show how information transmission becomes harder as distance through the banker network increases. Furthermore, we are able to show how commercial bankers can transmit information not just between two distinct borrowers, but between two distinct lending banks

[4]One potential concern with this inference setup is that interstate branching deregulation could increase access to capital for firms and therefore increase their ability to expand and form new alliances. This concern is, however, alleviated by Rice and Strahan (2010) who find that branching deregulation did not lead to an overall increase in capital but rather a shift from public bond markets to bank loans, meaning this violation of the exclusion restriction is unlikely to drive our result.

by using their professional network. Finally, we document information transmission through a network of professionals, rather than just for pairs of connected individuals (Engelberg, Gao, and Parsons, 2012; Karolyi, 2017).

Two other related papers are Ivashina et al. (2009) and Fee, Subramaniam, Wang, and Zhang (2017), who show that banks seem to transmit information between their clients in the context of mergers. We add to their findings by showing that the mechanism of transmitting information through banks does not just facilitate M&A transaction but also strategic alliances. We also document that individual bankers are the conduit of this information and can broker alliances even across different banks. We can further directly measure network distance between both alliance partners. Importantly, both Ivashina et al. (2009) and Fee et al. (2017) document that banks gather important, non public information about borrowers even for large, publicly traded corporations as in our sample. These results lend plausibility to our assumption that individual bankers have private information about those large, transparent borrowers.[5]

One premise of our paper is that the brokering of alliances is a valuable service provided by banks to borrowers. This premise is supported by our data, in particular by the strategic alliances in the sample being accompanied by statistically significant positive announcement returns. In addition, a number of papers demonstrate that strategic alliances are associated with positive stock market reactions upon announcements (Chan et al., 1997), increased operational productivity (Allen and Phillips, 2000; Bodnaruk, Massa, and Simonov, 2013) and a higher rate of survival during economic stress (Babina, Garcia, and Tate, 2017).[6]

[5]In discussions with current and former commercial bankers we were able to confirm that bankers matter even for large borrowers. In addition, Uzzi and Lancaster (2003) provide further evidence from interviews that bankers are important information transmitters in the mid market loan segment. About one third of the firms in our sample fall in the mid market segment which comprises firms with annual sales of up to $500mn.

[6]These positive effects of alliances upon initiation are mirrored by negative effects of their sudden termination (Boone and Ivanov, 2012). A number of papers investigates specific channels through which alliances create value for firms (Gomes-Casseres et al., 2006; Robinson, 2008; Ozmel, Robinson, and Stuart, 2013). Gonzalez-Uribe (2017) finds that firms sharing the same VC fund collaborate on unobservable dimensions as well, such as cross utilizing patents. If the same mechanism was at work for banks, our estimates of the value generated through brokered alliances were a lower bound of the actual value created.

Our paper also adds to a recent literature that has investigated the role of individual commercial bankers in the lending process to large, publicly traded corporations (Herpfer, 2017; Gao et al., 2017).

The remainder of this paper is structured as follows: Section 2 develops the hypotheses to be tested. Next, Section 3 discusses the data and Section 4 presents the estimation methodology and results. Finally, Section 5 concludes.

2 Hypothesis development

Asymmetric information can impact the creation of alliances in two ways: First, if the number of potential partners is high, searching for a match can be costly both in terms of time and resources. Since bankers interact with a number of different borrowers, they are likely to have an overview of potential partners. Second, even if there are relatively few potential partners, selecting the right match can be difficult if alliance success relies on privately available information. If an alliance requires a certain managerial or technological capability or cultural fit, bankers can identify a potential alliance partner using the private information they have gathered about borrowers. One banker interviewed in Uzzi and Lancaster (2003) describes the process through which bankers provide information to firms like this: "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 they have information about. One way a banker can increase the number of potential alliance partners she can offer is by asking colleagues for recommendations. If alliances are beneficial to borrowers, bankers might be willing to broker an alliance even if one of the partners is not their own client but somebody else's, since improved borrower performance aids bankers' career (Gao, Kleiner, and Pacelli, 2018). Theoretically, bankers could broker alliances even if none of their own clients are directly involved in the deal by connecting other bankers to each other. Since the coordination of information transmission becomes more complicated with increased distance between bankers, and bankers get fewer benefits from brokering an alliance that does not involve any of their own clients, the ability of bankers to broker alliances should decrease in the distance between individual bankers. We therefore formulate

Hypothesis 2: Two firms are more likely to enter a strategic alliance if they deal with different bankers that know each other. This effect dissipates as the distance between bankers increases.

Asymmetric information and the challenge to find an alliance partner ex ante are the key friction bankers can help overcome. We will therefore test

Hypothesis 3: The role of bankers for transmitting information should be more pronounced in circumstances with high information asymmetries.

Our last hypothesis is that brokered alliances should benefit both borrowers and brokering bankers. We therefore investigate

Hypothesis 4a: Alliances brokered by banks should be associated with a positive stock market reaction;

Hypothesis 4b: Borrowers reward banks for brokering alliances through additional business.

3 Data

3.1 Data on bankers

We 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. 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 a primary source for DealScan (see Chava and Roberts, 2008). The majority of loan contracts contains a section that features the names and functions of all banks involved in the deal. In addition, the signature page usually contains the names and titles of all bankers representing those banks.

We use a search algorithm to identify loan contracts from EDGAR and extracts the name of each banker involved in the deals. Figure 1 shows the layout of such a signature page and marks the data items extracted by the algorithm. Many loans for large, publicly traded borrowers are syndicated between multiple banks. Since the algorithm extracts the names of all bankers involved in a syndicated loan, our data do not just allow us to track individual bankers, but also to construct a network of linkages between bankers based on whether they have syndicated a loan in the past.

