Information Intermediaries: How Commercial Bankers Facilitate Strategic Alliances

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

A Anecdotal Evidence on the Role of Bankers in Brokering Collaborations

We spoke to three individuals with first hand experience in how bankers broker strategic alliances. Our first interview was with a current commercial banker with more than 20 years of experience, who is employed at a major national lender on the U.S. West Coast and is also part of our dataset. This banker told us that miscellaneous consulting services to borrowers, such as pitching them potential collaboration partners, was an important part of building relationships with borrowers. She explained that her edge in brokering these alliances was two-fold. First, she had direct lines of communications to senior management at various companies. Approaching a potential collaboration partner is significantly harder when "cold calling" and an introduction through a common lender can significantly ease the process. Second, the banker explained that customers often needed very specific capabilities in collaboration partners, and it was not necessarily public knowledge which firms had them. Connections to a large number of firms allow bankers to directly point borrowers to a good fit, reducing the need to search for a suitable partner.

Our first interview partner then set us up to talk to one of her clients, the CFO of a medium sized U.S. corporation on the West Coast. This second interview partner stressed that brokering collaborations was an important aspect of relationship building with his banker, and that these types of consulting services were a precondition for a banker receiving lucrative mandates. He stressed the costs of finding collaboration partners in the presence of asymmetric information and how bankers can overcome these frictions.

Our third contact used to work as a banker in a large developing economy for a globally operating U.S. bank. This former banker told us that brokering relationship among clients was an important part of relationship building. He specifically mentioned a collaboration between his country's railway operator and two major heavy industry corporations that he was involved in as an example of how bankers can broker collaboration even among large borrowers.

Additional evidence on the role of bankers in matchmaking can be found in the press. In 2016, PricewaterhouseCoopers (PwC) interviewed the CEO of Silicon Valley Bank, Greg Becker, for their CEO survey (PwC US, 2016). Becker stressed the matchmaking role as part of the value added his bank can provide to customers: "We are so concentrated in the target market we go after, our ability to make an introduction to another CEO that's going through the same sort of challenges is higher than that of any other institution. Our ability to make introduction to a potential partnership–because we understand that business better than maybe one of our competitors would. The value added we give to our clients, whether it is making an introduction to a potential client or making an introduction to a potential partnership [...] Why is that so important for technology companies? The most important thing for technology companies is speed and execution." An example of such matchmaking, in this case between customers and producers, is Silicon Valley bank's brokering of both sales and takeovers between tech investors and Napa Valley wine makers (The Street, 2015). These public statements confirm similar information we received from market participants during our private conversations.

A 2016 article highlights the role bank matchmaking plays for connections across borders (China Daily, 2016). Chen Siqing, president of Bank of China (BOC, a commercial bank) argues that "pushing forward cooperation among Chinese and Central and Eastern European companies is a crucial step in BOC's program". One client interviewed for the article argued that "BOC helped us make a breakthrough by introducing us to our first overseas client."

Finally, banks can also act as matchmakers between borrowers and strategic investors. In May 2019, Bank of America CEO Brian Moynihan made a contact between their borrower Occidental Petroleum Corp., Berkshire Hathaway Inc., and oil company Anadarko Petroleum Corp (Bloomberg, 2019). According to Buffet, the bank was crucial in making the introduction: "Last Friday, I got a call in the middle of the afternoon from Brian Moynihan, the CEO of Bank of America, and he said that they were involved in financing the Occidental deal and that the Occidental people would like to talk to me."

These examples highlight the various ways in which banks can act as matchmakers between clients.

B Additional Tests for the OLS Specification

For robustness, we re-estimate the specification in Table 3 with additional firm-year fixed effects for both firms. We thereby control for both observable and unobservable time-varying characteristics on the firm level that might introduce an omitted variable bias. The results are displayed in Table E2. Even in this heavily saturated fixed effect specification, sharing the same banker remains a statistically and economically significant predictor for whether two firms enter a strategic alliance. The coefficients on indirect connections retain their sign, albeit their slightly smaller magnitude means they lose most of their statistical significance in this specification. The exception is the coefficient for sharing any network connection in Column 2, which remains on the margin of statistical significance.