In order to formally model the effect of bankers on the formation of corporate cooperation, 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 if they ever 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 while representing the loan syndicate's lead arranger, in which case we assume the syndicate's lead banker has a professional relationship with the borrowing firm.[7] 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. We likely understate the true number of clients since our dataset limits us to publicly traded borrowers.[8] Figure 2 illustrates on a simplified example how firms are connected through the banker network.

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.[9]

3.2 Data on strategic alliances

Data on strategic alliances comes from Standard and Poor's (S&P's) Capital IQ and SDC Platinum. 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. 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

[7] See Esty (2001) for a case study on the syndication process and the relationship formation between lead banks and borrowers as well as Herpfer (2017) for empirical evidence on the importance of lead bankers

[8] Uzzi (1999) finds that bankers in the mid market segment have between 6 and 50 clients

[9] In un-tabulated results we confirm that both the LPM and sequenced conditional logit estimates are robust to increasing this lag to two years.

merge the resulting data sets. We aggregate all strategic alliances by the ultimate parent of the announcing firm and retain only those alliances where all parties involved have an ultimate parent that is publicly listed and incorporated in the United States. For every firm-pair, we only retain the first alliance announcement over the sample period. 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.[10] 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)*. 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

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

distance being one. Low distances are therefore most common. To reduce the impact of outliers, the banker network distance has been winsorized from above at three.[11]

4 Results

We begin our analysis with a univariate tests for firms' propensity to ally with partners they are connected to via the banker network, as compared to their overall propensity to enter strategic alliances. We then estimate OLS specifications that add controls for common alternative drivers of alliance propensity such as geographical proximity, sharing the same bank as well as firm-pair and time controls.

The OLS approach cannot account for the dynamic way in which strategic alliances form over time (e.g., a firm choosing to ally with a partner might be less likely to engage in an alliance with another partner in the same field in the future). We therefore present estimates based on the maximum-likelihood based sequenced conditional logit model developed by Lindsey (2008). Subsequently, we argue that our results are not driven by endogeneity by presenting instrumental variable estimates that exploit arguably exogenous shocks to firms' banker network size to address the concern that firms might both form an alliance and borrow from the same banker (network) due to unobserved similarities. We then present an extension to the basic sequenced conditional logit model that illustrates the economic rationale - information production ex ante - behind bankers' involvement in the formation of strategic alliances. Our final set of results use an event study to show that strategic alliances brokered by bankers increase firm value, and that banks get rewarded for brokering them through subsequent mandates to underwrite securities.

[11]The winsorization affects less than 2% of observations

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, as in Lindsey (2008). We implement this 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 a 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

$$Within\text{-}network\ alliance\ ratio_j = \frac{C_j}{n_j} \tag{1}$$

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, the results of which are displayed in Panel A of Table 3.[12] The test rejects the null hypothesis of equality in means at the 1% level, implying that firms are significantly more likely to enter strategic alliances with partners they are connected to via the network of bankers.

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

[12] Means and standard errors have been scaled by 100 to improve readability.

purpose, we calculate two statistics for every banker in the sample, similar to the firm-level test above. 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[13] 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 therefore represents the total number of potential alliance nodes that could be formed within a banker's portfolio. It follows that this ratio 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 and n is the total number of sample firms. This second ratio is again designed to capture firms' unconditional propensity to form alliances. We compare the two ratios by means of a t-test for equal means. The results, displayed in Panel B of Table 3, reject the null hypothesis at the 1% level, implying that firms are significantly more likely to form alliances if they share a banker.

[Table 3 here]

Of course there are numerous reasons why banks sharing the same banker should be more likely to initiate a strategic alliance, such as bankers specializing in certain industries and regions, and a higher propensity of firms to ally with others in their own industry and geographic proximity. In a second 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 state.

[13] An alliance node is defined as a firm in an observed alliance. There are two nodes in a bilateral alliance.

We first 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, firms can only enter alliances with firms from a particular industry if alliances between firms from these two industries actually exist in the data.[14] 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.[15] 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

$$Alliance_{it} = \beta Network\ connection_{it} + X_{it}\gamma + \theta_t + \xi_i + \varepsilon_{it} \tag{5}$$

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 vector X_{it} represents control variables that are common across all specifications. Since there is evidence that sharing the same bank can increase the likelihood of M&A transactions between firms (Ivashina et al., 2009), X_{it} includes a control for whether the two alliance partners shared the same (lead) bank in the past. Similarly, we include a control for whether two firms are headquartered in the same state since both alliance formation (Reuer and Lahiri, 2013) and banking relationship formation (Petersen and Rajan, 2002; Herpfer, Mjøs, and Schmidt, 2017) tend to be stronger among local partners.

Since both the rate of alliance formation and bank lending can vary over time, we include

[14]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 trying to avoid 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.

[15]Firms are not allowed to self-match and duplicates from permutations of the same pair of firms are eliminated

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 cluster standard errors by firm-pair 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, being located in the same state, and time variation in alliance likelihood. Importantly, the inclusion of firm-pair fixed effects absorbs the time invariant propensity of two firms to ally. We therefore only draw inference from observations that change their network distance 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.[16] Both of these estimates are statistically significant at the one percent level. The economic magnitude of our estimate of sharing the same banker is high both in absolute and relative terms: It is more than five times the effect of sharing the same bank.

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

[16]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.

connected through their banker network from past loans. The estimated coefficient on this indicator is 0.21 percent 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 goes up. 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. 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. Against our prediction, the estimated coefficient on *banker network distance* is both statistically and economically insignificant.

The results from the specifications in columns 2 and 3 cannot fully rule out a scenario in which only direct connections through sharing the same banker matter and higher degrees of indirect connections are irrelevant. We therefore directly estimate the impact of the various degrees of separation by including indicator variables for each distance in column 4 of Table 4. The reference group consists of firm pairs which are not connected through the banker network at all. The magnitude of the coefficient estimates is monotonously decreasing in the distance, with the coefficients on $distance = 0$ (0.0081), $distance = 1$ (0.0022) and $distance = 2$ (0.0010) all being statistically significant at the 1% level.[17] 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, and once the chain of bankers exceeds three people there is no more measurable

[17] We pool observations with distances of three or more into a single group due to the small number of such observations.

impact on alliance formation.[18]

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, for robustness' sake 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. We therefore match both firms in an observed alliance to their nearest neighbour given a number of observable characteristics including industry, size and age and construct the control pair from the two nearest neighbours. The results displayed in Appendix C confirm the results of the main analysis in Table 4.

4.2 Accounting for interdependence: The sequenced conditional logit model

The fundamental unit of observation in our data is that of a firm-pair-year and the variable of interest, i.e. whether two firms enter a strategic alliance in a given year or not, is binary and takes a value of either one or zero. Importantly, observations cannot be assumed to be independent as a firm's choice of entering a strategic alliance might affect its decision to enter additional alliances in the future. The data therefore has a correlation structure that cannot fully be accounted for by clustering standard errors in regression estimates because the same firm will sometimes show up as the first and at other times as the second partner to an observed alliance.[19] In addition, if firms in some industries are overall more likely to enter strategic alliances than firms in others, the data will have a group structure that leads to standard logit and probit models of discrete choice resulting in inconsistent estimates (Chamberlain, 1980).

[18]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.

[19]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.

To account for these characteristics of the data, we 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 account for the firm-level clustering of observations by explicitly modeling the sequential way in which alliances form over time while also incorporating the group structure of the data.[20]

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 (i.e. that firms' capacity to enter alliances is variable). 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

[20] While the sequenced conditional logit has the advantage of correcting for the aforementioned biases, it also comes with drawbacks. The reported coefficients are logit coefficients and can therefore not be economically interpreted. Unlike in standard logit models, it is not possible to directly calculate margins in conditional logit models due to the different reference groups for each firm pair.

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 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

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

Appendix A 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 and the same state of headquarters. In addition, we include a control *previous alliances* for the number of alliances the two firms in each pair have previously entered (this control is absent in the fixed capacity version of the model). Note that the regression setup controls for industry and year effects implicitly. 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. Table C2 in the appendix adds such control variables (sales, the ratio of tangible to total assets and financial leverage) and shows that our results remain economically and statistically very similar.

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 two, 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 (significant at the 1% level) for a distance of zero to 0.256 for a distance of one, with all additional coefficients being statistically insignificant. As in the OLS specifications coefficients drop monotonically with each additional level of distance added.

Unlike in the OLS analysis, there are no firm-pair fixed effects in the sequenced conditional logit regressions which allows us 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 three 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 four 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* $= 1$).[21] In summary, Table 5 shows that our results hold in a specification that accounts for the dynamic nature of alliance formation.

We then 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 in each column follow those from Table 5. 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 statistically significant at the 10% level in the continuous setting (column 3).

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

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 both the coefficients for $distance = 0$ and $distance = 1$ being statistically significant. The coefficient estimate for *same bank* is positive and statistically significant across. 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.

4.3 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. In particular, while we might be able to control for some alternative connections between CEOs and bankers, it is impossible to control for all potential links. We directly address this concern by instrumenting for firms' banker-network position using interstate banking regulations.[22] 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 directly affect the pair's likelihood of entering a strategic alliance. 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

[22]In addition to partially observable variables such as shared CEO educational history or interlocking boards, there are many completely unobservable 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.

for the network distance between two borrowers.

Rice and Strahan (2010) track four 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: a minimum age requirement of at 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. The Rice-Strahan index counts the number of these provisions, so an index value of four stands for most restrictive and an index value of zero for least. 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 B.

The estimation based on the Rice and Strahan (2010) index is founded on the fact that most firms tend to borrow from banks located in their physical vicinity (Petersen and Rajan, 2002; Herpfer et al., 2017). 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. High index values are therefore associated with larger banker-network distances between two firms in an alliance. Keil and Müller (2017) find that states with fewer interstate bank branch deregulation indeed showed an increase in lending from out of state lenders.[23] A potential concern could be that the lifting of state-level restrictions might increase the amount of funding available for expansion and therefore impact firms' general propensity to ally. In this case the instrument would violate the exclusion restriction. However, Rice and Strahan (2010) find that firms located in states that lifted restrictions on interstate branching did not increase their financial leverage subsequently, but

[23] Keil and Müller (2017) also find a shift from syndicated to single lender loans. Our data cover both syndicated and single lender deals, with 14% of loans in our sample being single lender. Since LPC DealScan focuses on syndicated loans, we can not fully rule out that we are missing some of the additional single lender loans, but any omissions should bias us against finding a significant effect on firms' banker network in the first stage.

rather substituted for part of their market-based borrowing with bank loans. Hence these firms were unlikely to be financially constrained before the introduction of interstate bank branching, 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 bond markets somehow impedes alliance formation compared to borrowing from banks, although we are not aware of any such argument.

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).[24] For robustness, we also implement a 2SLS estimator in which an OLS specification similar to the one 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

$$Network\ connection_{ijt} = \alpha + \beta z_{it} + X_{it}\gamma + \theta_t + \xi_j + \varepsilon_{ijt} \tag{9}$$

where i indexes firm-pairs, t years and j industries, $Network\ connection_{ijt}$ is either *same banker*, *banker network distance* or *banker network connection*, X_{it} is a vector of control variables, θ_t a year fixed effect, ξ_j an industry fixed effect and ε_{ijt} the error term. z_{it} stands for the instrumental variable, which is the firm-pair average of the Rice-Strahan index as described above. The second stage estimate follows equation 5 except that the fitted value for $Network\ connection_{ijt}$ from the first stage is used as the independent variable.