Another potential concern with the fixed effect specification in Table 3 is that it cannot fully distinguish whether a network connection precedes a strategic alliance or whether the opposite is the case. Strategic alliances could therefore systematically precede network connections, in which case the results could be driven by reverse causality. To alleviate this concern, Appendix E presents results from first difference regressions that relate changes in alliance status to concurrent changes in network connections. The first difference setup is substantially more conservative than the baseline OLS results because it identifies the impact of banker networks on alliance formation only based on alliances entered in the first period after the network connection is first established.[25] All results retain their statistically significance in the first difference specifications. As expected, the economic magnitude of the estimated coefficients is lower, reflecting that they only represent the increase in the probability that two firms enter an alliance immediately after becoming connected through a

[25]As mentioned in section III.A, network connections are lagged by one period in all estimations.

banker network. Since, in addition, the sequenced conditional logit results in Section C hereafter are unaffected by this issue by construction, the overall evidence strongly suggests that our results are not driven by alliances preceding connections through the banker network.

An additional robustness test presented in Appendix E is concerned with the time-dimension of the network. The main specification in Table 3 assumes that connections between firms, bankers and banks last forever. The robustness test introduces time-phased connections by limiting the lifetime of all connections (bank to firm, banker to banker and banker to firm) to five years. The results of this specification are both economically and statistically close to those in Table 3 as well.

In addition, there are relatively few alliances (about 3000) compared to the overall sample size. We are unaware of any evidence indicating that the skewed nature of the dependent variable in the estimation above could render our coefficient estimates biased or inconsistent. Nevertheless, we repeat the LPM analysis on a reduced sample consisting of all firm-pairs that enter an alliance over the sample period and a single control pair for each one in a final robustness test. We select the control firm pair by matching both firms in an observed alliance to their nearest neighbor given a number of observable characteristics including industry, size and age and construct the control pair from the two nearest neighbors. The results displayed in Appendix E confirm that sharing a banker, or being connected through the banker network, are associated with a higher likelihood of forming a strategic alliance.[26]

Finally, we investigate if our results are driven exclusively by bankers working for large banks. The syndicated loan market is dominated by a small number of large banks.[27] We re-estimate our network of bankers excluding those large banks, and then estimate if the network of bankers from small banks is as useful in explaining strategic alliance formation as the un-abridged network. Since firms connected through the main network exhibit a substantially higher propensity to form strategic alliances, leaving them in the sample would strongly bias us against finding an effect of the non-central network. We therefore drop those firm-pairs which are connected through the real network, but not the limited network, from our sample for these tests. In effect, when we estimate our main specification with the limited network we test the likelihood of forming an alliance for firms connected through the network of bankers at small banks compared to unconnected firms.

Interestingly, the results in Appendix Table E5 show that connections through the network of smaller banks are, if anything, slightly more powerful in creating strategic alliances compared to the large bank network. For example, the coefficient estimate on "Banker network connection" in Column 2 is 0.28 – about 40% larger in magnitude than the coefficient estimate on banker network connection in the unabridged model. This result is consistent with the model in Stein (2002) which suggests that larger banks rely more on hard, transmittable information. This implies that larger banks rely less on the expertise of individual bankers in shaping their business, consistent with the empirical evidence in Herpfer (2021).

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

[27]In our sample, Citi, Bank of America, Wells Fargo, JPMorgan Chase, SunTrust and U.S. BankCorp have lead syndicates for more than 300 loans each.