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

$$Network\ connection_{st} = f(z_{st}, X_{st}, \varepsilon_{st}^{first\ stage}) \tag{10}$$

[24] 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).

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 the second stage, which is a variable capacity sequenced conditional logit model as described in Section 4.2.

Table 7 presents the results of our two instrumental variable specifications. 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. For ease of exposition, the results of the first stage regressions are displayed in Appendix C; our instrumental variable is not just highly statistically significant as determinant of the variables of interest but exhibit strong economic significance as well.[25] We therefore conclude that the Rice Strahan Index appears to fulfil the relevancy criterion. The results for the second stage are presented in Table 7 below.

[Table 7 here]

Columns one to three of Table 7 show the second stage results for the 2SLS model. The coefficient on sharing the same banker is 0.158 and statistically significant at the 1% level. 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. The coefficient for *banker network distance* is -0.024 and statistically significant at the 1% level. The coefficient estimate for the indicator variable *banker network connection* is 0.371 but statistically insignificant. This result is however not surprising, given the lack of power of our instrument in the first stage for this specification.

Columns four to six 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) as the second stage. The *first stage residual* is statistically

[25] An exception is the 2SLS specification for *banker network connection* based on the Rice-Strahan index, for which the F-statistic falls below the required threshold. To remain consistent, we still display the second stage regression for that estimation.

significant and positive in columns four and five, 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* (0.265) being of similar magnitude as those in the main specification in Table 5 and statistically significant at the five and one percent level, respectively. The coefficient on *banker network distance* on the other hand is neither statistically nor economically significant in these regressions.

Overall, the results in this section provide evidence that our main finding, which is 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. In Appendix 5 we provide analogous results using an alternative instrument. Following Ivashina et al. (2009), we exploit situations where one of the two firms switches lenders as a shock to this bank's banker network. Borrowing from a new bank adds a new banker connection to a firm, hence the new lending relationship should reduce a firm's network distance towards other potential alliance partners and should increase the likelihood of sharing the same banker or any network connection with them. Table C4 demonstrates that our results for the 2SLS estimation using this alternative identification strategy stay consistent with those in the main part, whereas the 2SRI results lose their statistical significance.[26]

4.4 Bankers are more important for brokering alliances between firms when asymmetric information is high

Our third hypothesis predicts that bankers' ability to broker alliances should exhibit cross-sectional differences based on borrower characteristics. Lindsey (2008) shows that venture

[26] A challenge during the implementation of this instrumental variable is that the decision to borrow from a new bank also positively impacts the *same bank* variable, which violates the exclusion restriction. To address this challenge, we limit the sample to those firm-pairs that never share the same bank over the sample period, leading to a substantial reduction in sample size.

capital funds' ability to broker alliances is driven by, among other things, their ability to overcome asymmetric information. Banks, like venture capital firms, do have private information on their borrowers which might allow them to bridge information asymmetries between two parties to a potential strategic alliance. We test the cross-sectional prediction that greater opacity should amplify the role of bankers in brokering alliances in Table 8.

[Table 8 here]

The results in columns one and two of Table 8 are for the variable capacity version of the sequenced conditional logit model.[27] For robustness, the same tests are repeated using a linear probability model in columns three and four. 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 positive at 0.660 and statistically significant at the 5% level. Sharing the same banker therefore has a significantly more positive impact on the formation of strategic alliances when there is less publicly available information about either one or both parties. 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 fraction of intangible assets. We find that the estimated impact of the interaction *one high intangibles* with *same banker* is indeed positive at 0.615 and statistically significant at the 1% level.[28] The linear probability model in columns 3 and 4 delivers similar results for the interaction with *one high intangibles*, statistically significant at the 1% level, while the estimates for credit ratings is statistically

[27] 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.

[28] Another intuitive 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 in line with Ivashina et al. (2009) who demonstrate that banks have sensitive inside information even for the largest, most transparent firms.

and economically insignificant. Overall, the results in this section provide evidence that firm opacity indeed amplifies the role of bankers in brokering alliances.

4.5 Alliances brokered by bankers are valuable for firms

To investigate whether strategic alliances arranges by bankers are beneficial for firms, we first calculate cumulative abnormal returns (CARs) for every alliance announcement over a three-day event window centred on the announcement date, and 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.[29] 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 below.

[Table 9 here]

The intercept is statistically significant at the 1% level in all specifications, suggesting 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 three and four are lower at 0.2%, implying that small firms, in relative terms, benefit disproportionately from strategic alliances. The observation that strategic alliances are generally valuable for firms is consistent with the literature (e.g. Chan et al., 1997). The specifications in columns one and three control for whether the firms in an announced alliance share either the *same banker* or the *same bank*, columns two and four do the same for whether there exists any *banker network connection*. The estimated coefficients for all of the network characteristics are statistically

[29] We require at least 220 observations in the event 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 (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) as proxies for the market return and the risk-free rate, respectively.

insignificant at the 5% level, therefore not providing any evidence that alliances brokered through banker networks are either better or worse than the average alliance. We interpret this result as banker-brokered alliances adding to firms on the extensive, rather than the intensive margin: they benefit firms because they facilitate additional strategic alliances, which are valuable but not of higher quality than the average strategic alliance.[30]

4.6 Relationship banks are compensated with additional mandates when they broker alliances

There are two reasons for why a bank might be interested in helping a borrower enter a strategic alliance. First, strategic alliances increase firm value and performance (Chan et al., 1997; Allen and Phillips, 2000; Bodnaruk et al., 2013). Better firm performance decreases the likelihood of bankruptcy (Altman, 1968), and additional strategic alliances thereby benefit the lender's existing loans.

Second, a strategic alliance might increase the firm's future need for external financing and thereby increase the likelihood of the borrower being asked to arrange additional loans. Third and finally, borrowers might compensate a relationship bank directly for brokering a strategic alliance by giving it preferential treatment when selecting an intermediary for its interactions with capital markets in the future, e.g. when raising debt or equity capital, or engaging in M&A transactions.

We test for the existence of this third reason, compensation through additional mandates, explicitly on an annual panel of firm-bank pairs. Fore each firm, we consider all banks that served as lead arrangers on a loan in the past. The dependent variable of interest is whether the bank is given a particular mandate to arrange an additional syndicated loan, serve as the underwriter in a securities offering or to advise in an M&A transaction over the subsequent five year period, starting with the current year. Our main explanatory variable is the number

[30]Consistent with brokered alliances adding to firms' total number of alliances is the positive pairwise correlation of 0.12 between firms' yearly number of new alliances and their number of banker network connections.

of strategic alliances the firm has entered with a partner it shared the bank with ex ante.[31] The control variables include the number of strategic alliances and the number of mandates of a particular type. Data on seasoned equity offerings, bond issues and advisory mandates in mergers and acquisitions comes from Capital IQ, data on syndicated loans from LPC DealScan.

Table 10 below displays the results of these tests. The estimates indicate a positive impact on the probability of being selected to arrange a syndicated loan or underwrite a securities offering, both statistically significant at the 1% level, but no significant impact for M&A advisory services. For robustness, all tests are repeated based on a linear probability model with standard errors clustered by firm, yielding similar results. For the logistic regressions, marginal effects are displayed.

[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 the same year by 28.8 percentage points (the corresponding LPM estimate suggests a 30.8 percentage point increase). The marginal effect for securities underwriting services is lower at only 2.9 percentage points (the corresponding LPM estimate being 10.4 percentage points). This difference in magnitude might have both economic and mechanical 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 indicate that, as expected, the likelihood of receiving any mandate (syndicated loan, securities underwriting, M&A advisory) is positively related to the firm's

[31]The underlying assumption is that the shared bank connection played a role in brokering the strategic alliance, see Section 4.1. Firms sharing the same bank can initiate alliances independently from their shared lender, which might bias our estimates.

number of 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 assisting in brokering it.

5 Conclusion

We investigate how individual bankers help broker alliances between firms. Bankers can use their knowledge of borrowers obtained from prior lending transactions to help overcome the asymmetric information challenge faced by firms that are looking for an alliance partner. We document that two firms are significantly more likely to enter a strategic alliance if they share the same banker. Bankers can therefore act as a conduit for information to form new links between firms.

The information transmitting role of bankers does not just bridge across 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 have two different bankers which have a connection through joint prior lending. The ability of bankers to broker alliances is strongest for informationally opaque firms, and decreases as the network distance between bankers increases.

Our results are robust to a wide range of controls and estimation techniques. We further address endogeneity concerns through instrumental variable estimates that exploit restrictions to interstate bank branching (Rice and Strahan, 2010) as quasi-exogenous factors driving firms' banker network size.

Our results highlight a novel way through which banking relationships benefit borrowers besides providing access to capital, a result underscored by the positive abnormal stock returns firms experience after they announce a strategic alliance. Furthermore, we find that borrowers reciprocate by mandating banks that broker alliances for them with arranging additional loan syndicates and underwriting of securities offerings in the future. We also contribute to the literature on the role of individual bankers in the corporate lending market; in particular, we find that individual bankers have the ability to coordinate across bank-boundaries for the benefit of their borrowers.

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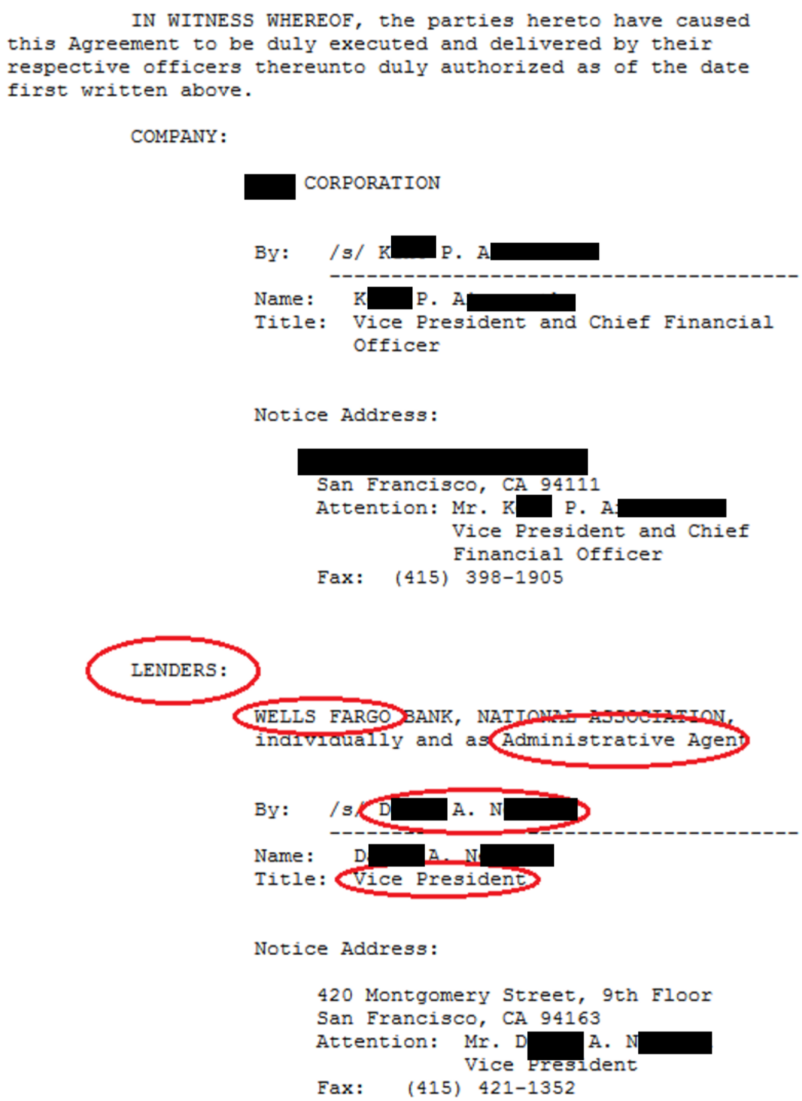
Figures