C A Dynamic Model of Alliance Formation Based on the Sequenced Conditional Logit Model

C.1 Overview

The unit of observation in our data is that of a firm-pair-year. Because a firm's choice of entering a strategic alliance might affect its decision to enter additional alliances in the future, observations for a particular firm-pair are potentially correlated with all other observations involving either of the two firms forming the pair. The result is a complicated correlation structure that conventional clustering of standard errors cannot fully account for.[28] Robust inference in the presence of such *dyadic* data, where the unit of observation is a pair, is still an active area of research (Fafchamps and Gubert, 2007, Cameron and Miller, 2014, Tabord-Meehan, 2018). Unfortunately, the size of our data set and the large number of corresponding fixed effects means implementing the existing estimators for dyadic data is impossible for computational reasons. According to the results of Monte-Carlo simulations in Cameron and Miller (2014), however, our choice of clustering standard errors twice both along the first and second dimension of the dyad is the most conservative among the alternatives and provides the closest approximation to full dyadic clustering.

To account for the firm-level dependence in alliance choice more comprehensively, we instead apply the sequenced conditional logit model developed by Lindsey (2008), a discrete choice model based on the standard conditional logit model (e.g., Chamberlain, 1980) but different in that it allows the set of conditioning outcomes to vary over time. This approach allows us to explicitly model the sequential way in which alliances form over time while also incorporating the group structure of the data.[29]

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

$$PR(ALLIANCE = 1) = \frac{e^{X_s^t \beta}}{\sum_{s \in S} e^{X_s^t \beta}} \tag{C.1}$$

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

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

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

pair of firms is realized, the pair is removed from S in subsequent years.

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

The likelihood L^p for industry-pair p, with N_p realized alliances between time 1 and T is then the product of the probability of all realized alliances, i.e.

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

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

$$L = \prod_{p\in P} L^p(s_1, ..., s_{N_p}) \tag{C.3}$$

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 E6.

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

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

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

The conditional logit model, in general, does not allow for the unconditional marginal effects associated with individual regression coefficients to be recovered, but the exponential of the estimated coefficients can be interpreted as an odds ratio. If a pair of firms shares a banker (*same banker=1*) it is 1.462 times as likely to enter a strategic alliance in any given year as it would be if it did not. Similarly, the odds ratio for being connected through the banker network in any manner (*banker connection=1*) is 1.336, so a firm-pair is 1.336 as likely to enter an alliance if it is connected every year. The base case for the interpretation of the odds ratio in Column 3 is a firm-pair that shares the same banker. Hence a firm pair connected indirectly with *distance=1* is only 0.839 times as likely to enter a strategic alliance as it would be if it shared the same banker, decreasing further to 0.705 for *distance=2*, 0.592 for *distance=3* and so on. Finally, in the discrete specification in Column 4 the base case is that of a firm-pair unconnected through the network, implying a pair of firms connected directly (*distance=0*) is 1.533 times as likely to enter a strategic alliance than it would be if it was unconnected, decreasing to 1.292 times for an indirect connection of order 1 (*distance=1*).[30]

In summary, Table E6 shows that our results hold in the sequenced conditional logit specification. Because our unit of observation is a firm-pair, we do not have a clear prior on the impact of individual firms' financial characteristics on a pair's propensity to enter an alliance and therefore do not control for them in our main specification. A robustness test in Appendix E adds controls for sales, tangibility of assets and financial leverage, and shows that our results remain economically and statistically very similar.

An additional robustness test in Appendix E estimates the sequenced conditional logit model in its more restrictive fixed capacity specification. The corresponding results are both economically and statistically very similar to those in the variable capacity model.

C.2 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.

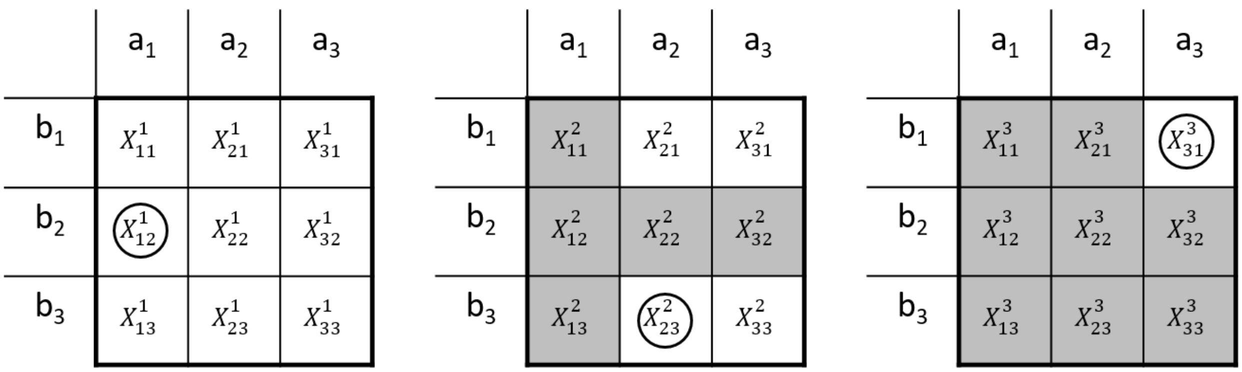
[30]Note that the odds ratio for *same banker* in Column 1 and *distance* $= 0$ in column four are different because the base case is a different one; in Column 1 the base case is not sharing the same banker, in Column 4 it is not having any connection, even an indirect one, through a banker network.

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 C1 illustrates the set of conditioning outcomes at each point in time for the fixed capacity model.

Figure C1: 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) $t = 3$

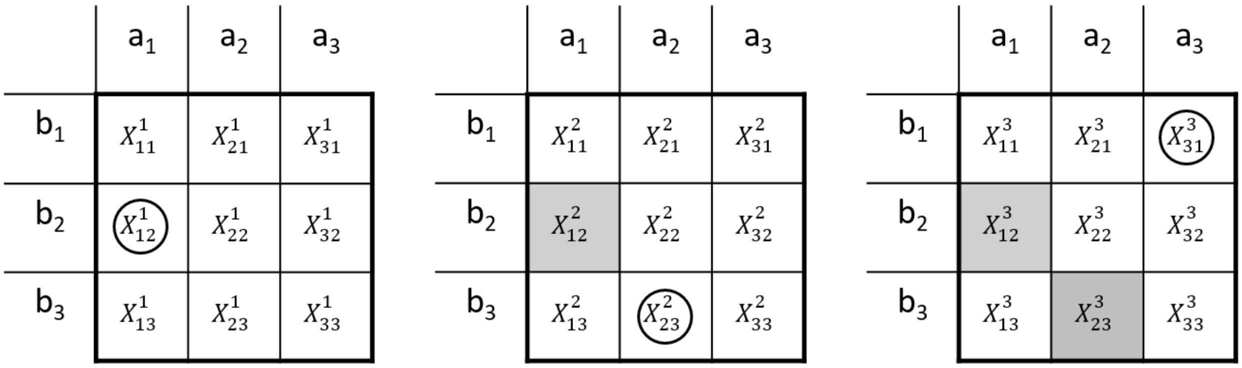
At $t = 1$, there are nine different alliances to choose from. The probability of observing $\{a_1, b_2\}$ is $\frac{e^{X_{12}^1 \beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X_{ij}^1 \beta}}$. Because both a_1 and b_2 only enter one alliance each, both have reached their alliance capacity and are removed from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

$$L^{ab} = \left(\frac{e^{X_{12}^1 \beta}}{\sum_{i=1}^3 \sum_{j=1}^3 e^{X_{ij}^1 \beta}} \right) \left(\frac{e^{X_{23}^2 \beta}}{e^{X_{21}^2 \beta} + e^{X_{23}^2 \beta} + e^{X_{31}^2 \beta} + e^{X_{33}^2 \beta}} \right) \tag{C.4}$$

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 C2 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.