Figure 1: 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.



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

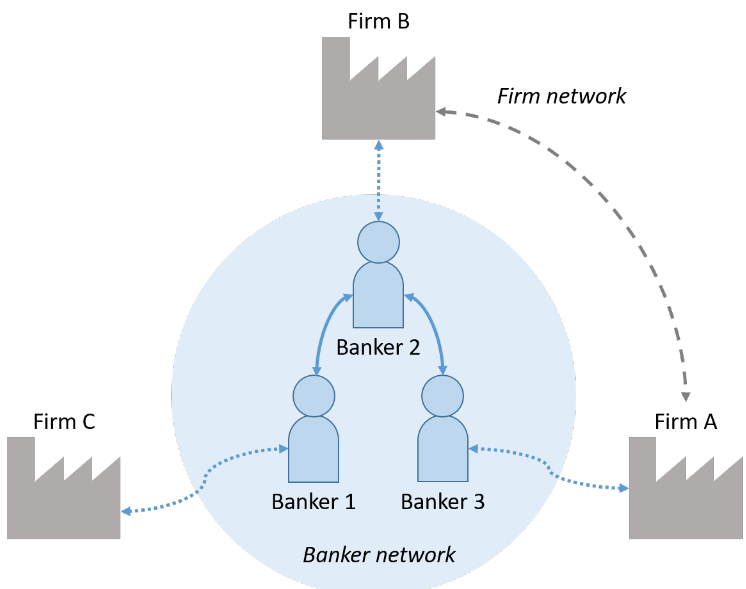
By: /s/ D[redacted] A. N[redacted]

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

Figure 2: Illustration of the banker network.
The shaded area represents the banker network. Solid lines symbolize banker-to-banker connections. Dotted lines represent banker-to-firm connections. Dashed lines symbolize strategic alliances. Connections between bankers exist if the bankers have ever shown up as signatories on the same syndicated loan contract. Connections between firms and bankers are established when the banker, but only as the syndicate's lead arranger, signs a syndicated loan contract with the firm. In the example below, the banker network distance between firms A and B is one and between firms A and C is two. Our hypothesis would predict that firm A is more likely to engage in a strategic alliance with firm B than firm C due to the shorter network connection.



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 B.
One switched banks	Either one or both firms took out a loan from a new bank in the preceding year.
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.
Both have a syndicated loan	Both parties to an alliance have borrowed in the syndicated loan market.

Table 2: Summary statistics for observed initial alliance pairs
This 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	1.73	0.96	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 of this table 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
This 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 universe of firms is that of publicly listed US firms in Compustat that enter at least one strategic alliance over the sample period. *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 clustered by firm-pair. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.0071***			
	(6.33)			
Banker network connection		0.0021***		
		(6.75)		
Banker network distance			0.0004	
			(0.91)	
Distance = 0				0.0081***
				(7.11)
Distance = 1				0.0022***
				(5.32)
Distance = 2				0.0010***
				(2.93)
Distance > 2				0.0007
				(1.60)
Same bank	0.0013***	0.0012***	0.0012*	0.0010***
	(5.94)	(5.54)	(1.82)	(4.87)
Firm-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,396,582	6,396,582	364,134	6,396,582
R^2	0.7444	0.7444	0.8367	0.7444

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

This 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. 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 four is two firms *not* being connected through the network (i.e. infinite distance). Parentheses contain z-statistics. Industry-pair 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

This 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. 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 four is two firms *not* being connected through the network (i.e. infinite distance). Parentheses contain z-statistics. Industry-pair 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 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 1000 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 residual* is the residual of the first stage regression. Parentheses contain z-statistics. Standard errors for the 2SLS estimates are clustered by firm-pair. Industry-pair-year fixed effects for columns four to six 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	0.158***			0.326**		
	(2.63)			(2.07)		
Banker network connection		0.371			0.265***	
		(1.22)			(3.45)	
Banker network distance			-0.024***			0.262
			(-2.92)			(0.02)
Same bank	-0.004	-0.073	-0.008**	0.031	0.004	0.276
	(-1.37)	(-1.16)	(-2.05)	(0.51)	(0.06)	(0.04)
Same state	0.001***	0.005*	0.006***	0.393***	0.378***	0.484
	(4.73)	(1.79)	(3.05)	(7.46)	(7.15)	(0.45)
Previous alliances				0.025***	0.025***	0.020
				(13.37)	(13.25)	(0.55)
First stage residual				0.054***	0.026***	-0.437
				(4.45)	(3.19)	(-0.04)
Year FE	Yes	Yes	Yes	No	No	No
Industry-pair FE	Yes	Yes	Yes	No	No	No
N	6,245,738	6,245,738	360,793	517,136	517,136	24,888