Figure C2: 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) $t = 3$

This time, the likelihood function L^{ab} for industry-pair $\{a, b\}$ is given by

(C.5)

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

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 $\{c, d\}$.

D Additional Description of the Data

Table D1: 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.
Bank loan related characteristics	
BANKER_NETWORK_DISTANCE	Minimum distance between the two firms' loan officers through the network, zero meaning both have the same loan officer. The measure has been winsorized from above at three.
SAME_BANK	Both firms have taken out at least one loan from the same lead arranger/lead agent.
SAME_BANKER	Both firms have taken out a loan from the same banker.
BANKER_CONNECTION	The two firms are connected through the banker network (regardless of distance).
ONE_HAS_A_SYNDICATED_LOAN	At least one party to a strategic alliance has borrowed in the syndicated loan market since the inception of electronic filing.
BOTH_HAVE_A_SYNDICATED_LOAN	Both parties to an alliance have borrowed in the syndicated loan market since the inception of electronic filing.

E Additional Results

Table E1: First Difference Model
The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers based on a first difference model. The unit of observation is a firm-pair-year and the dependent variable is the first difference in alliance status, i.e. an indicator variable equal to one if a certain firm-pair enters a strategic alliance during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. SAME_BANKER is equal to one if the firm-pair has a banker in common. BANKER_NETWORK_DISTANCE measures how many banker to banker connections are required to establish a connection between the two firms, zero indicating none. BANKER_NETWORK_CONNECTION is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double clustered by firm one and firm two. For ease of exposition, all coefficients have been multiplied by 100. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Δ SAME_BANKER	0.1498***			
	(2.74)			
Δ BANKER_NETWORK_CONNECTION		0.0462***		
		(2.58)		
Δ BANKER_NETWORK_DISTANCE			0.0043	
			(0.24)	
Δ (DISTANCE = 0)				0.1839***
				(3.17)
Δ (DISTANCE = 1)				0.0523**
				(1.98)
Δ (DISTANCE = 2)				0.0311**
				(2.14)
Δ (DISTANCE > 2)				0.0267
				(1.00)
Δ SAME_BANK	0.0309***	0.0300***	0.0817**	0.0289***
	(3.00)	(2.94)	(2.19)	(2.85)
Industry 1-year FE	Yes	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes	Yes
N	5,533,280	5,533,280	309,532	5,533,280
R^2	0.0006	0.0006	0.0036	0.0006

Table E2: Linear Probability Model with Firm-Year Fixed Effects

The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers. The tests follow Table 3 but are augmented with firm 1-year and firm 2-year fixed effects. 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 before or during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. SAME_BANKER is equal to one if the firm-pair has a banker in common. BANKER_NETWORK_DISTANCE measures how many banker to banker connections are required to establish a connection between the two firms, zero indicating none. BANKER_NETWORK_CONNECTION is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double clustered by firm one and firm two. For ease of exposition, all coefficients have been multiplied by 100. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
SAME_BANKER	0.4220***			
	(3.26)			
BANKER_NETWORK_CONNECTION		0.0753*		
		(1.93)		
BANKER_NETWORK_DISTANCE			0.0510	
			(0.90)	
DISTANCE = 0				0.4777***
				(3.40)
DISTANCE = 1				0.0821
				(1.51)
DISTANCE = 2				0.0238
				(0.62)
DISTANCE > 2				0.0005
				(0.01)
SAME_BANK	-0.0013	-0.0008	0.0117	-0.0044
	(-0.06)	(-0.04)	(0.17)	(-0.21)
Firm 1-year FE	Yes	Yes	Yes	Yes
Firm 2-year FE	Yes	Yes	Yes	Yes
Firm-pair FE	Yes	Yes	Yes	Yes
N	6,370,712	6,370,712	359,605	6,370,712
R^2	0.7493	0.7493	0.8436	0.7493

Table E3: Linear Probability Model with Time-Phased Network Connections
The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers. The tests follow Table 3 but banker-to-firm, bank-to-firm and banker-to-banker connections require that at least one interaction between the parties took place *within the last five years.* The unit of 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 before or during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. SAME_BANKER is equal to one if the firm-pair has a banker in common. BANKER_NETWORK_DISTANCE measures how many banker to banker connections are required to establish a connection between the two firms, zero indicating none. BANKER_NETWORK_CONNECTION is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors double clustered by firm one and firm two. For ease of exposition, all coefficients have been multiplied by 100. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
SAME_BANKER	0.1726*			
	(1.76)			
BANKER_NETWORK_CONNECTION		0.1219***		
		(2.81)		
BANKER_NETWORK_DISTANCE			0.0149	
			(0.49)	
DISTANCE = 0				0.2247**
				(2.10)
DISTANCE = 1				0.1540***
				(2.76)
DISTANCE = 2				0.0676**
				(2.00)
DISTANCE > 2				0.0517
				(1.35)
SAME_BANK	0.0159	0.0121	0.0586	0.0117
	(0.68)	(0.51)	(1.47)	(0.49)
Firm-pair FE	Yes	Yes	Yes	Yes
Industry 1-year FE	Yes	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes	Yes
N	6,370,758	6,370,758	189,307	6,370,758
R^2	0.7443	0.7443	0.8684	0.7443

Table E4: Influence of Banker Networks on the Formation of Strategic Alliances: Matched-Pairs OLS Regression Results
The table displays estimates for firms' likelihood of entering a strategic alliance given whether and how closely they are connected through the network of bankers. The unit of 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 or earlier during the sample period. For each firm-pair that ever enters a strategic alliance, a pair of control firms is chosen and added to the sample. Control firms are selected by choosing the firm in the same industry group that, during the year in which the alliance is observed, minimizes the Mahalanobis-distance for the natural logarithm of sales, the natural logarithm of age, the ratio of intangibles to total assets and the market-to-book ratio between the original and the matched firm and that is not a member of the original firm-pair entering the alliance. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. SAME_BANKER is equal to one if the firm-pair has a banker in common. BANKER_NETWORK_DISTANCE measures how many banker to banker connections are required to establish a connection between the two firms, zero indicating none. BANKER_NETWORK_CONNECTION is an indicator equal to one if the two firms are connected through the network of bankers. Parentheses contain t-statistics calculated from standard errors clustered by firm one and firm two. For ease of exposition, all coefficients have been multiplied by 100. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
SAME_BANKER	3.7268			
	(1.52)			
BANKER_NETWORK_CONNECTION		9.6516***		
		(4.65)		
BANKER_NETWORK_DISTANCE			3.3968	
			(1.36)	
DISTANCE = 0				8.8698***
				(3.04)
DISTANCE = 1				9.4838***
				(4.05)
DISTANCE = 2				10.8591***
				(3.76)
DISTANCE > 2				9.4218
				(1.47)
SAME_BANK	0.1092	-0.5318	6.7435**	-0.5133
	(0.07)	(-0.32)	(2.15)	(-0.30)
Firm-pair FE	Yes	Yes	Yes	Yes
Industry 1-year FE	Yes	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes	Yes
N	43,946	43,946	5,605	43,946
R^2	0.7073	0.7083	0.7971	0.7083