Table 8: Banker networks by firm opacity
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 a particularly high ratio of intangible to total assets. Parentheses contain z-statistics for the conditional logit model and t-statistics for the LPM. Industry-year fixed effects are implicit in the sequenced conditional logit model. Standard errors for the LPM have been clustered by firm-pair. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	Sequenced cond. logit		LPM	
	(1)	(2)	(3)	(4)
Same banker	0.174	0.039	0.009***	0.004**
	(1.37)	(0.22)	(4.95)	(2.24)
Same banker × one unrated	0.660**		-0.004	
	(2.52)		(-1.32)	
One unrated	-0.439***		-0.001***	
	(-8.05)		(-5.34)	
Same banker × one high intangibles		0.615***		0.009***
		(2.67)		(3.11)
One high intangibles		-0.040		0.000
		(-0.87)		(1.02)
Same state	0.394***	0.359***	0.001***	0.001***
	(7.79)	(6.71)	(5.07)	(4.61)
Same bank	-0.130**	0.052	0.000	0.001***
	(-2.07)	(0.86)	(1.57)	(3.62)
Previous alliances	0.024***	0.025***	0.001***	0.001***
	(27.97)	(28.61)	(25.49)	(25.29)
Industry-pair-year FE	No	No	Yes	Yes
N	529,323	480,006	6,396,582	5,887,678
Prob > χ^2	0.000	0.000		
R^2			0.028	0.029

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

This table displays coefficient estimates from regressions of cumulative abnormal returns (CARs) over a [-1;1] event window around alliance announcements on network characteristics. 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 are clustered by alliance. The unit of observation in columns one to two is a firm in an observed alliance. The unit of observation in columns three to four 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 this 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, the underwriter for a bond or seasoned equity offering or the advisor in an M&A transaction 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.

	Syndicated loans		Bond/SEO underwriting		M&A advisory	
Probability model	Logit	LPM	Logit	LPM	Logit	LPM
	(1)	(2)	(3)	(4)	(5)	(6)
No. of alliances brokered by bank	0.288***	0.308***	0.029***	0.104***	0.001	0.006
	(23.13)	(11.45)	(13.06)	(7.10)	(1.41)	(1.27)
Number of syndicated loans	0.114***	0.138***				
	(103.87)	(14.52)				
Number of bond issues and SEOs			0.000***	0.001***		
			(13.66)	(3.39)		
Number of M&A transactions					0.001***	0.003***
					(18.08)	(4.22)
Number of alliances	0.009***	0.010**	0.004***	0.010***	0.000***	0.001***
	(15.18)	(2.53)	(28.37)	(4.64)	(7.14)	(2.73)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	233,779	233,779	266,573	266,573	266,573	266,573
(Pseudo) R^2	0.065	0.076	0.029	0.016	0.056	0.006

Appendix for
"Information intermediaries: How commercial bankers facilitate inter-firm alliances"

A Sequenced conditional logit estimation example

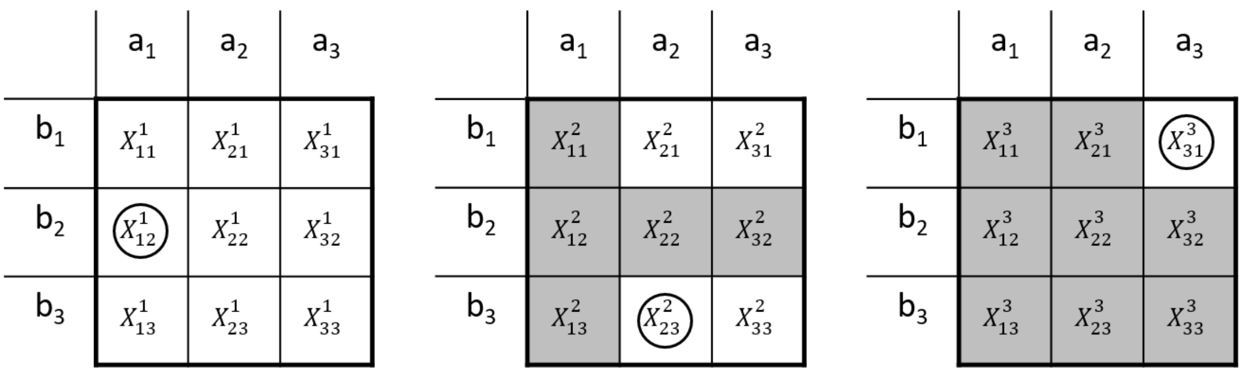
This section illustrates the sequenced conditional logit model developed by Lindsey (2008) on an example. Substantial parts of this example are reproduced from the same source. In practice, the sequential structure is accounted for when forming the data panel and the same maximum likelihood estimation 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 A1 illustrates the set of conditioning outcomes at each point in time for the fixed capacity model.

Figure A1: 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) $t = 3$

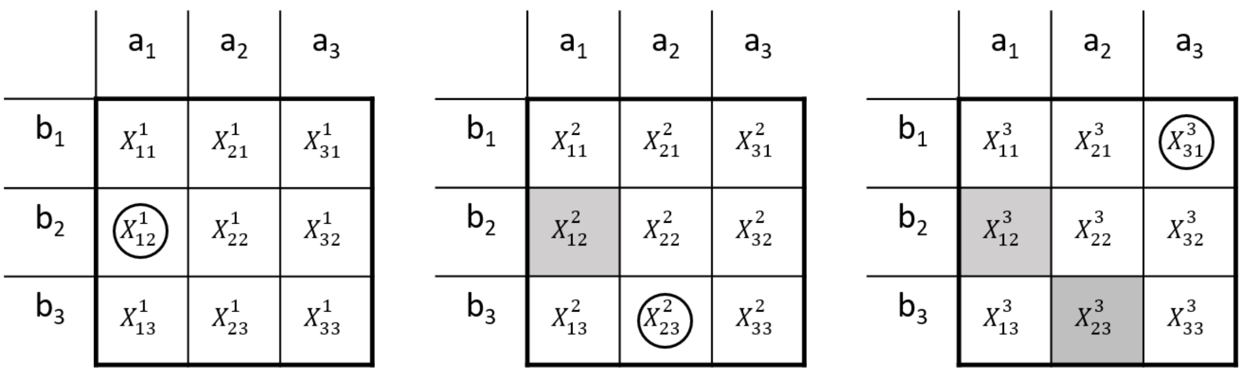
At $t = 1$, there are nine different alliances to choose from. The probability of observing $\{a_1, b_2\}$ is $\frac{e^{X_{12}^1 \beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X_{ij}^1 \beta}}$. Because both a_1 and b_2 only enter one alliance each, both have reached their alliance capacity and are removed from 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