Table E5: Banker Networks Outside the Large Banks
The table displays results from linear probability models regarding the effect of banker connections when limiting the network to smaller banks. We re-estimate our network dropping the largest underwriters in our sample (JPMorgan Chase, Citi, Bank of America, Wells Fargo, U.S. Bancorp and SunTrust). All other variables are defined as before. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. Parentheses contain t-statistics. Standard errors have been double clustered by firm one and firm two. For ease of exposition, all coefficients have been multiplied by 100. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
SAME_BANKER	0.7059***			
	(3.06)			
BANKER_NETWORK_CONNECTION		0.3125***		
		(3.36)		
BANKER_NETWORK_DISTANCE			0.0262	
			(0.51)	
DISTANCE = 0				0.8354***
				(3.33)
DISTANCE = 1				0.3020***
				(2.88)
DISTANCE = 2				0.2048***
				(2.66)
DISTANCE > 2				-0.0319
				(-0.67)
SAME_BANK	0.3327***	0.3300***	-0.0821	0.3274***
	(3.45)	(3.41)	(-0.29)	(3.39)
Firm-pair FE	Yes	Yes	Yes	Yes
Industry 1-year FE	Yes	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes	Yes
N	6,056,406	6,056,406	50,500	6,056,406
R^2	0.7484	0.7484	0.8778	0.7485

Table E6: Influence of Banker Networks on the Formation of Strategic Alliances: Variable Capacity Model

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

	(1)	(2)	(3)	(4)
SAME_BANKER	0.380***			
	(3.31)			
BANKER_NETWORK_CONNECTION		0.290***		
		(4.28)		
BANKER_NETWORK_DISTANCE			-0.175*	
			(-1.92)	
DISTANCE = 0				0.427***
				(3.69)
DISTANCE = 1				0.256***
				(2.81)
DISTANCE = 2				0.244
				(1.63)
DISTANCE > 2				0.071
				(0.24)
SAME_BANK	0.042	0.019	0.017	0.006
	(0.71)	(0.31)	(0.12)	(0.11)
SAME_STATE	0.382***	0.390***	0.452***	0.387***
	(7.57)	(7.72)	(2.72)	(7.65)
PREVIOUS_ALLIANCES	0.025***	0.025***	0.019***	0.025***
	(30.17)	(30.21)	(7.92)	(30.19)
N	529,323	529,323	24,844	529,323
Prob > χ^2	0.000	0.000	0.000	0.000

Table E7: Variable Capacity Sequenced Conditional Logit Model with Additional Control Variables

The table displays results from a maximum likelihood estimation of the variable capacity sequenced conditional logit model as the one displayed in Table E6 but controlling for additional firm-pair characteristics. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. The unit of observation is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance during the year of observation. A firm's maximum alliance capacity is assumed to be unlimited. SAME_BANKER is equal to one if the firm-pair has a banker in common. BANKER_NETWORK_DISTANCE measures how many banker to banker connections are required to establish a connection between the two firms, zero indicating none (i.e. the firms share the same banker). BANKER_NETWORK_CONNECTION is an indicator equal to one if the two firms are connected through the network of bankers. The (omitted) base category for the indicator variables in Column 4 is two firms *not* being connected through the network (i.e. infinite distance). Financial characteristics have been winsorized at the 2 and 98% level. Parentheses contain z-statistics. Industry-pair-year fixed effects are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
SAME_BANKER	0.291**			
	(2.44)			
BANKER_NETWORK_CONNECTION		0.238***		
		(3.39)		
BANKER_NETWORK_DISTANCE			-0.052	
			(-0.53)	
DISTANCE = 0				0.333***
				(2.77)
DISTANCE = 1				0.197**
				(2.12)
DISTANCE = 2				0.253*
				(1.69)
DISTANCE > 2				0.083
				(0.27)
Ln(TOTAL_SALES)	0.296***	0.295***	0.284***	0.295***
	(20.06)	(19.94)	(3.46)	(19.93)
AVG_TANGIBILITY_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 E8: Influence of Banker Networks on the Formation of Strategic Alliances: Fixed Capacity Model

The table displays results from a maximum likelihood estimation of the fixed capacity sequenced conditional logit model. The unit of observation is a firm-pair-year and the dependent variable is an indicator variable equal to one if a certain firm-pair has entered a strategic alliance during the year of observation. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. A firm's maximum alliance capacity is assumed to be 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_NETWORK_CONNECTION is an indicator equal to one if the two firms are connected through the network of bankers. The (omitted) base category for the indicator variables in Column 4 is two firms *not* being connected through the network. Parentheses contain z-statistics. Industry-pair-year fixed effects are implicitly embedded in the conditional logit estimation procedure. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
SAME_BANKER	0.298***			
	(2.59)			
BANKER_NETWORK_CONNECTION		0.181***		
		(2.63)		
BANKER_NETWORK_DISTANCE			-0.156*	
			(-1.67)	
DISTANCE = 0				0.327***
				(2.81)
DISTANCE = 1				0.156*
				(1.69)
DISTANCE = 2				0.080
				(0.52)
DISTANCE > 2				0.008
				(0.03)
SAME_BANK	0.176***	0.167***	0.008	0.153**
	(2.94)	(2.77)	(0.06)	(2.50)
SAME_STATE	0.319***	0.324***	0.398**	0.321***
	(6.26)	(6.37)	(2.35)	(6.30)
N	308,459	308,459	12,866	308,459
Prob > χ^2	0.000	0.000	0.031	0.000

Table E9: First Stage Results of IV Estimation

First stage estimates for the IV results displayed in Table 4. The instrumental variable BANKER_MOVED is an indicator for whether at least one banker with a previous relationship with one firm moved to a new employing bank that has previously extended a loan to the other firm over the previous two years. Parentheses contain t-statistics. Standard errors have been double clustered by firm one and firm two. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. For ease of exposition, all coefficients have been multiplied by 100.

	SAME_BANKER	BANKER_NETWORK_CONNECTION	BANKER_NETWORK_DISTANCE
BANKER_MOVED	4.4786***	7.5338***	-8.0028***
	(3.51)	(3.58)	(-3.30)
SAME_BANK	1.9028***	10.0114***	-7.3787***
	(8.28)	(10.65)	(-4.70)
Firm-pair FE	Yes	Yes	Yes
Industry 1-year FE	Yes	Yes	Yes
Industry 2-year FE	Yes	Yes	Yes
N	6,370,752	6,370,752	359,662
Kleibergen-Paap F.	12.3459	12.7831	10.8773

Table E10: Banker Networks and Physical Distance

The table displays results from linear probability models regarding the heterogeneous effect of banker connections based on physical distance. The variable DISTANCE_BETWEEN_FIRMS_AND_BANKERS measures the average physical distance between the two firms in a pair and their respective banker, DISTANCE_BETWEEN_FIRMS is the measure of the physical distance between the two firms in a pair. The sample consists of all publicly listed non-financial US firms in Compustat that enter at least one strategic alliance between 2002 and 2013. Parentheses contain t-statistics. Standard errors have been double clustered by firm one and firm two. For ease of exposition, all coefficient estimates have been multiplied by 100. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)
SAME_BANKER	2.2337**	2.0540**
	(2.34)	(2.34)
SAME_BANK	0.0744**	0.9708**
	(2.12)	(2.19)
SAME_BANKER × Ln(DISTANCE_BETWEEN_FIRMS_AND_BANKERS)	0.1026*	0.0880*
	(1.83)	(1.70)
SAME_BANKER × Ln(DISTANCE_BETWEEN_FIRMS)	-0.3605**	-0.3207**
	(-2.34)	(-2.23)
SAME_BANK × Ln(DISTANCE_BETWEEN_FIRMS)		-0.1568***
		(-2.79)
SAME_BANK × Ln(DISTANCE_BETWEEN_FIRMS_AND_BANKERS)		0.0317
		(1.06)
Ln(DISTANCE_BETWEEN_FIRMS_AND_BANKERS)	0.0152	0.0088
	(1.14)	(0.84)
Firm-pair FE	Yes	Yes
Year FE	Yes	Yes
N	922,135	922,135
R^2	0.8477	0.8477