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

Figure A2: 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 A2 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

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

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 $\{c, d\}$.

B Updates to the Rice-Strahan index

Table B1: 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
California	0	01/01/2012	No	Yes	Yes	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

C Additional results

Table C1: Influence of banker networks on the formation of strategic alliances: matched-pairs OLS regression results
This 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 resulting dataset is a panel of firm-pairs spanning the years 2002 to 2013. The universe of firms is that of publicly listed US firms in Compustat. *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 clustered by firm-pair. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Same banker	0.0482*			
	(1.88)			
Banker network connection		0.1169***		
		(6.83)		
Banker network distance			0.0231	
			(0.90)	
Distance = 0				0.1085***
				(3.95)
Distance = 1				0.1206***
				(5.91)
Distance = 2				0.1189***
				(4.26)
Distance > 2				0.1047*
				(1.66)
Same bank	-0.0216*	-0.0292**	0.0420	-0.0291**
	(-1.85)	(-2.51)	(1.34)	(-2.51)
Firm-pair FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	44,068	44,068	5,427	44,068
R^2	0.7035	0.7050	0.7708	0.7050

Table C2: Variable capacity sequenced conditional logit model with additional control variables

This 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 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 four 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 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 C3: 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). The partial R^2 measures the explanatory power of the instrumental variable alone.

	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	-0.001***	-0.000	0.047***	-0.207***	-0.118***	0.039***
	(-8.47)	(-1.35)	(12.25)	(-14.08)	(-17.23)	(3.56)
Same bank	0.048***	0.205***	-0.505***	3.437***	2.388***	-0.599***
	(62.39)	(134.03)	(-82.69)	(115.78)	(184.56)	(-27.99)
Same state	0.002***	-0.008***	-0.010	0.538***	-0.154***	-0.111***
	(6.45)	(-10.21)	(-0.72)	(15.83)	(-8.41)	(-2.96)
Previous alliances				0.003***	0.012***	-0.002***
				(5.29)	(40.89)	(-4.29)
Year FE	Yes	Yes	Yes	No	No	No
Industry-pair FE	Yes	Yes	Yes	No	No	No
Kleibergen-Paap F.	71.73	1.82	150.01			12.68
Partial R^2	0.0001	0.0000	0.0025			0.0020
Partial pseudo R^2				0.0116	0.0074	
N	6,245,738	6,245,738	360,793	525,399	525,399	33,035

Table C4: Alternative instrumental variable estimates

This table presents estimates based on an alternative instrumental variable, whether either firm in a firm-pair has borrowed from a new bank in the preceding period. The sample in excludes all firm-pairs that ever share the same bank. Standard errors for the two-stage residual inclusion (2SRI) estimates have been calculated using block bootstrap, re-sampling industry-pair-years 1000 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 residual* is the residual of the first stage regression. Parentheses contain z-statistics. Standard errors for the 2SLS estimates are clustered by firm-pair. Industry-pair-year fixed effects for columns four to six are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Second stage						
	Two-stage least squares			Two-stage residual inclusion		
	(1)	(2)	(3)	(4)	(5)	(6)
Same banker	0.611***			0.263		
	(9.81)			(0.47)		
Banker network connection		0.031***			0.291*	
		(11.33)			(1.70)	
Banker network distance			0.000			2.980
			(0.15)			(0.01)
Same state	0.001***	0.002***	0.005**	0.433***	0.437***	0.825
	(4.79)	(6.65)	(2.12)	(3.70)	(3.68)	(0.10)
Previous alliances				0.027***	0.027***	0.047
				(11.47)	(11.39)	(0.04)
First stage residual				0.019	0.007	-3.158
				(0.58)	(0.66)	(-0.01)
Year FE	Yes	Yes	Yes	No	No	No
Industry-pair FE	Yes	Yes	Yes	No	No	No
N	5,413,062	5,413,062	153,858	103,466	103,466	4,506

Panel B: First stage						
	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)
One switched banks	0.001***	0.020***	-0.115***	0.121	0.110***	-0.133***
	(18.98)	(84.89)	(-27.42)	(1.48)	(4.46)	(-6.60)
Same state	0.000**	-0.005***	0.011	0.405***	-0.338***	-0.055
	(2.11)	(-7.83)	(0.50)	(4.66)	(-10.30)	(-0.81)
Previous alliances				0.016***	0.020***	-0.007***
				(10.74)	(34.08)	(-5.66)
Year FE	Yes	Yes	Yes	No	No	No
Industry-pair FE	Yes	Yes	Yes	No	No	No
Kleibergen-Paap F.	360.15	7,205.55	751.96			43.52
Partial R^2	0.0002	0.0026	0.0050			0.0046
Partial pseudo R^2				0.0002	0.0003	
N	5,413,062	5,413,062	153,858	110,588	110,588	10,530